Support Online Material

For

Precipitation variability of the past 400 years in the Xiaolong Mountain (central China) inferred from tree rings

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Designs of the Artificial Neural Network (ANN)

Tree-ring based reconstruction methods commonly employed often assume a linear relationship between the tree-ring data and the instrumental target (Fritts, 1976). In most cases these assumptions are shown to be broadly met, but questions related to so-called divergence phenomena (D'Arrigo et al., 2004) merit further explorations on the possible nonlinear associations between tree growth and climate. We used a feed-forward backward-propagation network, a commonly used ANN model in dendroclimatology (Guiot et al., 2005; Ni et al., 2002; Woodhouse, 1999, 2001; Zhang et al., 2000), to model the nonlinear climate-growth relationships. Examples where growth may not follow a linear relationship could be when warming exceeds a threshold (D'Arrigo et al., 2004) or the differential ability of tree rings to record wet versus dry (Fritts, 1976).

Our ANN model includes (1) the input layer with monthly mean temperature and/or monthly precipitation, (2) the hidden layer with three neurons, and (3) the output layer of the chronology indices. In order to mitigate the potential model overfiting (Woodhouse, 1999), only the monthly climate variables showing high, significant correlations with tree growth were selected to model tree growth. The six input monthly climate variables used were: the averaged April-May temperature, the mean temperature in June and July, the monthly total April-May precipitation, and the June and July precipitation. The nonlinearity was employed by using the nonlinear transfer functions (logistic sigmoid function) between the input and hidden layers and the complex dimension of ANN. The transfer function between the hidden and output layers is a linear function. During the training process, 60% of randomly divided (31 years) monthly climate data (calibration dataset) were fed in the model to adjust the weights between three layers in order to minimize the sum of squared errors between estimated and actual data, using the Levenberg-Marquardt algorithm. The ANN model was validated using 20% of the randomly-selected data and was tested by 20% of the independent data (testing dataset). The validation was employed to check the network performance and to stop training before overfitting, whereas the testing procedure relies upon completely independent data to assess ANN performance. The trained ANN was used to simulate tree growth for some scenarios of input monthly climate variables and to examine the nonlinear climate-growth relationships (Zhang et al., 2000). In each simulation, we changed the values of two monthly climate variables and the other four variables were set at their mean values in the instrumental period. Further details on the ANN model are provided in the Appendix.

Details on the Matlab-based ANN-based Analyses

The ANN modeling is implemented using the MATLAB toolbox. The network includes three layers with one hidden layer with three neurons. The training function in the toolbox is TRAINLM, the learning function is LEARNGD, and the model performances were examined using the MSE (mean squared error) statistics. The data were randomly selected for training data (60%), validation (20%) and testing (20%). The training process in our study was implemented with thirteen iterations. The correlation for the actual and simulated data during the training process is 0.785, the validation correlation is 0.604, the correlation for the testing datasets is 0.836, and the correlation for all the data is 0.759. The training parameters used in the MATLAB toolbox are as below.

Training parameters

Show: 25

Show window: true

Show command line: false

Epochs: 1000

Time: inf

Goal 0

Max-fail 6

Mem-reduc 1

Min-grad 1e-010

Mu 0.01

Min_grad:1e-010

Mu:0.001

Mu_dec: 0.1

Mu_inc: 10

Mu_max: 10000000000

The ANN-based Precipitation Reconstruction

A nonlinear reconstruction was conducted using an ANN method with three layers. The first layer is the input tree-ring chronology and hidden layers with 2 neurons and the third layer is the output layer with seasonally averaged April-July precipitation. The model was running using the same parameters as above. The model was trained with 7 iterations. The correlation between data of the training process is 0.701, the correlation for validation datasets is 0.827, the correlation for the testing datasets is 0.209, and the correlation for all the data is 0.665. The explained variances between ANN-based reconstruction and the instrumental April-July precipitation is 44.6%, close to the values of the explained variance of the linear reconstruction. The linear reconstruction agrees well with the nonlinear reconstruction. This may suggest that most of the precipitation values fall within the range that shows linear relationships with tree growth. We therefore merely showed the linear reconstruction in the main text.

References:

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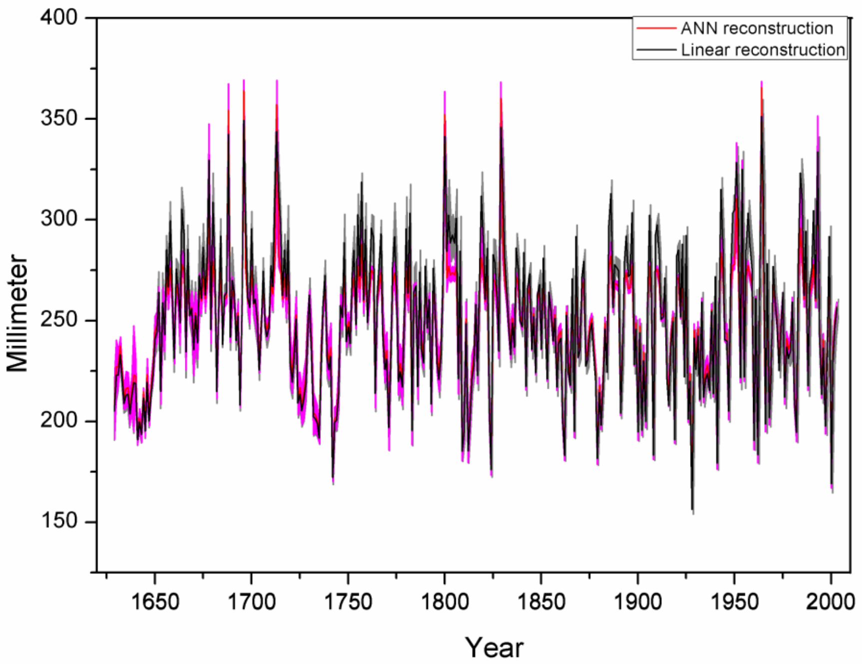

Figure S1. Comparisons between (red line) ANN-based nonlinear reconstruction and (dark) linear reconstruction of the April-July precipitation. The errors for both the ANN-based reconstruction and the linear reconstruction are also shown in grey shaded area and pink area. The reconstruction errors were based on the signal strength of the tree-ring chronology, which were derived from the standard errors of ring-with values of a given year among individual series.

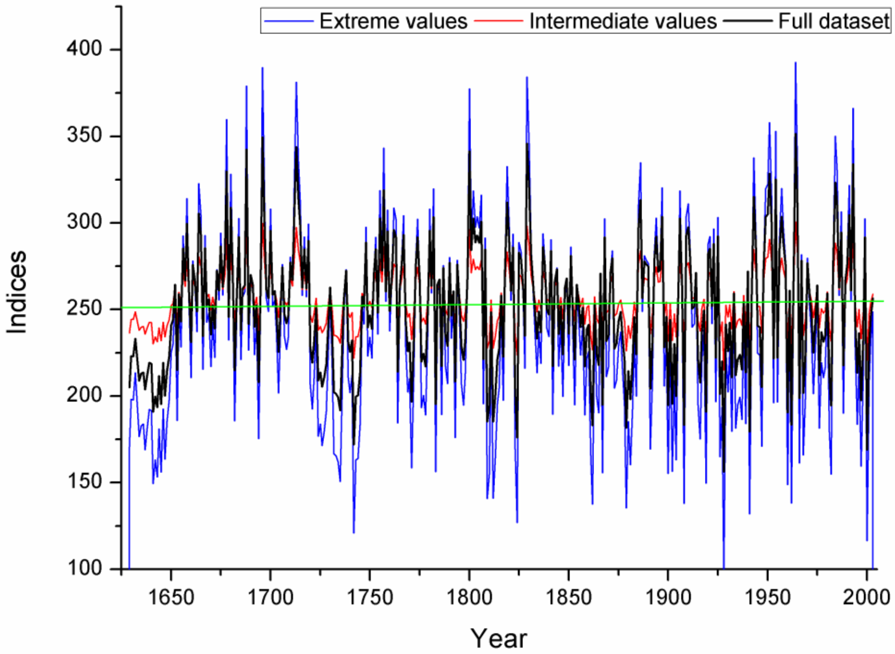

Figure S2. Linear tree-ring based precipitation reconstructions based on solely the (blue lines) extreme values of 16 years (> mean + SD or < mean - SD), the (red line) intermediate values of 37 years (> mean - SD and < mean + SD) and the (dark line) entire dataset during the common period from 1951 to 2003.