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Modeled intermittency risk for small streams in the Upper Colorado River Basin under climate change

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SUMMARY

Longer, drier summers projected for arid and semi-arid regions of western North America under climate change are likely to have enormous consequences for water resources and river-dependent ecosystems. Many climate change scenarios for this region involve decreases in mean annual streamflow, late-summer precipitation and late-summer streamflow in the coming decades. Intermittent streams are already common in this region, and it is likely that minimum flows will decrease and some perennial streams will shift to intermittent flow under climate-driven changes in timing and magnitude of precipitation and runoff, combined with increases in temperature. To understand current intermittency among streams and analyze the potential for streams to shift from perennial to intermittent under a warmer climate, we analyzed historic flow records from streams in the Upper Colorado River Basin (UCRB). Approximately two-thirds of 115 gaged stream reaches included in our analysis are currently perennial and the rest have some degree of intermittency. Dry years with combinations of high temperatures and low precipitation were associated with more zero-flow days. Mean annual flow was positively related to minimum flows, suggesting that potential future declines in mean annual flows will correspond with declines in minimum flows. The most important landscape variables for predicting low flow metrics were precipitation, percent snow, potential evapotranspiration, soils, and drainage area. Perennial streams in the UCRB that have high minimum-flow variability and low mean flows are likely to be most susceptible to increasing streamflow intermittency in the future.

1. Introduction

The effects of climate change on river discharge in the western US are of strong interest to scientists, resource managers and policy makers. Some studies have revealed that peak streamflow timing has shifted to earlier in the spring over the last century and that runoff is likely to continue to occur earlier under most future climate scenarios (Hodgkins et al., 2003; Stewart et al., 2005; Rood et al., 2008; Clow, 2010). In addition, streamflow magnitude during late spring and summer has also shown a marked decline over the last century (Zhang et al., 2001; Burn and Hag Elnur, 2002; Rood et al., 2008; Leppi et al., 2011). According to several studies, mean annual streamflow is projected to decrease significantly over the next 100 years in the southwestern US (Christensen and Lettenmaier, 2007; Barnett and Pierce, 2009; Jerla et al., 2012; Seager et al., 2013). However, some have suggested strong seasonal signatures will be associated with this change in average conditions, with winter precipitation and streamflow increasing (especially in northern latitudes) and late summer and fall precipitation and streamflow declining (especially in southern latitudes) under climate change in western North America (Milly et al., 2005; Cayan et al., 2008; CWCB, 2010; Seager et al., 2013). In arid and semiarid regions of the western US where intermittent streams are common, some studies show potential increases in minimum flow (Döll and Schmied, 2012) but most studies predict that minimum flows will decrease and the number of zero-flow days will increase in the future (Das et al., 2011; Leppi et al., 2011; Jaeger et al., 2014). Decreased minimum flows could lead some perennial streams to shift to intermittent streamflow regimes under climate-driven changes in timing and magnitude of precipitation and runoff, and increases in temperature.

Decreasing flows and the potential for streams to shift streamflow regime from perennial to intermittent could have significant implications for human water use as well as riverine ecosystems

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(Arthington et al., 2013). Changes to key hydrologic factors, such as minimum flow duration and riparian water tables, are likely to affect important ecological functions. In the southwestern US, it has been shown that both riparian plant and aquatic macroinvertebrate community structure depend on the dominant hydrologic regime (intermittent vs. perennial streams) and ecoregion (desert vs. mountain streams) (Stromberg et al., 2005, 2010; Shaw and Cooper, 2008; Brasher et al., 2010; Miller and Brasher, 2011). A critical first step to proactive management of these river basins is to better understand hydrologic thresholds associated with shifts from perennial to intermittent streamflow, so that we can model where such thresholds are likely to be crossed under potential future climate regimes.

In this study, we establish basic hydrologic relationships for small streams in the Upper Colorado River Basin (UCRB) and then build upon those relationships to understand how hydrology may shift under future projected climate change. Our first objective was to understand historic relationships between inter-annual variability in climatic factors (annual precipitation and temperature) and streamflow intermittency along gaged streams that already experience some intermittency. We focused our research on streams in the UCRB, a region that is projected to experience large future climate shifts (Christensen and Lettenmaier, 2007; Clow, 2010; Seager et al., 2013).

Our second objective was to model minimum flow metrics from existing daily discharge time series. Hydrologic modeling efforts that aim to simulate future streamflow conditions generally predict synthetic metrics (such as mean annual flow), which do not lend insight into possible future minimum flows (Christensen and Lettenmaier, 2007; Barnett and Pierce, 2009). Where modeling of minimum flows is attempted, estimates are generally associated with a large degree of error (Wenger et al., 2010) although recent efforts have shown considerable improvement (Leppi et al., 2011; Jaeger et al., 2014). Our approach was to examine existing streamflow gage data to relate historic low flow measures to commonly modeled flow metrics (mean daily flow, peak flow, and peak flow timing). We reasoned that annual timing of peak runoff, mean daily flow, and annual maximum flow would explain some variation in the observed annual minimum flows across these sites and thus provide a basis for estimating the likelihood of future low flows and the vulnerability of perennial streams becoming intermittent under future changes in mean flows, peak flows, and peak flow timing (Poff and Ward, 1989).

Our third objective was to understand the distribution of low flow hydrology across the landscape by spatial modeling of several selected streamflow metrics using environmental variables such as climate, geology, soils and land cover. With an understanding of the environmental conditions that are likely to drive variation in low flow across the landscape, we can suggest where thresholds of stream intermittency currently exist and where future vulnerabilities may occur in a drying climate (Snelder et al., 2013).

2. Methods

2.1. Study area

The Colorado River is one of the most intensively managed river systems in the world and a vital water resource in the western US, supplying water for cities, agriculture, energy production, and natural ecosystems across seven states and two countries (Sabo et al., 2010). The Upper Colorado River Basin (UCRB) extends from southwestern Wyoming to northern Arizona and New Mexico, and includes the western half of Colorado and the eastern half of Utah (Fig. 1). The headwater streams of the basin form at high elevations in the Wind River, Uinta, Wasatch and Rocky Mountains. Annual precipitation varies widely across the region with the higher elevations receiving as much as 67 cm and lower elevations receiving 13–25 cm (Hereford et al., 2002). Precipitation in the headwaters is dominated by snow accumulation from November to March/April, which subsequently melts during the late spring and early summer months and average peak snow thickness varies widely with elevation and land cover (Clow et al., 2012). Correspondingly, higher elevation and northern streams in the basin are characterized by snowmelt peak runoff in the late spring that decreases to base flow in the late summer and early fall (Poff and Ward, 1989). Streams in the southern portion of the basin may experience a second streamflow peak in mid-to-late summer associated with rainfall from the North American Monsoon, and this monsoon rainfall is often the primary driver of annual flow in smaller, southern UCRB streams (Hereford and Webb, 1992; Ely, 1997; Hereford et al., 2002; Gochis et al., 2006).

2.2. Gage selection

We identified streamflow gages within the UCRB from the National Hydrography Plus Data Set (NHD+, http://www.horizon-systems.com/nhdplus/index.php) and acquired information on all USGS gages that operated between 1895 and 2009 for a total of 1146 gages. We eliminated gages that failed to meet several specific criteria. First, gages not on streams or rivers (e.g., canals and diversions) were eliminated, as were gages on large rivers. We defined large river reaches with a subjectively-chosen threshold of mean daily flow greater than 28 m^3/s and eliminated them because they are unlikely to shift hydrologic regime from perennial to intermittent. Next, we narrowed our sample to gages with at least 8 years of data, based on a detailed period-of-record analysis in our study region that determined 8 years to be a minimum record length necessary for certain low, mean and peak flow statistics to be reliable (Moline, 2007). We used some of the same low flow and high flow timing metrics that passed Moline's period-of-record ANOVA tests as well as mean flow metrics that are more stable year-to-year. Most of our gage records covered the second half of the twentieth century, at least overlapping the years 1975–1990, and included both dry and wet years (Cayan et al., 1998; Hereford et al., 2002; Appendix 1). Length of record for our study gages ranged from 8–83 years (median = 36 years). Sixteen perennial and fourteen intermittent stream gages had lengths of record 8–20 years, 26 perennial and 11 intermittent stream gages had lengths of record 21–40 years, and 44 perennial and four intermittent stream gages had lengths of record 41–83 years (Fig. 1, Appendix 1).

To identify gages with flows largely unaltered by human activities we gathered information from a variety of sources. We began by including those classified as unimpaired in the Hydro-Climate Data Network (HCDN, http://water.usgs.gov/GIS/metadata/usgswrd/XML/hcdn.xml). We compiled information about impacts for each gage location from USGS Annual Stream Gage Data Reports, The Nature Conservancy's database on stream diversions, the National Hydrography GIS layer, and the GAGES II dataset (Horizons System, 2006; TNC, 2010; USGS, 2010; Falcone, 2011). We eliminated stream gages with upstream dams and reservoirs, and with diversions greater than 20% of mean daily flow during the growing season (May–September). We chose 20% diverted flow as a threshold because "reference" streams are commonly defined on a sliding scale of impairment and there is not a widely-accepted standard for "minimally impacted streams" (Stoddard et al., 2006). We included 30 gages (25 perennial and 5 intermittent) that Falcone (2011) categorized as "non-reference" because they either had (a) more than 8 years of data between 1975 and 1990, which met our criteria, but less than 20 years of data, which failed Falcone's criteria, or (b) small diversions that we accounted for

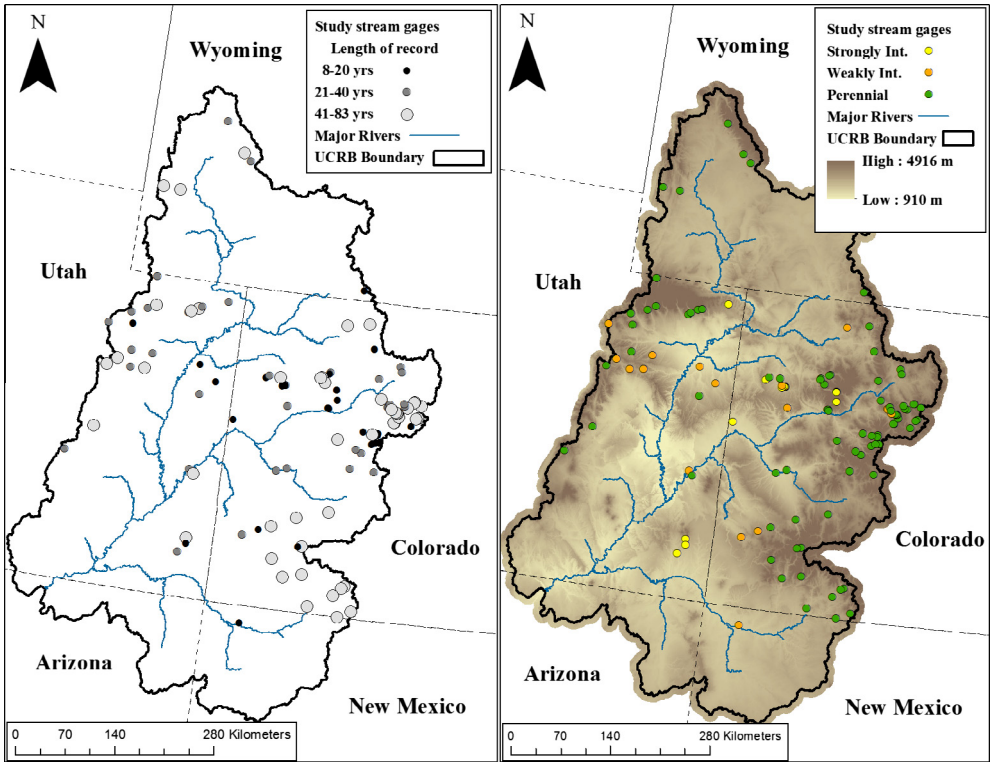

Fig. 1. Left panel: a map of the Upper Colorado River Basin (UCRB) study area showing major rivers and study gage locations by their length of record signified by size and color. Right panel: a map of the UCRB study area showing shaded elevation, major rivers, and study gage locations: strongly intermittent, weakly intermittent and perennial streams by color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

but did not meet Falcone's criteria, or (c) mining-related impacts that likely affected water quality but not discharge, thus meeting our criteria but failing Falcone's criteria for reference.

Our final gage set comprised 115 stream gages distributed broadly across the UCRB (Fig. 1). We calculated the annual minimum and maximum of daily mean flow, number of zero flow days, day of year of minimum flow and day of year of maximum flow for each year in each gage record. We also calculated 171 flow metrics for our study stream gages using Hydrologic Index Tool (HIT) software (Olden and Poff, 2003; Heasley, 2006). We selected nine of the 171 flow metrics most relevant to mean and low flows for spatial modeling, see *Objective* 3.

2.3. Streamflow categorization

Degree of intermittency is usually characterized along a continuum using the number and frequency of zero flow events and the percent of a flow record with zero flow (Poff and Ward, 1989; Knighton and Nanson, 2001; Larned et al., 2010; Stromberg et al., 2010). We used the flow indices "number of zero flow days" (mean number of zero flow days/year) and "zero flow months" (the percent of months in the flow record that had no flow for the entire month) to choose subjective thresholds for intermittency categories, similar to how others have categorized intermittent streams (Larned et al., 2010; Stromberg et al., 2010). We categorized stream reaches as strongly intermittent (SI) when >5% of months over the period of record were zero flow months and the number of zero flow days averaged across years was greater than 20 per year; weakly intermittent (WI) when 0–5% of months were zero flow months and the number of zero flow days averaged across years was 1–19 days per year; and perennial (P) when both the percent of zero flow months and the number of zero flow days averaged across years were zero. For example, if a stream had a twenty-year period of record (240 months), at least 12 months of the record would have to have zero flow for the entire month, and an average across years of at least 20 days per year of zero flow, for the stream to qualify as SI. The SI stream category may also include ephemeral streams; however, we did not distinguish between SI and ephemeral streams. Although we combine the SI and WI into one "intermittent" category for several of our analyses below, we have kept the distinction between SI and WI streams for visualization purposes, to understand their distribution on the landscape, and under *Objective* 3 to understand which flow metrics best predict intermittency.

To describe our population of study stream gages on the landscape, we compared elevation and drainage area among the three stream type categories by conducting a Welch's two-sample *t*-test for unequal samples between each category for both elevation and drainage area (*t* test function of the *stats* package in R; R Development Core Team; http://www.r-project.org/).

2.4. Objective 1 – climate drivers of flow intermittency

To assess relationships between climate and flow intermittency on an annual basis, we analyzed how annual variability in temperature and precipitation influences the number of zero flow days for intermittent streams. We modeled the number of zero flow days per year for intermittent (SI and WI combined) study streams with 5 temperature and precipitation variables that represent annual and seasonal trends in climate from the WorldClim Global Climate Database: annual precipitation, precipitation of the warmest quarter, precipitation of the coldest quarter, mean temperature of the warmest quarter, and mean temperature of the coldest quarter (http://www.worldclim.org/bioclim, Hijmans et al., 2005). Bioclimatic variables were preferable to monthly values of precipitation and temperature because they better represent the seasonality and

extremes of the regional climate (http://www.worldclim.org/bioclim). Annual values for each bioclimatic variable were extracted from GIS layers for a headwater point upstream of each stream gage location in each year. We also obtained annual values of the Palmer Drought Severity Index (PDSI) from the National Climate Data Center for the Upper Colorado River Basin climate divisions. PDSI is a composite index of dryness calculated from measured temperature and rainfall data (http://www.ncdc.noaa.gov/paleo/drought/drght_pdsi.html). For an explanation of the PDSI equation please see http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/cdus/palmer_drought/wpdanote.shtml and Palmer (1965). We used a mixed-effects multiple regression with Poisson errors to model the relationship between climate variables and the number of zero flow days in each year of stream gage record. Our mixed-effects model treated "site" as a random effect which considers each site as drawn randomly from a larger population, but data within each site as non-independent, thus correcting for potential within-site autocorrelation. We implemented the model using penalized quasi-likelihood and a Poisson error structure which accounts for over-dispersed, zero-inflated count data such as ours. This statistical approach allows for inference to the landscape scale from which sites were selected (*glmmPQL* function of the *MASS* package in R; Bolker et al., 2009).

2.5. Objective 2 – flow intermittency, low flows, and common flow metrics

To model the relationship between minimum daily flow and the predictor variables of mean daily magnitude, maximum daily magnitude, and maximum flow timing, we analyzed intermittent streams (SI and WI combined) separately from perennial stream gages, because intermittent streamflow data are zero-inflated. For both perennial and intermittent stream gages, data were tested for normality and natural log transformed $\ln(X + 0.001)$ as needed. For both perennial and intermittent analyses, we used mixed-effects models with "site" as a random effect, for reasons explained above, allowing for inference to landscape variables associated with the observed flow metrics and correction of potential within-site autocorrelation.

For perennial streams, we analyzed the relationship between annual mean daily flow and annual minimum daily flow with a mixed-effects linear regression on ln-transformed data. We also analyzed the relationships between timing (day of year) of maximum flow and annual minimum daily flow, and timing of maximum flow and annual mean daily flow with mixed-effects linear regressions on ln-transformed data (*lme* function of the *nlme* package in R).

For intermittent streams, we first analyzed the relationship between mean daily and minimum daily flows using only years with reported minimum flows greater than zero to avoid zero-inflation, and conducted a mixed-effects linear regression on ln-transformed data. We then analyzed the relationship between mean daily flow and the number of zero flow days, and annual maximum daily flow magnitude and the number of zero flow days using mixed-effects quasi-Poisson regressions on years with one or more zero flow days. We assumed a Poisson error structure because the number of zero flow days are counts and employing a quasi-Poisson regression accounts for over-dispersion in the count data (Crawley, 2007). We also analyzed the relationship between timing (day of year) of maximum daily flow and number of zero flow days using a mixed-effect quasi-Poisson regression. Last, we analyzed the relationship between timing of maximum flow and annual mean daily flow with mixed-effects linear regressions on ln-transformed data (*glmmPQL* function of the *MASS* package and *lme* function of the *nlme* package in R). Statistical modeling approaches for *Objectives* 1 and 2 are summarized in Table 1.

2.6. Objective 3 – landscape drivers of flow intermittency and low flows

To understand how low flow hydrology is conditioned by environmental variables we modeled the relationship between nine flow metrics related to minimum flow, mean flow and flow variability (Table 2) and environmental variables using conditional inference (CI) trees and random forests (Breiman, 2001; Hothorn et al., 2006; Strobl et al., 2009; Booker and Snelder, 2012). To derive environmental variables, we rectified our sample of stream gages to geographic data layers measuring climate (17), soils (2), geology (13), and land cover (7) based on Falcone (2011). We then calculated environmental variable values associated with the gage site location or the upstream watershed as appropriate for each environmental variable (Table 3). We used CI trees to understand environmental thresholds that relate to levels of stream flow metrics (Breiman, 2001; Cutler et al., 2007). We used random forests to reveal variables that are important for a flow metric but may have been masked in the CI tree by the highest ranking variables for a given split and also to rank flow metric models by predictive ability (Cutler et al., 2007). To improve explanatory power and fit of each random forest model, we conducted a model selection process where we optimized model fit with the fewest number of variables. We calculated a model improvement ratio for each variable: $\lfloor I_n/I_{\max} \rfloor$ where I_n is the importance value of a given variable and $I_{\max}$ is the maximum importance value for the given model (Murphy et al., 2010). We then iterated through model improvement ratio thresholds from 0 to 1 in 0.1 increments and kept all variables that fell above each given threshold. We selected the model that kept the minimum number of variables, minimized Mean Square Error (MSE) and maximized percentage of variation explained for each flow metric (Murphy et al., 2010). We assessed model fit with percentage of variation explained (psuedo-R^2), MSE, and a calculated *P*-value for the best model for each flow metric (Murphy et al., 2010).

Further, to understand which flow metrics best predict intermittency, we used a CI tree to model intermittency by minimum and mean flow values leaving out zero flow days and months to avoid circularity since we used those originally to define intermittency. To model CI trees we used the *ctree* function of the *party* package in R and to model random forests we used the *randomForest* function of the *randomForest* package of R.

Finally, we used the results from the intermittency CI tree and the best performing RF models to choose flow metrics to illustrate potential thresholds of stream intermittency under a drier future climate.

3. Results

3.1. Streamflow categorization

Approximately 75% of gaged stream reaches included in our analysis were perennial and the rest had some degree of intermittency (Table 4, Fig. 1). Perennial stream reaches were higher in elevation than strongly intermittent (SI) streams ($t = -2.30$, $P = 0.04$) and weakly intermittent (WI) streams ($t = -3.03$, $P = 0.007$). Perennial stream reaches also had larger drainage areas than SI streams ($t = -1.96$, $P = 0.064$); however, WI stream reaches varied greatly in drainage area (Fig. 2).

3.2. Objective 1 – climate drivers of flow intermittency

Mixed-effects multiple regression indicated that none of the individual precipitation or temperature variables had significant explanatory power; however, the Palmer Drought Severity Index

Table 1
Descriptions of statistical models used to address *Objectives* 1 and 2 for perennial and intermittent streams. Models are listed with corresponding response variables, predictor variables, and random effects.

Model	Response variable	Predictor variables	Random effect
Objective 1			
All streams			
Welch's two-sample *t*-test	Streamflow intermittency category	– Drainage area – Elevation	
Intermittent streams			
Mixed-effects Poisson multiple regression	Number of zero flow days/year	– Precipitation Annual Winter Summer – Temperature Winter Summer – Palmer Drought Severity Index	Site
Objective 2			
Perennial streams			
Mixed-effects linear regression	Annual minimum daily flow	– Annual mean daily flow – Timing of maximum flow	Site
	Annual mean daily flow	– Timing of maximum flow	Site
Intermittent streams			
Mixed-effects linear regression	Annual mean daily flow	– Annual minimum daily flow (when > 0) – Timing of maximum flow	Site
Mixed-effects quasi-Poisson regression	Number of zero flow days (when > 0)	– Annual mean daily flow – Maximum daily mean flow – Timing of maximum flow	Site

Table 2
Stream flow metrics modeled by environmental variables in the Upper Colorado River Basin under *Objective* 3 (units in parentheses).

Stream flow metric	Definition (units)
Intermittency	Strongly intermittent, weakly intermittent or perennial streams. See full definition of intermittency under *Objective* 1 methods
Minimum flow CV	Standard deviation of annual minimum flows times 100 divided by the mean of annual minimum flows (%)
Baseflow	The mean of the ratios of the minimum annual flow to mean annual flow for each year times 100 (dimensionless)
Zero flow days	Mean annual number of zero flow days (days)
Zero flow months on record	The number of months during which there was no flow, over the entire record (months)
7 day minimum	Mean of the annual minimums of a 7-day moving average for each year (cubic feet per second)
Frequency of low flow pulses	Mean of the annual average number of events below 5% of the mean flow for the entire record (number of events/year)
Specific minimum flow	Mean of the annual minimum flows divided by drainage area (cubic feet per second/square mile)
Specific mean daily flow	Mean for the entire flow record divided by drainage area (cubic feet per second/square mile)

(PDSI) was a significant predictor of the number of zero-flow days per year for SI and WI streams. PDSI was negatively related to zero-flow days; as PDSI decreased (dry years), number of zero flow days increased (Table 5).

3.3. Objective 2 – flow intermittency, low flows and common flow metrics

For perennial streams, there was a positive, significant relationship between annual mean daily flow and annual minimum daily flow. There was also a positive relationship between annual timing of maximum flow and annual mean daily flow: later maximum flow dates corresponded with higher annual mean daily flows. There was no relationship between annual timing of maximum flow and minimum daily flow (Table 6, Fig. 3).

For intermittent streams (SI and WI combined), there was also a positive relationship between annual mean daily flow and annual minimum daily flows. There was a negative relationship between the number of zero flow days per year and annual mean daily flow, but not maximum daily flow or its timing. There was, however, evidence of a negative relationship between timing of maximum flow and annual mean daily flow (Table 6, Fig. 4). The statistical significance of these relationships is not always obvious in a scatterplot (Fig. 4) because the mixed model accounts for the random effect "site", which is challenging to depict graphically.

In a posthoc *t*-test comparison, perennial and intermittent streams did not differ in mean day of peak flow ($t = 1.45$, $P = 0.157$); however, intermittent streams showed significantly greater variance in day of peak flow ($F = 15.86$, $P < 0.0001$). Annual mean daily flow was also significantly higher in perennial versus intermittent streams ($t = -6.74$, $P < 0.0001$).

3.4. Objective 3 – landscape drivers of flow intermittency and low flows

Of our nine random forest models, one explained 82% of variation and six explained 45–50% of the variation in flow metrics (Table 7). Precipitation, forest land cover, and PET were the most important variables for predicting mean flow. For low flow metrics, precipitation, percent snow, PET, R factor, and drainage area were important.

The CI tree model for the best random forest model (specific mean daily flow: mean flow adjusted by drainage area) corresponded to the important variables in the random forest model (Fig. 5, Table 7). Streams with higher flows corresponded to higher April precipitation, and lower flows to lower April precipitation (Fig. 5). December precipitation, percent forest cover, R factor, and annual basin precipitation also provided important variable thresholds for specific mean daily flow. For the other flow metric

Table 3
Environmental variables used to predict flow metrics on gaged streams in the Upper Colorado River Basin under *Objective* 3. Adapted from Falcone (2011). For full explanation of variables, see Falcone (2011).

Variable	Units	Data source
Watershed drainage area	km^2	USGS stream gage information
Mean annual precipitation	cm	800 m PRISM data, 1971–2000
Relative humidity	%	2 km PRISM data, 1961–1990
Average days of measurable precipitation	days	Derived from 2 km PRISM, 1961–1990
Mean-annual potential evapotranspiration (PET)	mm/year	Estimated using the Hamon (1961) equation on PRISM data 1961–1990
Snow percent of total precipitation (percent snow)	%	Mean for period 1901–2000; (McCabe and Wolock, 2009)
Average soil permeability	in/h	(Wolock, 1997)
Soil Rainfall and Runoff factor ("R factor")	100 s ft-tonf in/h/ac/yr	Rainfall and Runoff factor ("R factor" of Universal Soil Loss Equation); average annual value for period 1971–2000, PRISM
Mean January precip	cm	800 m PRISM data, 1971–2000
Mean February precip	cm	800 m PRISM data, 1971–2000
Mean March precip	cm	800 m PRISM data, 1971–2000
Mean April precip	cm	800 m PRISM data, 1971–2000
Mean May precip	cm	800 m PRISM data, 1971–2000
Mean June precip	cm	800 m PRISM data, 1971–2000
Mean July precip	cm	800 m PRISM data, 1971–2000
Mean August precip	cm	800 m PRISM data, 1971–2000
Mean September precip	cm	800 m PRISM data, 1971–2000
Mean October precip	cm	800 m PRISM data, 1971–2000
Mean November precip	cm	800 m PRISM data, 1971–2000
Mean December precip	cm	800 m PRISM data, 1971–2000
Dominant surficial geology (11)	n/a	Highest percent of area, surficial geology, Hunt (1979)
Dominant bedrock permeability (2)	n/a	Highest percent of area, bedrock geology (Wolock et al., 2004)
Watershed percent Developed	%	2006 NLCD data, Sum of classes 21–24
Watershed percent Forest	%	2006 NLCD data, Sum of classes 41–43
Watershed percent Planted/cultivated	%	2006 NLCD data, Sum of classes 81 and 82
Watershed percent Natural Barren	%	2006 NLCD data
Watershed percent Shrubland	%	2006 NLCD data
Watershed percent Herbaceous	%	2006 NLCD data
Watershed percent Wetlands	%	2006 NLCD data, Sum of classes 90 and 95

Table 4
Stream gages analyzed in this study, divided into "degree of flow intermittency" categories. See *Objective* 1 methods for category definitions. For each streamflow category four metrics are shown: number of gages, mean annual minimum flow (m^3/s), mean minimum flow coefficient of variation (CV, the standard deviation divided by the mean of the annual minimum flows times 100 (%)), mean baseflow index (mean of the ratios of the minimum annual flow to mean annual flow for each year).

Degree of flow intermittency	Number of gages	Mean annual minimum flow (m^3/s)	Mean minimum flow CV (%)	Mean baseflow index (ratio)
Perennial	86	0.38 ± 0.06	36.06 ± 2.19	0.172 ± 0.011
Weakly intermittent	17	0.021 ± 0.005	133.94 ± 16.01	0.071 ± 0.016
Strongly intermittent	12	0.001 ± 0.0007	299.67 ± 41.83	0.002 ± 0.001
Total study gages	115			

CI tree models, PET, drainage area, precipitation variables, and percent snow were again the most important variables (Appendix 2).

Stream flow intermittency in a CI tree model was best predicted by minimum flow CV and specific mean daily flow (Fig. 6). Greater minimum flow CV was associated with greater intermittency. Based on these results from the intermittency CI tree and the best performing RF models, we used the metrics "specific mean daily flow" and "minimum flow CV" to illustrate potential thresholds of stream intermittency under a drier climate. The intermittency CI tree model specified 61.84% minimum flow CV and 0.096 specific mean daily flow as threshold values separating sets of streams (Fig. 6). Streams that had greater than 61.84% minimum flow CV and greater than 0.096 specific mean daily flow included some of the driest streams: all WI and SI streams (Fig. 7). Streams that had greater than 61.84% minimum flow CV but less than 0.096 specific mean daily flow were moderately dry streams: they did not include any SI streams but included a mix of WI and perennial streams. We plotted specific mean daily flow and minimum flow CV values by stream type and included the thresholds 61.84% minimum flow CV and 0.096 specific mean daily flow to illustrate which perennial streams are the driest and may be the most threatened by climate drying (Fig. 7).

4. Discussion

Our results indicate that individual climate variables are poor predictors of inter-annual variation of zero-flow days on intermittent streams (SI and WI streams combined, Table 2). However, the composite precipitation and temperature index, Palmer Drought Severity Index (PDSI), was highly correlated with degree of stream intermittency. Dry years with combinations of high temperatures and low precipitation led to more zero-flow days. These findings suggest that potential increases in drought conditions under climate change will increase zero flow days. Studies of PDSI and other drought indices show that droughts will increase in frequency and intensity in southwestern North America due to increased temperature and evaporation (Cayan et al., 2010; Seager and Vecchi, 2010; Strzepek et al., 2010; Gutzler and Robbins, 2011; Wehner et al., 2011). Even if precipitation stays the same or increases in the future, increased evaporation due to warming is likely to outweigh changes in precipitation and increase overall aridity (Smith and Wagner, 2006).

Annual minimum flow for both intermittent and perennial stream reaches was most closely related to average flow. Although this relationship was significant for both intermittent and perennial

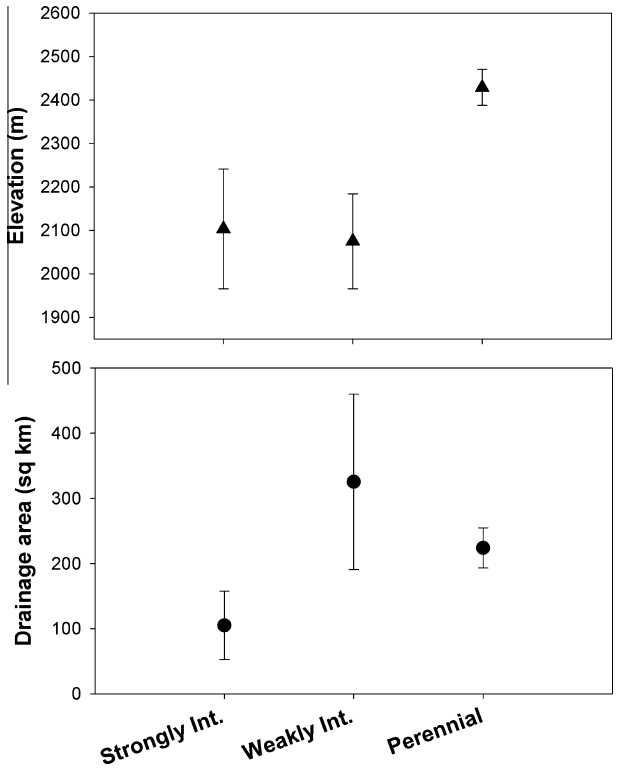

Fig. 2. Mean elevation ± SE (m, upper panel) and mean drainage area size ± SE (sq km, lower panel), for strongly intermittent, weakly intermittent and perennial study stream reaches.

streams, the relationship was somewhat noisier for intermittent streams (Table 6, Figs. 3 and 4). This is likely because the range of both mean and minimum flow values is larger, period of records are longer, and the sample size is larger for perennial streams. In addition, the physical conditions governing flow generation (soil moisture conditions, potential evapotranspiration, groundwater recharge, baseflow, etc.) are often different and sometimes more variable on intermittent streams than on perennial streams (Smakhtin, 2001). We also found that the number of zero flow days (for intermittent stream reaches: SI and WI combined) each year was best predicted by average flow. These findings suggest that under a drier future climate (Seager et al., 2007), decreased mean flow will be associated with reduced minimum flow and increased number of zero flow days. Our results provide empirical support from the historical record for prior studies that show mean and minimum flows decreasing under a projected warmer, drier future climate in the UCRB (Seager et al., 2007; Cayan et al., 2008; Koirala et al., 2014).

Surprisingly, we found only weak evidence that changes in the timing of maximum streamflow related to minimum flow. Our results suggest that a shift in maximum flow to earlier in the year (e.g., Clow, 2010), may not significantly modify minimum flow or zero flow days. Alternatively, the effect may be more complex than our analysis could detect. For example, the timing of maximum flow might interact with the magnitude of maximum flow and hydrologic conditions later in the summer to determine inter-annual variation in zero flow days. Further analyses are needed to determine if timing of maximum flow influences minimum flow magnitude and if other hydrologic variables condition the relationship.

We also found the negative relationship between average flow and maximum flow timing for intermittent streams to be counter-intuitive. However, in a posthoc analysis to explore timing of maximum flow in perennial versus intermittent streams, we found that although the average day of maximum flow for perennial and intermittent streams was not different, intermittent streams had greater variability in the day of maximum flow. This suggests that the intermittent stream group includes streams that have late-summer monsoon-associated peak flows as well as spring snowmelt peak flows. Intermittent streams also, on average, had lower average daily flows. Monsoon peak flow streams, whose peak flow occurs later in the year, are usually lower in elevation and have smaller mean annual flows than snowmelt streams (Moline, 2007). In comparison, snowmelt peak flow streams have relatively early peak flow and are associated with larger mean annual flows. Because our grouping of intermittent streams included both snowmelt peak streams with larger annual flows and monsoon peak streams with smaller annual flows, this leads to a negative relationship between maximum flow timing and average flow.

As expected, many of the landscape variables associated with climate and aridity were important for predicting mean and minimum flow metrics in our spatial analysis. Monthly and annual precipitation, potential evapotranspiration (PET), and percent snow were highly ranked variables for almost all of the mean and minimum flow metrics modeled. Higher precipitation, lower PET and higher percent snow were associated with higher mean and minimum flows and lower flow variability. Forest land cover also ranked highly for predicting mean flow, and the rainfall and runoff soil factor (R factor) was important for some of the lesser-ranked models. Unexpectedly, none of our geology variables proved important for predicting any of the flow metrics. Others such as Kroll et al. (2004) have also found that geologic variables are poor predictors of low flow. However, they used soil characteristics as a proxy for geology and then suggested that subsurface geologic variables, such as those we employed, should actually improve models of stream low flows (Kroll et al., 2004). Although the lack of importance of our geology variables is surprising, this result indicates that climate variables outweigh our chosen geologic

Table 5
Results of a mixed-effect multiple regression with Poisson errors modeling the number of zero flow days per year for intermittent streams with climate predictor variables (*Objective* 1). Climate predictor variables include annual precipitation, and precipitation and mean temperature in the warmest and coldest quarters (www.worldclim.org, Hijmans et al., 2005). Significant ($P < 0.05$) variables are shown in bold type.

Fixed effects	Estimate	SE	*t*-Statistic	*P*-value
Intercept	**2.9290**	**0.9024**	**3.2458**	**0.0012**
Annual precipitation	−0.0004	0.0003	−1.2024	0.2296
Precipitation of the warmest quarter	−0.0006	0.0008	−0.6569	0.5115
Precipitation of the coldest quarter	0.0007	0.0004	1.6640	0.0966
Mean temp of the warmest quarter	0.0520	0.0492	1.0577	0.2906
Mean temp of the coldest quarter	0.0082	0.0236	0.3490	0.7272
Palmer Drought Severity Index	**−0.0656**	**0.0172**	**−3.8237**	**0.0001**
Random effect	Variance	SD		
Site	1.5678	7.9672		

Table 6
Results from mixed-effect models used to model minimum flows and zero flow days by mean and maximum flows for perennial (top half) and intermittent (lower half) streams (*Objective* 2). For each model, the relationship modeled, resulting *t*-statistic, and *P*-value are given. Models where the predictor variable is significant are in bold type.

Mixed model fixed-effect relationships	*t*-Statistic	*P* value	Random effect "site"
Perennial streams			SD estimate
Ln(minimum flow) = 0.55 ∗ Ln(mean daily flow) − 1.96	**31.67**	**<0.001**	**0.83**
Ln(minimum flow) = 0.04 ∗ Ln(max flow day) − 2.16	0.85	0.39	1.42
Ln(mean daily flow) = 0.12 ∗ Ln(max flow day) − 0.56	**2.70**	**0.007**	**1.26**
Intermittent streams			
Ln(minimum flow) = 0.64 ∗ Ln(mean daily flow) − 3.54	**10.88**	**<0.001**	**0.69**
Zero flow days per year = exp(−1.50 ∗ mean daily flow + 4.63)	**−4.34**	**<0.001**	**0.78**
Zero flow days per year = exp(−0.04 ∗ maximum daily flow + 4.50)	−1.61	0.11	0.84
Zero flow days per year = exp(−0.0004 ∗ max flow day + 4.48)	−0.82	0.41	0.88
Ln(Mean daily flow) = −0.30 ∗ Ln(max flow day) − 1.21	**−3.00**	**0.003**	**1.87**

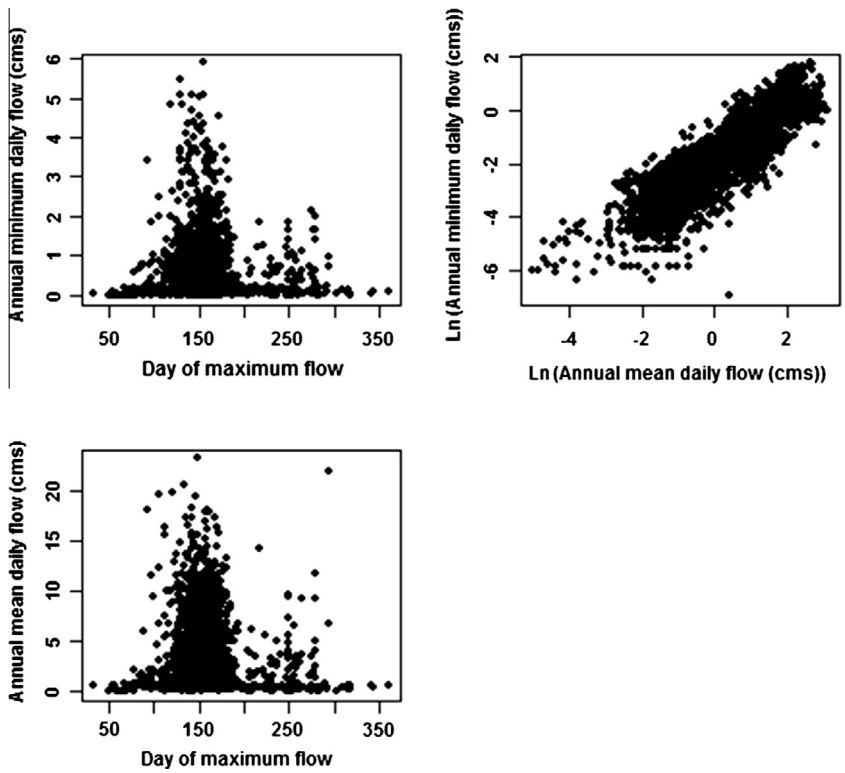

Fig. 3. For perennial study stream gages in the Upper Colorado River Basin: annual minimum daily flow (m^3/s) as a function of the day of the year of annual maximum daily mean flow (upper left panel), the natural log (Ln) of annual minimum flows plotted as a function of Ln of annual mean daily flows (upper right panel), and annual mean daily flow (m^3/s) as a function of the day of the year of annual maximum flow (lower left panel). Each point in each graph represents a year for a particular study stream reach.

variables for predicting these flow metrics in this region and at this scale. Results from our random forest and conditional inference tree modeling further support the idea that increased aridity in this region will decrease minimum flows, mean flows, increase minimum flow variability, and potentially increase zero flow days.

We used zero flow days and months to define intermittency in our study, however, we also tested which of the other flow metrics best predicted intermittency. Interestingly, intermittency was most strongly related to minimum flow variability (Fig. 6). Streams with zero flow days had much higher minimum flow variability, a relationship which has also been shown in other studies (Poff, 1992; Moliere et al., 2009; Kennard et al., 2010). If mean flows decrease and flow variation increases under drying summer conditions, then perennial streams with relatively high minimum flow CV and lower mean flow will be more likely to incur zero flow days and thus be at risk of crossing into intermittency (Fig. 7).

We acknowledge the likelihood that current hydro-climatic relationships (e.g., between drought and streamflow) will change under novel conditions in the future (Milly et al., 2008). Non-stationarity is an on-going challenge for climate change scientists; our understanding of past relationships is an important tool for trying to understand future relationships, but it is almost certain that the parameter values will change (Milly et al., 2008). Our study represents one starting point for understanding how low flows may change in the future and our predictions may be adjusted as our understanding of future hydroclimatic trends improves.

In general, individual streams will vary in their susceptibility to reduced minimum flows under drier conditions depending on other components of the physical environment that we were not able to measure, such as groundwater hydrology and floodplain soil characteristics (Murphey et al., 1977; Smakhtin, 2001; Tague et al., 2008). For example, streams that receive perennial groundwater inflows may not incur zero flow days, at least in the short term, despite increases in drought. In the long term, groundwater levels and inflows may also decrease in response to shifts in precipitation and increased drought; however, the lag time between

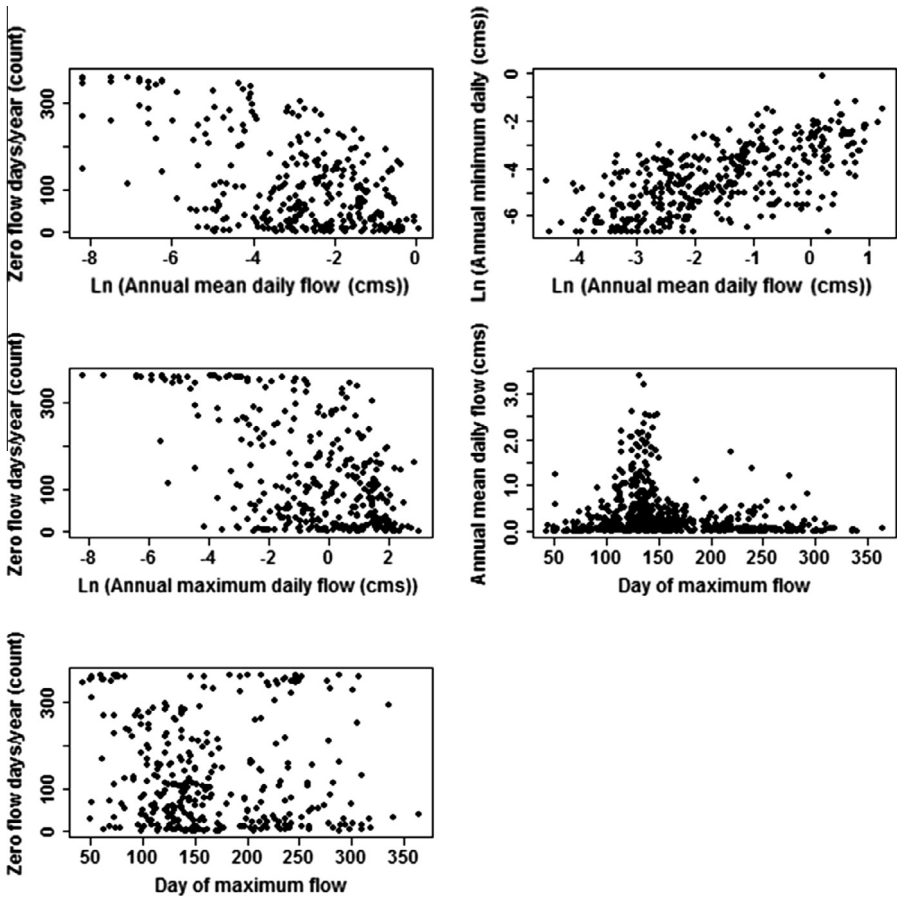

Fig. 4. For intermittent study stream gages in the Upper Colorado River Basin: zero flow days (count) plotted as a function of the natural log (Ln) of annual mean daily flow (m^3/s, upper left panel) and zero flow days (count) as a function of Ln annual maximum daily mean flow (m^3/s, middle left panel). Although in our statistical analysis we modeled un-transformed zero flow days with annual mean daily flow and with annual maximum daily mean flow, for visualization LN transformation was necessary for the predictor variables. Other plots include Ln of annual minimum daily flows (m^3/s) as a function of Ln of annual mean daily flows (m^3/s, upper right panel), annual mean daily flow (m^3/s) as a function of the day of the year of annual maximum flow (middle right panel), and zero flow days (count) as a function of the day of the year of annual maximum flow (lower left panel). Each point in each graph represents a year for a particular study stream reach.

Table 7
Results of random forest models using landscape variables to predict streamflow metrics (*Objective* 3). Models with better than 50% of variance explained are in bold type.

Stream flow metric	Top five predictor variables (in decreasing importance)	Variance explained (%)	*P*-value
Specific mean daily flow (adjusted by drainage area)	April precip, Percent forest land cover, Average days of measurable precipitation, Average annual basin precip, PET	**82.55**	**<0.001**
Frequency of low flow pulses	February precip, June precip, PET, May precip, Dec precip	**50.3**	**<0.001**
Minimum flow CV	Percent Snow, November precip, PET, February precip, R factor	49.8	<0.001
7 day minimum	Drainage area, August precip, October precip, September precip, January precip	49.4	<0.001
Zero flow months on record	R factor, Percent snow, December precip, Average days of measurable precipitation, Percent barren land cover	48.1	<0.001
Specific minimum flow (adjusted by drainage area)	December precip, Average annual basin precip, November precip, February precip, April precip	47.6	<0.001
Zero flow days per year	Percent snow, December precip, February precip, R factor, November precip	45.3	<0.001
Intermittency	Percent barren land cover, Drainage area, PET, June precip, November precip	OOB[a] error rate: 20	
Baseflow	Drainage area, February precip, Average annual basin precip, May precip, March precip	26.9	<0.001

[a] OOB = out-of-bag error rate which is a cross-validation measure calculated by classification random forests. Better models have lower OOB error rates. See Cutler et al. (2007) for details.

changes in climate and groundwater response will depend on the system and could vary from decades to centuries (Guay et al., 2004; Liu et al., 2004).

Stream flow patterns in ephemeral streams may be less modified by decreases in annual or minimum flows because these systems already flow only in direct response to individual precipitation events. An analysis by Botter et al. (2013) found that rain-driven streams with erratic hydrology will be more resilient and more likely to maintain their flow regimes under future climate changes than streams with more predictable flow regimes. Extreme events, such as large storms, are predicted to increase in frequency under climate change, and this could lead to over-all increased flows in ephemeral streams (Diffenbaugh et al., 2005; Stromberg et al., 2010).

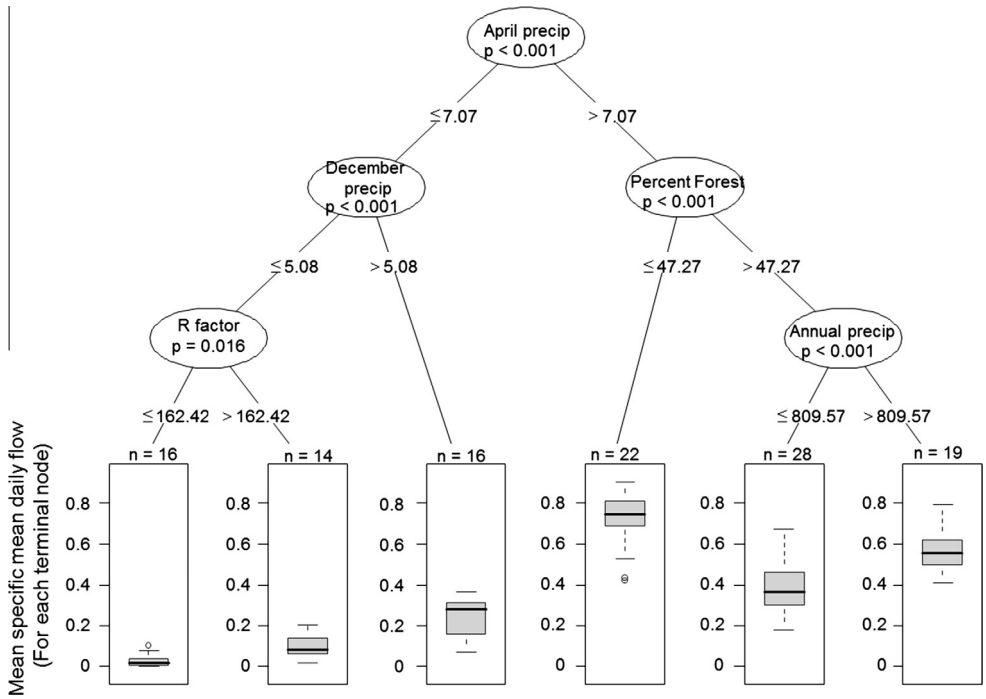

Fig. 5. Conditional inference tree model of specific mean daily flow using landscape predictor variables. See Table 3 for a definition of the predictor variables used. Ovals indicate the most significant variable for each split in the tree and the lines below each oval indicate the threshold value of that variable for the split. Box plots indicate the mean and variance of specific mean daily flow for the gage sites within each terminal node. N = the number of gage sites within a terminal node. At each terminal node, no predictor variable had a significant ($P < 0.05$) relationship to specific mean daily flow and thus no further subdivision was warranted.

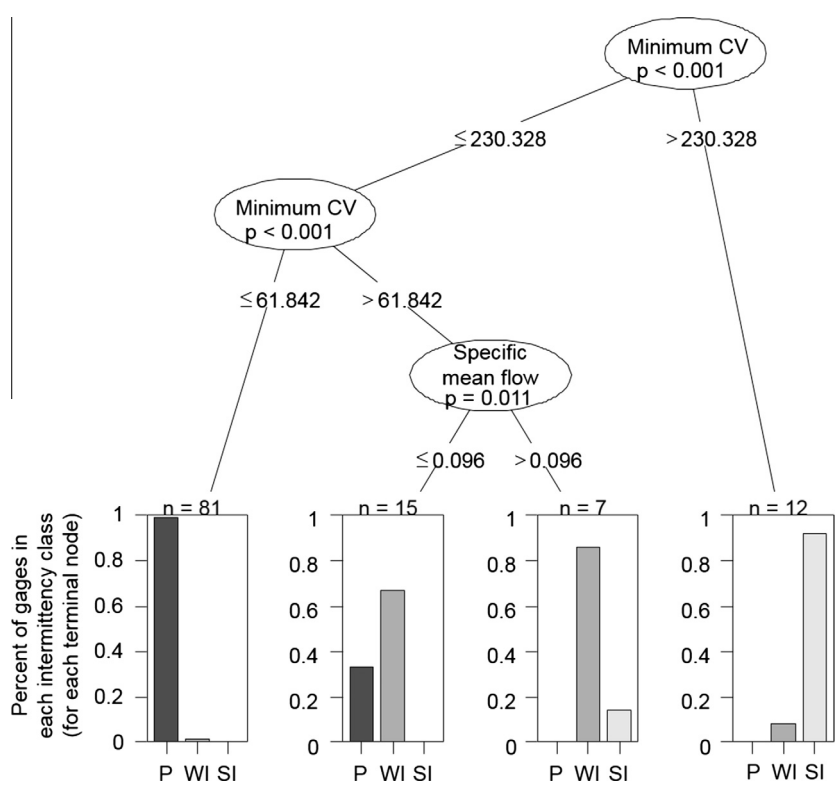

Fig. 6. Conditional inference tree model intermittency using stream flow predictor variables, except zero flow days and months. See Table 2 for a definition of the stream flow predictor variables used. Ovals indicate the most significant variable for each split in the tree and the lines below each oval indicate the threshold value of that variable for the split. Vertical bars show the proportion of strongly intermittent (SI, light gray), weakly intermittent (WI, medium gray), and perennial streams (P, dark gray) stream gages at a terminal node. N = the number of gage sites within a terminal node. At each terminal node, no stream flow predictors had a significant ($P < 0.05$) relationship to specific mean daily flow and thus no further subdivision was warranted.

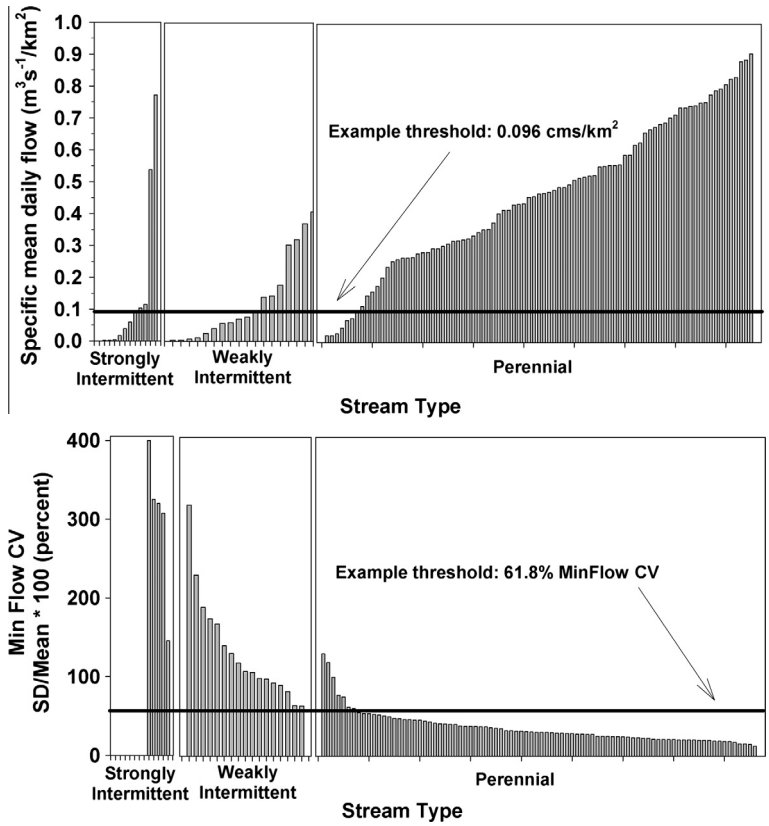

Fig. 7. Top: Specific mean daily flow (mean daily flow divided by drainage area, cm/km^2) for all study stream reaches by streamflow type: strongly intermittent (left panel), weakly intermittent (middle panel), and perennial (right panel). Example threshold value line is shown at 0.096 cm/km^2. Bottom: Minimum flow coefficient of variation (CV, standard deviation/mean $*$ 100, %) for all study stream reaches by streamflow type: strongly intermittent (left panel), weakly intermittent (middle panel), and perennial (right panel). Example threshold value line is shown at 61.8% minimum flow CV.

Hydrologic analyses on intermittent streams are challenging for a number of reasons, largely because there is a dearth of records and information on intermittent streams compared to perennial streams (Snelder et al., 2013; Datry et al., 2014). Stream gages are more often installed and have longer periods of record on perennial streams than intermittent streams (Moline, 2007; Carlisle et al., 2010; Snelder et al., 2013) Because of this, our analysis was biased towards perennial streams that are mostly in the northern portion and higher elevations of the basin whereas many ungaged, low-order intermittent streams are located in the southern part of the basin (Hereford, 1984; Poff, 1996; Moline, 2007). Thus, our analysis probably underrepresents intermittent streams and streams that are likely to shift toward greater intermittency under drier summer conditions. Further, the gage records that do exist on intermittent streams in the region are, on average, shorter than those on perennial streams (Fig. 1, Appendix 1). We used 8 years as a minimum period of record, based on Moline (2007) who analyzed 172 hydrologic metrics on 10 streams in our study region and calculated flow metrics at intervals between 5 and 48 years of record, starting in the same year. Moline (2007) concluded that at least 8 years of record was necessary for metrics to stabilize and be reliable. This is a shorter period than Kennard et al. (2010) determined was necessary for flow metrics to stabilize on intermittent streams in Australia (15 years). More period of record analyses on intermittent streams in different regions around the world are needed, given the potential for differences in multi-decadal wet and dry cycles to influence results (Mauget, 2003; Kennard et al., 2010). Lastly, another limitation of stream gage records is that they may not capture longitudinal variation in streamflow that is common, such as where perennial and intermittent reaches occur on the same stream (Larned et al., 2010; Jaeger et al., 2014). The limitations of our analysis and the lack of existing literature highlight the need for a better understanding of intermittent stream hydrology, supported by more empirical data (Smakhtin, 2001; Snelder et al., 2013).

5. Conclusions

Our results indicate that perennial streams in the UCRB with low minimum flows and high minimum flow variability may be vulnerable to increasing streamflow intermittency in the future. Large-scale hydrologic modeling efforts to project future streamflow in the UCRB indicate there will be declines in mean annual flow (Christensen and Lettenmaier, 2007; McCabe and Wolock, 2007; Barnett and Pierce, 2009). We have demonstrated a relationship between mean annual flow and minimum flows, indicating that declines in mean annual flows are likely to correspond with declines in minimum flows. Moreover, our spatial analysis showed that mean flow and minimum flow are closely tied to climate variables, also supporting the idea that increased aridity will lead to increased flow intermittency.

Projected increases in aridity and drought in the UCRB under climate change are expected to have substantial consequences for water resources and river-dependent ecosystems in the region (Diffenbaugh et al., 2005; Cayan et al., 2010). Streams that incur more zero flow days per year may see declines in riparian water table levels and shifts in associated riparian and aquatic ecosystems (Lite et al., 2005; Stromberg et al., 2010). Our study attempted to deal with un-impacted rivers and did not account for human

water use interactions with future hydrologic conditions. However, both human and natural ecosystems will be affected by a warmer and drier future climate and associated water resource limitations (Palmer et al., 2008).

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhydrol.2015.02.025.

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