This file describes files output by TRISH for reconstruction method MLR1-noPCA (Multiple Linear Regression 1, not on Principal Components), a two-stage method for reconstruction of a hydologic time series, $y$, from a network of tree ring chronologies, X, using stepwise multiple linear regression of $y$ on previously generated single-site reconstructions (SSRs) of $y$. A similar approach has previously been used in  reconstruction of annual precipitation in the USA western Great Plains (Stockton and Meko 1983).

The first stage of the reconstruction method 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 dendrclimatology (e.g., Stockton and Fritts 1973; Fritts 1976;  Stockton and Meko 1983; Meko and Graybill 1995; Cook et al. 1999).

TRISH allows variation on the SSR model. From TRISH screens you can choose to prewhiten chronologies and order-p autogressive model (AR(p)) where p is 1 2 or 3.  Prewhitening at the site chronology level (Meko et al. 1993) is slightly different than the prewhitening at the individual-core level used to generate so-called "residual" chronoogies, but experience has shown that the resulting site chronologies are very similar. This option eliminates the need for you upload separate networks of standard and residual chronologies to TRISH to check whether a better hydrologic signal might be obtained from a network of residual rather than standard chronologies. TRISH also allows you to optionally dispense with lags in the SSR models.

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. Prior to MSR, the SSRs are screened for strength of 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 reduction-of-error (RE) statistic (Fritts et al. 1990) greater than zero, 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 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 a model including just past years' $x$ (e.g., this year's precipitation predictable from a model including just past years' tree-ring index).

Before before moving on to MSR modeling, a decision has to be made on how many, and which, SSRs to include in the pool of potential predictors for the MSR model. To lessen the chance of over-fitting the model, the size of the pool is kept to a small fraction of the sample size (number of years) for calibration of the MSR model. The default in MLR1-noPCA is to prioritize the SSRs by their correlation with $y$, such that the pool of potential predictors includes only the $m$ SSRs most highly correlated with $y$. Specifically, by default, the pool is restricted to size $m<fN$, where f=0.10. In other words the pool of potential predictors is constrained to be less than 1/10 the number of ovservations in the calibraiton period (e.g., 100 years of calibration dictates no more than 9 SSRs in the pool). The user can optionally override the default for restricting the size of the pool of potential predctors by specifying $f\neq0.10$.

An additional, optional, step  to allow the reconstruction to come as close to present as possible when the SSRs have different ending years is to extend all SSRs toward the present statistically. In the exttreme, all can be extended to end in the year of the most recently ending SSR.  Such extension might apply when chronologies have various endng years, (e.g., 2018 to 2022).  The extension is done by a quantile method with the following steps for any SSR  -- the "key" SSR -- requiring extension: 1) find a common period, A, covered by all SSRs, and compute the correlation matrix of the key SSR with all

others for that period; 2) find the highest correlated (Spearman r) SSR that also has data in the year, $t_0$, that the key SSR needs replacement of a missing value; 3) for the common period of the two SSRs (key and predictor) find the quantile of the predictor SSR for year $t_0$ in the common period of the two SSRs; and 4) replace the missing value in the key SSR in year $t_0$ with its same quantile for the common period. In the special case of the predictor SSR for year $t_0$ outside its range for the common period, the maximum or minimum (whichever is more appropriate) of the key SSR for the common period replaces the missing value. A diagnostic figure (Figure 3) is provided by TRISH to help the user decide whether to apply this optional extension of SSRs. For example, one would not want to extend if the only SSRs remaining in the last few years (predictors must come from these) are SSRs with weak signals for $y$.

The MSR itself is a done by forward stepwise regression of $y$ on the SSRs in the pool of potential predictors. A cross-validation stopping rule (e.g., Wilks 2019) is used to stop entry of predictors in the stepwise MSR model whenever skill, as measured by cross-validation RE, would decrease with entry

of an additional predictor. Regardless of the change in RE, the stepwise entry is not allowed to proceed beyond the step of "approximate maximum" adjusted R-squared of calibration (Myers 1990). "Approximate maximum" means that the user can specify a minimum acceptable increment (e.g., 0.01) in increase in adjusted R-squared. If the next variable to enter stepwise would give less of an increase in adjusted R-squared, entry stops.

Reconstruction in TRISH by method MLR1-noPCA yields various files in an output directory:

1. **Fourteen figure files**. Figures 1-4 are for the SSRs.  Figures 5-14 are for the MSR.
2. **Six tables of statistics**. Tables 1-2 are for the SSRs. Tables 3-6 are for the MSR.
3. **Three files with tab-separated time series.** One file has the full-length time series of the screened SSRs. A second file has the calibration-period data of predictand and predictors (SSRs) for the MSR model. A third file lists observed *y*, reconstructed *y*, with a 50% confidence interval for the reconstruction. Files are described in more detail below.

**FIGURE 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≤N1 chronologies in the user-drawn map polygon, 3) the N3 ≤N2 chronologies with sufficient time  coverage for SSR modeling, and 4) the N4≤N3 chronologies passing screenng for strength and temporal stability of hydrologic singal.

   Screening consists of several stages, startng 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.

   The following criteria for SSR screening must all be satisfied for a chronology and its SSR to be accepted for later use in multi-site reconstruction: 1) significant calibration signal, as defined  regression overall F having p<0.05, 2) cross-validation reduction of error (REcv) greater than zero, and 3) split-sample validation RE>0 for both halves of the data (validating on second half the model fit to first half, and validation on first half of model fit to second half).
2. **Figure02-SSR2  Bar charts summaring 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.

   A SSR regression model is a stepwise regression of the predictand, y, on the tree-ring chronology lagged -2  to +2 years from y.  Variables are entered forward stepwise according to maximum reduction in residual variance. Entry is stopped at the earliest step one of the following conditions are found: 1) adjusted R-squared of calibration reaches a maximum, or 2) cross-validation REcv reaches its first local maximum.
3. **Figure03-SSR3**. **Drop in maximum SSR signal-strength with loss of chronologies toward present**. X-axis is number of chronologies, from N4 at left end to 1 at right end. Left y-axis is number of chronologies, or SSRs, available in each year. Right y-axis is the maximum adjusted R-squared of the SSR models for those chronologies. Depending on year of collection,

chronoogies may drop out of the network before the most recent year available for any of the screened SSRs. Reconstruction method LR1 statistically extends all screened SSRs to the ending year of the most recently ending SSR to allow a maximum possible length of calibration period for the MSR.  This may not be a good strategy if the SSRs with the strongest signals drop out before that most recent ending year.

TRISH gives and option for specifying the end year of the calibration period, and this plot will help guide you by indicating loss of signal with data extension. 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 R2 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 R2 after some year (say, 2004), you might want to specify 2014 as the end year for calibration of the MSR.

You may wonder how the SSRs are extended statistically to the year of most recent coverage by any SSR. This is done by combination of correlation analysis and quantile ranking. For any year that needs to be estimated for some SSR, the first step is to find which other SSR has data for year in question and also has the highest bivariate Pearson correlation with the SSR needing estimation (correlation based on full available overlap of pairs of SSRs). One SSR would then be the predictor for the missing value of the other SSR. If the year to be estimated is 2017, say, the overlap period of the two SSRs would be examined and the quantile matching the 2017 value of the predictor SSR determined. The same quantile for the predictand in that overlap would be assigned as the SSR for the predictand series in 2017.

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. The correlation coefficient is annotated on the plot. This figure plot gives a quick view of the strength of signal for y in the set of screened SSRs and whether the 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**. Bar plot of correlations and autocorrelations. Blue bars have length proportional to the correlation of the predictand, y, and the screened SSRs. Magenta bars are lag-1 autocorrelations of the SSRs. A 95% confidence band on the correlations is plotted by default, but the user con change this to 90% or 99% within TRISH. No adjustment of significance for autocorrelation is made for the correlations  The autocorrelation of y is show with a horizontal magenta line. Difference in the height of this line and the heights of the magenta bars shows whether the tree-ring chronologies, after conversion to SSRs, are more or less autocorrelated than the hydrologic variable to be reconstructed. It is important to recognize that the lag-1 autocorrelation can reflect long-memory (e.g., trend) as well as short-memory processes.

6. **Figure06-Calibration2**. Summary of calibration of MSR model. A scatterplot of reconstructed against observed y is at upper left. A time series plot showing tracking of observed y by the reconstruciton is at the bottom. Calibration statistics of the MSR model are annotated at upper right.

7. **Figure07-Calibration3**. Histograms and autocorrelation functions (acf's) of observed and reconstructed predictand for period of calibraiton. The histograms at left allow comparison of distributions of observed and reconstructed y. These histograms have the same x-axis scale, which readily shows how much the distribution of reconstructed y is compressed relative to that

of observed y. Such compression is a property of regression modeling, and reflects the inability of the tree-ring chronologies to explain all of the variance of y. The acf's similarly allow comparison of the autocorrelation properties of observed and reconstructed y over a common period.

8. **Figure08-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 is annotated at top of the histogram.

    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 "heteroscedastic."  Heteroscedastic means that there is a dependence of variance of residuals on the fitted values of the regression. Visually, one common example of heteroscedasticity residuals that fan out, or become more spread, toward higher fitted values.

9. **Figure09-AnalysisResiduals2**. Analysis of residuals for trend. Regression residuals are plotted as a time series and are tested for trend using the non-parametric Mann-Kendall trend test (Wilks 2019). The plot includes a non-parametric best-fit line as described by 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 reflect possible adjustment of significance of trend for autocorrelation in the residuals, beyond the autocorrelation represented by the 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).

10. **Figure10-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, and 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.

11. **Figure11-Validation1**. Time plots illustrating tracking of observed predictand 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 prediction 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 no tree-ring data used to provide a cross-validation prediction are also used in calibrating 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 were included in the pool of potential predictors, m=1+4(2)=9 observations are left out.

12. **Figure12-Validation2.** Validation summary statisitics. 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 distibution of unspecified mean and variance. Ideally, these residuals are normally distributed.

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 yhat±1.96 RMSEcv, where yhat is the reconstructed y.

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. Split-sample validation by default uses an even split of 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 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 (Fritts et al. 1990).

13. **Figure13-Reconstruction1**. Full-length reconstruciton with confidence interval. The full-length reconstruction of y is plotted with its 50% confidence interval computed as yhat±0.67449 RMSEcv, where yhat is reconstructed annual y. Note that 0.6449 is the 0.75 quantile of the standard normal distribution and RMSEcv is the root-mean-square error of cross-validation of the MSR model. This confidence interval therefore assumes normally distributed errors.

14. **Figure14-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 whether the reconstruction is more or less autocorrelated in the instrumental period than in previous years, and whether the distribution (e.g., spread and level) of reconstructed y is greater or less in the instrumental period than in earlier years.

**TABLES OF STATISTICS  (all tab-sep .txt)**

***When viewing tables on screen with text editor, use monospaced font; otherwise columns will not line up properly with headings.***

1. **Table1-SSR1.txt.** Summary statistics of SSR models for all chronologies fit with reconstruction models.
   1. **$N_1$**: sequential number in this table
   2. **$N_2$**: 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. **R2a**: adjusted R-squared of model; this is the regression R-squared adjusted downward as a penalty for number of predictors in the model.
   8. **pF**: p-value of the overall F of regression (pF<0.05 indicates significant model at 0.05 level)
   9. **REcv**: Reduction of error (RE) statistic from leave-9-out cross-validation
   10. **REa**: Split sample RE for fitting model to first half of record and validating on second half
   11. **REb**: Split sample RE for fitting model to second half of record and validating on first half
   12. **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. .
   13. **Gor**: First year of reconstruction.
   14. **Endr**. Last year of reconstruction.
   15. **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≥0.05
       2. REcv≤0
       3. REa≤0 or  REb≤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 peirod
   2. **YearStop:** last year of calibration period
   3. **Npool**: number of SSRs in the pool of potential predictors
   4. **Npredictors**: number of predictors (SSRs) in MSR model
   5. **R2:** regression R-squared
   6. **F:** overall-F of regression
   7. **pF:** p-value of F
   8. **R2adj**: adjusted regression R-squared
   9. **RMSEc** is root-mean-square error of calibraton, which is also called the "standard error of the estimate.
4. **Table4-AnalysisResiduals1.txt**.  Normality, autocorrelation, trend, heteroscedasticity
   1. **YearGo:** Start ear of calibration period
   2. **YearStop**: End ear 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-parametricfit 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 homoscedasticity of residuals)
   9.  **dfBP:** degress 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 homoscedastic at 005 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 ealy split-sample period
   5. **YearGoB, YearStopB**: first and last years of ealy 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-CoefficientsMSR.** Estimated regression coefficients of the MSR model
   1. **Intercept:** constant term in the regression
   2. <remaining rows>: each row corresponds to SSRs included in the model; variables are labeled by the site code of the tree-ring chronology for the SSR (e.g., "Russ259"). No physical meaning should be imparted to the signs of the coefficients because the individual SSRs are inter-correlated.

**TIME SERIES OUTPUT**

1. **ScreenedSSRtimeSeries.** Listings of time series o the screened SSRs. Note that the final multi-site rconstruction (MSR) model may include just a subset of these as predictors (see Table 6). First, the restriction of the pool of potential predictors could have been reduced because it is restricted to be smaller than some decimal fraction (input f) times the number of years in the calibration period. Second, the stepwise regression might select just some of the predictors from the pool of potential predictors.
2. **RegressionInputTimeSeries.txt.** Listing of predictand and predictor time series for the calibration period of the MSR model. User could repeat the regression model outside of TRISH by regressing the data in the second column on the data in the remaining columns.
    1. **Year:** year of data
    2. *<predictand (units)>* The predictand for the regression model
    3. *<predictors – SSRs>*: the SSR time series used as predictors in the MSR model, in same order as the coefficients are listed in Table 6.
3. **ReconstructedWithConfidenceIntervalTimeSeries.txt**. Listing of time series of observed predictand, reconstruction, and confidence interval on reconstruction (5 columns). Call the observed predictand  y and the reconstruction yhat. Confidence interval is estimated assuming that reconstuction 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 50% CI:** true (unknown) value of predictand has 50% chance of being lower than this threshold of the confidence interval (CI)
    5. **Upper 50% CI:** true (unknown) value of predictand has 50% chance of being higher than this threshold of the confidence interval (CI)

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