

This file describes files output by TRISH for reconstruction method SLR1 (Simple Linear Regression 1), a two-stage method for reconstruction of a hydrologic time series, y , from a network of tree ring chronologies, X , using simple linear regression of y on the mean of single-site reconstructions (SSRs) of y . The method has been used in reconstructions of annual flows of the Colorado River (Woodhouse et al. 2020) and Sacramento River (Hutton et al. 2021). The two-stage approach to dendroclimatic reconstruction in general was introduced in the context of precipitation reconstruction by Meko (1997).

The first stage is to convert individual tree-ring chronologies to single-site reconstructions (SSRs) of y by distributed-lag stepwise multiple linear regression. Assume a time series matrix X whose columns, x , are standard or residual tree-ring chronologies. Each x is converted into a separate SSR of y by stepwise regression (Weisberg 1985) of y on x lagged -2 to +2 years from y . Such a regression, called “distributed lag” regression, has a long history of application in dendroclimatology (e.g., Stockton and Fritts 1973; Fritts 1976; Stockton and Meko 1983; Meko and Graybill 1995; Cook et al. 1999). The SSR model is cross-validated by leave-9-out cross-validation Meko (1997) and split-sample validation (Snee 1977) at each step as variables are entered in order of maximum reduction of the residual variance. Entry into the model is stopped if the next predictor to enter would result in decreased skill, as indicated by a drop in cross-validation reduction-of-error statistic, RE (Fritts et al. 1990). This approach to stopping entry of predictors in stepwise regression is a cross-validation cutoff rule (Wilks 2019). Regardless of the change in cross-validation RE, entry of variable is not allowed to proceed beyond the step at which the model reaches maximum adjusted R^2 (Myers 1990). In summary, entry of variables into the SSR model is guided by a cross-validation cutoff rule and entry is limited by the maximum adjusted R^2 .

TRISH can be run with either standard or residual chronologies (Cook and Kairiukstis 1990) as input. An option for whitening site chronologies within TRISH allows you to get a reasonable estimate of how residual chronologies would perform without actually uploading a matrix of residual chronologies to TRISH. From TRISH screens you can choose to prewhiten chronologies with an order- p autoregressive model (AR(p)) where p is 1 2 or 3. Prewhitening at the site chronology level (Meko et al. 1993) is not the same as prewhitening at the individual-core level, as done in computing residual chronologies, but the resulting chronologies are generally very similar.

Although the SSRs are specifically intended to deal with lagged response of tree-growth to climate that might vary site to site, it is possible to apply TRISH to reconstruction without lagged predictors. An option allows you to specify that lag-0 only is allowed in the pool of potential predictors.

The second stage of reconstruction is multi-site reconstruction, or MSR, whose objective is to combine the information from the individual SSRs into a final reconstruction. The second stage consists of simple linear regression of y on the arithmetic mean of a screened subset of the SSRs. The SSRs are screened for strength and temporal stability of the signal for y . The screened network includes only those SSRs with the following properties: 1) a statistically significant ($p < 0.05$) overall-F of calibration, 2) positive skill of cross-validation, as reflected in a positive reduction-of-error (RE) statistic (Fritts et al. 1990), 3) positive skill of split-sample validation, as reflected in $RE > 0$ for both halves of split-sample validation, and 4) a physically logical lag structure given the expected causative relationship of climate and tree rings. This last constraint means that the the SSR is rejected if the lags imply that the current year's y is predictable from just past years' x , and is underlain by the logic that a response should not precede the stimulus in a dynamic system. TRISH options do allow you to make the screening less stringent by optionally removing constraints (3) and (4).

The time series matrix of screened SSRs mentioned above covers all years in common to those SSRs plus any additional years until the last year of the most recently ending SSR. Any SSR with an

earlier ending year than that last year is extended statistically by a quantile-analog procedure described later (see “**Figure03-SSR3**”).

Reconstruction in TRISH by method SLR1 yields various files in an output directory:

1. **Thirteen figure files.** Figures files 1-4 are for the SSRs and files 5-13 are for the MSR. Files are described in more detail below.
2. **Six tables of statistics.** Tables 1-2 are for the SSRs and Tables 3-6 are for the MSR. Files are described in more detail below.
3. **Two tab-separated time series matrices.** One has the calibration-period data for predictand and predictor of the MSR model. The other has observed y , reconstructed y , and 50% confidence interval for reconstructed y . Files are described in more detail below.
4. **Two miscellaneous files.** These files, MyDataSLR1.dat and progressTRISH.txt are used by the interactive TRISH tool, but are not important to the user and so are not described below.

GRAPHICS FILES (all .png)

1. **Figure01-SSR1. Summary of chronology screening by single-site reconstruction (SSR).** Bar chart at left shows the number of chronologies at various stages of screening. Box plots at right summarize distributions of adjusted R-squared of SSR models for the subset of chronologies suitable for modeling. Screening tally as follows: 1) the $N1$ chronologies in the source tree-ring network, 2) the $N2 \leq N1$ chronologies in the user-drawn map polygon, 3) the $N3 \leq N2$ chronologies with sufficient time coverage for SSR modeling, and 4) the $N4 \leq N3$ chronologies passing screening for strength and temporal stability of hydrologic signal.

Screening consists of several stages, starting with a user-specified network of $N1$ chronologies. First is the reduction to $N2$, which includes only those chronologies both in the user-drawn map polygon and with full time coverage over some specified interval. Second is reduction to $N3$, which includes only those chronologies whose time coverage has sufficient time coverage for some specified calibration interval. Third is reduction to $N4$, which includes only those chronologies passing SSR screening, described previously.

Only $N3$ chronologies are SSR-modeled, and only $N4$ of those pass SSR screening. Because the F-level of adjusted R-squared is one of the screening criteria, the box plots usually indicate that the $N4$ screened chronologies have higher adjusted R-squared than the large set of $N3$ chronologies fit to SSR models.

2. **Figure02-SSR2. Bar charts summarizing lags in SSR models.** At left is a histogram of the number of models that include lags $t-2$ to $t+2$ relative to y for the $N3$ chronologies subjected to SSR modeling. At right is a similar histogram for just the $N4$ chronologies passing screening.

The histograms are useful for a quick assessment of whether lags are important for the chronologies modeled. It is not unusual for some models to include positive lags but not lag-0, meaning a delayed response of growth to climate.

3. **Figure03-SSR3. Drop in maximum SSR signal-strength with loss of chronologies toward present.** Depending on the input specifications, SSR models may have been fit to a specific uniform calibration period, or to whatever overlap period of y is available for each chronology (variable calibration period). The maximum R-squared (left y-axis) applies to that calibration period. Chronologies generally have different ending years, so that the nearer to the present the fewer the available chronologies (or SSRs), because each chronology is modeled by an SSR).

The red line shows the drop in available chronologies from an initial year when all $N4$

SSRs are available, to the last year with any chronologies are available. The black line, and right y-axis, shows the corresponding maximum adjusted R-squared of the SSR models that extend to the given year. For example, if the SSR with the strongest signal (highest R-squared) also happens to be the chronology with the most recent time coverage, the the black line will be at a constant over the time period of dropping sample size.

The plot is intended as interactive feedback to allow you to pick a reasonable ending year for the calibration period of SSR models, and equivalently, of the final MLR model. You would not want the calibration period to extend past the last year of tree-ring data with a strong SSR model. For example, if all screened SSRs were complete through 1998, and if chronologies dropped out such that only one was available in 2017, you could specify an ending year for calibrating the MSR model anywhere in the interval 1998-2017. If the chronology with the strongest signal (highest R-squared of SSR) had the end year 2017, it might make sense to to specify the end year for MSR calibration as 2017. But if there was a big drop in maximum R-squared after some year (say, 2004), you might want to specify 2004 as the end year for calibration of the MSR.

The currently specified last year of the default calibration period is annotated on the figure as “calibration end year.” Calibration of models is not allowed to include any y data after that year. The actual calibration periods of SSR models might not extend to the specified year, depending on the ending date of chronologies. “NA” as “calibration end year” means that you have allowed the data itself to set the maximum possible calibration period depending on the overlap of the chronology with y . If you happen to set the calibration end year to “NA,” the actual calibration period for all SSR models will extend to the year of the most recently collected tree-ring chronology. Calibration periods of individual SSR models are listed in the tables in output files Table1-SSR1.txt and Table2_SSR1.txt.

How is it possible to specify an ending year of the calibration period later than the end of one of the chronologies. This is possible because before MLR modeling, TRISH extends all of the SSRs by a quantile analog method to the year of the most recently ending SSR. Extension is done by combination of correlation analysis and quantile ranking, as follows, assuming **A** is the SSR needing extended in year k . (1) A common period of length at least 50 years is identified for which all SSRs are complete – no missing data. (2) The correlation matrix (Spearman) of SSRs is computed for the common period, and correlations are sorted from largest to smallest. (3) The SSR that is most highly correlated with **A**, has data in year k , and has at least 100 year of overlap of complete data with **A** is defined as the predictor SSR, or series **B**. (4) The quantile of the value of **B** in year k is computed in the overlap period of **A** and **B**. (5) The same quantile of **A** in that overlap period is defined as the estimate of **A** in year k . Steps 3-5 are repeated until all SSR series have been extended to the ending year of the most recently ending SSR.

To avoid using extended SSRs in the reconstruction, specify at the TRISH input window an ending year of calibration that is the same as the last year of coverage by all of the screened SSRs before extension. This year can be identified from Figure 03.

4. **Figure04-SSR4. Scatterplot of the mean of the N4 SSRs of y against observed y .** The plot also has a fitted least-squares straight line, a locally-weighted (loess) fit to the scatter of points, and separate loess fits to the positive and negative residuals from the loess-fit to the points (Martinez and Martinez 2002). The correlation coefficient is annotated on the plot. This figure gives a quick view of the strength of signal for y in the mean of the screened SSRs and whether the relationship of observed y with the mean of the SSR is linear, curvilinear, restricted to one particular part of the range of y , or driven by outliers.

5. **Figure05-Calibration1. Summary of calibration of MSR model.** The scatterplot of reconstructed y against observed y graphically shows the accuracy of the reconstruction. Curvature in the scatter could indicate non-linearity poorly handled by the model. Fanning out of points in the scatter toward the right, say, indicates heteroskedasticity of errors, in that error variance increases toward higher observed y .

The time series plots of reconstructed and observed y show the ability of the reconstruction to track temporal variation of y in the calibration period. Years or multi-year period of good or bad agreement are readily seen in the plots. Any diverging trends in observed and reconstructed y can also be seen in these plots. The plots in this way can visually corroborate any significant trend in residuals that might be identified in the analysis of residuals described later.

The annotated MSR calibration statistics summarize the final regression model. Statistics generally in tree-ring reconstruction papers are included. More detailed information on the model can be found in output Table 3 and Table 6 (described below).

6. **Figure06-Calibration2. Histograms and autocorrelation functions (acf's) of observed and reconstructed predictand for the calibration period.** The histograms at left allow comparison of distributions of observed and reconstructed y . These histograms have the same x-axis scale so that the compression of variance imposed by regression is readily seen: the distribution of reconstructed y is compressed relative to that of observed y . Such compression is a property of regression, and reflects the inability of the tree-ring data to explain all of the variance of y . This compression is not a flaw in the regression process. It merely reflects that tree rings are imperfect recorders of y . The temptation to “scale” the variance of the reconstruction by amplifying the departures from the mean such that the variances of reconstructed and observed y are equal in the calibration period should be resisted because the sign of the noise component for years before the calibration period is unknown (residuals assumed to have zero mean and constant variance).

The acf's allow comparison of the autocorrelation properties of observed and reconstructed y over a common period. The acf reflects persistence of above-mean or below-mean values, and so is related to duration of wet and dry periods. Greatly different acf's could indicate that the reconstruction overestimates or underestimates such duration.

7. **Figure07-AnalysisResiduals1. Analysis of residuals for normality and constancy of variance.** Analysis of residuals is an essential part of any regression modeling, and has the goal of checking that the regression assumptions on statistical properties of residuals are not violated. Texts on regression (e.g., Draper and Smith 1981; Myers 1990) cover most aspects of analysis of residuals relevant to TRISH.

Normality can be checked visually by the histogram of residuals, at left, and statistically by the annotated results of the Lilliefors Test (Conover 1980). The p -value for Lilliefors Test, annotated at top of the histogram, indicates whether we can reject the null hypothesis that the residuals come from a normal distribution.

Constancy of variance is checked visually with the scatterplot of residuals against predicted values (right), and statistically tested with the Breusch-Pagan (Breusch and Pagan 1979). The scatter plot ideally shows no noticeable pattern (e.g., fanning out, curvature) that might be evidence of violation of the assumption of constancy, or homogeneity, of variance of residuals (Myers 1990). The p -value for the Breusch-Pagan test should be greater than 0.05. Otherwise you must reject the null hypothesis of homogeneous variance of residuals, and conclude that the residuals are “heteroskedastic.” Heteroskedastic means that there is a dependence of variance of residuals on the fitted values of the regression. Visually, one

common example of heteroskedasticity residuals that fan out, or become more spread, toward higher fitted values.

8. **Figure08-AnalysisResiduals2. Analysis of residuals for trend.** Regression residuals are plotted as a time series and the time plot is tested for trend using the non-parametric Mann-Kendall trend test (Wilks 2019). The plot includes a non-parametric best-fit line, following Haan (2002), and is annotated with results of the Mann-Kendall test and with the estimates of the fitted parameters of the line as well as a variance inflation factor (VIF). The VIF reflects possible adjustment of the significance of trend for autocorrelation in the residuals – that is, autocorrelation in addition to that due to trend. The autocorrelation adjustment follows Wilks (2019), and its application is indicated by a $VIF > 1.0$. If $VIF = 1.0$, the residuals after removal of linear trend have no significant lag-1 positive autocorrelation (one-sided test, $\alpha = 0.05$).

Residuals ideally have no trend. Trend might indicate that some factor, with trend, other than the reconstruction predictand, is influencing the tree-ring index. There could be other causes (e.g., nonclimatic growth trend still in tree-ring index after standardization).

9. **Figure09-AnalysisResiduals3. Analysis of residuals for autocorrelation.** The acf of residuals is plotted with a 95% confidence interval for lags $k=0$ to $k=m$ years, where m is the minimum of 20 and $N/4$, where N is the length of the time series of residuals. The acf is annotated with results of a Durbin-Watson (DW) test of the null hypothesis that the population lag-1 autocorrelation of regression residuals is zero (Myers 1990). Ideally, the DW statistic is not significant, and the acf is within its 95% confidence interval for all lags $k > 0$.

One of the regression assumptions is that the residuals have zero autocorrelation.

Autocorrelated residuals could mean that the persistence of droughts and wet periods, say, is poorly represented in the reconstruction. Use of lags in the regression model, or use of residual rather than standard chronologies, can affect the autocorrelation of the regression residuals.

10. **Figure10-Validation1. Cross-validation predictions.** Time plots illustrating tracking of observed predictand, y , by reconstruction and cross-validation predictions. The observed y is plotted as a time series along with two versions of predicted y : 1) as provided by the reconstruction model, and 2) as provided by cross-validation. The latter are the cross-validation predictions. The two versions of predicted y will differ more and more as validation becomes poorer. Note that the cross-validation is leave- m -out rather than leave-1-out to ensure that with a lagged regression model, tree-ring data used to provide a cross-validation prediction are not also used to calibrate the model that gives that prediction (Meko 1997). How many observations are left out in cross-validation is computed as $m = 1 + 4k$, where k is the maximum positive or negative lag allowed on the predictors in the SSR regression models. For example, if lags -2 to +2 years are included in the pool of potential predictors, $m = 1 + 4(2) = 9$ observations left out. If no lags are used ($k=0$), leave- m -out cross-validation reduces to leave-1-out cross-validation.
11. **Figure11-Validation2. Validation summary statistics.** This figure summarizes the cross-validation and split-sample validation of the MSR model. At left is a histogram of the cross-validation residuals, with annotated test results (Lilliefors test) of the null hypothesis that those residuals are from a normal distribution of unspecified mean and variance. Ideally, these residuals are normally distributed. A test for normality is also applied to the regression residuals (Fig 7), and because those residuals generally are similar to the cross-validation residuals, the Lilliefors test result are also generally similar.

At right are annotated statistics for cross-validation and split-sample validation of the MSR model. The root-mean-square error (RMSE) of cross-validation is especially useful because combined with an assumption of normality, the RMSE of cross-validation can be applied to place confidence bands on the annual reconstructed y . For example, a 95%

confidence band is $\hat{y} \pm 1.96 \text{ RMSE}_{\text{cv}}$, where \hat{y} is the reconstructed y , and RMSE_{cv} is the cross-validation RMSE.

The reduction-of-error (RE) statistic is a measure of skill of the reconstruction when applied to data not used in calibrating the reconstruction model. RE is reported here for both cross-validation and split-sample validation (Fritts et al. 1990). The split-sample validation by default uses an even split on the overlap of y and x , with the early split one observation longer than the later split when the full overlap is an odd number of years. The statistic RE is not assigned “significance.” The typical interpretation is that $\text{RE} > 0$ is required for the model to have ANY skill relative to simply substituting the calibration-period mean of y as the reconstruction for each year.

12. **Figure12-Reconstruction1. Full-length reconstruction with confidence interval.** The full-length reconstruction of y is plotted with its 50% confidence interval computed as $\hat{y} \pm 0.67449 \text{ RMSE}_{\text{cv}}$ where \hat{y} is reconstructed annual y . Note that 0.6449 is the 0.75 quantile of the standard normal distribution and RMSE_{cv} is the root-mean-square error of cross-validation of the MSR model. This confidence interval therefore assumes normally distributed errors.

The last few years of the reconstruction will have amplified uncertainty if based on statistically extended SSRs (see description of Fig. 3, above). For that reason, you may want to truncate the reconstruction to end with the last year that all of the screened SSRs (before extension) have data. That way all years of the reconstruction are base on observed tree-ring chronologies rather than possibly being distorted because some tree-ring chronologies (their SSRs) are extended from other chronologies.

13. **Figure13-Reconstruction2. Autocorrelation functions (acf) and boxplots of reconstructed y for the calibration period of the MSR model and for earlier years.** These plots allow a quick graphical assessment of the calibration period y in a long-term perspective. The comparisons here are “apples vs apples” in that reconstructed y is compared with reconstructed y for different time intervals. It is of course possible to compare the pre-calibration reconstruction with observed y for the calibration period, but here variance of the reconstruction is necessarily compressed relative to observed y by the regression process. Such a comparison might incorrectly suggest that variance of y has increased in modern times.

TABLES OF STATISTICS (all tab-sep .txt)

1. **Table1-SSR1.txt.** Summary statistics of SSR models for all chronologies fit with reconstruction models.
 1. **N₁:** sequential number in this table
 2. **N₂:** corresponding site number in original tree-ring network
 3. **Site:** unique alphanumeric identifier for tree-ring chronology
 4. **Goc:** first year of model calibration period
 5. **Endc:** last year of model calibration period
 6. **Model:** code indicating lags in model and order that they entered stepwise. The five slots correspond to lags -2, -1, 0, +1, +2 years relative to the predictand year. For example, code [0 2 1 0 0] means lag 0 entered first, lag t-1 entered second, and no other lags are in the model.
 7. **Sign:** code that goes along with “Model” and tells the sign of the SSR regression coefficients on the the chronology lagged -2, -1, 0, +1, +2 years relative to the predictand year. Codes “P”, “N” ad “0” indicate positive coefficient, negative coefficient, and not in model. For example, [00P0P] means positive coefficient on lag 0, and positive coefficient on lag t+2.
 8. **R2a:** adjusted R-squared of model; this is the regression R-squared adjusted downward as a penalty for number of predictors in the model.
 9. **pF:** p-value of the overall F of regression (pF<0.05 indicates significant model at 0.05 level)
 10. **REcv:** Reduction of error (RE) statistic from leave-9-out cross-validation
 11. **REa:** Split sample RE for fitting model to first half of record and validating on second half
 12. **REb:** Split sample RE for fitting model to second half of record and validating on first half
 13. **Refit:** Logical (TRUE or FALSE) variable indicating whether the model was re-fit with expanded calibration period after exploratory stepwise regression.
 First the stepwise regression allows lags -2 to +2 in the model, which could restrict the calibration period if the tree-ring data happen to end in the same year or in the year after the end of y. For example, if y and the chronology end in 2019, the calibration period cannot have an ending year later than 2017, because of the possible need for lags +1 and +2 on the tree-ring series. The stepwise process might result in a model that does not include lags +1 or +2. If so, the model is re-fit, resulting in the maximum possible length of calibration period given the lags in the model and time coverage of y and the tree-ring chronology. “Refit” indicates whether the model was re-fit. .
 14. **Gor:** First year of reconstruction.
 15. **Endr:** Last year of reconstruction.
 16. **Reject:** Logical (TRUE or FALSE) variable indicating whether the chronology and its SSR are rejected from further use in the later step of multi-site reconstruction. Rejection occurs if any of the following are true:
 1. $pF \geq 0.05$
 2. $REcv \leq 0$
 3. $REa \leq 0$ or $REb \leq 0$
 4. Illogical causal model: the final model has y predicted from x at negative lags only from y. This is physically unreasonable, because past years’ tree-ring values alone should not be able to detect current year’s climate.

2. **Table2-SSR2.txt.** Summary statistics of SSR models for just those chronologies passing screening for hydrologic signal. These are the chronologies for which “Reject” is FALSE in Table 1. The columns are the same as those of Table 1.
3. **Table3-Calibration1.txt.** Calibration statistics of the multi-site reconstruction (MSR) model.
 1. **YearGo:** first year of calibration period
 2. **YearStop:** last year of calibration period
 3. **R2:** regression R-squared
 4. **F:** overall-F of regression
 5. **pF:** p-value of F
 6. **R2adj:** adjusted regression R-squared
 7. **RMSEc** is root-mean-square error of calibration, which is also called the “standard error of the estimate.
4. **Table4-AnalysisResiduals1.txt.** Normality, autocorrelation, trend, heteroskedasticity
 1. **YearGo:** Start year of calibration period
 2. **YearStop:** End year of calibration period
 3. **pNormal:** p-value of Lilliefors test for normality (pNormal<0.05: reject H0 that residuals from normal distribution)
 4. **DW:** Durbin-Watson statistic
 5. **pDW:** Durbin-Watson statistic p-value (pDW<0.05: reject H0 that population lag-1 autocorrelation of regression residuals zero)
 6. **TrendSlope:** slope coefficient of non-parametric fit of trend of residuals
 7. **pTrend:** Slope of trend line, with p-value from Mann-Kendall test
 8. **BP Test ChiSq:** Breusch-Pagan Chi-squared statistic (test for homoskedasticity of residuals)
 9. **dfBP:** degrees of freedom for BP test: equals number of predictors in model 1
 10. **pBP:** p-value for BP test; pBP<0.05 indicate reject H0 that residuals homoskedastic at 0.05 level
5. **Table5-Validation1.txt.** Cross-validation and split-sample validation statistics of MSR model.
 1. **NleaveOut:** Cross-validation how many left out
 2. **RMSEcv:** Cross-validation root-mean-square error
 3. **REcv:** reduction of error (RE) statistics from cross-validation
 4. **YearGoA, YearStopA:** first and last years of early split-sample period
 5. **YearGoB, YearStopB:** first and last years of early split-sample period
 6. **REsplitA:** split-sample RE for calibration on early (A) and validation on late (B)
 7. **REsplitB:** split-sample RE for calibration on late (B) and validation on early (A)
6. **Table6-MSR-SLR1-Coefficients.txt.** Estimated coefficients of MSR regression model
 1. **Intercept::** constant term, or intercept in the regression
 2. **meanSSR:** coefficient on the mean of the screened SSRs, which is the sole predictor in the MSR Model

TIME SERIES OUTPUT

1. **RegressionInputTimeSeries.txt.** Listing of predictand and predictor time series for the calibration period of the MSR model. User, if incined, could repeat the regression model outside of TRISH by regression the data in the second column on the data in the third column.
 1. **Year:** year of data
 2. *<predictand (units)>* The predictand for the regression model
 3. **meanSSD:** the mean of the screened SSDs; this mean is the sole predictor in the MSR model.
2. **ReconstructionWithConfidenceIntervalTimeSeries.txt.** Listing of time series of observed predictand, reconstruction, and confidence interval on reconstruction (5 columns). Call the observed predictand y and the reconstruction \hat{y} . Confidence interval is estimated assuming that reconstruction errors are normally distributed with a standard deviation equal to RMSEcv.
 1. **Year:** year of data
 2. **y:** observed predictand
 3. **yhat:** the reconstruction
 4. **Lower limit of 50% confidence interval on yhat**
 5. **Upper limit of 50% confidence interval on yhat**

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