# Synchronous variability changes in Alpine temperature and tree-ring data over the past two centuries

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The understanding of extremes and their temporal distribution is useful in characterizing the behaviour of the climate system, and necessary for understanding their social and economic costs and risks. This task is analogous to the study of pointer years in dendrochronological investigations. Commonly used dendroclimatological methods, however, tend to result in an equalization of variance throughout the record by normalizing variability within moving windows. Here, we analyse a larger network of high-elevation temperature-sensitive tree sites from the European Alps processed to preserve the relative frequency and magnitude of extreme events. In so doing, temporal changes in year-to-year tree-ring width variability were found. These decadal length periods of increased or decreased likelihood of extremes coincide with variability measures from a long-instrumental summer temperature record representative of high-elevation conditions in the Alps. Intervention analysis, using an F-test to identify shifts in variance, on both the tree-ring and instrumental series, resulted in the identification of common transitional years. Based on a well-replicated network of sites reflecting common climatic variation, our study demonstrates that the annual growth rings of trees can be utilized to quantify past frequency and amplitude changes in extreme variability. Furthermore, the approach outlined is suited to address questions about the role of external forcing, ocean–atmosphere interactions, or synoptic scale changes in determining patterns of observed extremes prior to the instrumental period.

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Understanding climatic extremes and temporal shifts in the occurrence of extremes in instrumental data is useful in characterizing the behaviour of the climate system and in understanding the social and economic costs and risks to society by such events. The warm and dry summer of 2003 in Europe triggered much discussion on the return intervals and characteristics of extreme events (e.g. Schär *et al*. 2004; Luterbacher *et al*. 2004; Rebetez 2004). This event occurred within the context of noticeably warmer regional instrumental temperatures during the past decade or so, relative to the past 240 years (e.g. Böhm *et al*. 2001), and relative to the past 500 years based on multi-proxy reconstructions (Luterbacher *et al*. 2004). Furthermore, this regional event occurred within the global setting of highest recorded temperatures since 1851 (Jones & Moberg 2003) and highest reconstructed temperatures since the so-called 'Medieval Warm Period' (Mann *et al*. 1999; Esper *et al*. 2002; Cook *et al*. 2004; Moberg *et al*. 2005).

Climatic extremes over a wide variety of time scales, from daily events to multi-decadal and longer periods, can be defined in a number of ways, including rarity, intensity or impact on environment and society (e.g. Beniston & Stephenson 2004). In simple terms, extremes can be defined as events occurring towards the tail ends of statistical distributions. However, assumptions about stationarity and time periods used to estimate distributions complicate this notion (Benestad 2004). For example, return frequency estimates for the summer of 2003 in Europe in Luterbacher *et al*. (2004) and Schär *et al*. (2004) differ by over three orders of magnitude, indicative of the sensitivity to such assumptions. Changes in the occurrence frequency of extreme events can be conceptually related to changes in the mean, the standard deviation (SD) or both of these parameters (Meehl *et al*. 2000), with changes in a distribution's width regarded to have a greater impact on the frequency of extreme events than changes in the mean (Katz & Brown 1992; Meehl *et al*. 2000). It has been proposed that the extreme 2003 European summer can best be explained by a shift in the SD of Alpine temperature variability (Schär *et al*. 2004), and it has been suggested that anthropogenic contributions have doubled the risk of such an extreme heatwave (Stott *et al*. 2004).

The instrumental record can be used to quantify changes in extremes in more recent times (e.g. Easterling *et al*. 2000 and references therein; Frich *et al*. 2002). However, to assess variations over many centuries, and to characterize the long-term evolution and characteristics of climatic change, proxy data are

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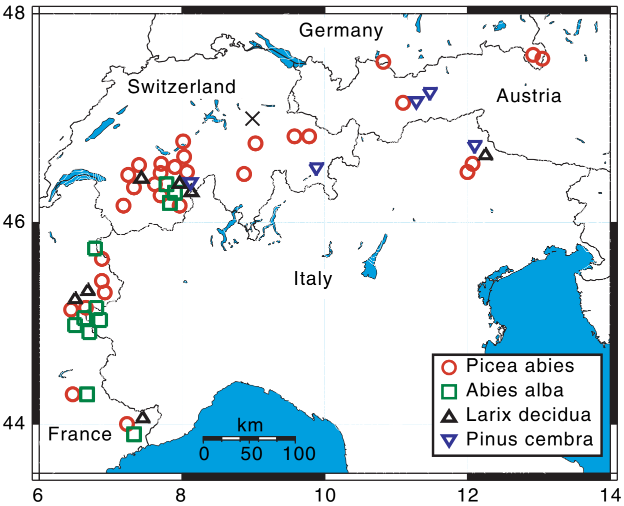


*Fig. 1.* Map showing the 53 tree-ring sites from four coniferous species used in this study. All sites are from elevations above 1500 m a.s.l. The location of the instrumental gridpoint (Böhm *et al*. 2001) used for comparison is indicated by the cross symbol in central-eastern Switzerland.

necessary. To this end, tree-ring records have played a valuable role (e.g. Jones & Mann 2004). However, methods utilized for the study of extreme years in dendrochronology (Cropper 1979; Schweingruber 1990; Meyer 1999), typically result in the equalization of variance of extreme years during the filtering and standardization processes. This equalization of extremes makes such methods unsuitable for understanding the characteristics and distribution of extreme events over time.

Here, we analyse a network of summer temperature-sensitive tree-ring data from high elevations across the European Alps. We have attempted to specifically process these annual ring-width data to preserve the magnitude of extreme changes in ring-width. We then compare these data and some of their statistical characteristics with seasonal (June–August) instrumental data, and demonstrate their skill for the reconstruction of frequency and magnitude changes of extreme events back in time.

## Tree-ring and instrumental data

The tree-ring width data set used in this study is a network of 53 high-elevation (≥1500 m a.s.l.) sites from the central and western Alps (Fig. 1). The climatic response and spatial signal of these sites have been described elsewhere (Frank & Esper 2005a), and based on this data set regional reconstructions of temperature have been developed (Frank & Esper 2005b). The network contains four species: *Picea abies*, *Abies Alba*, *Larix decidua* and *Pinus cembra*, with the majority (30) of sites being *Picea abies*.

The climatic responses of these species tend to be similar, with greatest differences between *Abies alba* and the other three species. A response maximum of all of these species is reasonably captured by the June–August season, and the signal is reasonably homogeneous across the geographical region covered by the tree-ring data. The coherent signal of the network is demonstrated via principal components analysis of the 45 (conventionally standardized with a 300-year spline) sites sharing the 1850–1973 common period: 20% of the network's variance was explained by the first principal component, with all sites (except for a single *Abies alba* site) having positive loadings on this component (Frank & Esper 2005a).

Instrumental data used in this study are from the low-elevation $1\times1°$ gridded data set described by Böhm *et al.* (2001) integrating homogenized temperature series from some of the longest station records in Europe. As this data set extends back to AD 1760 and compares well with respective high-elevation measurements (Böhm *et al.* 2001), it provides a good basis for extended comparisons with tree-ring data. For this study a single gridpoint (47°N, 9°E) is used (Fig. 1). The temperature record from this gridpoint is similar to the surrounding gridpoints, and was chosen for its long time-span and its location near the centre of the tree-ring network. Temperature data were highpass-filtered using a 5-yr kernel filter to make them comparable with the highpass-filtered tree-ring data (see below).

Analyses of the instrumental data have demonstrated coherent variability in the summer signal across the network (Böhm *et al.* 2001; Frank & Esper 2005a). For example, the average correlation of June–August temperature from stations located about 450 km apart is above 0.8 (Frank & Esper 2005a). Based on the common regional signal found in both the tree-ring and instrumental networks, we have made no regional or species differentiation for the study of extreme events.

## Tree-ring chronology processing

Tree-ring chronologies were developed by first applying an adaptive power transformation to the individual ring-width measurements. This transformation was employed to stabilize changes in variance related to the mean level of growth (Cook & Peters 1997). The method uses unity minus the slope of the regression line, in logarithmic space, between the local mean and local variance to best determine the power by which the measurement series should be raised to minimize any heteroscedasticity. When a strong spread versus level relationship for a series is determined (i.e. slope near unity), the data are subjected to a stronger transformation. Similarly, when nearly no spread versus level relationship is found (i.e. a slope near zero), the series are raised to a power near unity, and hence remain nearly unchanged (details in Cook & Peters 1997).

Residuals between the power-transformed series and a 5-year moving kernel filter (Gasser & Müller 1984) were computed, and the values divided by the SD of the entire series, to give all records the same mean and SD. The detrended tree-ring data were then averaged for each site using an arithmetic mean, yielding individual site chronologies. These chronologies were truncated at a minimum of five series to eliminate periods when signal strength is weak due to low sample size.

The truncated site chronologies were normalized over their entire lengths, and years with positive or negative anomalies ≥1.0 SD threshold were categorized as extreme growth years. These years were tallied for all sites and expressed as a percentage of sites having either positive or negative extremes in that year, thereby making both a positive and a negative extreme year chronology. A similar approach was used by Watson & Luckman (2001). Ultimately, we merged the positive and negative extreme year chronologies by addition to yield a single regional estimate for extreme growth occurrences (merged growth extreme chronology; hereafter MGEC). However, before determining the final chronology we tested three different thresholds, corresponding to 0.5, 1.0 and 1.5 SD.

## Results

Figure 2A shows a scatterplot with the percentage of positive versus negative extremes for the three different threshold values. The dashed line shows the location that all points would fall upon if years were classified as positive or negative anomalies with no threshold; conversely, all points would fall towards the zero-zero point at the lower right-hand corner of the graph for an arbitrarily high threshold. Results for the three thresholds display these tendencies, where, for the 0.5 SD threshold, the percentage of sites classified as having an extreme reaction was always greater than 28. The implication of using the 0.5 SD threshold is that relatively few 'average' years are identified. In contrast, the 1.5 SD threshold results in years significantly clustered towards values of no extremes, with no year having more than 64% of all sites classified with an extreme growth reaction. This results in a relatively high percentage of near 'average' years. We then merged the positive and negative extreme year series and compared their probability distributions with that from the filtered instrumental data (Fig. 2B). The 1.0 SD threshold results in a distribution similar to that of the instrumental data. Based on these results, the series defined by the 1.0 SD threshold were retained for analysis. It should be noted, however, that the three MGECs all correlate above 0.83, and that the estimates for the distributions of the highpass-filtered and unfiltered instrumental data are also similar.

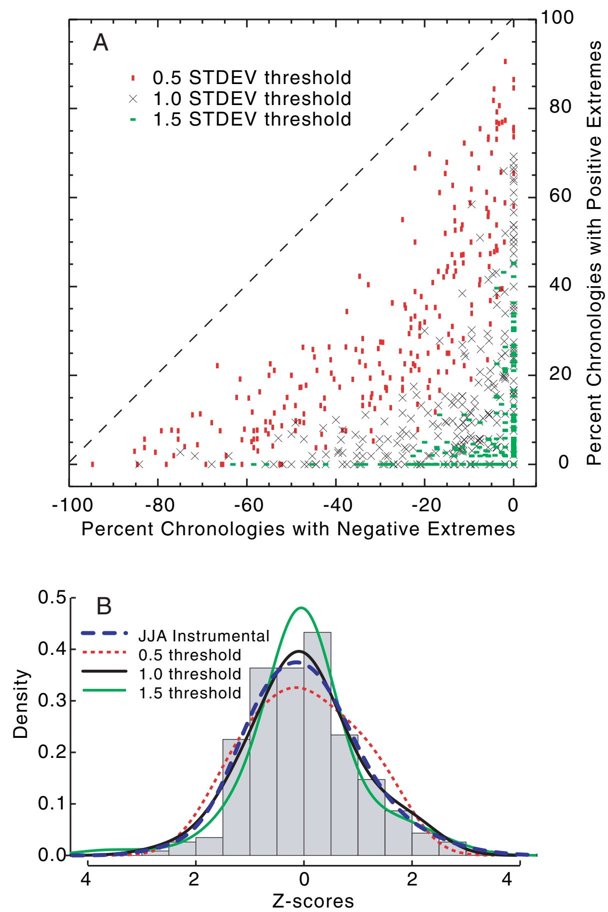


*Fig. 2.* A. Scatterplot showing the percentage of chronologies with positive versus negative extremes as a function of the different SD thresholds (i.e. 0.5, 1.0, 1.5) used to define extreme events. The dashed line shows the location that all points would fall upon if years were classified as positive or negative anomalies with no threshold; conversely, all points would fall at the zero-zero point at the lower right-hand corner of the graph for an arbitrarily high threshold. B. Histogram of JJA instrumental data (after highpass filtering) and density estimates for these instrumental data plotted along with density estimates for the merged extreme growth series defined by the three different thresholds. The 1.0 SD threshold results in a distribution that most closely fits that of the instrumental data. All series were normalized over the 1763–1990 period.

The positive and negative extreme series from the 1.0 SD threshold approach are shown in Fig. 3 for the 1700–1990 period, along with the number of chronologies available in each year. A high degree of similarity exists between these two series, resulting from both how these records are defined and the common, primarily JJA temperature, forcing (Frank & Esper 2005b). Notable are times of a seemingly greater frequency and intensity of extremes (e.g. *c*. 1950, 1910 and 1810) and times of lower interannual variability, such as around 1940, 1900, 1875 and 1770.

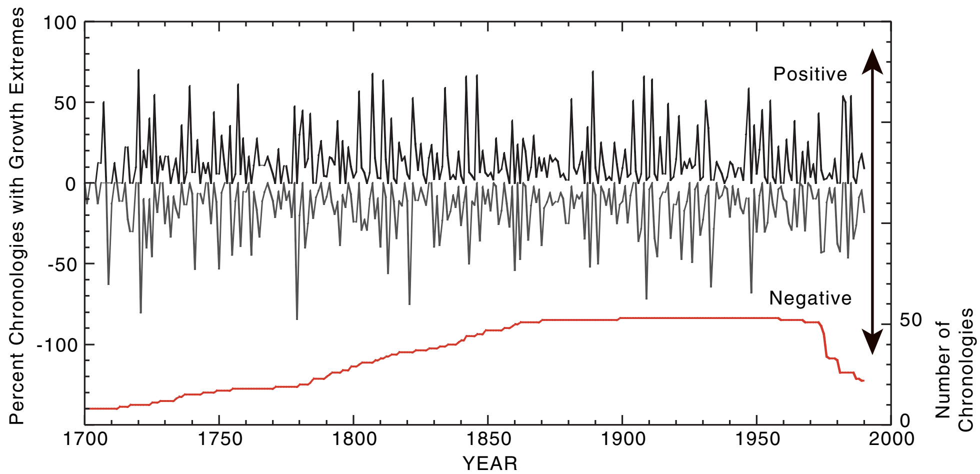


*Fig. 3.* Percentage of chronologies with positive and negative extremes as defined by the 1.0 SD threshold (upper) and the number of chronologies available for each year (lower).

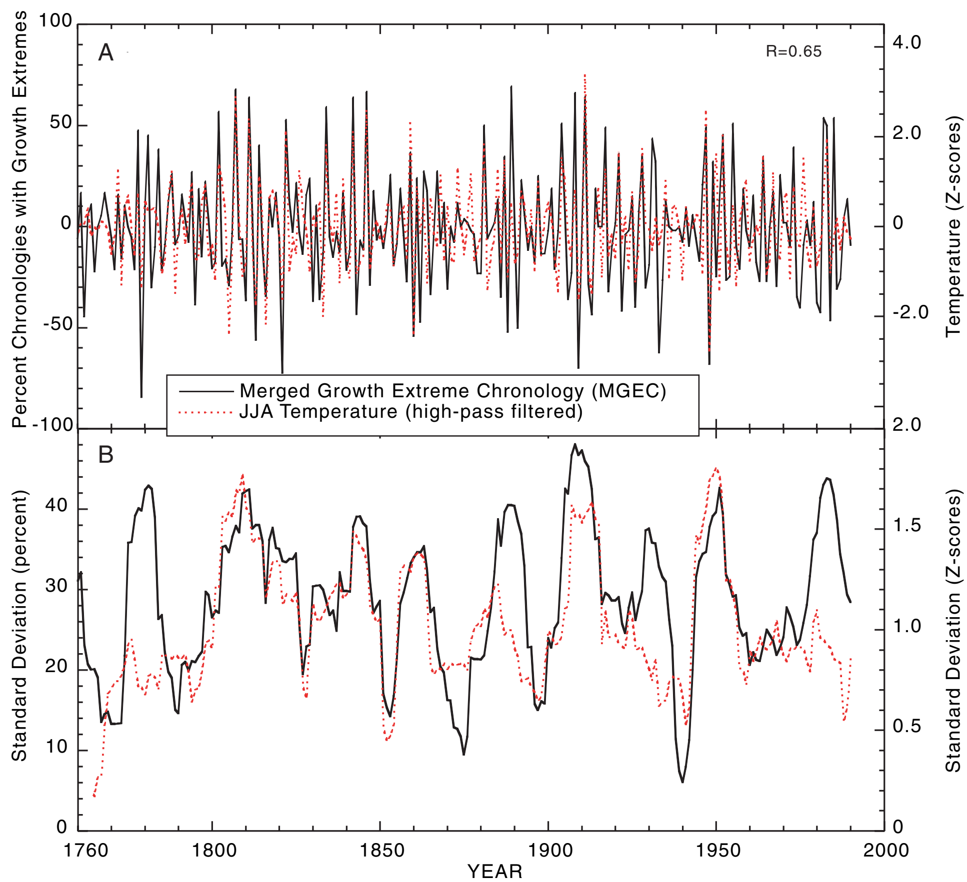


*Fig. 4.* Comparisons between average JJA instrumental temperatures (highpass filtered) and merged extreme growth chronology (A) for the individual records, and (B) a running SD of these records in a 9-year window.

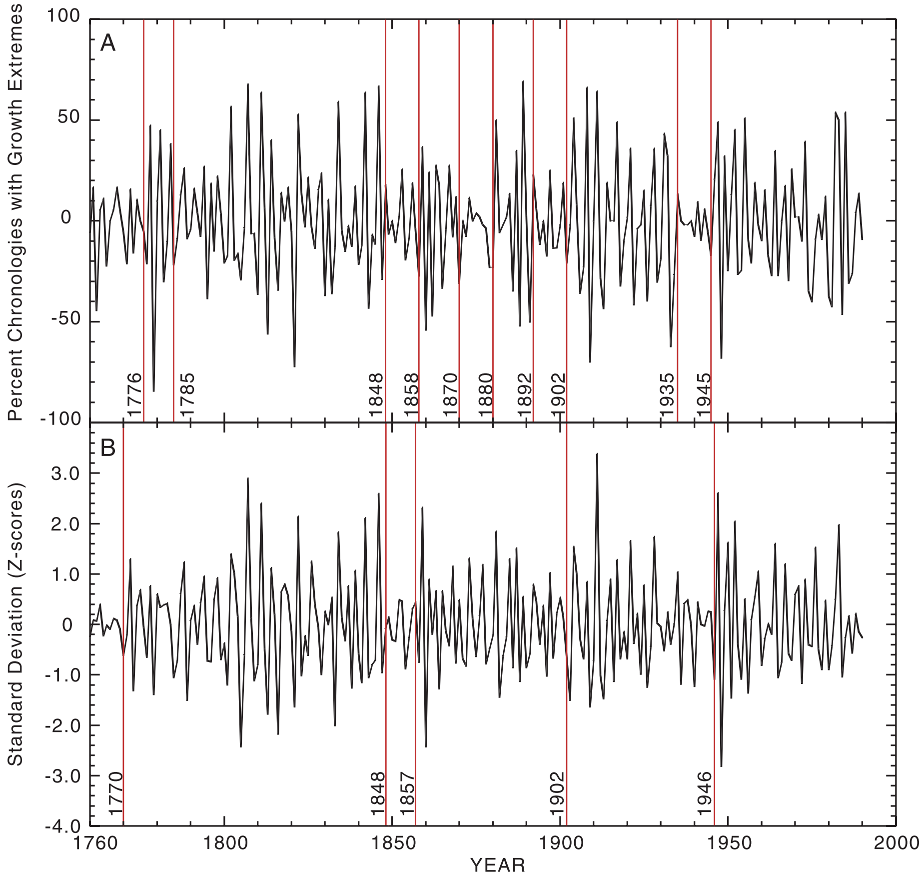


*Fig. 5.* F-test intervention analysis for (A) the merged growth extreme chronology (MGEC), and (B) the high-filtered average JJA instrumental data. Two 9-year windows were used, with a $p<0.02$ used to indicate significant changes in variance. See text for details.

Figure 4A displays the MGEC together with the highpass-filtered instrumental JJA temperature data. The MGEC retains characteristic periods of enhanced and reduced extremes and, furthermore, possesses a reasonable degree of similarity with the instrumental data. The records correlate at 0.65 over the 1760–1990 period, and notably seem to display coinciding shifts in the intensity and frequency of extreme events.

To quantify the changes in the occurrences of year-to-year extremes, Fig. 4B shows a moving 9-year SD window applied to both the MGEC and instrumental series. The periods of enhanced and reduced extremes, discussed above and seen in Fig. 3, are evident in the tree-ring-based running SD. Furthermore, these changes in variability of extreme events coincide reasonably well with the changes observed in the instrumental records. The times of enhanced (i.e. *c*. 1950, 1910, 1810) and reduced (i.e. *c*. 1940, 1900, 1875, 1770) variability in the MGEC coincide with times of above and below average levels of the instrumental record's standard deviation, respectively. The times of disagreement between these two records tend to occur when the MGEC exhibits greater variability than the instrumental data (i.e. *c*. 1985, 1930, 1890, 1780).

To determine if specific variance transition years common to both the MGEC and instrumental temperature data could be identified, we performed a modified intervention analysis using an F-test (rather than the more normally used *t*-test that assesses changes in mean state; Box & Tiao 1975) to identify significant differences in the variance between contiguous 9-year windows (Fig. 5). A threshold of $p<0.02$ was applied. Five transition years (1770, 1848, 1857, 1902, 1946) were derived for the instrumental data and 10 in the MGEC. Common transitions are identified in 1848 and 1902 for both records, while 1945 and 1858 identified in the tree-ring series are one year 'off' from the transition year determined in the instrumental series. In these cases, as well as for 1770 in the instrumental record and 1776 in the tree-ring record, overlap exists in the candidate years (i.e. having *p*-values $<0.02$) identified for the transition time periods. However, out of these candidate years, the year with the lowest *p*-value differs between the records. The greater number of transition years identified in the MGEC reflects its more variable nature than the instrumental data.

As a further test of these results, we highpass-filtered the June–August temperature reconstruction derived from these same tree-ring data (Frank & Esper 2005b). This record correlates with the highpass-filtered instrumental record at 0.74 over the 1760–1990 period, which is higher than the corresponding correlation of 0.65 for the MGEC. Over the 1760–1863 period (outside the calibration period of the reconstruction), the highpass-filtered reconstruction and MGEC correlate more similarly with the filtered instrumental data with values of 0.74 and 0.72, respectively. However, when the same intervention test was performed on the filtered reconstruction (not shown), only two transition years were identified during the 1760–1990 period: 1902 and 1945. These years occur during the calibration period, and suggest that the variability changes preserved in the merged extreme record are lost with the more traditional standardization and reconstruction methods used in Frank & Esper (2005b). This highlights how any single standardization approach is unlikely to fulfil all possible data and analysis requirements simultaneously, and the exact standardization chosen should be related to the data and their intended uses.

## Discussion and conclusions

The method we have applied to specifically preserve the frequency and magnitude of extreme events and their changes over time identified decadal and multidecadal periods of enhanced and diminished interannual variability. The presented results, backed by correlations, moving SD calculations and F-test intervention analyses for changes in variance, have shown reasonable agreement between changes in variability in the MGEC and the instrumental record. The analogous behaviour of the MGEC and instrumental records indicates that the method applied here to preserve frequency and amplitude changes in the occurrence of extreme events in tree-ring data can be used for further studies of climatic variability prior to the instrumental period. The occurrence of variability shifts during preindustrial times suggests a strong natural component to such changes. There does not appear to be any significant trend in the timing of these shifts or extremes in either the long-instrumental data or the MGEC.

The periods of disagreement between these records (see Fig. 4B) tend to occur where the MGEC has a relatively higher variance than the instrumental record. In general terms, it seems plausible that these additional extremes occur in the tree-ring data due to influences outside the JJA temperature window, due to, for example, precipitation variations during the (longer) growing season, temperature influences during spring, and so on. Opposing biological feedbacks could also result in enhanced variability after seasons of extreme growth.

Declines in the number of available chronologies towards the most recent (after 1975) and earlier (before 1850) time periods in the tree-ring network also result in lower statistical quality during these times. Furthermore, the signal quality within tree-ring chronologies is not constant and typically declines towards the beginning of chronologies as the number of trees decline. Similarly, the early instrumental data are prone to additional uncertainties, including necessary homogenization adjustments, and simply that fewer and fewer stations are available back in time. Before 1790, for example, where significant disagreement between MGEC and instrumental data is seen (Fig. 4B), seven instrumental stations are available for gridding. This number declines to three stations in 1760, with two of them north (Geneva and Basel) and one south (Torino) of the Alps (Böhm *et al.* 2001). Anthropogenic factors could also affect the tree response at any point throughout the record, and, more recently, stratospheric or near surface ozone changes might additionally change the growth responses towards modern times (e.g. Briffa *et al.* 2004; Ollinger *et al.* 1997).

The choice of initial filtering, significance thresholds applied and analysis window size can have a marked effect on the results. Furthermore, the presence of outliers can bias the intervention analysis and running SD plots. However, despite these sensitivities, the variability changes in the growth of trees, largely linked to the variability of extremes in JJA temperature, have been preserved. Further, the F-test intervention analysis essentially captured the salient features in both the tree-ring and instrumental data.

Methodologically, the different thresholds that we tested for determining extreme growth reactions vary the shape of the final data distribution (Fig. 2B). Jones *et al.* (2003), and references therein, discuss a similar situation when transforming documentary sources into temperature estimates, where indices are commonly defined by either uniform or normal distributions. Yet, we found little difference in the correlation between instrumental data and series derived by differently defined thresholds. Correlations between indices derived by the 0.5 and 1.5 SD thresholds and the temperature data are only slightly lower than that for the 1.0 SD threshold (0.64 and 0.62, respectively, over the 1760–1990 period). Nevertheless, such considerations affect the form of the reconstruction and the relative magnitude of extreme events when linear relationships are assumed and modelled.

Climatic extremes can be defined in a variety of ways, including values exceeding a certain SD threshold over a fixed period, or allowing a more 'flexible climatology' by analysing the distributions about a smoothing function. These approaches (and assumptions, periods or smoothing chosen within) can lead to differing estimates of the return intervals of extreme events. This is evidenced by the differences in return intervals for the warmth of the 2003 summer in Europe by Luterbacher *et al.* (2004) and Schär *et al.*

(2004). Here, we have removed the trend from the proxy and instrumental data, implicitly assuming a flexible climatology, and in so doing we have looked at extremes and changes in interannual variability about this local climatology. The changing variability in the tree-ring and instrumental data, as measured by the 9-year moving SD (Fig. 4B), correlates insignificantly with a 9-year running mean of the non-detrended instrumental mean temperature data at –0.07 and –0.04, respectively (1764–1990 period). These results suggest that the temporal changes in observed extremes are independent of mean temperatures, at least within the range of temperature variations experienced over the past couple of hundred years. This would counter the notion that increases in temperature will lead to greater temperature variability, as has been suggested for example for storm intensity and precipitation (IPCC 2001). However, a recent spatial analysis of changes in the statistical distributions of mean temperature variability in Europe found differences between the 1976–1999 and 1946–1975 periods, which they hypothesize are related to anthropogenic warming over the more recent time period (Klein Tank *et al*. 2005).

Our results show that summer temperatures in the European Alps expressed greater intensity and frequency of extremes around 1800–1810, 1840–1860, 1890, 1910 and 1950, while times of lower interannual variability occurred around 1770–1800, 1850, 1870–1880, 1890–1900 and 1940. Prior to the instrumental data, the tree-ring network shows enhanced variability around 1720, and reduced variability between about 1700 and 1715. It is not yet clear whether these temporal patterns in variability represent effects from shifts in the regional synoptic system (e.g. North Atlantic Oscillation; Wanner *et al*. 1997; Beniston & Jungo 2002), external forcing, or simply reflect 'random' changes associated with a distribution of events around a climatological mean. However, this approach can provide a baseline for studies of long-term changes of extreme events.

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