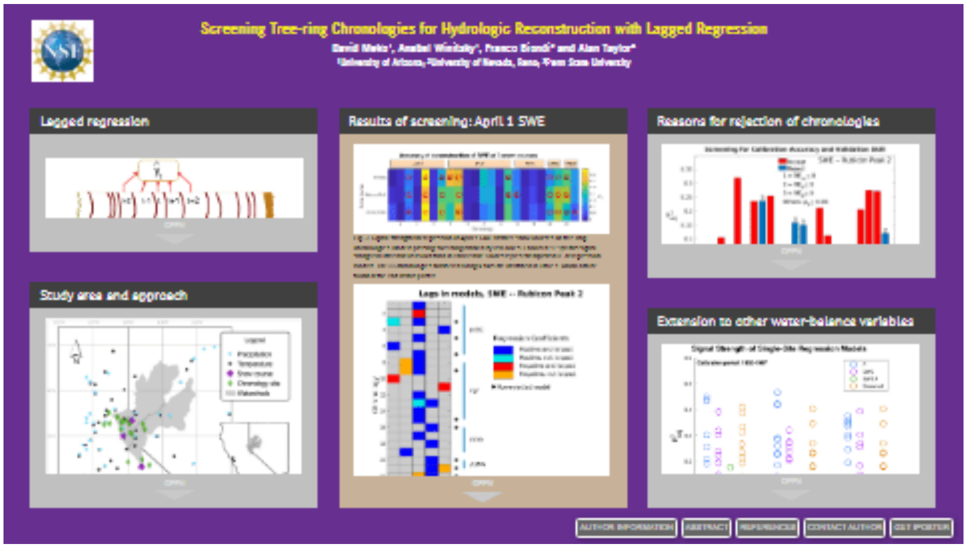
Screening Tree-ring Chronologies for Hydrologic Reconstruction with Lagged Regression



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Frontiers in Hydrology

LAGGED REGRESSION

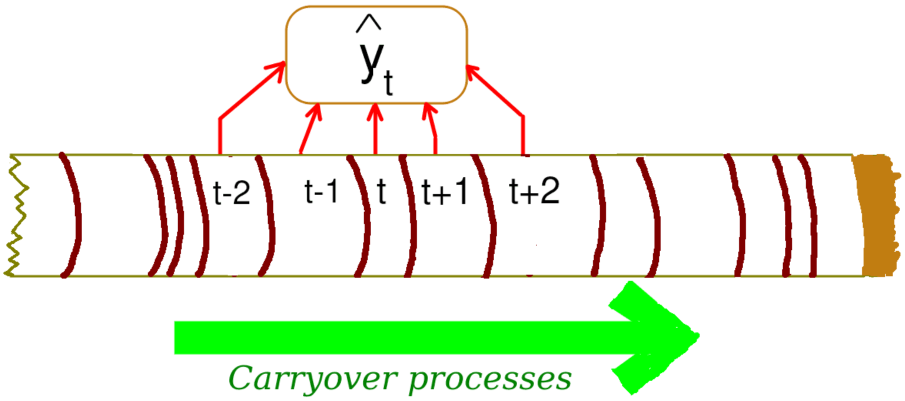

Fig. 1. Sketch of lagged regression with five tree rings contributing to estimation of some hydrologic predicatnd in year t.

Introduction

Reconstruction of annual hydrologic time series from tree-ring widths can be complicated by persistence in the biological and physical systems governing tree-growth and the water balance (Fritts 1976). Carryover biological processes, such as storage and needle retention, for example, can spread the impact of hydroclimate of the current year over multiple growth rings. Conversely, the hydrologic signal in a given growth ring may be conditional on past years' tree vigor, as reflected in those years' ring widths (Stockton and Fritts 1973; Stockton and Meko 1983; Meko and Graybill 1995; Meko et al. 2011; Meko et al. 2012).

Screening large networks of chronologies for use in dendrohydrology should take persistence into account. In this poster, we illustrate screening by stepwise regression of hydrologic variables on lagged tree-ring indices. Because persistence is most likely expressed short-term, we propose a restricted five-year window for the assessment (Fig. 1).

The screening method proceeds site by site for a given hydrologic variable (e.g. April 1 snow-water equivalent (SWE) measured at a snow course. To facilitate comparison, we use the same calibration interval for all chronologies evaluated. To be accepted, the single-site-reconstruction (SSR) model for a chronology must satisfy several conditions:

- Significant (α=0.05) overall-F of calibration
- Positive reduction-of-error (RE) statistic in leave-9-out cross-validation; multiple observations left out to ensure that no tree-ring values used to calibrate the model for a cross-validation prediction are also used in generating the cross-validation prediction (Meko 1997).
- Positive RE statistic for both halves of a split-sample validation (Snee 1977) of the model
- Causally logical lag structure: not implying that the current year's hydrologic variable can be reconstructed from past tree rings only

A cross-validation stopping rule (Wilks 2019) is also used in the forward-stepwise entry of predictors from the initial pool of five potential predictos. By this rule, entry is stopped when cross-validation RE reaches its first maximum (e.g., next variable to enter actually results in a lower skill of validation).

STUDY AREA AND APPROACH

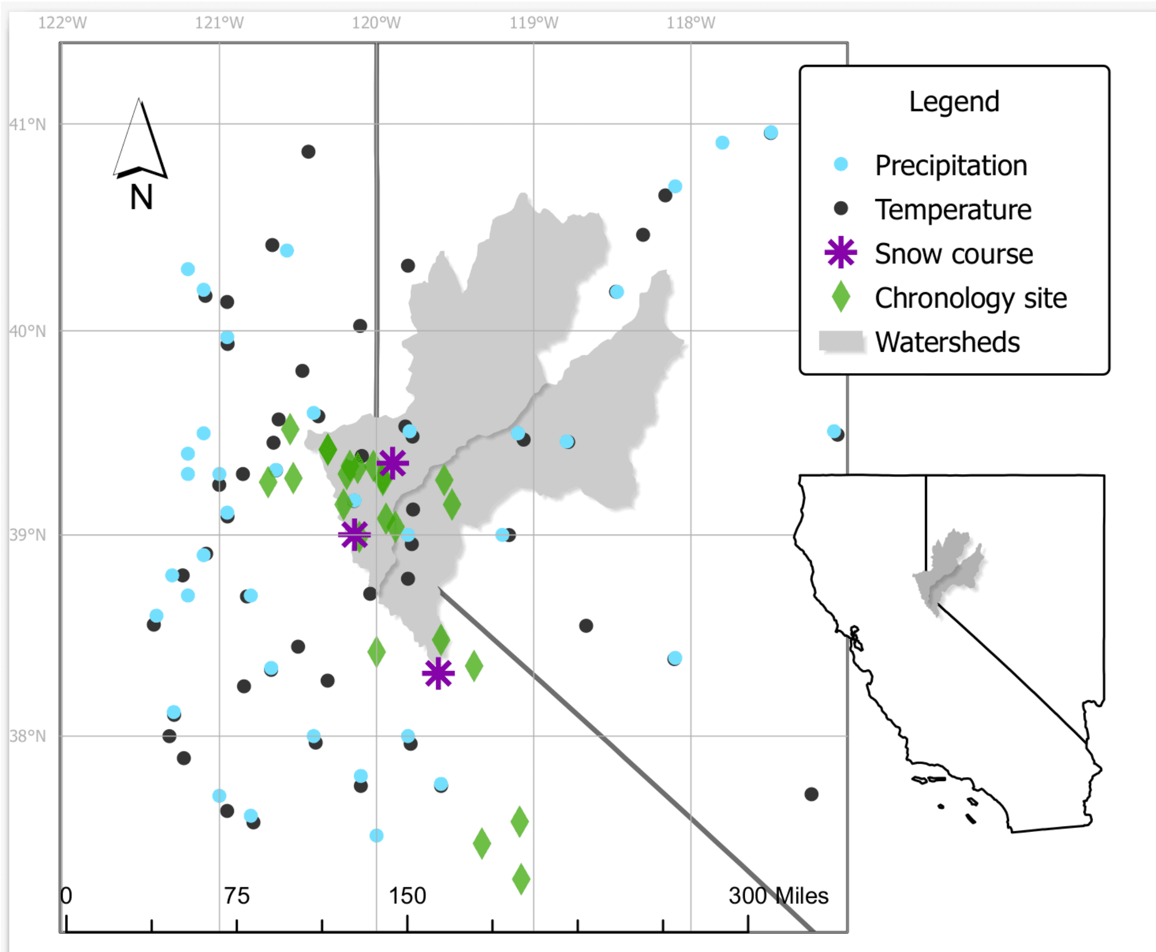

Fig. 2. Data locations. Snow courses, N-to-S, are Rose Peak, Rubicon #2 and Sonora Pass. Temperature and precipitation stations are from the GHCN monthly network. The 23 standard chronologies used in this study represent five conifer species in the snow belt. Truckee and Carson Basins are shaded.

Network and approach

Lagged-regression screening is illustrated for a network of 23 chronologies of five different species in the Sierra Nevada (Fig. 2). An annual hydrologic time series (e.g., April 1 snow-water equivalent (SWE) at a snow course) is regressed on a chronology and its lags by forward stepwise regression. We illustrate the approach with SWE and water-balance variables at three different snow-course locations (Fig. 2).

Hydrologic variables

- SWE: April 1, measured at snow courses
- P: water-year total precipitation, inverse-distance weighted from Global Historical Climate Network (GHCN) station data to snow-course locations
- Snowmelt: model-output water-year total snowmelt from monthly GHCN P and temperature (T) input to a climatological water-balance model (McCabe and Markstrom 2007)
- SWE.P: residual of a regression of SWE on P, representing that part of SWE not explainable by P

Tree rings

- Standard total-width chronologies, minimum accepted time coverage 1838-1999
- Five tree tree species represented: *Juniperus occidentalis* (JUOC), *Pinus jeffreyi* (PIJE), *Pinus ponderosa* (PIPO), *Abies magnifica* (ABMA), and *Tsuga mertensiana* (TSME)
- Uniform processing

    - Ring widths truncated to exclude years before 1800 (only two of the 23 chronolgoies begin later than 1800)
    - Individual ring-width series that end before 1950 excluded to avoid series with fewer than 20 years overlap with the hydrologic series used to calibrate the regression models
    - Standardization by ratio method using 50-year spline for fitted trend line

Stepwise regression

- A total of 276 models (3 snow-course locations, 4 hydrologic variables, 23 chronologies) are addressed in this poster
- Calibration period 1930-1997
- Cross-validation stopping rule (Wilks 2019) and strict criteria in screening for temporal stability of hydrologic signal (see screening criteria in text following Fig. 1)

Emphasis for poster

- Screening results for SWE, in particular the results for Rubicon #2 snow course (central, from N-to-S, of courses in Fig. 2)
- Difference in screening results across target snow courses
- Species-related lag patterns in regression models
- Reasons for rejection of chronologies

RESULTS OF SCREENING: APRIL 1 SWE

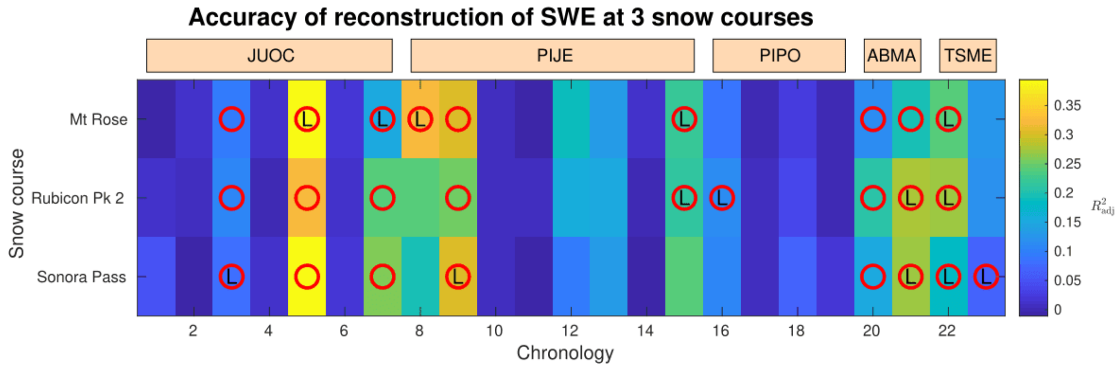

Fig. 3. Signal strength for regression of April 1 SWE at three snow courses on tree-ring chronologies. Models passing screening marked by red cicles. Enclosed "L" means signal stonger in later half of record than in earlier half. Colors represent adjusted R^2 of regression models. The 23 chronologies numbered along x-axis are identified in Table 1, which can be found at the end of this poster.

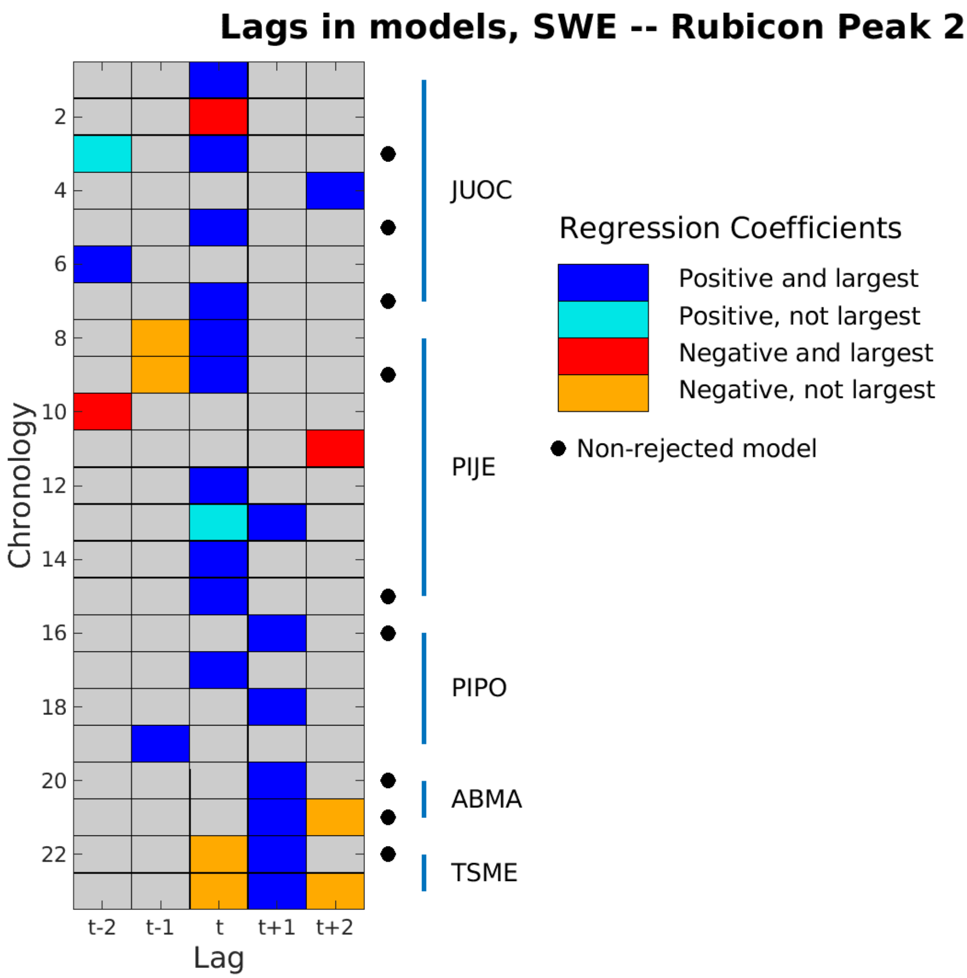

Fig. 4. Lags in regression models for reconstruciton of April 1 SWE at snow course Rubicon Peak #2. Color coding indicates relative importance and sign of coefficients on lagged predictors. Only those models not rejected by screening (marked by black dots) are worthy of interpretation.

SWE model findings

The above two figures summarize screening results and lags for SWE regression models. Regression R^2 of the models for the three snow courses is color-mapped in Fig. 3. The lag properties of the models for the Rubicon #2 snow course are shown in Fig. 4.

1. Nearness to the target snow course is relatively unimportant to the variance explained or to acceptance/rejection. With a couple exceptions, the same chronologies are accepted for models keyed on each of the three courses.
2. No one species dominates for strength of SWE signal. ABMA stands out for having no rejected models, but only two ABMA chronologies were suitable for evaluation in this study. .
3. At most, 39% of SWE variance is explained by a single chronology (site #5, species JUOC; see Table 1). In contrast, some JUOC chronologies have no appreciable signal for SWE.
4. For the accepted models, there is a hint of a stronger SWE signal in the last half of the calibration period than in the first half. This is indicated in Figure 3 by the "L" in the red circle, which means the reduction of error (RE) statistic for verifying on the last half of the record in split-sample validation is at least 0.10 greater than on the first half. For none of the accepted models is the signal stronger in the first half than in the last half.
5. Lags appear to be more important in the SWE response for ABMA and TSME than for JUOC (Fig. 4). For the three accepted JUOC models, the no-lag regression coefficient dominates the model and is positive in sign (high SWE this inear --> wide ring this year). In contrast, for ABMA and TSME, the lag +1 year coeffient dominates. The lag structure for those species suggests that a deep snowpack this year is associated with a wide ring the following year.

REASONS FOR REJECTION OF CHRONOLOGIES

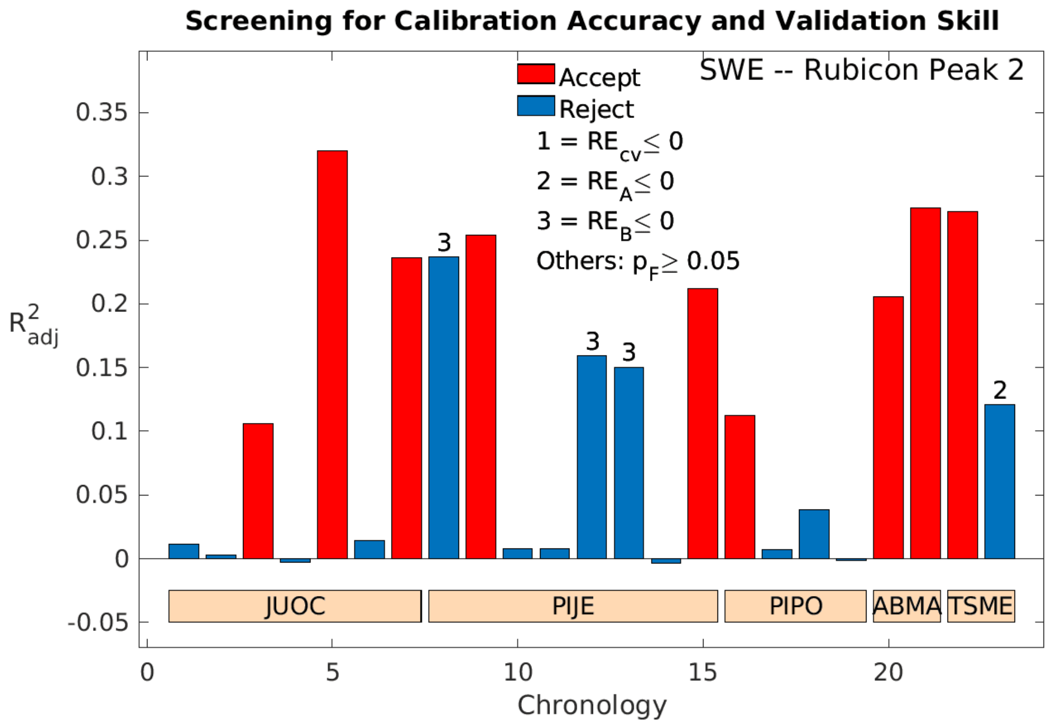

Fig. 5. Accepted and rejected chronologies and reasons for rejection. No number above blue bar means rejection because of weak calibraton signal (non-significantl overall-F of regression).

Findings: rejection of chronologies

- Fourteen of the 23 chronologies are rejected for reconstruction of SWE at Rubicon #2.
- An insufficiently strong calibration signal (low overall-F of regression) is the most common reason for rejection.
- Three PIJE chronologies have a sufficiently strong calibration signal but are rejected because of no split-sample validation skill on the first half of the data (code 3 above blue bar).
- The failure of the early-half validation for PIJE is consistent with a strengthening of the SWE signal over time, which may reflect a trend toward increasing moisture sensitivity at higher-elevation sites as climate warms, less precipitation falls as snow, and the snowmelt regime changes. Other researchers have also reported a shift toward stronger moisture-sensitivity in subalpine tree species in the region (Dolanc et al. 2013; Lepley et al. 2020).

EXTENSION TO OTHER WATER-BALANCE VARIABLES

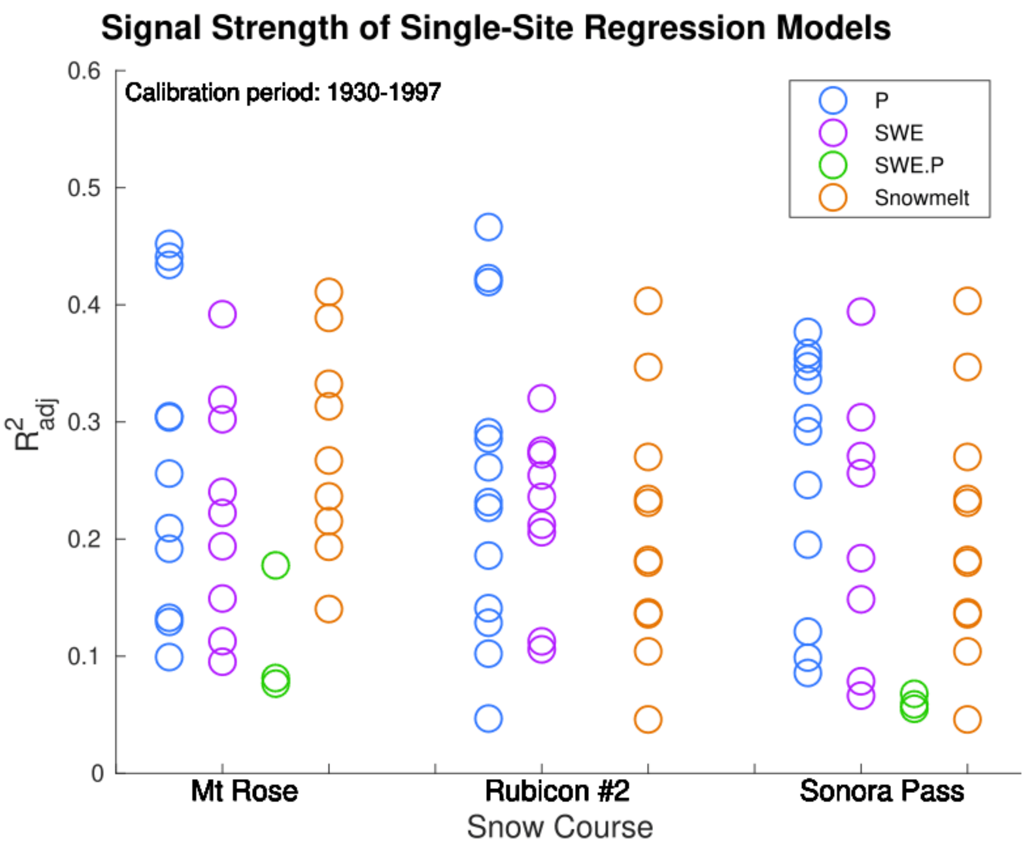

Fig. 6. Signal-strength of non-rejected models for regression of four water-balance variables on individual chronologies. Hydrologic variables are water-year precipitaiton (P), April 1 SWE, April 1 SWE with linear dependence on P removed (SWE.P), and water-balance-model output total snowmelt for the water year.

SWE signal inseparable from precipitation signal

- SWE.P is that part of the April 1 SWE that cannot be predicted by simple linear regression of SWE on annual precipitation. This component of SWE could depend on many factors, including differences from year to year in the monthly distribution of snowfall, the percentage of annual precipitaiton falling as snow, and snowmelt patterns. Although SWE and P are highly correlated with one another, the variance of SWE.P is still amost half (~45%) that of SWE itself for the snow courses studied.
- Very few of the 23 chronologies have a signal for that non-trivial variance component represented by SWE.P. Regression R^2 of SWE.P models dpes not reach 0.20 for any of the models generated, and none of the chronologies pass screening for SWE.P signal at Rubicon #2 (Fig. 6).
- An Improved signal for the snow-versus-rain contribution to the water balance might be possible from tree-ring variables other than total ring width -- such as sub-annual ring measurements or quantitative wood anatomy.

Conclusions

1. Lagged stepwise regression is a useful dendrohydrologic tool for screening tree-ring chronologies.
2. Site selection of tree-ring chronologies is critically important for capturing hydrologic signals in the Truckee-Carson Basin.
3. A positiive growth response of multiple species to a heavy snowpack can be delayed a year in the snow-dominated hydrologic regime of the Sierra Nevada.
4. Some statistical approach to dealing with lagged hydrologic influence is essential in hydrologic reconstruction, especially for ABMA and TSME.
5. Lags appear least important to JUOC chronologies, which also stand out for an exceptionally large range of strength

of hydrologic signal from one site to another -- from very strong to none.

6. The moisture sensitivity of chronologies, notably PIJE, is increasing in recent decades, perhaps in response to decreasing snowpack linked with climate warming.
7. This shift suggests caution in inferring the accuracy of long-term reconstruction in the region from calibration and validation statistics based on recent data.

Table 1. Site information for the 23 chronologies analyzed in this study. Site numbers N1 correspond to numbers of sites along axes in figures 3, 4 and 5.

N	Code	Spec	Source	Lat	Lon	Elev	First	Last
1	CA630	JUOC	ITRDB	38.42	-120.00	2591	-420	1999
2	CA631	JUOC	ITRDB	39.52	-120.55	1921	930	1999
3	CA632	JUOC	ITRDB	39.33	-120.12	2268	1010	1999
4	CA698	JUOC	ITRDB	39.15	-120.21	1809	1600	2014
5	DGS	JUOC	Biondi	38.35	-119.38	2370	-300	2000
6	IVJ	JUOC	Taylor	39.28	-119.96	2563	1142	2000
7	KAIM	JUOC	Meko	37.28	-119.08	2730	1140	2011
8	CA677	PIJE	ITRDB	39.34	-120.17	1688	1415	2010
9	CA678	PIJE	ITRDB	37.57	-119.09	2499	1304	2010
10	DLB	PIJE	Taylor	38.99	-120.11	2004	1306	2000
11	IVP	PIJE	Taylor	39.27	-119.96	2332	1305	2000
12	LEM	PIJE	Biondi	39.34	-120.02	2008	1542	2020
13	LSF	PIJE	Biondi	38.48	-119.59	2416	1474	2020
14	LTV	PIJE	Biondi	39.15	-119.52	2006	1418	2020
15	SSP	PIJE	Taylor	39.08	-119.94	2132	1190	1999
16	CA694	PIPO	ITRDB	39.30	-120.19	1975	1829	2014
17	CA695	PIPO	ITRDB	39.26	-120.69	1537	1838	2014
18	CPRMTR	PIPO	Biondi	39.27	-119.57	2507	1474	2020
19	NOD	PIPO	Biondi	37.46	-119.33	1539	1539	2002
20	CA691	ABMA	ITRDB	39.42	-120.31	2478	1540	2015
21	CA696	ABMA	ITRDB	39.28	-120.53	2008	1799	2014
22	CA692	TSME	ITRDB	39.42	-120.31	2478	1615	2015
23	GPH	TSME	Taylor	39.04	-119.88	2728	1349	2000

N: chronologies as numbered in Figures 4,5, and 6
Code: site code
Spec: species code: JUOC (Juniperus occidentalis), PIJE (Pinus jeffeyi), PIPO (Pinus ponderosa), ABMA (Abies magnifica), TSME (Tsuga mertensiana)
Source: immediate source of ring-width data for development of site chronology: ITRDB (International Tree-Ring Data Bank), Biondi (Frando Biondi), Taylor (Alan Taylor), Meko (David Meko)
Lat, Lon: latitude and longitude in decimal degrees east and north
Elev: elevation in meters above mean sea level
First, Last: first and last years of tree-ring measurements at site; note that we truncated ring-widths to start in 1800 before developing our versions of the chronolgoies with uniform settings for standardization

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ABSTRACT

Reconstructions of river discharge and other hydrologic variables often exploit large available networks of tree-ring chronologies from multiple species and hydrologic settings. A common early step in such studies is screening to reduce the predictor data set and focus on chronologies with a strong hydrologic signal. A stepwise regression approach to screening is proposed and illustrated for reconstruction of April 1 snow-water equivalent (SWE) at three snow courses in the northern Sierra Nevada and Lake Tahoe region from a multi-species tree-ring network. SWE is regressed separately on each chronology lagged t-2 to t+2 years from the year of SWE. A chronology is accepted based on specified criteria for temporal stability of signal and skill of the lagged model in predicting SWE outside the calibration space. A cross-validation stepwise cutoff rule is applied to guard against over-fitting the lagged model. Illustration for a network of 23 chronologies of five snow-adapted species (*Juniperus occidentalis*, *Pinus jeffreyi*, *Pinus ponderosa*, *Abies magnifica*, and *Tsuga mertensiana*) underscores the critical importance of lags in the tree-ring response to SWE. For *Abies* and *Tsuga*, in particular, chronologies passing screening are characterized by lagged models with a positive coefficient on the year following the hydrologic anomaly (deep snowpack this year, wide ring the following year) and no dependence or a negative coefficient on the current year (deep snowpack, narrow current ring). The SWE signal is strongest for one particular *Juniperus* chronology whose regression explains 39% of the SWE variance at two snow courses. The strength of SWE signal varies greatly over sites within species. More than half of the *Juniperus* and *Pinus* chronologies were rejected by screening because of either weak or temporally unstable signal. A repeat of the regression screening using water-year precipitation (Global Historical Climate Network) instead of SWE suggests that different subsets of chronologies are optimal depending on the target hydrologic variable. Few chronologies have a significant signal for the residual of SWE regressed on water-year precipitation. This suggests little snow-specific information on the moisture signal in annual ring width. Sub-annual ring measurements and quantitative wood anatomy are suggested as possible ways to help discriminate the rain and snow signals in tree rings from the region.

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