Global Climate Variations Over the Past 250 Years: Relationships with the Middle East

Michael E. Mann
Raymond S. Bradley
Department of Geosciences, University of Massachusetts

ABSTRACT
We analyze recent global temperature reconstructions over several centuries in time based on calibrations of temperature patterns against global networks of long instrumental and “proxy” data (natural archives such as ice cores, corals, and tree rings), focusing on long-term climatic variations in the Middle East. The pattern of global warming of the past century does not show a strong influence in this region. Instead, patterns of natural low-frequency variability appear to dominate the region. One of these patterns is associated with the well-known “North Atlantic Oscillation” and leads to changes on interannual and decadal timescales. Another distinct pattern appears to relate to influences of low-frequency variability in the North Atlantic ocean circulation and overlying atmosphere circulation, and describes changes that are predominantly multidecadal in timescale. This latter pattern is especially important in predicting possible climate change scenarios in future decades in this region.

INTRODUCTION
Documenting the patterns of large-scale climate variability during the past several centuries is important to understanding the significance of long-term trends and low-frequency variations in the global climate. Once such large-scale patterns of variability are established and statistically verified, they can provide a context for understanding the variations present in particular regions of the globe, including those regions of importance in the history of human civilization. Unfortunately, there is no instrumental climate data available on the century and longer timescales of interest in this context. However, widespread networks of high-resolution proxy climate indicators and the few very long instrumental and historical climate indicators available several centuries back can be combined into a global “multiproxy” network that can potentially be used to describe annual global temperature patterns during past centuries. Here we analyze climatic variability back to the mid-18th century based on the multiproxy-reconstructed global surface temperature patterns of Mann et al. (1997a). We focus here on the variations in the Middle East region and its relationship with larger-scale patterns of climate variability. We can thus examine in detail the relationship between Middle Eastern climate and global climatic variations several centuries back in time.

DATA
The reconstructed surface temperature patterns of Mann et al. (1997) are based on the multivariate calibration of globally distributed annual resolution proxy climate indicator network. The net-
work includes (see Figure 1, left) the collection of annual resolution
dendroclimatic, ice core, ice melt, and long historical records used
by Bradley and Jones (1992) combined with other coral (Lough
1991; Quinn et al. 1993; Dunbar et al. 1994), dendroclimatic (Jacoby
and D’arrigo 1989, 1990; Briffa et al. 1992), and long instrumental
(Jones and Bradley 1992) records. The available instrumental
records are formed into annual mean anomalies relative to the 1902-
1980 reference period, and gridded onto a 5 degree by 5 degree grid,
consistent with the instrumental gridpoint data described below.
This provides 11 temperature gridpoint records, 12 precipitation
gridpoint records, and 3 station surface pressure gridpoint records
dating back to 1820 or earlier.

The instrumental temperature anomaly data (Figure 1, right)
used to train the proxy dataset span the interval 1902-1993 and are
taken from a gridded combined land air and sea surface temperature
dataset of Jones and Briffa (1992). Although there are notable spatial
gaps, this network covers significant enough portions of the globe to
estimate a global mean (“GLB”) temperature, and enough of the
Northern hemisphere and of the extreme eastern equatorial Pacific
to construct highly faithful estimates of both the Northern Hemi-
sphere mean (“NH”) temperature series, as well as certain indices of
particular importance (e.g., the “NINO3” index important in the
context of the El Niño phenomenon). A box including all gridpoints
in the region 30N to 50N latitude, 20E to 40E longitude is used to
construct a Middle Eastern (“MNET”) temperature index. An instrumental estimate of the North Atlantic Oscillation (NAO) taken from Hurrell (1995) is also made use of in our analysis.

MULTIPROXY CALIBRATION

Multiproxy networks appear to provide the greatest opportunity for large-scale climate reconstruction (Bradley and Jones 1993; Hughes and Diaz 1995) and climate signal detection (Mann et al. 1995; Barnett et al. 1996). While limitations (e.g., dating errors) in the individual proxy indicators must be carefully accounted for in constructing an appropriate multiproxy network (see Mann et al. 1997a), the mutual information contained in a widely distributed set of independent climatic indicators can more faithfully capture the consistent climate signal that is present, reducing the compromising effects of biases and weaknesses in the individual indicators.

The reconstructions of which we make use (Mann et al. 1997a) are based on a calibration of such a multiproxy network against widespread instrumental surface temperature data of the 20th century. Multivariate statistical calibration approaches have previously been applied to proxy climate data for local or regional climate reconstruction, particularly in the field of dendroclimatology (see e.g., Fritts et al. 1971; Cook et al. 1994). Related statistical methods have more recently been applied to the problem of interpolating sparse early instrumental climate observations through training them against the dominant large-scale patterns of variability isolated in shorter, but more widespread recent climate fields (Kaplan et al. 1997). Our approach to long-term climate pattern reconstruction combines these traditionally distinct applications. We first decompose the instrumental training data into its dominant patterns of variability, and subsequently perform a multivariate calibration of the climate proxy indicators against the time histories of these different patterns. In doing so we make a number of important assumptions. We assume (1) that the indicators in our multiproxy trainee network are linearly related to one or more of the instrumental training patterns. In the relatively unlikely event that a proxy indicator represents a truly local climatic phenomenon which is uncorrelated with larger-scale climatic variations, or represents a highly non-linear response to climatic variations, this assumption will not be satisfied. We further assume (2) that a relatively sparse but widely distributed sampling of long proxy and instrumental records may nonetheless sample most of the relatively small number of degrees of freedom in climatic patterns at interannual and longer timescales. Regions not directly represented in the trainee network may nonetheless be indirectly represented through teleconnections.
with regions that are. Finally, we assume (3) that the patterns of variability captured by the multiproxy network have analogs in the patterns we resolve in the shorter instrumental data. This latter assumption represents a fairly weak “stationarity” requirement—we don’t require that the climate itself be stationary. In fact, we expect that some sizeable trends in the climate may be resolved by our reconstructions. We do, however, assume that the basic spatial patterns of variation that the climate has exhibited during the past several centuries are similar to those by which it has varied during the past century. Studies of instrumental surface temperature patterns suggest that such a form of stationarity holds up at least on multi-decadal timescales, during the past century (Kaplan et al 1997). The statistical cross-validation exercises we describe later provide the best evidence that these key underlying assumptions are reasonable.

We isolate the dominant patterns of the instrumental surface temperature data through principal component analysis (PCA) (Preisendorfer 1989). PCA provides a natural smoothing of the temperature field in terms of a small number of dominant patterns of variability “empirical eigenvectors” that describe 20th century temperature variations. Each of these eigenvectors is associated with a characteristic spatial pattern or “Empirical Orthogonal Function” (EOF) and its characteristic evolution in time, or “principal component” (PC). The first 5 eigenvectors describe a fraction ($\beta = 0.27$, or 27%) of the total multivariate variance (“MULT”) in the raw data, 90% of GLB, 85% of NH, 67% of NINO3, and 76% of the detrended (“DETR”), interannual-to-multi-decadal timescale variability in NH. The first 40 eigenvectors, for comparison, describe nearly all of the GLB and NH annual mean variance, about 90% of the NINO3 annual mean variance, and 73% of MULT. The rank of the eigenvectors orders the fraction of variance they describe in the standardized data ($1=12\%, 2=6.5\%, 3=5\%, 4=4\%, 5=3.5\%$). The first eigenvector describes a modest 12% of the full spatiotemporal variance in the dataset, but a majority of variance in GLB (88%) and NH (73%) estimated temperatures. This eigenvector is associated with the significant global warming trend of the past century. The second eigenvector describes 8% of the multivariate data variance, and is associated with much of the ENSO-scale variability, describing 40% of the variance in the NINO3 index. This eigenvector exhibits a modest negative trend. The third eigenvector describes much of the traditional NAO pattern (verified through correlation analyses described later), with opposed centers of warm and cold anomalies in and neighboring the North Atlantic. The fifth eigenvector is associated with variability centered in the Atlantic basin exhibiting significant multi-decadal variability (see Kushnir 1994; Mann and
Figure 2 shows the EOFs for eigenvectors 1, 2, 3 and 5. (The verification exercises described briefly below and in detail in Mann et al. (1997a) indicate that the fourth eigenvector can not be skillfully resolved by the present multiproxy network). The associated PCs are shown along with their reconstructed counterparts (“RPC”s) below. Note that both EOFs 3 and 5 have large projections in the Middle East. Indeed, as discussed below, these two independent patterns compete for influence on Middle Eastern temperature variations.

As described in detail by Mann et al. (1997a), we calibrate the multiproxy data network against these empirical eigenvectors at annual mean resolution during the training (1902-1980) interval. This multivariate calibration provides a transfer function that can be applied to the multiproxy network to reconstruct temperature patterns before the calibration interval on an annual basis, with a spatial coverage dictated only by the spatial extent of the instrumental training data. The statistical skill of the temperature reconstructions is established through independent cross-validation or “verification” exercises. Verification statistics were determined based on two

Figure 2  EOFs of the leading eigenvectors (#’s 1,2,3,5) of the global temperature data from 1902-1980 retained in the analysis. The EOFs are renormalized to remove the areal weighting factor which tends to diminish the amplitudes of the pattern at higher latitudes.
distinct verification datasets described by Mann et al. (1997a). Here we will discuss the results from one of these verification datasets, the sparse subset of the gridded data \(M' = 219\) gridpoints) for which independent values are available from 1854-1901 (see Figure 1, right). NH and GLB verification statistics are computed, as is the multivariate ("MULT") gridpoint level verification statistic.

A sequence of multiproxy calibration experiments were performed in which progressively lower rank eigenvectors are retained. Sensitivity to the exclusion of certain intermediate rank eigenvectors was also investigated. While calibration described variance increases monotonically with increased retained eigenvectors, an optimal subset of eigenvectors can be isolated which maximizes the verification described variance. In this study, that subset corresponds to only a handful of the highest ranked eigenvectors. We also test the network for sensitivity to the inclusion or elimination of particular trainee data (e.g., instrumental records, the Northern treeline dendroclimatic indicators of North America, and tropical coral records). The technical results and details regarding calibration/verification are described by Mann et al. (1997). These experiments demonstrate that the multiproxy network appears able to capture much of the variance that can potentially be described by the modest retained set of eigenvectors generated by cross-validation exercises. Although more widespread proxy data are available, the network used here is intentionally sparse, illustrating the principle that skillful pattern reconstruction can be performed with a relatively sparse trainee network. More widespread proxy networks should allow an increasingly large number of eigenvectors to be skillfully retained, and a consequently increased fraction of described variance. The patterns of calibration and verification \(\beta\) for the full reconstructed patterns are shown in Figure 3.

In Figure 4, we show the comparison of the raw and reconstructed MNET temperature index during the 1902-1980 calibration interval. The match is excellent, with a correlation of \(r = 0.5\) between the raw and reconstructed series \(r^2 = 0.25\) and a value of \(\beta = 0.17\) for described variance. Note that the values for this coarse-averaged regional index are better than for the individual gridpoints making up the index because of the large-scale optimality of our EOF-based reconstruction approach. Although the 1854-1901 verification dataset poorly samples the rectangular region used to construct the MNET index, the verification \(\beta\) values for the gridpoints which are present are with one exception statistically significant at the 99% level, albeit negative—the impact of quality problems with the instrumental data themselves before the 20th century is unknown and
may artificially degrade the apparent skill of the reconstructions. We thus believe the reconstructed MNET index to be quite faithful.

TEMPERATURE RECONSTRUCTIONS

The reconstructions discussed below are derived from the optimal eigenvector subsets for the period 1760-1980 as described by Mann et al. (1997a), reconstructed with EOF #s 1,2,3,5. To illustrate the effectiveness of the proxy pattern reconstruction procedure, we show as an example (Figure 5) the raw, EOF-filtered, and reconstructed temperature patterns for a year during the calibration interval (1941).

It is clear that the proxy network in this example is capable of resolving much of the structure that is resolved by the 4 EOFs themselves used in calibration. Figure 6 shows the 4 reconstructed princi-
The positive trend in RPC 1 during the 20th century is clearly exceptional in the context of the long-term variability in the associated pattern, and indeed describes much of the unprecedented warming trend evident in the NH reconstruction. Equally interesting is the negative trend in RPC 2 during the past century which is also anomalous in the context of the longer-term evolution of the associated pattern. The recent negative trend is associated with the modest long-term cooling trend in the eastern tropical Pacific (superimposed on warming associated with the pattern of eigenvector #1) which may be a modulating negative feedback of global warming (Cane et al. 1997). The third eigenvector exhibits much of the NAO signature in the data. The fifth eigenvector exhibits notable multi-decadal variability throughout both the modern and pre-calibration interval, associated with the wavelike trend of warming and subsequent cooling of the North Atlantic this century that has been discussed elsewhere (Kushnir 1994; Mann et al. 1994, 1996; Schlesinger and Ramankutty 1994) and longer-term multi-decadal oscillations in that region detected in a previous analysis of proxy...
climate networks (Mann et al. 1995). This variability may be associated with ocean-atmosphere processes related to the North Atlantic thermohaline circulation (Delworth et al. 1993, 1997). Table 1 shows the correlations between the MNET index, the NAO, and the four reconstructed principal components of this study.

Middle Eastern climate is known to have a significant relationship with NAO on inter-annual timescales (see Cullen and Demenocal 1997). This is certainly substantiated in Table 1. However, of particular interest here are the patterns of variation influencing the region on longer timescales as well. The correlations also show that a distinct pattern of variation associated with EOF 5 has considerable influence on Middle Eastern temperature. The long-term trend in the reconstructed NH series exhibits a general period of coolness through 1850, and warming thereafter. In Figure 7, we show the reconstructed NH series along with the MNET index.

Although there are some broad similarities, MNET does not track NH on the longer timescales. In particular, the marked NH warming of the 20th century is not evident in the MNET index, although there is multi-decadal variability as described below. This difference appears to be associated with multi-decadal cool periods in the Middle East associated with the pronounced multi-decadal variations in RPC 5. These variations favor negative temperature anomalies in MNET during the early and late 20th century, offsetting times at which the global warming trend and its weak projection onto the region was most rapidly accelerating.

A comparison of the power spectra (Figure 8) of the MNET series, RPCs 3 and 5, and the NAO provides considerable insight into the natural of the patterns of variability influencing Middle East temperatures on different timescales.

![Figure 6](image.png)

Table 1: Correlations of RPCs with NAO and MNET indices over two different periods of time during the reconstructed 1760-1980 time interval.

<table>
<thead>
<tr>
<th>RPC</th>
<th>r(NAO)</th>
<th>1864-1980 r(MNET)</th>
<th>1760-1980 r(MNET)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.28</td>
<td>0.26</td>
<td>0.28</td>
</tr>
<tr>
<td>2</td>
<td>-0.06</td>
<td>-0.30</td>
<td>-0.18</td>
</tr>
<tr>
<td>3</td>
<td>0.41</td>
<td>-0.63</td>
<td>-0.68</td>
</tr>
<tr>
<td>4</td>
<td>-0.09</td>
<td>-0.32</td>
<td>-0.26</td>
</tr>
</tbody>
</table>
Figure 7  Reconstructed Northern Hemisphere mean (NHEM) temperature series along with reconstructed MNET index.

It is evident that the MNET temperature index exhibits enhanced power (which is statistically significant) in the “multi-decadal” frequency range of \( f = 0.01\text{-}0.02 \) cycles/year (50-100 years period) as well in the decadal \( f = 0.05\text{-}0.1 \) (10-20 years period) frequency range. These spectral peaks are most pronounced in the longer 1760-1980 data interval. This is distinct from the behavior of the NAO which, although displaying a secular peak during the past century (i.e., a near-zero frequency trend isolated in the above figure), does not exhibit significant decadal or multi-decadal spectral peaks. The long-term multi-decadal variability is a robust feature of the North Atlantic climate (Mann et al. 1995) which appears unrelated to the NAO, and in fact nearly orthogonal to it, probably associated with the response of atmosphere to multi-decadal changes in surface heating by the ocean (Kushnir 1993; Mann and Park 1994, 1996). These multi-decadal variations appear to be associated with a stochastically-excited eigenmode of the coupled ocean-atmosphere system (Delworth et al. 1993; 1997). This relationship is also shown in Figure 9. The multi-decadal variations in MNET have a close relationship with intervals during which the RPC 5 (associated with the pattern EOF 5) favors warming (negative) or cooling (positive) in the Middle East. In contrast, the inter-annual/decadal variations in MNET have a closer relationship with episodes during which the RPC 3 associated with NAO-like pattern EOF 3 favors warming (negative) or cooling (positive) in the region.
Figure 8  Power spectra for (upper left) reconstructed Middle/Near Eastern “MNET” temperature index, (upper right) NAO index, and (bottom) RPCs 3 and 5. The spectra are based on the multitaper method, with best red noise median power levels and 90%, 95%, and 99% confidence levels (dashed) lines estimated by the robust method of Mann and Lees (1996).

In Figure 10, we show some example patterns for different reconstructed years.

The warm MNET year 1760 appears to have been associated with a particularly prominent NAO-type pattern superimposed on the otherwise cool multi-decadal period. 1783, a strong El Niño year (Quinn and Neal 1992) exhibits, by contrast, a prominent negative MNET temperature anomaly. A (weaker) negative MNET anomaly is also observed during the very strong (Quinn and Neal 1992) El Niño year 1878 shown. Analysis of ENSO variability in these reconstructions is discussed in more detail elsewhere (Mann et al. 1997b).

The pattern of 1816 shows anomalous cooling throughout much of the globe (even relative to this generally cold decade) but with a quadrupole pattern of warmth near southern Greenland and the Middle East, and enhanced cold in the eastern United States and Europe. This latter pattern is indeed consistent with the anomalous atmospheric circulation associated with the North Atlantic Oscillation (NAO) pattern observed in empirical (Kelly et al. 1996) and model-based studies (Kirshner 1995) of the atmospheric response to volcanic forcing. This latter pattern is evident in neither the following nor preceding year, and is likely associated with the large
CONCLUSIONS

With the large-scale temperature reconstructions that we have available over the past couple of centuries, we are able to document the importance of at least two distinct patterns on the climate of the Middle East. One of these patterns is associated with the North Atlantic Oscillation (NAO) and dominated by inter-annual and decadal timescales. The other pattern is distinct from the NAO and more consistent with the atmospheric response to multi-decadal oceanic variations (Delworth et al 1993; Kushnir 1994; Mann and Park 1996). This suggests that patterns not easily resolvable in the short instrumental record (in particular, patterns distinct from the NAO) may be of increasing relative importance on progressively longer timescales, and are important to understanding climatic variations in the Middle East on multi-decadal and longer timescales. As increasingly larger numbers of high quality proxy reconstructions become available in diverse regions of the globe, it will be possible to assimilate a more globally representative multiproxy data network. Given the high level of skill possible in large-scale reconstruction back to 1450 with the somewhat sparse network of the present study, there is reason to believe that it may soon be possible to reconstruct much of the spatio-temporal variability of the global climate back over the last 500 to 1000 years. With such reconstructions in hand, we will be able to document more confidently the climatic variations in the Middle East during the Tambora eruption of April 1815 both in terms of the hemispheric coldness and the superimposed NAO-like pattern.
the past millennium. Such reconstructions should be useful for understanding changes in human land use and patterns of civilization in that region on longer timescales.

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Figure 10 Reconstructed large-scale temperature patterns for (i) 1760, (ii) 1783, (iii) 1816, (iv) 1878. Middle Eastern box used to compute MNET index is shown. The color scale indicates regions which exceed (either positively or negatively) the threshold indicated. The zero baseline is defined by the 1902-1980 climatological mean for each gridpoint.
REFERENCES


MICHAEL MANN is currently Alexander Hollaender Distinguished Postdoctoral Fellow of the Department of Energy and holds an adjunct faculty position at the University of Massachusetts. He specializes in the study of climate signal detection, and climate change and variability studies. He received his Ph.D. in Geology & Geophysics from Yale University where he also completed M.S and M. Phil in Physics.

Michael E. Mann, Department of Geosciences, Morrill Science Center, University of Massachusetts, Amherst, MA 01003. Tel: 413. 545. 9573, mann@snow.geo.umass.edu

RAYMOND S. BRADLEY is professor of climatology and petroclimatology and head of the Department of Geosciences at the University of Massachusetts. He holds degrees from Southampton University and the University of Colorado. He was awarded a Distinguished Faculty Research Fellowship at the University of Massachusetts in 1991 and the Chancellor’s Medal in 1996.

Raymond S. Bradley, Department of Geosciences, Morrill Science Center, University of Massachusetts, Amherst, MA 01003. Tel: 413. 545. 9573, bradley@snow.geo.umass.edu