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Probabilistic Prediction of Multidecadal Climate Shifts

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The problem: Recent research has shown that decadal-to-multidecadal (D2M) climate variability is associated with environmental changes that have important consequences for human activities, things like water availability, frequency of hurricanes, and so forth. As scientists, how do we convert these relationships into decision support products useful to water managers, insurance actuaries, and others, whose principal interest lies in knowing when a future climate regime shift will occur that affects their activities? Unfortunately, numerical models are far from being able to make deterministic predictions for future D2M climate shifts. However, the recent development of paleoclimate reconstructions such as the Gray et al. (2004) tree proxy for the Atlantic multidecadal oscillation (AMO) give us a viable alternative: to estimate distribution functions for climate indices that allow us to calculate the probability of future D2M regime shifts.

In this paper, we show how probabilistic decision support tools can be developed for a specific climate mode — the AMO as represented by the Gray et al. (2004) tree ring reconstruction. The methods are robust and can, in principle, be applied to any D2M climate mode for which a sufficiently long index series exists.

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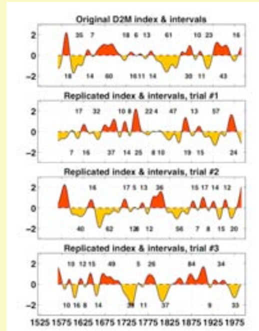

Using the method of Ebisuzaki (1997), the 424-year smoothed tree ring proxy series for the AMO (Gray et al. 2004) (top panel) can be used to generate additional series of the same length and with the same power spectrum, as in the three lower panels. Doing so is equivalent to taking similar samples of the AMO over a much longer time period for which we assume the AMO to be stationary, i.e., its statistical characteristics remain unchanged. We are specifically interested in doing a Monte Carlo-style resampling of the intervals between AMO phase shifts, as defined by the zero crossings of the series (plotted numbers in years).

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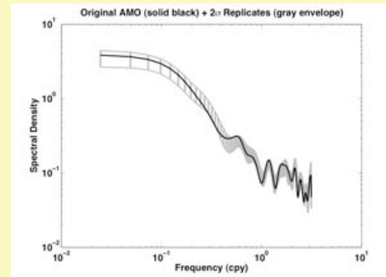

The dark curve is the autospectrum of the Gray et al (2004) proxy index. The light-shaded envelope is the mean $\pm 2\sigma$ spectrum of 50 resampled time series. The Ebisuzaki resampling method consists of transforming the original time series into the frequency domain, randomizing the phases, and reverse transforming back to the time domain.

As can be seen, the autospectrum of the original data is preserved by the Monte Carlo samples.

The resampling can be done as many times as needed to obtain a statistically viable collection of AMO phase intervals

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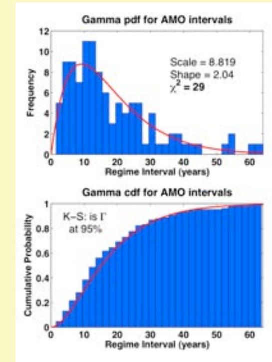

The empirical distribution (blue histogram) of multiple-resampled AMO phase intervals can be fitted by the skewed Gamma (Γ) probability density function as shown in the top panel, resulting in the estimated shape (A) and scale (B) parameters for the hypothesized distribution. A Kolmogorov-Smirnov goodness-of-fit test of the cumulative distributions (lower panel) typically shows the Gamma fit to be successful at the 95% significance level. Stable estimates of A & B are obtained by repeating the procedure many times and averaging.

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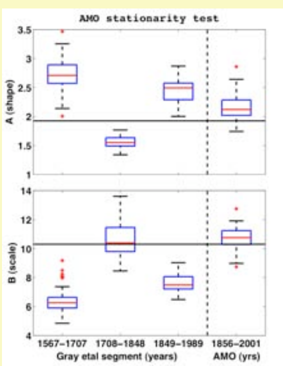

The 424-year proxy series is divided into three 141-year segments and 50 parameter estimates of shape (A, above) and scale (B, below) are obtained for each. Box & whiskers are shown to the left of the dotted line. The same is done for the 146-year instrumental series (right). The mean of 50 estimates for the entire proxy series (424 years) is shown by the horizontal black lines. We see that the 424-year means are bracketed by the segments and that the instrumental values fall in the same ranges. However, it appears that the segment ranges are distinct, indicating that the AMO interval statistics are nonstationary. This means that the segment statistics, not those of the entire series, must collectively be used for uncertainty estimates.

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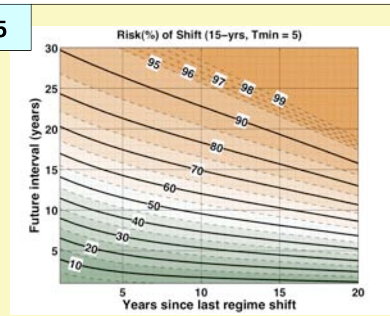

Using the mean Gamma parameters for the 424-year proxy series, we can now calculate and graph the conditional probability of an AMO phase change within the next Y years (ordinate) given that X years have elapsed since the last change (abcissa). The AMO went positive circa 1994 (X=11), indicating a probability of ~30% for a reverse shift within the next 5 years, and ~70% for a shift within the next 15 years. There is an *rms* uncertainty of about 4-5% associated with the 99% confidence interval of segment parameter estimates about the 424-year mean.

Contingent impacts issue from these probabilities. Thus, e.g., a shift to an associated cycle of Florida droughts appears likely (> 50%) sometime before about 2015-2020.

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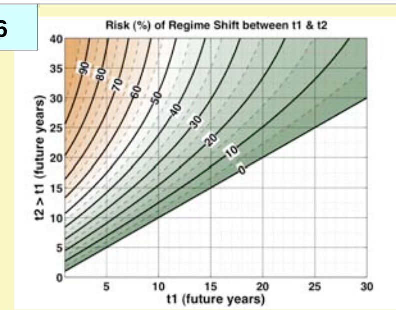

Note that, on the previous graph one can subtract the probability for Y=t1=5 years from the probability for Y=t2=15 years to obtain the probability that a change will occur between 5 and 15 years from the present. The difference is slightly more than 40%. For the case of X=11 we can now plot the probability P(t1<T<t2) on a nomogram as a function of t2 (ordinate) versus t1 (abcissa). Of course, with each year that passes the graph must be updated. For the example at hand (t1=5, t2=15) the nomogram indicates a probability of 42%.

These are the sorts of decision support tools that can be developed from D2M proxy climate indices to reduce the uncertainty in management decisions over a wide range of activities affected by D2M climate cycles, e.g., water management, hurricane risk, etc. Other products can be developed as well, such as the joint probability of changes in two D2M modes, e.g., the AMO and the PDO.

Discussion:

The methods shown here demonstrate ways in which paleoclimate proxy series can be used to develop useful decision support products for water managers and others involved in activities affected by decadal-to-multidecadal (D2M) climate variability. The methods are not confined to a single climate mode; they can be applied to any climate mode series of sufficient length.

Conclusions:

1) Given a long enough (proxy) time series for a climate mode index, it is possible to randomly "resample" the longer statistical population from which the observations are obtained, and to fit a Gamma distribution to the intervals between climate shifts (zero crossings).

2) Although further testing may show that the statistics are nonstationary, this does not invalidate the approach, it merely increases the uncertainty of the results.

3) The AMO, as represented by the Gray et al. (2004) proxy index, is indeed nonstationary over a 400+ year interval. The resulting uncertainty in probability calculations is about 4-5%.