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LETTER

Topographically modified tree-ring chronologies as a potential means to improve paleoclimate inference

A letter

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Paleoclimate records from tree rings are important for understanding climate variability during the late Holocene. Some of the tree-ring chronologies of greatest interest are collected on high mountains dominated by complex terrain. Often individual trees growing at the same site will occupy discrete microenvironments particular to their own location due to the topographical differences of the landscape. These topographical differences influence how the tree records climate in its particular setting. Thus, a mean ring-width chronology from a particular site may be composed of trees from highly varied topographic positions. Such a "topographically-mixed" chronology can be confounded in terms of its climate signal. For example, ring widths of trees that are primarily recording summer temperature might be averaged with ring widths of trees that are primarily precipitation recorders. Here, we describe how dendrochronologists can use the topographic setting of individual trees within a single area to extract different growth signals and potentially improve the inference of past climates. As an example, we show how topography modifies the growth and climate associations of 69 high elevation bristlecone pine trees from the White Mountains of California and how sampling according to explicit topographic parameters might permit better understanding of complex climate-growth associations.

Climate sensitive tree-ring records extending back in time more than a thousand years are relatively rare. The dry interior of the western United States has an uncommonly high density of millennial or multi-millennial tree-ring records, mainly from five-needle pines (*Pinus* spp.). Perhaps most noteworthy of these records are the Great Basin bristlecone pines (*P. longaeva* D.K. Bailey) from the White

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Mountains in California which are extremely long-lived (some individuals living close to five thousand years).

We recently showed that increased growth during the twentieth century in bristlecone pine close to the upper elevational limit of the species is unique in recent millennia and coincident with increased temperatures over the instrumental thermometer record (Salzer et al. 2009). We also confirmed that variations in both temperature and moisture availability influence ring growth. The degree of mixing of these signals varies not only according to elevation, but also depending on the specific tree location. This occurs not only in the case of bristlecone pine in the White Mountains of California, but also in tree-ring width records of various five-needle pine species throughout western North America (Kipfmueller and Salzer 2010). We propose a strategy for disentangling these signals by exploiting complex topography in mountain systems to isolate different patterns of growth based on different limiting factors. If this can be done successfully and in a manner consistent with mechanistic understanding of the control of tree-ring variability, the calculation of climate reconstructions from data from these trees could be placed on a firmer, clearer, basis.

The current paradigm in dendroclimatology rests on networks of "site chronologies" (Fritts 2001; Hughes 2011). These site chronologies are estimates of the common temporal variability found in site collections of tree-ring samples. The procedure is to collect increment cores or cross-sections from a number of trees within a site, sufficient in number to provide a stable and robust estimate of the common signal shared by trees of that species in that site. The "site" is an area judged to be homogenous with respect to factors influencing the climate control of tree-ring variability, such as slope, aspect, substrate, and stand history. Typically the specimens appearing oldest are selected for sampling. The underlying assumption is that any common signal identified in the samples contributing to the site chronology results from their similar responses to the same growth-limiting factor or set of factors. For instance, a ring width laid down during the growing season in dry environments may well be limited by the water available to the plant, which is in turn a function, *inter alia*, of precipitation in the months leading up to the time of growth. If that univariate growth response is found to be robust, then the growth signal can be used as a proxy and backcast to infer some past climate signal. On the other hand, individual variations not driven by such common limiting factors are assumed to behave as noise that may be effectively averaged out by combining a sufficiently large number of samples in the site chronology. These individual variations may include differing individual tree histories of interaction with neighbors, for example, or the effects of very local topographic variability on response to climate. Here, we seek to make use of this second source of variability, rather than discarding it.

We suggest that even in relatively small areas, the complexity of terrain in high mountain systems can alter the operation of limiting growth factors and that it may be of value to identify and use this effect. Using topographic models from digital elevation models, it is possible to partition the landscape into relatively fine elements most likely to limit growth, on scales of tens of meters (Bunn et al. 2005). The rugged and sparsely forested areas common to upper elevation bristlecone pine offer particular promise for this approach in that it is possible to select individual trees on the basis of their topographic position either *a priori* or *post hoc* to improve paleoclimate modeling.

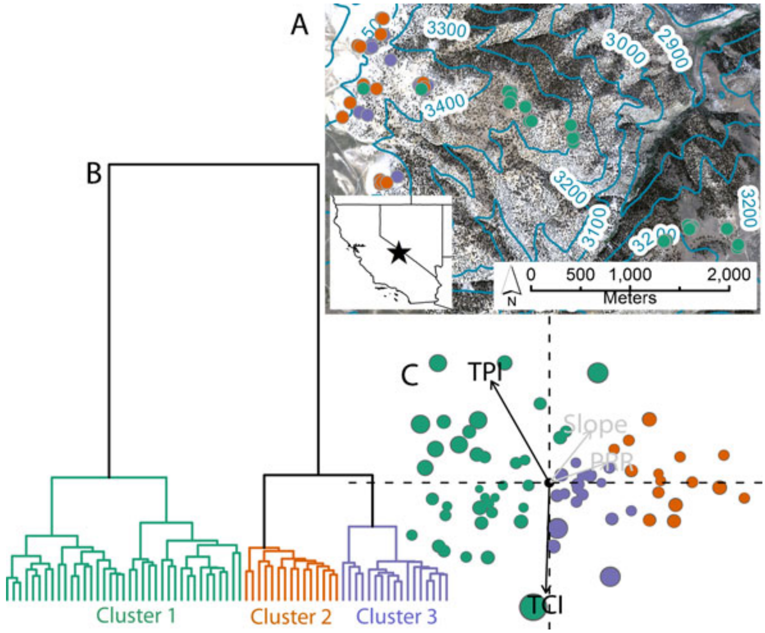


Fig. 1 **a** The study site in the White Mountains of California, USA included 69 bristlecone pine trees contained roughly within the 3100 to 3500 m.a.s.l. contours. The upper elevational limit of tree growth is ∼3500 m.a.s.l. **b** A cluster analysis partitioned each tree into one of three groups using radial growth from 1806 to 2005 by hierarchical clustering based on Ward's minimum variance dissimilarities. The length of the edges in the diagram represents the distinctness of the clusters. **c** The growth of each tree from 1806 to 2005 was ordinated using Nonmetric Multidimensional Scaling and reduced to two dimensions (stress = 14.24). Each tree was mapped by cluster into the ordination space using weighted averaging. Smaller dots in the diagram demonstrate better goodness-of-fit (lower stress) for that tree. Topographic factors for each tree were fit to the ordination as vectors with Topographic Position Index (TPI) significantly correlated on both axes and TCI significantly correlated on axis two ($p \leq 0.01$). Slope and Potential Relative Radiation (PRR) were not significantly correlated ($p > 0.01$)

We calculated three indices using a 10-m digital elevation model for 69 bristlecone pines near and at upper treeline (Fig. 1a).[1] The topographic position of each tree was described using the local slope, Topographic Convergence Index (TCI) as a rough corollary for relative soil moisture, and the Potential Relative Radiation (PRR) Index as an index for insolation (Bunn et al. 2005). We also used the Topographic Position Index (TPI) as described by Van de Ven et al. (2007). Van de Ven and Weiss (2009) used TPI to develop minimum temperature lapse rates in the White Mountains. They demonstrated that TPI is the most important component of topographic models that capture temperature inversions of several °C at a scale of tens of meters.

[1]The data we used are a subset of Salzer et al. 2009. Those data are already available via the International Tree Ring Data Bank (http://www.ncdc.noaa.gov/paleo/treering.html). The climate and topographic data are available via http://myweb.facstaff.wwu.edu/bunna/bcp_ccl.

Salzer and colleagues (2009) used hundreds of bristlecone pine ring-width series to describe growth rates over the last three and a half millennia. One curious finding of that work was that trees growing only 150 meters below the upper forest border generally showed no increase in twentieth century radial increment as compared to trees at the upper forest border which showed extremely anomalously rapid ring growth in the twentieth century. In a *post-hoc* fashion, we used a subset of all those trees for which we have differentially corrected GPS coordinates with horizontal accuracy $\leq$2 m. We then attempted to use topography to isolate different characteristic growth patterns using two complementary methods. All analysis was done in the R programming environment version 2.10.1 (R Core Development Team 2010) relying mainly on three contributed packages: vegan (Oksanen et al. 2010), dplR (Bunn 2008, 2010), and fpc (Hennig 2010).

We averaged tree growth between multiple increment cores for each tree and divided each tree by its mean value to produce a standard ring-width index. We used a hierarchical cluster analysis based on Euclidean distance and Ward's minimum variance method to place each tree into a group based on its growth from 1806 to 2005 (Fig. 1b). The time period for clustering was chosen to provide a relatively long (200 year) record of growth common to all trees containing industrial and preindustrial eras but short enough to avoid potential juvenile growth in the trees which might require curve fitting to remove. We elected to separate the 69 trees into three clusters based on optimum average silhouette width using the PAM (Partitioning around Medoids) algorithm (Kaufman and Rousseeuw 1990). We assessed the stability of the clusters using a bootstrapping approach that subset across years and between trees and calculated similarities of the actual clusters to the clusters in the resampled data (Hennig 2007, 2008). Bootstrapped Jaccard similarities indicated that clusters two and three are robust (Clusterwise Jaccard means of 0.81 and 0.73 respectively) while cluster one is less stable (0.64). If cluster one is further separated into two clusters then both are highly stable. Using four total clusters (by splitting cluster one) instead of three clusters does not change the interpretation of this study's results.

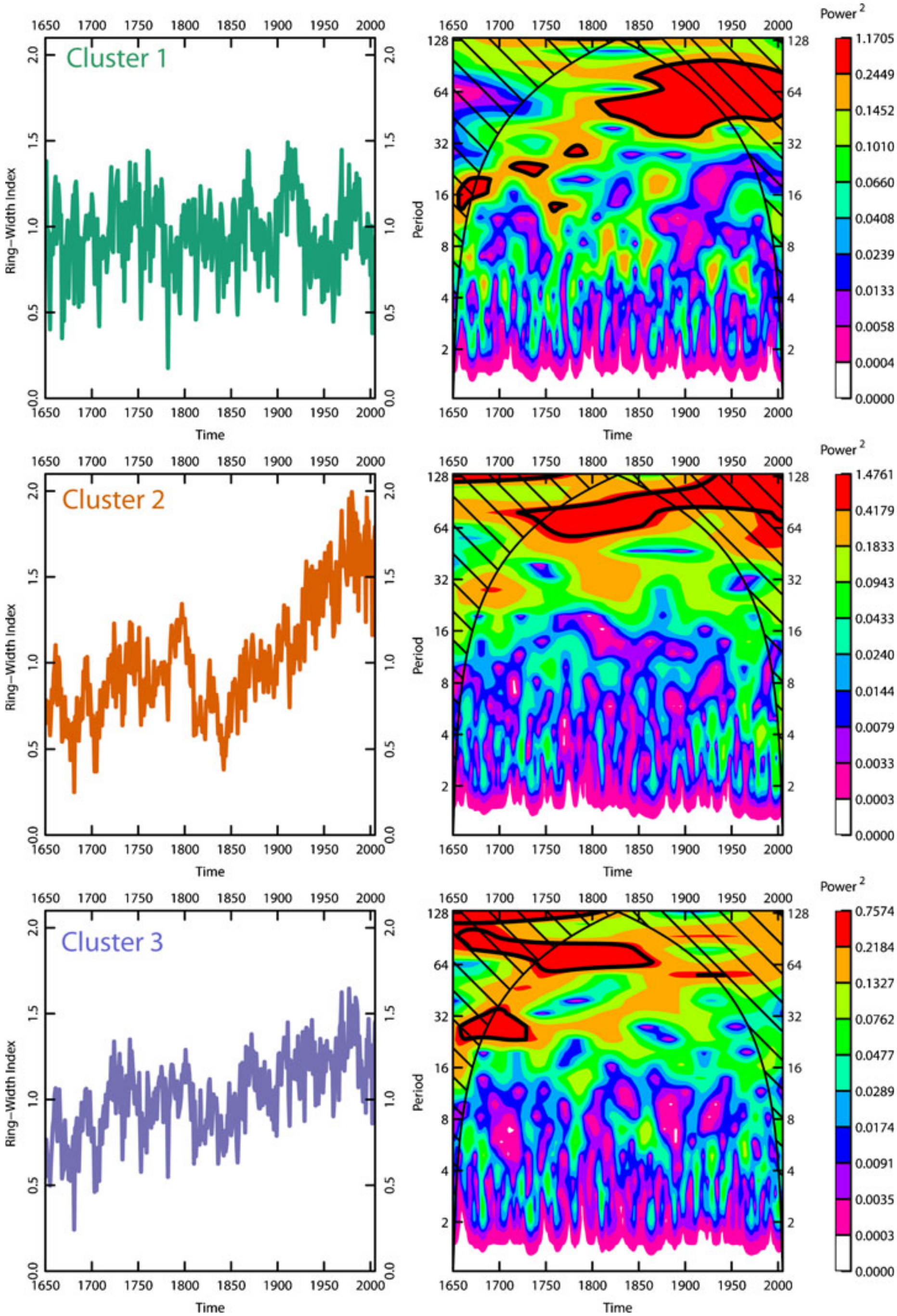
We then reduced the tree-growth matrix from 69 dimensions to two dimensions using non-metric multidimensional scaling and plotted each tree's location in this ordination space using weighted averaging. The data reduction produced very low stress (14.24) and the non-metric R^2 between the ordination distance and observed dissimilarity is 0.98. See references in Oksanen et al. (2010; and especially Minchin 1987) for a description of non-metric multidimensional scaling and weighted averaging. Finally, using the topographic data on each tree we were able to display the environmental variables in the ordination space using vectors for the significantly correlated variables (Fig. 1c). The significance for the environmental variables was assessed via permutation. Slope and PRR were not significantly correlated with the ordination ($p > 0.01$) while TPI and TCI were significantly correlated ($p \leq 0.01$).

The ordination and cluster analysis suggest that these data form distinct groups and that these groups are associated with topography. The analyses are complementary as the cluster analysis defines individual trees based on their growth with no data reduction while the ordination allows direct association of tree growth with environmental variables and allows visualization of each cluster in this space. We still refer to these as clusters one, two, and three rather than describe them by the topographic correlates but discuss below how a gradient analysis approach, with more data, might permit better descriptions of topographically modified chronologies. For instance, cluster two has the highest Jaccard index, is best defined in the ordination space (occupies the least space and has the lowest stress), and is associated with low values of standardized TPI which are in turn associated with colder minimum temperature anomalies—lower minimum temperatures relative to the surrounding area (Daly et al. 2008; Van de Ven et al. 2007; Van de Ven and Weiss 2009). When these data were previously analyzed (Salzer et al. 2009) a trend by elevation was prominent. That is still a robust finding, but we note that two of the lowest trees in the dataset growing at ~3130 m.a.s.l. clustered with much higher elevation trees in cluster two (mean elevation for cluster two is ~3428 ± 113 m.a.s.l.). Conversely, cluster one contains a few of the higher elevation trees. In both cases, the growth of these trees is aligned with their topographic position (e.g., the two low elevation trees that cluster with the higher elevation trees have low values of TPI and vice versa as suggested by the ordination).

Separate cluster-specific tree-ring chronologies showed markedly different patterns in growth in both the time and frequency domains (Fig. 2). Cluster two showed an increase in twentieth century growth and power was concentrated at low frequencies (multi-decadal to centennial scales). Cluster one, in contrast, was flat over the twentieth century and had greater power at decadal frequencies. Cluster two was the only grouping of trees that was significantly positively correlated to the instrumental temperature record and cluster three was the only one significantly sensitive to precipitation (Fig. 3). Cluster one showed significant negative correlations with temperature in most seasons. None of the clusters were confounded with significant ($p \leq 0.01$) dual temperature and precipitation correlations.

This mountain range has been an active dendrochronological research area for decades and a very large number of trees have been studied by many researchers. Our data subset includes samples from all those trees for which we have sufficiently precise spatial data. These particular samples have not been used in hemispheric-wide multi-proxy temperature reconstructions for which the bristlecone pines are well known (e.g., Mann et al. 2008). While some hemispheric reconstructions have been shown to be robust without the inclusion of any tree-ring data, the approach we describe here may improve our understanding of past climate at hemispheric scales. Regardless, we believe the "topographically modified chronology" approach will be beneficial in the reconstruction of local to regional scale climate. Networks of reconstructions at these spatial scales are critical to understanding past variability in the climate system.

We have shown how topography modifies tree growth response and suggest that this points to a method to improve the construction of climate-sensitive tree-ring chronologies. However, this analysis was *post hoc*—it was done without knowing what topographic information would be most closely associated with different modes of growth. Therefore the samples were not collected in a way to completely capture the relevant landscape heterogeneity. We intend to continue to test these findings by sampling more trees at high elevation in the White Mountains that fill in the topographic gaps along the TPI and TCI distributions—that is we will establish our sampling scheme in order to assess the robustness of using landscape heterogeneity to build better tree-ring chronologies. In doing so we will also evaluate alternative topographic factors to see if cold air pooling (Lundquist and Cayan 2007; Lundquist et al. 2008) or soil moisture contributions from snow fields improve our models. The correlation of the topographic convergence index on axis two of the ordination


Cluster 1
Cluster 2
Cluster 3
Ring−Width Index
Time
Period
Power 2
1.1705
0.2449
0.1452
0.1010
0.0660
0.0408
0.0239
0.0133
0.0058
0.0004
0.0000
1.4761
0.4179
0.1833
0.0943
0.0433
0.0240
0.0144
0.0079
0.0033
0.0003
0.0000
0.7574
0.2184
0.1327
0.0762
0.0477
0.0289
0.0174
0.0091
0.0035
0.0003
0.0000

◀ **Fig. 2** Tree-ring chronologies based on trees from each cluster showed markedly different patterns of growth in both time and frequency (shown as a continuous wavelet transformation). Clusters one and two were most different, most widely separated on axis one of the ordination in Fig. 1, and poorly correlated (r = 0.07). Cluster one displayed interannual and decadal variation and cluster two showed power concentrated at centennial scales. Clusters two and three were more similar, closer in the ordination space, and better correlated (r = 0.73) but varied in their periodicities and climate correlations. *Black contours* show significance at 99% confidence. Note that each wavelet transform is scaled by 10% quantiles to itself

suggests that there is potential for further separating temperature-sensitive trees from precipitation-sensitive trees if they are sampled accordingly. We also need to further understand the stability of growth in different subsets of trees over time and at specific frequencies (e.g., interannual vs. multidecadal periods). We especially need to move towards environmental correlates that have more meaningful scales rather than unitless indices from elevation models (e.g., lapse rates in K rather than approximations using units of TPI). As sampling density increases, these types of projects would ideally move towards a simpler gradient-based approach that might not need the combination of cluster analysis with ordination. Doing so will help move from statistical frameworks to eco-physiological frameworks based on better understanding of cambial cell division (e.g., Vaganov et al. 2006).

These kinds of heuristic methods are needed if we are to untangle complex climate-growth associations in dendroclimatology. The added cost and effort to do

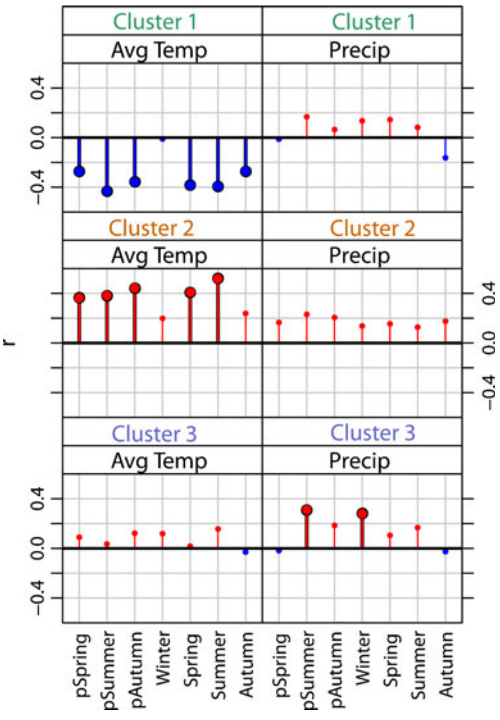


Fig. 3 The clusters correlated differently with climate data from the PRISM model (1896–2005). Note the separation of temperature and precipitation between clusters two and three. *Bold symbols* are significant at $p \leq 0.01$ and n is penalized for autocorrelation following Salzer et al. (2009). Winter = DJF; Spring = MAM; Summer = JJA; Autumn = SON; "p" denotes the previous year's season

so will be worthwhile if it allows radial growth to be placed into a mechanistic framework for better understanding xylogenesis and paleoclimatology.

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