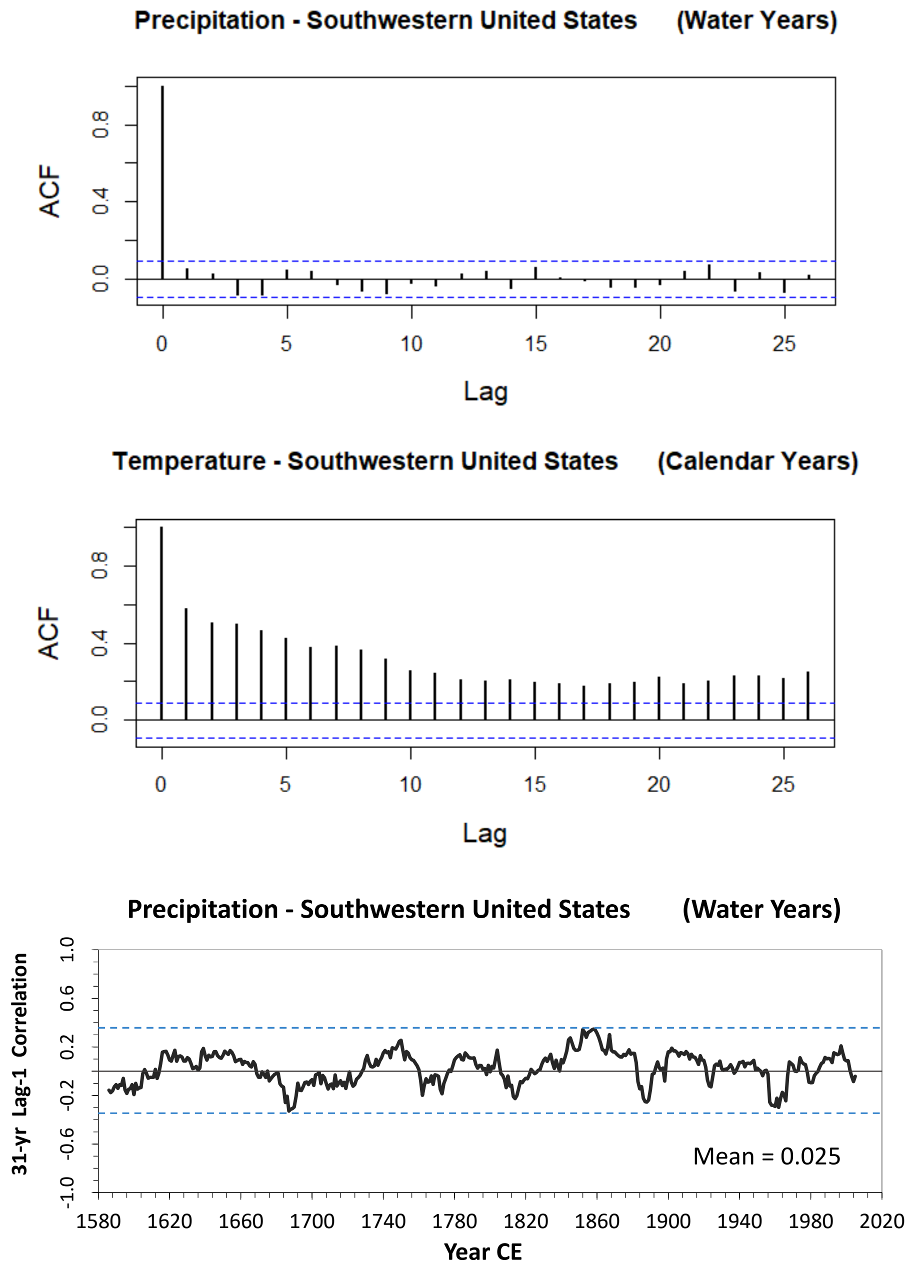
Supplementary Information



Supplementary Figure 1 SW historical precipitation and temperature autocorrelation and precipitation lag-1 running correlation. Autocorrelation functions (lags 0-26) for SW precipitation (top) and temperature (middle), 31-year lag-1 correlation for SW precipitation (bottom). All for full RECON+INST time series (Fig. 1). Dashed blue lines represent estimated 95% confidence intervals around 0 value. 31 years is used for the running lag-1 correlations to provide a relatively short, yet statistically robust sample size.

Supplementary Methods

Temperature and Precipitation Reconstructions – Additional Information

The truncated EOF–principal components spatial regression (TEOF-PCSR) methodology used to assess pre-instrumental climate in western North America was described and evaluated by Wahl and Smerdon[1] (cf. supplemental material therein), and details of its use to reconstruct precipitation in the North American Southwest are described in Diaz and Wahl[2] and Wahl et al.[3]. In TEOF-PCSR, standard least squares regression is applied to the principal component time series (PCs) of a truncated empirical orthogonal function (TOEF) representation of the instrumental climate field and a collection of leading PCs of the predictor data. In this procedure, the n number of reconstructed instrumental PCs, U_n, generated by the regression are substituted back into the singular value decomposition of the instrumental field, $\text{Precipitation}_{\text{field–fitted}} = U_n D_n V'_n$, to derive the reconstructed field (where the subscript n denotes the rank-reduced matrices). In this formula, U_n is the matrix of reconstructed instrumental PCs, as noted, D_n is the diagonal matrix of singular values, and V'_n is the transposed matrix of EOFs[3].

The reconstruction period is 1570-1980 for temperature and 1571–1977 for precipitation. The temperature RECON exhibits Pearson's r of 0.67 (at annual scale) with its instrumental target during the period of overlap with the SPEI instrumental data (1900-1980); the precipitation RECON exhibits a corresponding Pearson's r of 0.88 with its instrumental target (over 1900-1977). In the case of the temperature RECON, the predictor data were tree ring width and latewood density chronologies throughout temperate western North America, as detailed in[1]; for the precipitation RECON, the predictor data were tree ring-derived streamflow RECONs available in the same region, whose use and rationale are detailed in[2]. For both temperature and precipitation there is no nesting of reconstruction time periods; the same set of predictors was used throughout the reconstruction periods noted, and thus the possibility of reduced variability in the derived RECONs due to declining predictor richness back in time is not present. Further evaluation of the streamflow time series themselves shows no apparent reduction of variability over the RECON period, with the exception of one data set (the Gila River), which may have reduced variability prior to 1700[2] (cf. supplemental information therein). The impact of such a feature, if in fact present, would be negligible on the RECON because the streamflow data were entered into the EOF extraction algorithm in their primary units, so that the relative influence of the very large river/basin flows would strongly weight in the PCs used for reconstruction. In this case, the average reconstructed flow of the Gila River is less than two percent of the average for the largest streamflow time series – the Upper Colorado and Sacramento Rivers[2] (cf. supplemental information therein).

Streamflow RECONs were used as predictors in the precipitation RECON rather than the underlying tree-ring chronologies directly, based on the fact that precipitation determines streamflow to a large degree even in the seasonally dry western United States[4] (Figure 5 therein), and relatively large basins integrate precipitation over their full domain. Thus, the streamflow RECONs are expected to have significantly reduced the non-precipitation information present in the original tree-ring data used to drive them that is not useful from the perspective of reconstructing spatial precipitation fields. Added confirmation of the efficacy of using the streamflow RECONs as predictors is indicated by the absence in the reconstructed precipitation time series of the possible long-term memory bias identified in (at least some) long tree-ring-based precipitation RECONs[5], which those authors attribute to trees responding to local-scale soil moisture persistence along with their responses to larger-scale, white noise-like precipitation fluctuations (Supplementary Figure 1; cf. Figure S4 of Diaz and Wahl, 2015[2]).

<u>Determination of precipitation and temperature β Weights from the Living Blended Drought Atlas PMDI RECON Data</u>

We note that the ratios of the running precipitation and temperature β weights for the PMDI are compressed to limit their maximum size during the RECON period. The values of this ratio indicate the relative importance of precipitation and temperature in a single metric and are unrealistically high for a few years during the RECON period compared to their maximum value during the INST period. When this effect occurs, it is driven by a nearly complete breakdown in the influence of temperature on the PMDI for a particular 21-year time span, which does not occur for the INST data. The influence of precipitation on the PMDI does not exhibit this behavior, being similar throughout the full RECON+INST record. As a threshold for the limiting to take effect, we used the value of three times the maximum ratio during the INST period, which is equivalent in information theory terms to a value of 21.4 dB [10*log(3*46.037)][6]. This level is in the middle of the range of low but stable signal detectability within information systems (such as internet connectivity or reasonable speech intelligibility), 15-25 dB[6], representing a reasonable way to objectively establish the threshold. We emphasize that the "signals" to be identified in this case are the anomalous/unrealistically large standardized precipitation/temperature ratios. Without employment of a limiting threshold, the reduction in the influence of precipitation relative to temperature is 61%, which in our judgment represents a less realistic estimate of how the influence of precipitation has recently declined in the SW – in light of the 34% reduction determined from the INST SPEI data in conjunction with the white noise-like character of the full RECON+INST precipitation time series (Fig. S1, top panel).

Supplementary References

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