Supplemental material for "Narrowing streamflow distribution can alter water allocation timing and quantity"

Materials and Methods

Streamflow data

Daily stream discharge data was obtained from the United States Geological Survey (USGS) for basins included in the Geospatial Attributes of Gages for Evaluating Streamflow, version II (GAGES II) dataset[1]. These 9,322 stream gauges were selected as those with at least 20 years of continuous data or those that were active as of 2009. From this dataset, 2,057 gauges are classified as "reference" gauges - those with a minimal amount of disturbance. We calculated streamflow statistics only on reference gauge-years with at least 90% of data not missing. We assume that reported zero values are true zeros and not missing values. Stream gauges have a mean of 47 (± 25 standard deviation) years of data. This dataset is published with station locations and associated watersheds draining to each station.

We also calculated trends in Q, CT, and SDoT on non-reference gauges to evaluate the impact of the choice to select reference gauges only (Figures S10-12). Results suggested that the presence of non-reference gauges confounded the signal, so we retained reference gauges only for all other analyses.

Separately, for the Rio Grande case study, we secured daily flow records for the Del Norte gauge (USGS 0822000) on Rio Grande from the USGS National Water Information System. While not a reference gauge in the main data set, it is the gauge that is utilized to set priority cutoffs along the Rio Grande in Colorado.

Climate data

Several gridded climate products are available and could be used to evaluate streamflow sensitivity to climate; here, we use the NClimGrid product because of its long period of record, with monthly climate data dating back to 1895 [2]. We use the 4-km monthly gridded average air temperature and precipitation. We sum water year (Oct 1 - Sept 30) precipitation and average water year temperature over each grid cell. For each gauge in the reference GAGES II dataset, we then sum total water year precipitation and average water year temperature over the contributing watershed area to obtain estimates of major climate variables contributing to streamflow quantity and timing at each location.

Water right and diversion data

Because states, not the federal government, are generally vested with water rights jurisdiction, associated data is compartmentalized and of varying quality across states. To gain insights into general patterns of appropriative water rights, we accessed water right allocation data for the 17 western states from the Western States Water Data Access and Analysis Tool (WestDAAT) created by the Water Data Exchange (WaDE)[3], which has attempted to harmonize data sources across states, although coverage is not uniform. For instance, not all water rights have allocation amounts, including all the Texas data, leaving us to exclude that state, reducing our sample to 16 states. We keep only rights for surface water, coding them to be "flow" based if allocation flow is greater than zero, "volume" based if allocation volume is greater than zero, and "flow and volume" if both are greater than zero. We also code those with beginning dates of January 1 and ending dates of December 31 to not have timing restrictions. In total, we have 361,555 water right records, or 22,597 records per state on average. The range across states is wide, spanning from

88,434 in Montana to 1,538 in North Dakota. We summarize the distribution of water right allocations (flow, volume, or both) in Figure S19.

Water rights in Colorado are available from Colorado's Department of Water Resources, which we accessed from the Colorado Information Marketplace [4]. Matched to WDIDs (water district identification number), we limited these data to ditches or ditch systems that list the Rio Grande as its water source. These data provide appropriation date and quantity for each water right. Because ditches often acquire more than one right to diversify across priority, we create a flow-weighted average of the ditches' water rights before ranking them to arrive at a priority order.

We accessed monthly diversion records by WDID from the Colorado Department of Water Resources' HydroBase platform along the Rio Grande (Division 3) from water year 1950-2024. From these we construct water year total diversions. The data includes zeros as well as missing data for some ditches. We assume that missing data are likely truly missing, rather than zero, and so we treat them as such for our main analysis. However, missing data disproportionately appear for lower priority ditches and so we also conduct robustness checks where some or all of the missing data are treated as zeros instead.

Streamflow statistics

We focus on our calculations of total annual streamflow (Q), center of timing (CT), standard deviation of timing (SDoT) for each gauge, the Gini index, and Apportionment Entropy (AE), but also calculate a standard suite of streamflow metrics to further assess correlations of SDoT with other metrics.

Q is calculated by summing daily values, assuming the value reported for each day represents a daily average streamflow for that gauge.

CT is calculated as the weighted mean of days of the water year, with weights based on daily Q, as follows:

$$CT = \frac{\sum(t_i q_i)}{\sum q_i}, \tag{S1}$$

where t_i is the day of water year since October 1 and q_i is the flow on that day (Stewart et al., 2004; 2005).

In a new extension of the CT concept, we calculate SDoT as the weighted standard deviation of daily streamflow, where the standard deviation of days was weighted by the daily streamflow value:

$$SDoT = \sqrt{\frac{\sum q_i (t_i - CT)^2}{\frac{(N' - 1)\sum q_i}{N'}}}, \tag{S2}$$

where CT is defined as in equation S1 and N' is the number of non-zero observations each year. As flows become more concentrated around the CT, SDoT approaches zero but is undefined if the flow occurred entirely on one day. A uniform flow would equate to an SDoT of 105.5. SDoT will further increase if the hydrograph takes on a "convex" shape (low flows in the middle with higher flows at each end), hitting a maximum of 183 if the flows were split evenly between the first and last day of the year. Because SDoT results do depend on timing, they will be different if calculated using a different water year definition, such as a local water year [5], but the water year definition used here is widely accepted [6,7] and maintains consistency among gauges.

Alternative measures of inequality and "seasonality" in the literature include the Gini index and AE. The Gini index captures the "inequality" of water flows across the days of the year of streamflow distribution (Gudmundsson et al., 2019; Masaki et al., 2014). First developed for economic contexts by Corrado Gini in 1912 [8], the Gini index calculates the ratio of the area between the Lorenz Curve - the cumulative sum of the normalized resource under consideration on the y-axis having ordered the normalized "owner" population from the smallest share to the largest on the x-axis - and the curve of a perfectly equitably distribution line (45 degree line) relative to the entire area under the equal distribution line. In a discrete setting where the days have been sorted from lowest discharge to highest ($q_1 \leq q_2 \leq \ldots \leq q_{365}$), the formula is:

$$Gini = \frac{1}{N}\left(N + 1 - 2\left(\frac{\sum (N+1-i) q_i}{\sum q_i}\right)\right). \tag{S3}$$

Zero indicates perfect equality and one indicates extreme inequality with the top percentile commanding 100 percent of the resource. As seen by its construction, specifically the reordering of the days, the Gini index only captures inequality but is completely insensitive to timing; it does not consider *when* the larger or smaller flow days occur within the year whereas SDoT is sensitive to both the different amounts of discharge and when they occur.

AE measures variability, or randomness, of amounts across different groups. In hydrology this has been utilized to describe variability, described as seasonality, of precipitation occurring across months (Maruyama et al. 2005; Mishra et al. 2009; Feng et al. 2013) and more recently adopted for a similar purpose in streamflow seasonality (Wang et al. 2024). Defining r_1, r_2, …, and r_{12} as the total discharge in each of the 12 months, and R as the total annual discharge, AE is defined as:

$$AE = -\sum \left(\frac{r_i}{R}\right) log_2\left(\frac{r_i}{R}\right). \tag{S4}$$

It is inversely related to the Gini in that streamflow entirely concentrated in one month would result in a value of zero and then increase with more equal distributions until $\log_2(12)$ (about 3.58). This takes a step towards considering the concentration of the temporal relationship of low and high flows days to the extent they are lumped within calendar months. However, it still ignores whether the low flow or high flow months themselves are adjacent to one another in the year, and whether daily flows within months are uneven or clustered. For instance, should all the streamflow occur in a 30-day period and that happens to fall within a single calendar month, then AE will be zero, whether or not the flow occurs entirely on one day, evenly across those thirty days, or any other combination within that month. If the flow is spread over all 30 days, but those days are split across two adjacent months, the AE would be equal to 0.08. Furthermore, if the 30 days were split between any two months, not just adjacent months, the value would still be 0.08. SDoT, in comparison, treats the consecutive 30 days the same no matter the calendar months while being sensitive to if they are more separated in time.

In addition to possible relationships with the Gini index and AE, we also calculate a standardized set of streamflow metrics [9] to ensure that SDoT is not duplicative with other well-established metrics.

Gudmundsson et al. (2019) define CT as the day at which 50% of flow has passed the stream gauge, as in Regonda et al. (2005), Hidalgo et al. (2009), and others, rather than the flow-weighted average day of water year as in Stewart et al. (2004; 2005). We use the weighted average definition of CT throughout the manuscript but present both definitions here. On the whole, SDoT shows very little correlation except with the alternative measures of variability (Figure S5).

SDoT's highest correlation is with AE (Pearson's $r = 0.72$), followed by the Gini index (Pearson's $r = -0.63$), and it was somewhat correlated with the coefficient of variation (CV) ($r = -0.36$). SDoT is relatively uncorrelated with other statistics, though it tends to be slightly higher when low flows are higher. Notably, Gini, AE, and CV are generally more correlated with one another than with SDoT, with a particularly high correlation between AE and Gini ($r = -0.82$). The stronger correlations of SDoT with AE and the Gini index emerges due to a bounded relationship with SDoT reflecting that they all do capture disparate flows across days in different ways; for a given AE (Gini) value there is a maximum (minimum) SDoT value and vise-versa. With Gini, it is a linear bound whereas AE is curved due to the log function (Figure S6). Beyond this limit, the SDoT can be larger when the higher flow days are more spread out around the CT.

Trend analysis

We calculate a Sen's slope [10] for Q, CT, SDoT, Gini index, and AE at each gauge with at least 40 years of data in water years 1960-2023 and observations extending to 2023, based on observations that the number of new gauges began to plateau around 1960 (Figure S4). This results in analysis on 803 gauges. While SDoT is the focus of the present manuscript, we compare results against widely recognized metrics (Q, CT, and other inequality/seasonality) to provide additional context for the frequency and size of significant trends. Trends with Sen's slope p-value < 0.05 are denoted as locally significant. Field significance is evaluated using Monte Carlo methods as described in Livezey & Chen [11]. Specifically, we resample all water years between 1960-2023 N = 1000 times without replacement. We calculate Sen's slopes for all gauges in each sample and record the fraction of gauges with locally significant trends ($p < 0.05$). For each variable, we then develop an empirical cumulative distribution function (ECDF) of the fraction of statistically significant gauges in each sample and compare the fraction of significant gauges from the true time series with the ECDF to estimate the probability of randomly observing at least as many gauges with statistically significant trends as in the true time series. When the true fraction is outside the sampled range, we report $p < 1/N$, or $p < 0.001$.

Climate sensitivity

At each gauge with at least 30 years of data (n = 1343 gauges), we estimate annual Q, CT, SDoT, Gini index, and AE as a linear function of annual temperature and precipitation values at that gauge. As with the trend analysis, Q, CT, Gini index, and AE statistical relationships are calculated to provide context for the SDoT results. The slope values for temperature and precipitation, respectively, are reported to illustrate SDoT sensitivity to these climate variables at each gauge, and the p-value for each associated term is reported to illustrate the significance of SDoT dependence on interannual climate variability.

Water rights allocation simulation

We create the stylized, illustrative streamflows by altering normal distributions (using Stata software). We first convert the day of the year to a relevant range of values centered on zero ($\frac{day-365/2}{10}$) and then extract p-values from a standard normal distribution (standard deviation equal to one) and a wider distribution (standard deviation of two) based on those centered values to stand in for a fraction of the total flow on each day. We then shift the center of timing by 60 days to align closer to snowmelt-dependent hydrographs. To avoid (near) zero discharge days, we then add 0.0025 to all flows before recalculating the share of water discharged each day of the water year so that all years add up to a normalized total discharge value of one.

To simulate the senior/junior water user allocations, we set the senior's water right, arbitrarily, to be 0.01 units of flow. Using this threshold, we allocate the first 0.01 units of water to the seniors each day, letting the remainder, when present, accrue to the junior water user. Under the hydrograph created by the standard normal distribution, this amounts to 76 percent of the total flow over the year going to the senior water user. The specific values are of course sensitive to the cutoff for "senior", but the direction of the results are not. In practice, although "senior" and "junior" are discussed as if binary groups, it is a continuum of seniority and changing SDoT will potentially impact users differentially along the spectrum depending on the specifics.

Rio Grande water diversion analysis

To analyze the heterogeneous relationship between SDoT and annual water diversions across different levels of priority seniority, we combine the annual water year hydrograph characteristics (SDoT, Q, and CT) with the panel data of annual diversions by irrigation ditch each year. The panel spans 72 years from the water year 1951 to 2023. There are 83 distinct ditches leading to 6,059 total observations. However, as discussed in the data, a number of diversion records are missing (1,704, or 28%). The missing records are disproportionately in the lowest quartile of priority (those most junior) where 50 percent are missing (Figure S19). While there are recorded zeros, it amounts to just 1.1 percent of the annual records. Accordingly, we are suspicious that this signals an undercount of actual zeros. In the end, we treat the missing as missing for the main analysis, but conduct robustness checks with the extreme case that the missing values are all zeros as well as a more conservative middle ground where we replace the missing observation with a zero only after we observe a first non-missing diversion for that WDID and we stop replacing the missing data after the last non-missing is observed, conditional on that occurring prior to 2016. This replaces 311 records of missing diversions with zero.

To provide tractability to the empirical model, we bin the 83 ditches into quartiles based on their quantity-weighted priority date averages. The breakdown of the ditches and their priorities are shown in Figure S18. The earliest claims occurred in 1866. The most junior group does have initial claims dating back to 1874, but once weighted by volume consist of 1907 claims and later.

For regression analysis, we run a fixed effect model to predict how annual stream characteristics affect ditch diversions as follows:

$$\ln(q+1)_{ipy} = \sum_{p=1}^{4} \beta_p \mathbf{1}[Priority = p] \times SDoT_y + \gamma \ln(Q_y) + \pi CT_y + \boldsymbol{D_i} + \varepsilon_{ipy}. \qquad \text{(S4)}$$

The outcome is the natural log of the annual diversion q (+1 to account for zeros) of ditch i in priority quartile p during water year y. The coefficients of interests are β_1 through β_4, which estimate the percent change in diversion total for a ditch in a given priority quartile for a one day increase in SDoT. To account for the other stream characteristics that covary with SDoT and are expected to alter the diversion amounts too, we include total annual discharge (logged) Q for the water year and the center of timing CT or the center of mass of the hydrograph. To account for aspects of a given ditch that lends itself to more or less water on average (e.g. number, priorities, and amounts of water rights in its portfolio, place of diversion along the stream, etc.) we included a vector of ditch level fixed effects ($\boldsymbol{D}$). We are unable to include year fixed effects since our stream metrics only vary at this level. Finally, we cluster the error terms at both the ditch level and the water year level to account for heteroskedasticity and correlation within ditches and years.

In Table S2 we provide the estimated coefficients and standard errors. Column (1) presents those of the main model that are conveyed in Figure 5b in the main text. For the most senior quartile, a one day increase in SDoT increases total diversions by 0.024 log points. To arrive at the percent changes reported in the text, we multiply the coefficient by 10 (the effect of a 10 day increase in SDoT) and then subtract one from e raised to that number ($1-e^{0.24}$ = 0.271, or 27.1 percent). For the other priorities, the coefficients must first be summed. That is for the fourth quartile, the effect of a one day increase in SDoT is 0.0240-0.0715 = -0.0475. Then the same calculation can be made to arrive at a 38 percent reduction in diversions for the lowest priority group. The remainder of Table S2 provides results for our alternative treatments of missing diversion records and utilizing the alternative stream dispersion metrics, specifically AE and the Gini coefficient. Because these metrics are all scaled differently (Gini is also inversely correlated with other two), a direct comparison of the coefficient values is not appropriate. However, across all specifications, the qualitative result that increases in stream dispersion yields reductions in water diversions for more junior irrigators compared to senior irrigators holds.

Supplemental Figures, S1-S24

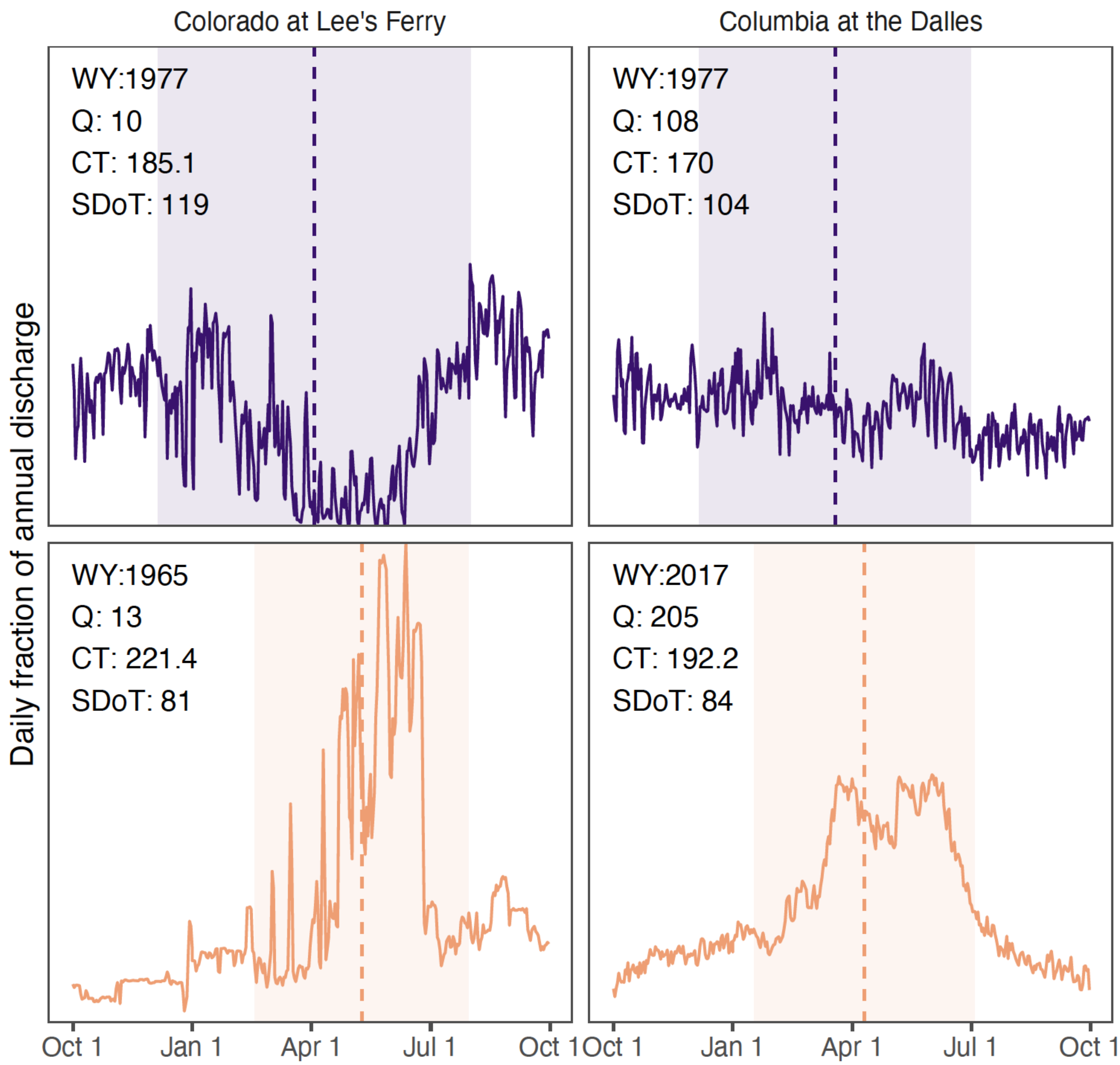


Figure S1. As in Figure 1 but after major dam construction on the Colorado and Columbia.

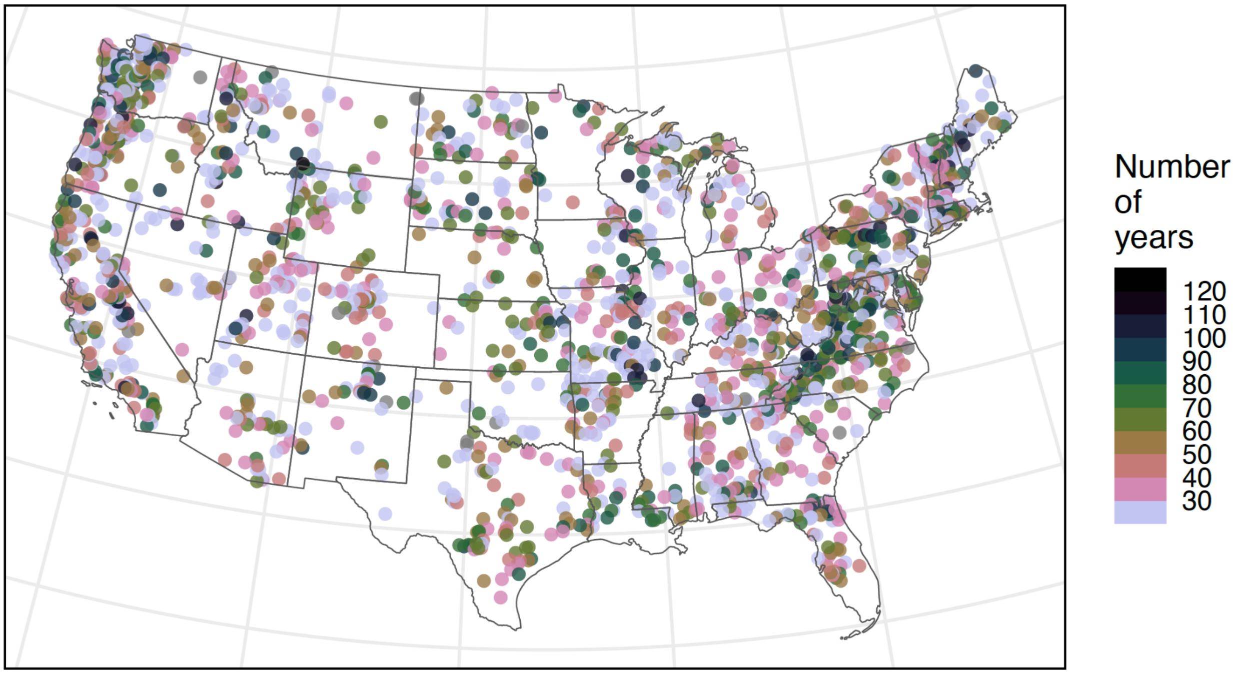
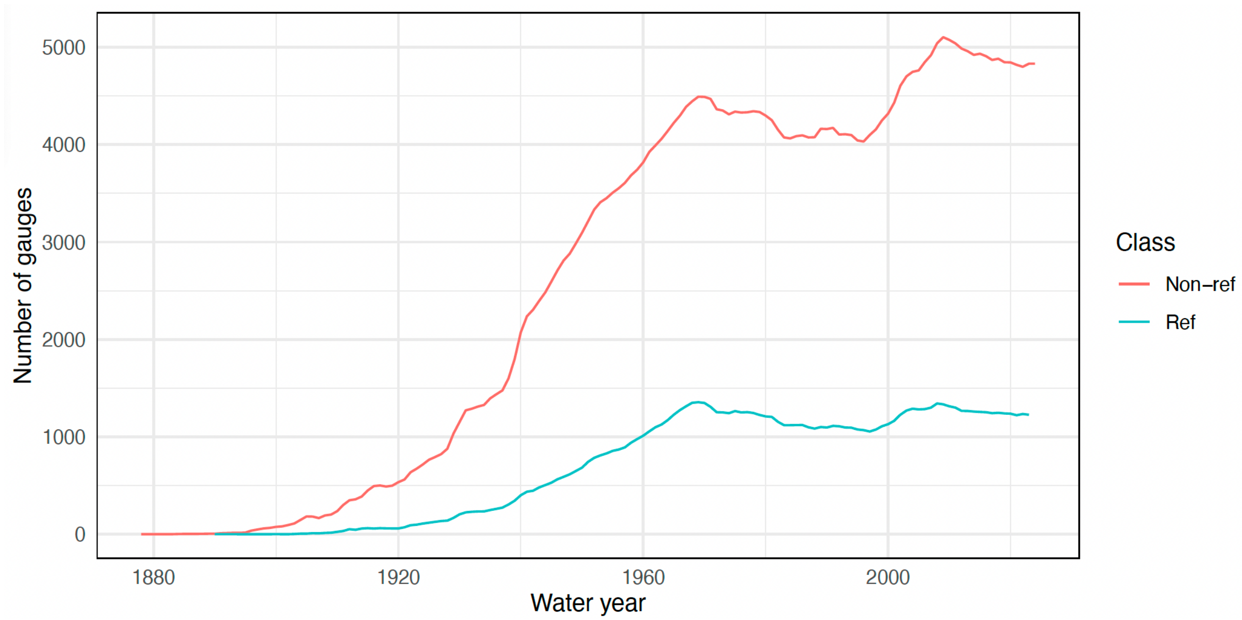


Figure S2. Years of data available at each gauge. While the number of available years of data varies, we note an absence of clear spatial patterns in data completeness, supporting the use of the full period of record for analysis of interannual variability.



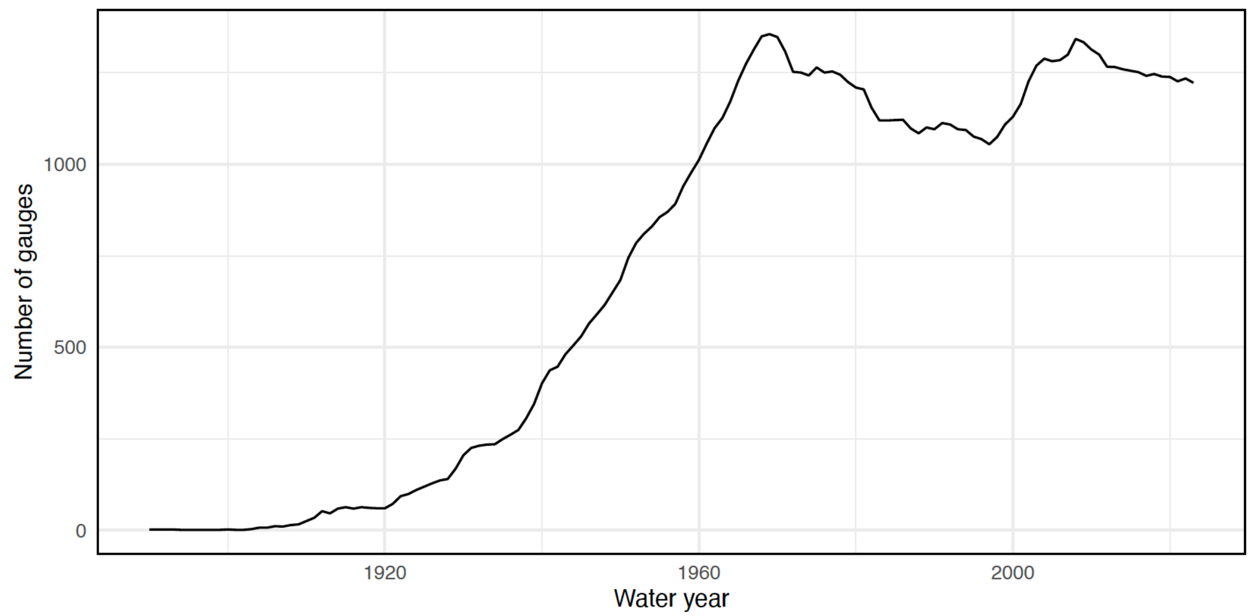


Figure S3. Number of streamflow gauges with at least 90% complete observations in the GAGES-II dataset.

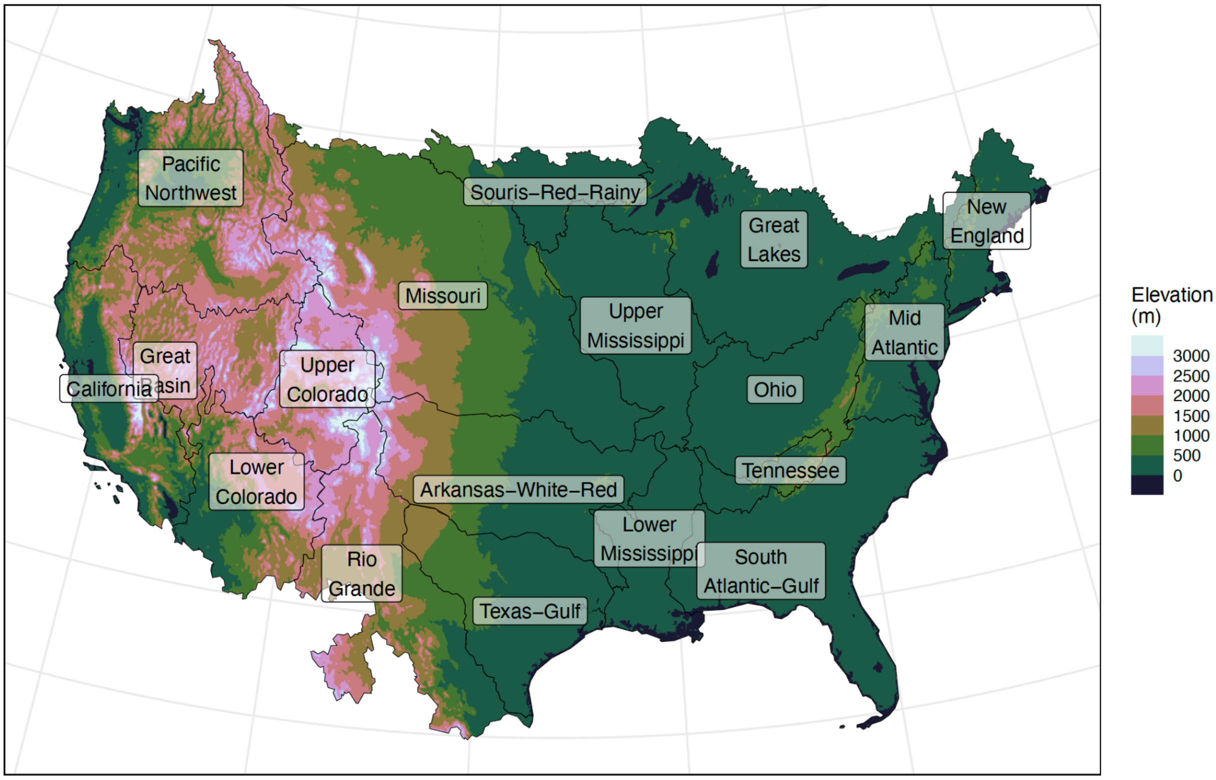


Figure S4. Map of HUC2 regions for reference to names mentioned in text.

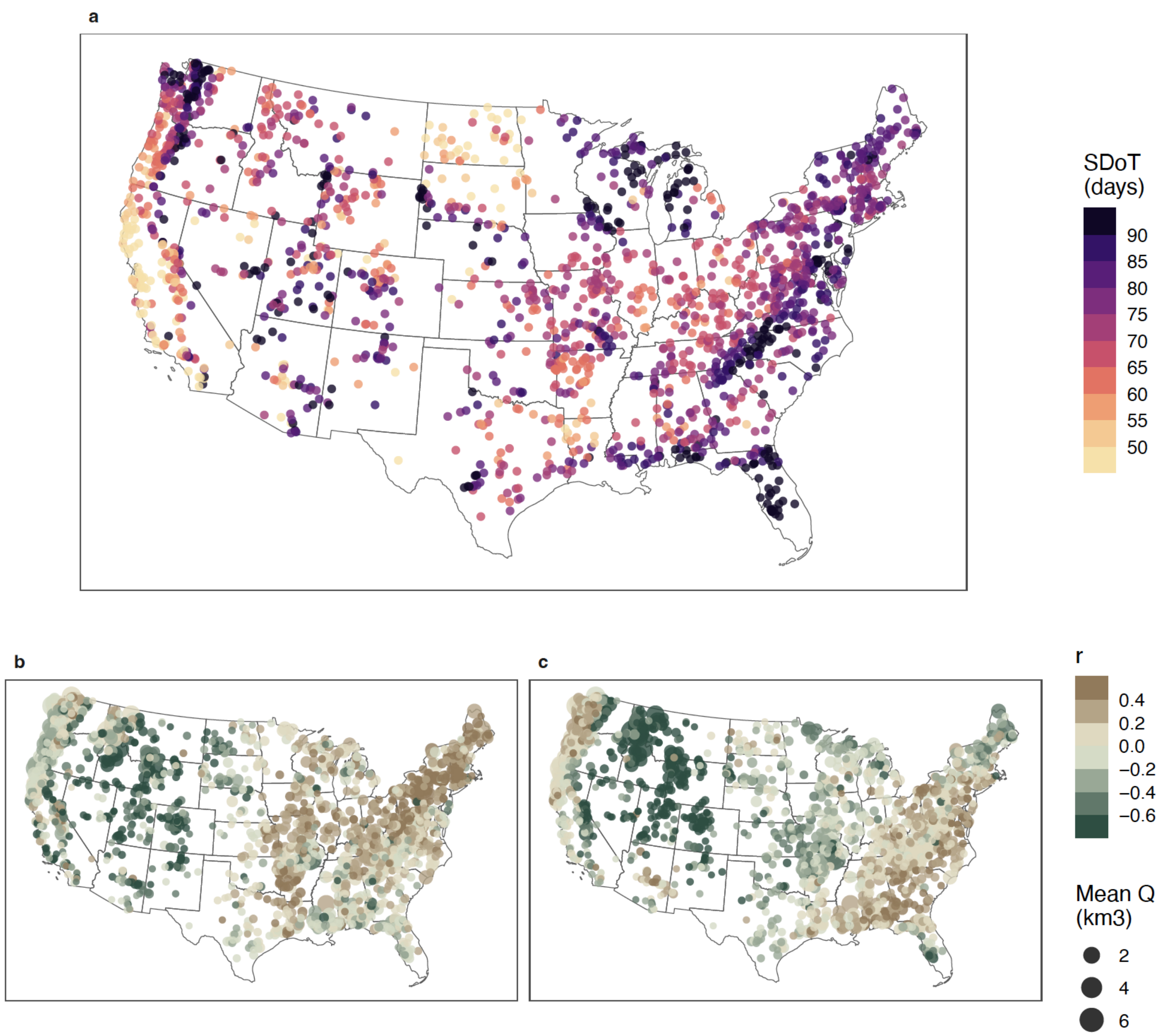


Figure S5. **SDoT and relationship with other streamflow variables.** (a) Mean SDoT across stream gauges, and Pearson correlation coefficient (r) among (b) Q and SDoT and (c) CT and SDoT.

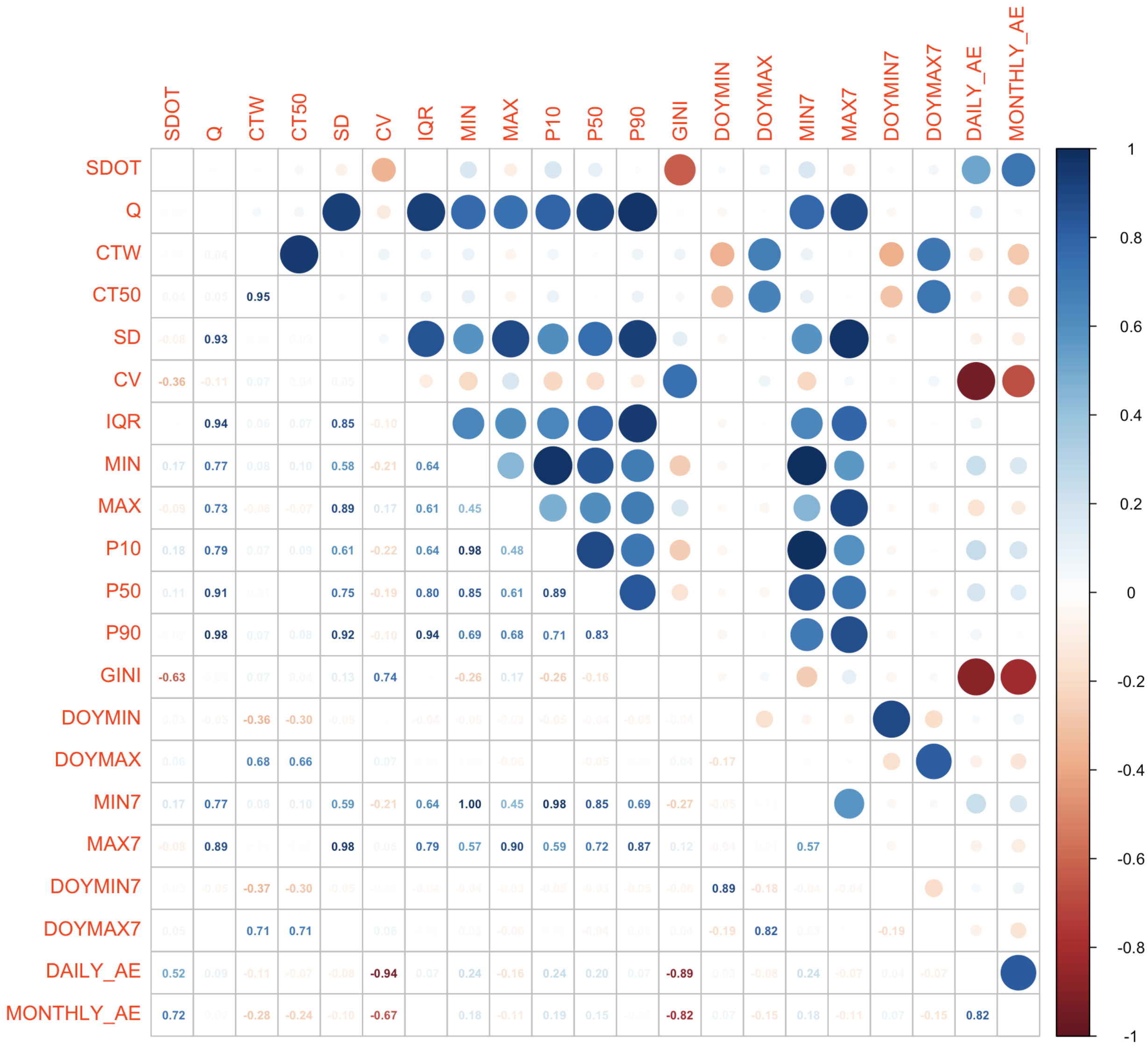


Figure S6. Correlation matrix among SDoT and streamflow metrics published by Gudmundsson et al. (2019) for all reference gauges with Gini index and Apportionment Entropy added. Q is total discharge over the water year. CT50 is the center of timing calculated as the day of the water year at which 50% of flow has passed a gauge; CTW is the center of timing using the flow-weighted average day. SD is daily standard deviation of flow; CV is daily coefficient of variation; IQR is the interquartile range of daily flows. MIN and MAX are minimum and maximum daily values. P10, P50, and P90 refer to the respective daily flow percentiles. GINI is the Gini index. DOYMIN and DOYMAX are the day of the water year on which minimum and maximum flow occur, respectively. MIN7 and MAX7 are the minimum and maximum 7-day moving average, while DOYMIN7 and DOYMAX7 refer to the days on which these values occur. Monthly and daily AE are appropriation entropy calculated on monthly and daily data, respectively [12].

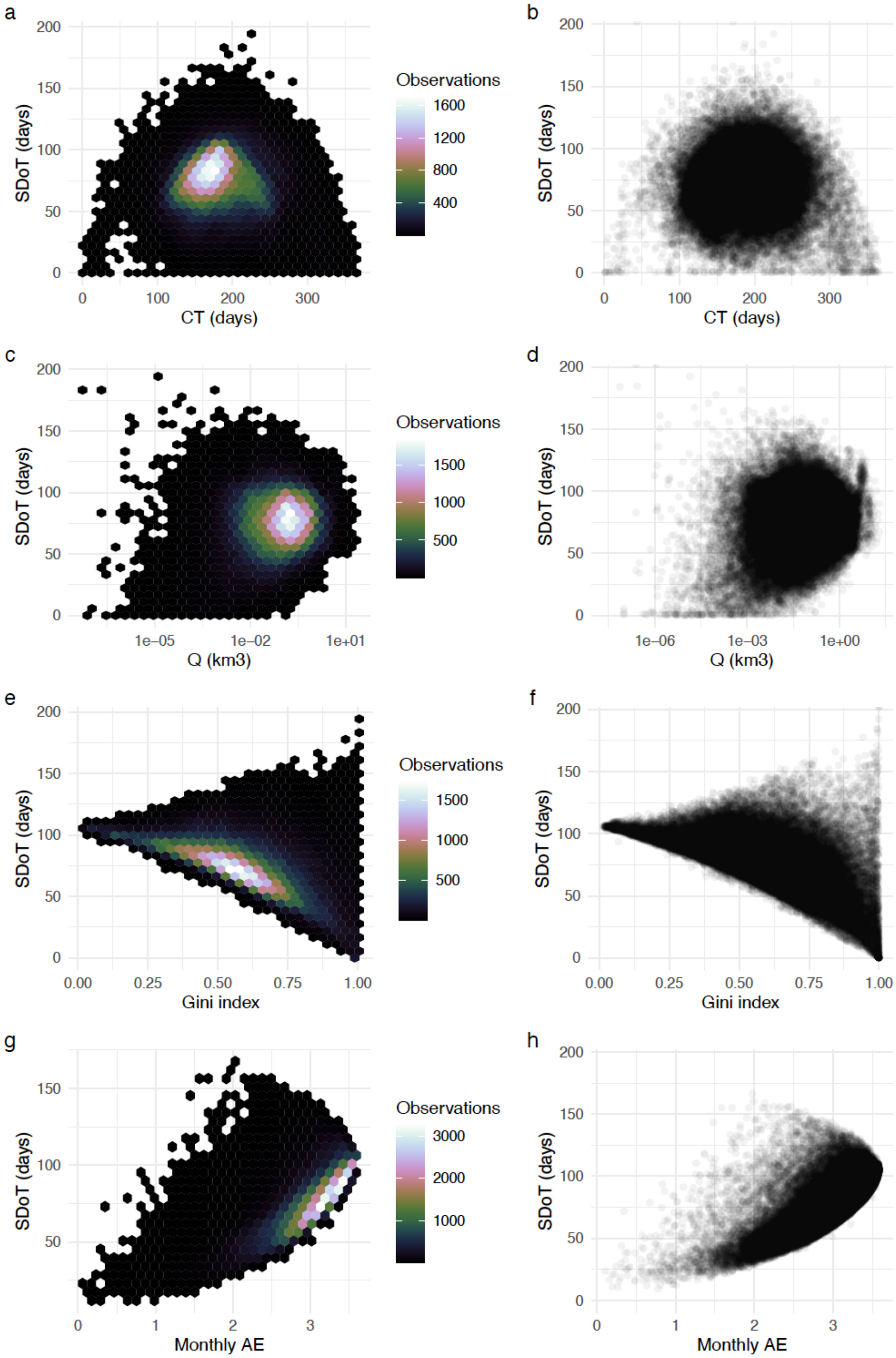


Figure S7. Scatter plots showing global relationship between (a, b) CT and SDoT as filled hexagons and points, (c,d) Q and SDoT, and (e,f) SDoT and the Gini index. Left column shows 2-dimensional density plots (with fill indicating number of observations), and right column shows scatter plot.

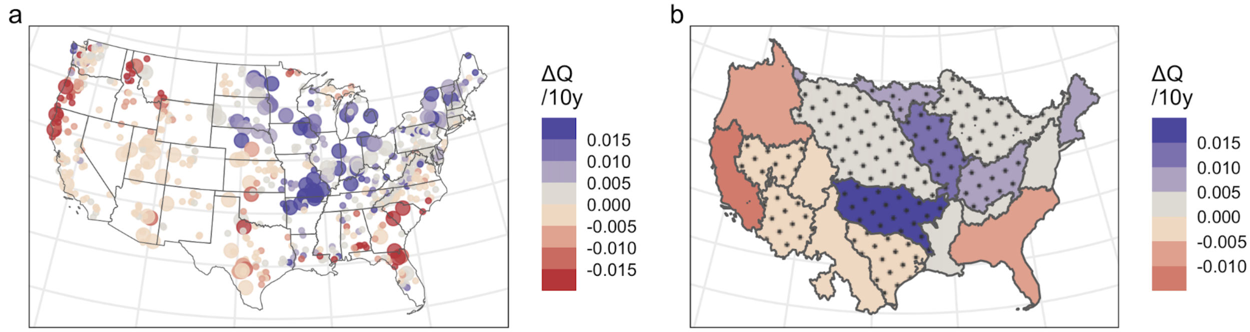


Figure S8. As in Figure 2, but for Q instead of SDoT.

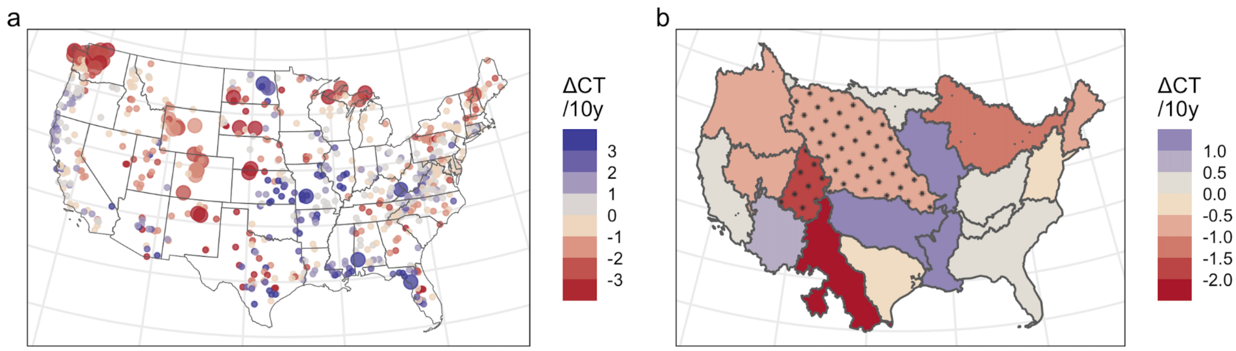


Figure S9. As in Figure 2, but for CT instead of SDoT.

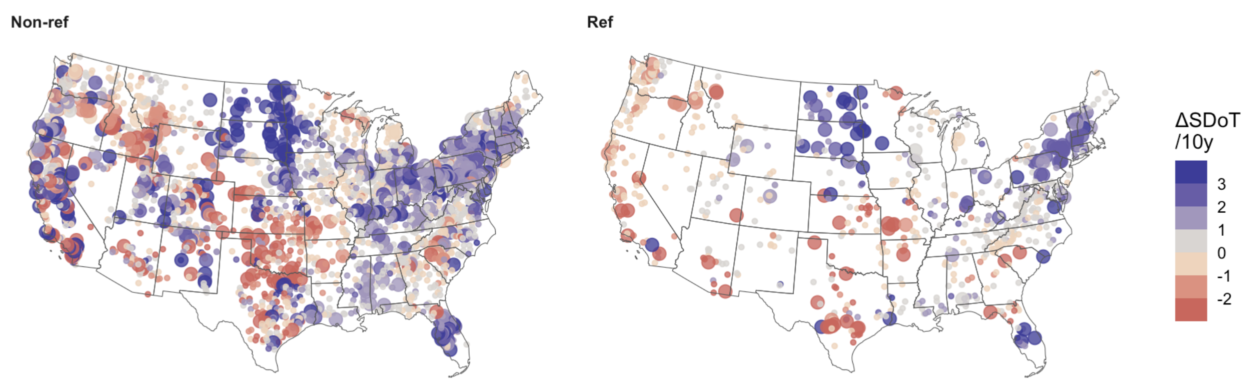


Figure S10. Trends in SDoT in non-reference (left) and reference (right) gauges.

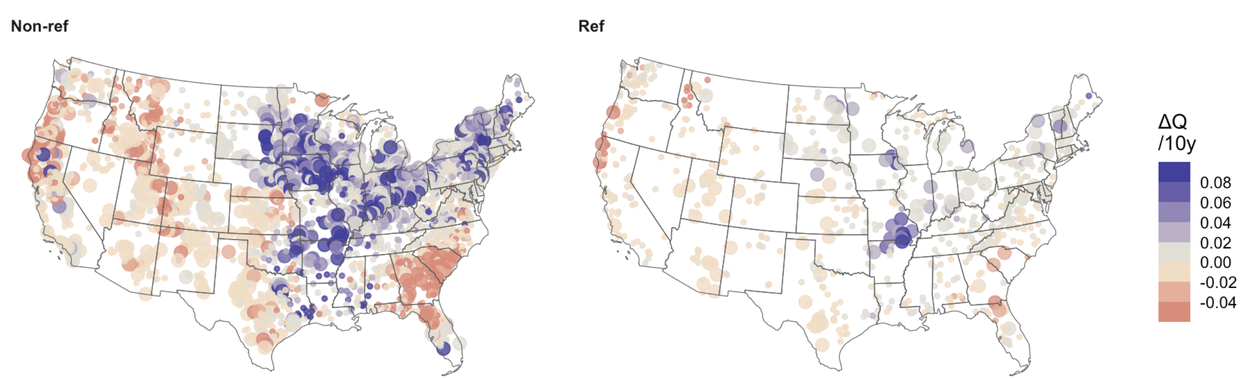


Figure S11. Trends in Q in non-reference (left) and reference (right) gauges.

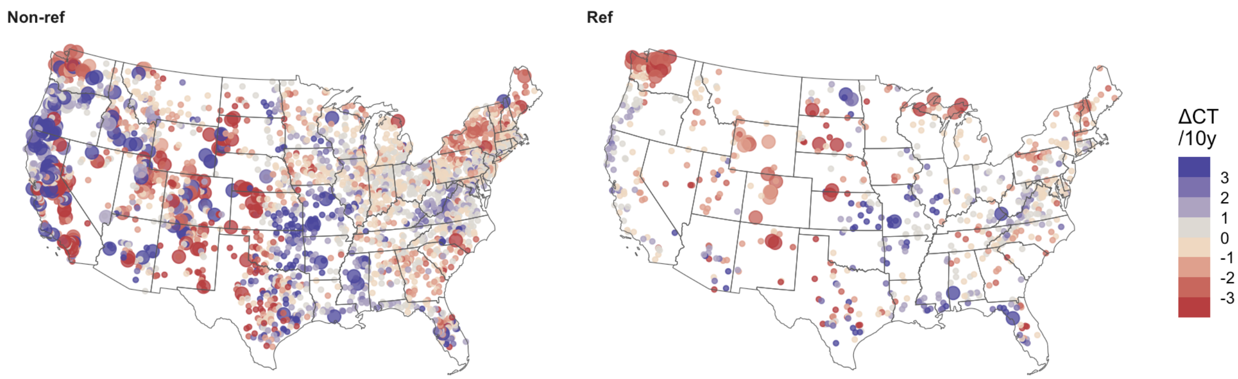


Figure S12. Trends in CT in non-reference (left) and reference (right) gauges.

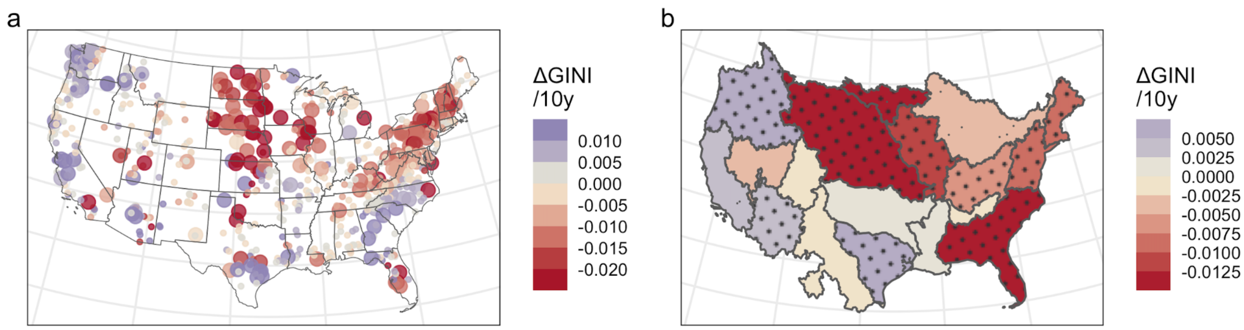


Figure S13. As in Figure 2, but for Gini instead of SDoT.

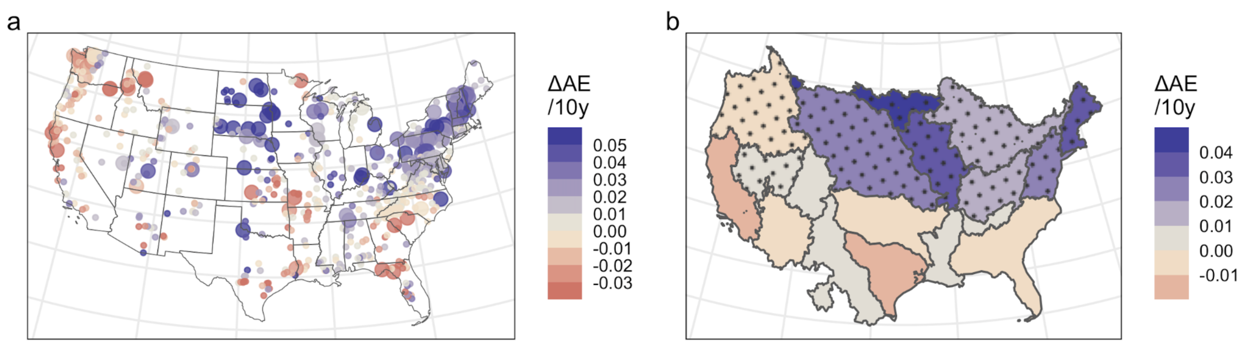


Figure S14. As in Figure 2, but for AE instead of SDoT.

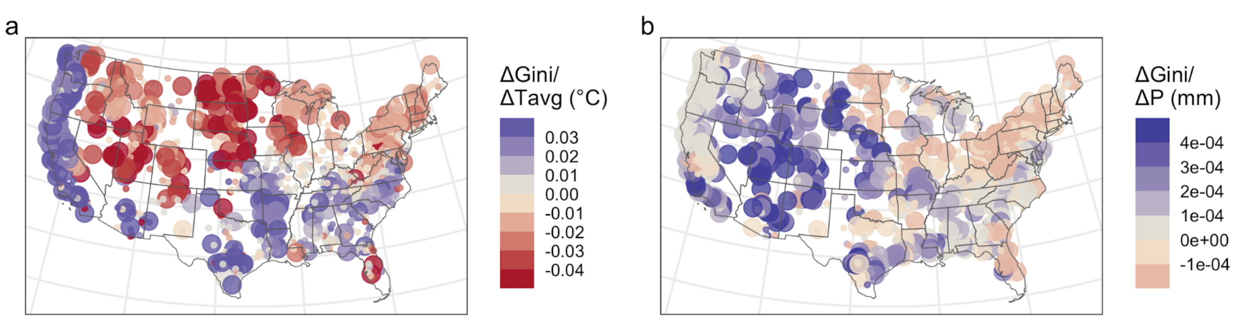


Figure S15. Sensitivity of annual Gini variability to temperature and precipitation, as in Figure 2.

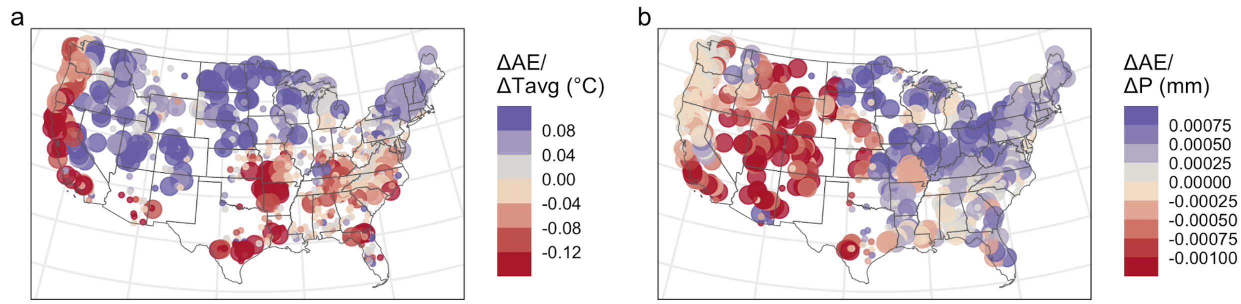


Figure S16. Sensitivity of annual AE variability to temperature and precipitation, as in Figure 2.

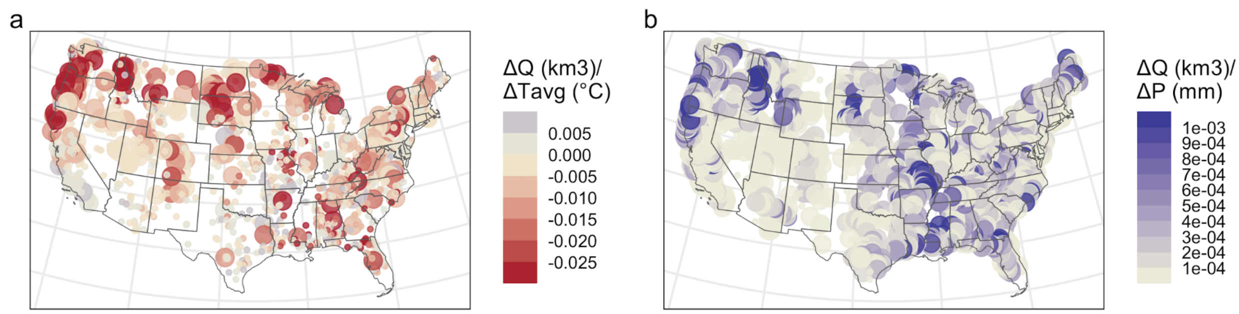


Figure S17. Sensitivity of annual Q variability to temperature and precipitation, as in Figure 2.

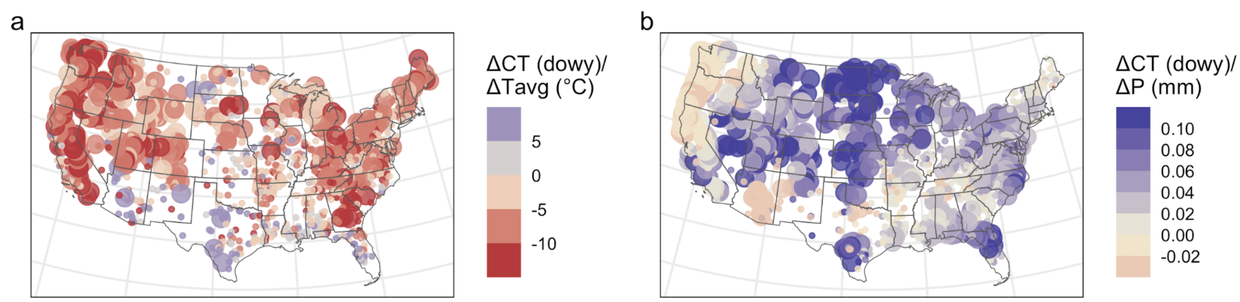


Figure S18. Sensitivity of annual CT variability to temperature and precipitation, as in Figure 2.

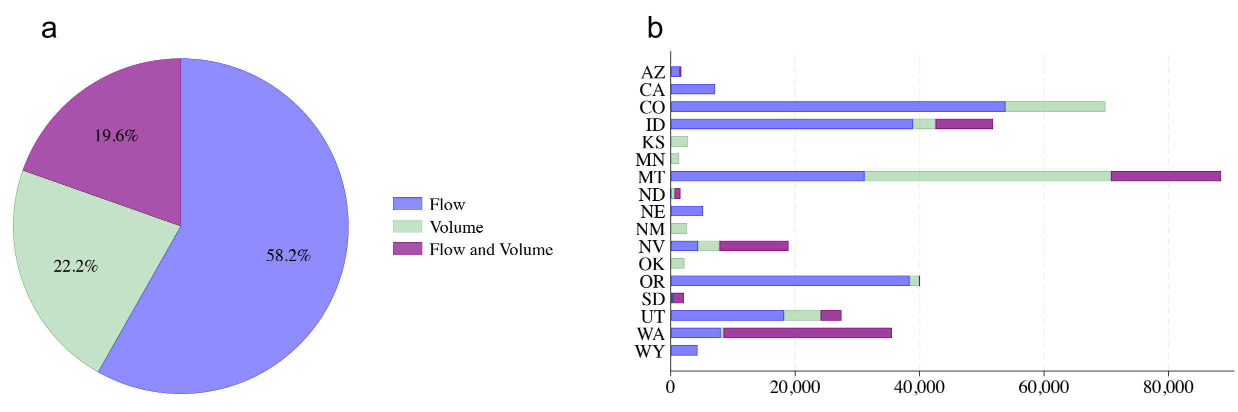


Figure S19 Distribution of demarcation units for surface water rights across the western states compiled from WestDAAT. N=361,555

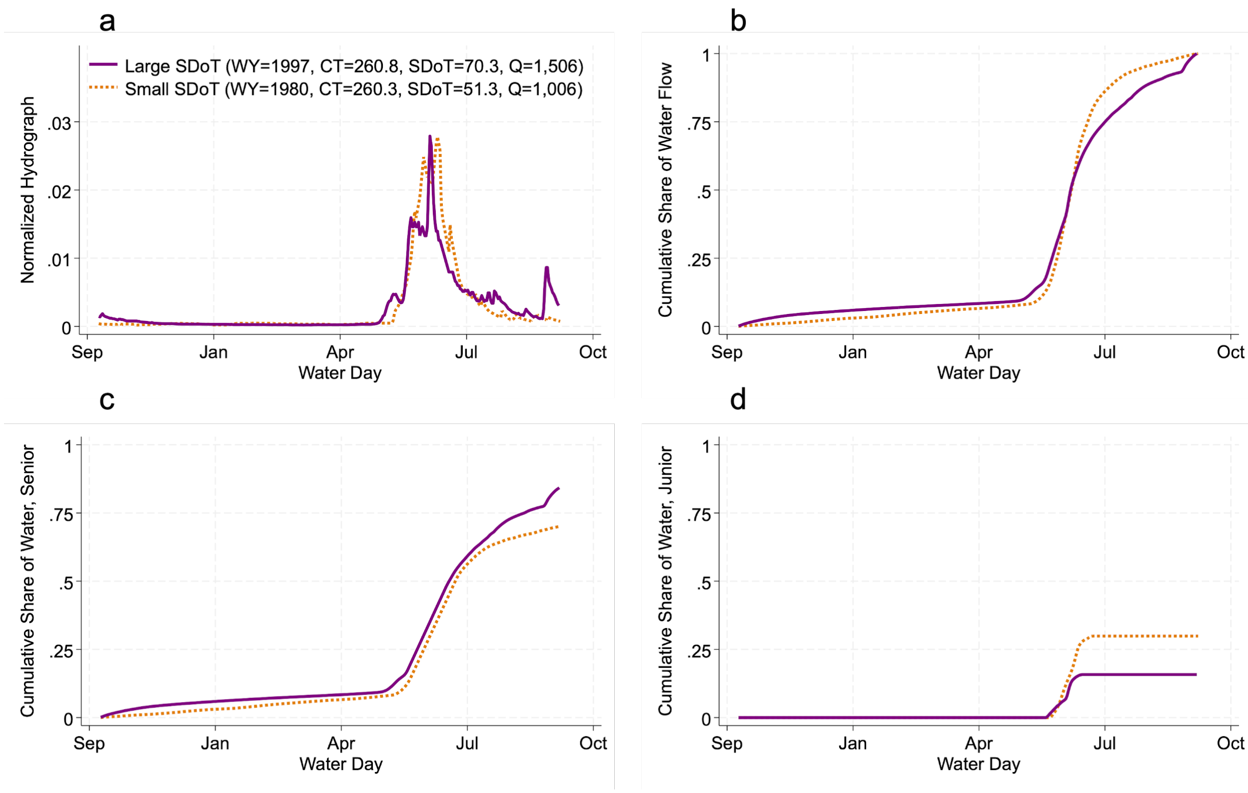


Figure S20. Shows normalized hydrographs as in Figure 3 but using real data from two years on Cameron Pass (USGS gauge 06614800) with nearly identical center of timings but different SDoTs. Senior water rights are provided the first 0.01 units of water each day in the simulation.

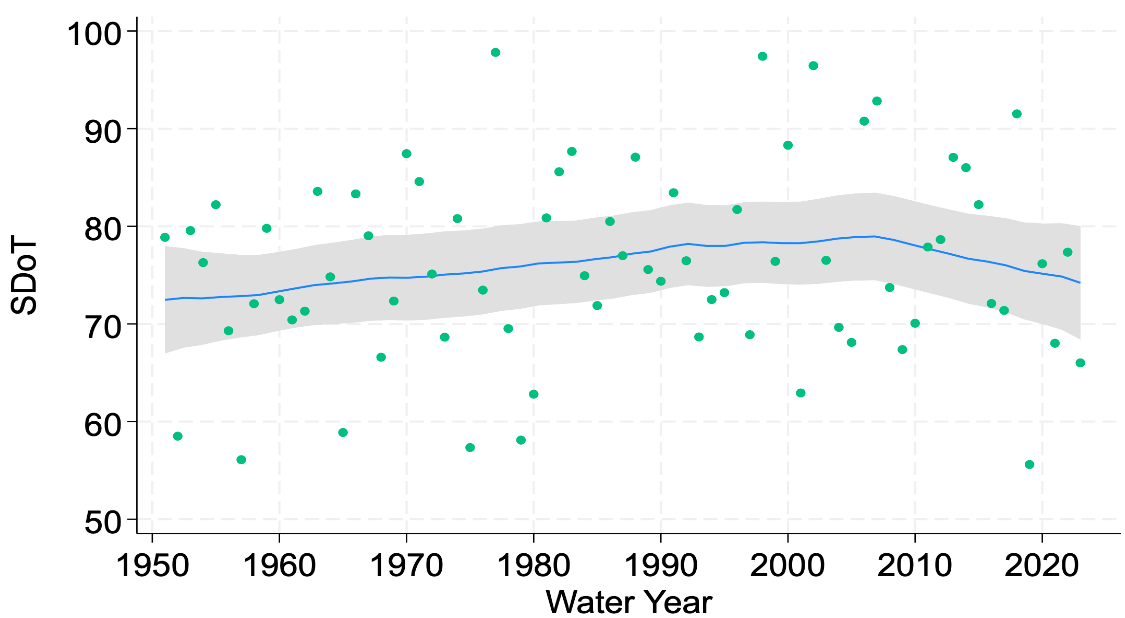


Figure S21. SDoT values for the Rio Grande, Colorado at the Del Norte gauge across time. Line is a local polynomial smoothed line flexibly tracing out the trend.

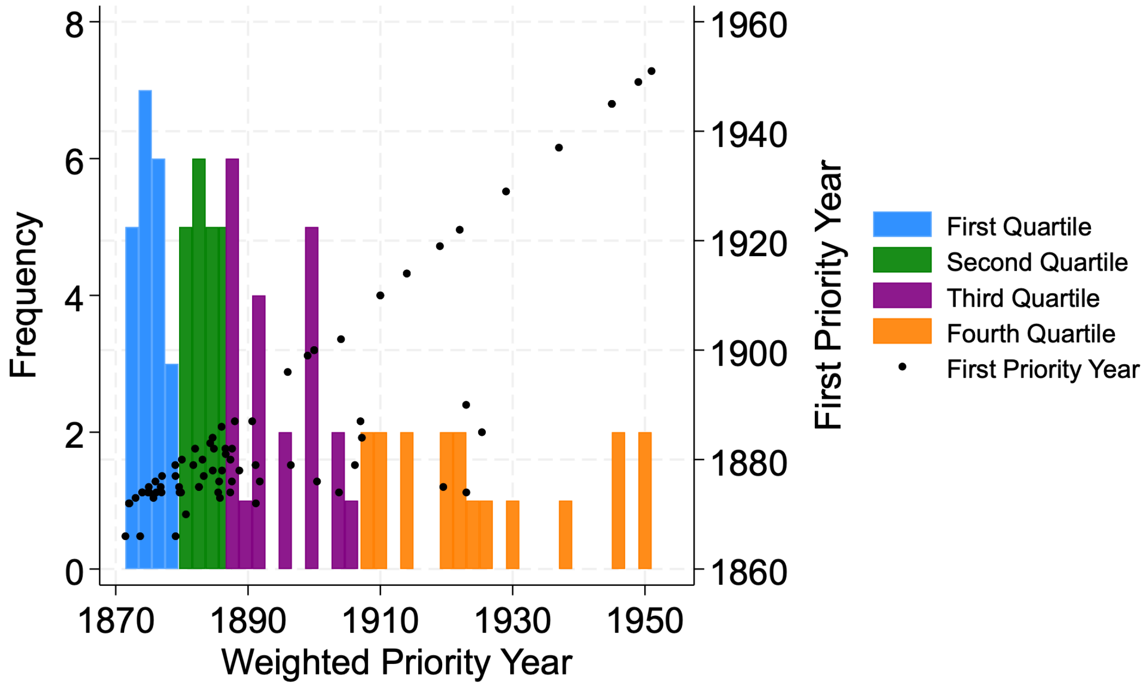


Figure S22. Priority years of ditches on the Rio Grande, Colorado. Frequency is the number of ditches falling in each weighted priority year. Scatter points compare the weighted priority year to the ditch's earliest priority year. Note that this graph excludes one ditch with a weighted priority year of 2000.

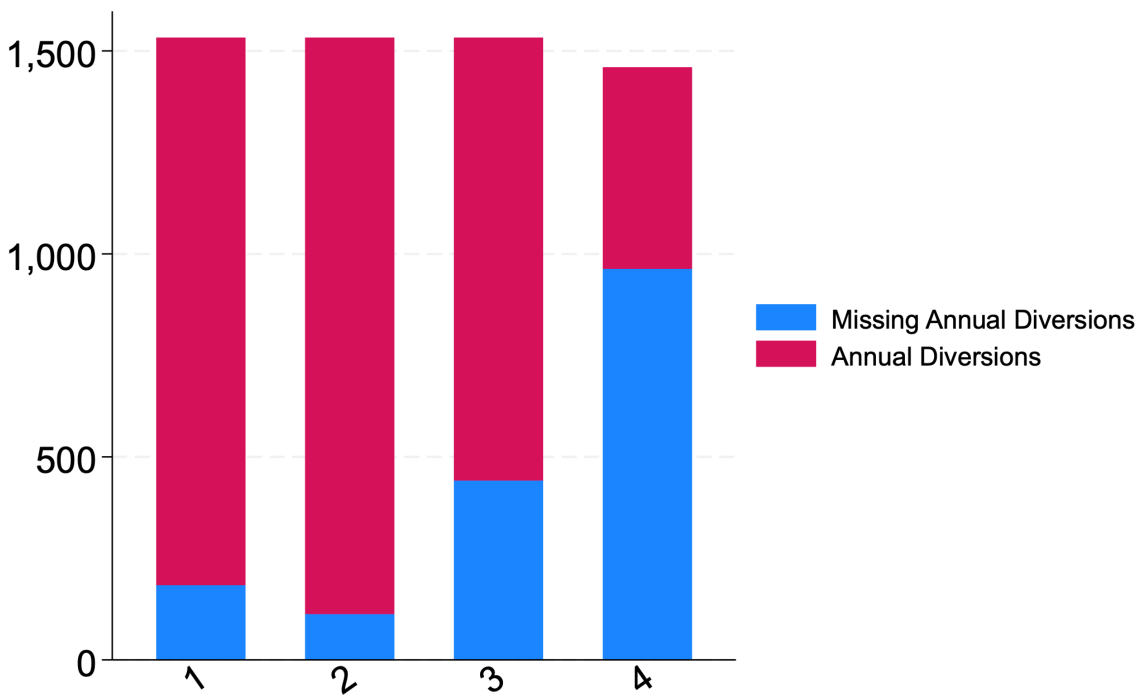


Figure S23. Missing diversion records by priority bin of ditches on the Rio Grande, Colorado.

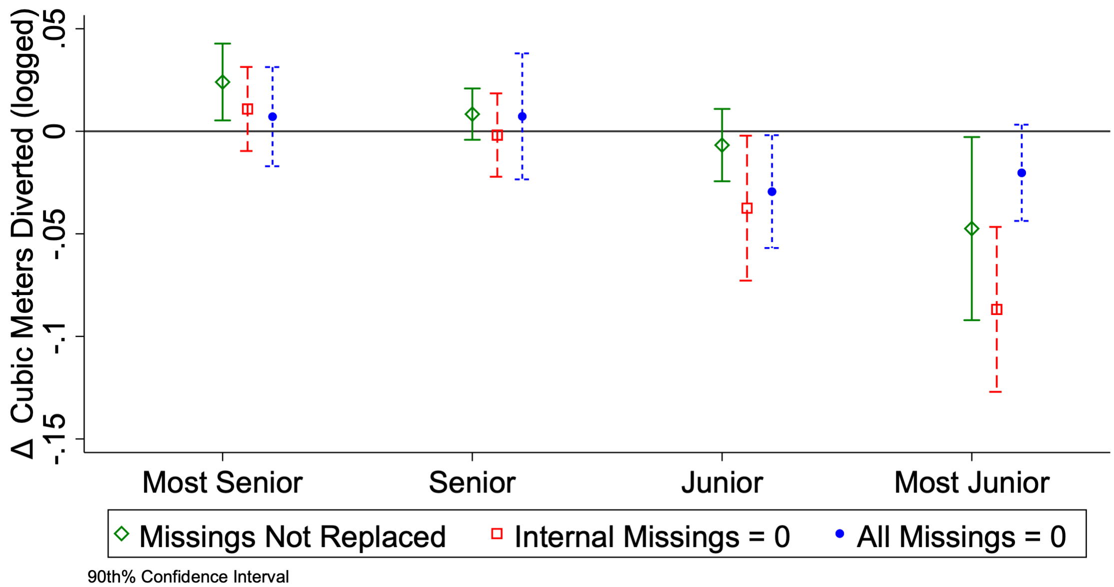


Figure S24. Point estimates of how much total annual diversions change due to a one day increase in SDoT by seniority quartiles. Three different regression results are presented for the alternative assumptions about missing diversion records. Each regression also includes Q, CT, and ditch fixed effects.

Supplemental Tables (S1-S2)

Table S1. Percent of reference gauges in the US with significant local trends ($p < 0.05$) for each streamflow variable of interest.

Variable	**Percent significant**	**Percent significant and positive**	**Percent significant and negative**
Annual Q	15.7	10.2	5.5
CT	6.4	0.8	5.6
SDoT	17.1	10.3	6.8
Gini	26.6	9.0	17.6
AE	19.9	15.1	4.8

Table S2. Estimated relationship between SDoT and water right seniority on total diversions, Rio Grande, Colorado.

y=ln(diversions+1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Stream Dispersion	0.0240**	0.0109	0.00713	1.240**	0.352	-0.170	-2.936**	0.470	1.759
	(0.0114)	(0.0125)	(0.0147)	(0.563)	(0.721)	(0.826)	(1.416)	(2.418)	(2.846)
Stream Dispersion x Priority Quartile 1	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Stream Dispersion x Priority Quartile 2	-0.0157	-0.0127	0.000136	-1.229	-0.979	-0.489	4.402*	3.705	2.703
	(0.0108)	(0.0131)	(0.0152)	(0.809)	(0.997)	(0.948)	(2.412)	(3.074)	(2.903)
Stream Dispersion x Priority Quartile 3	-0.0308**	-0.0483**	-0.0365**	-2.085**	-2.744**	-2.139**	6.619**	7.503*	6.291*
	(0.0136)	(0.0214)	(0.0148)	(0.889)	(1.368)	(1.056)	(2.510)	(3.922)	(3.204)
Stream Dispersion x Priority Quartile 4	-0.0715**	-0.0977***	-0.0274	-4.721**	-5.988***	-2.090**	15.27**	16.84***	6.214*
	(0.0353)	(0.0323)	(0.0194)	(2.307)	(1.926)	(0.989)	(6.301)	(5.567)	(3.170)
ln(Q)	0.593***	0.899**	1.299***	0.562***	0.754**	1.157***	0.486***	0.612*	1.020**
	(0.211)	(0.341)	(0.397)	(0.188)	(0.328)	(0.400)	(0.160)	(0.324)	(0.405)
CT	0.0148**	0.000230	-0.0135	0.0122**	-0.0000862	-0.0177	0.00909	-0.00488	-0.0224*
	(0.00662)	(0.00843)	(0.0113)	(0.00571)	(0.00763)	(0.0112)	(0.00608)	(0.00826)	(0.0121)
Constant	6.939*	6.693	-0.184	8.813***	11.50**	5.832	8.863***	7.003	1.853
	(3.586)	(5.192)	(5.350)	(3.192)	(5.362)	(6.420)	(2.546)	(4.350)	(4.799)
Observations	4355	4666	6059	4355	4666	6059	4355	4666	6059
Adjusted R-squared	0.634	0.656	0.806	0.635	0.656	0.806	0.638	0.657	0.807
Dispersion Metric	SDoT	SDoT	SDoT	AE	AE	AE	Gini	Gini	Gini
Missing Data	As is	Zero within Ditch records	Zeros	As is	Zero within Ditch records	Zeros	As is	Zero within Ditch records	Zeros

Note: Coefficients from estimating equation S4. All regressions include ditch fixed effects. Columns (1)-(3) measures stream dispersion with our preferred metric, SDoT. Column (1) treated missing diversions as missing. Column (2) treats missing records between non-zero diversion records as zeros, but missing outside of that. Column (3) treats all missing records as zero. Columns (4)-(6) repeat using AE to measure stream dispersion and Columns (7)-(9) uses the Gini coefficient. Standard errors, clustered by WDID and water year, in parentheses. * p<0.1 ** p<0.05 *** p<0.01

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