The Probabilistic Projection of Climate Risk

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The last 15 years have seen much research on decadal to multidecadal (D2M) climate modes and their global and regional impacts. At least some of these D2M modes suggest compelling climatic and ecological impacts. Both the Pacific Decadal Oscillation (PDO) and the Atlantic Multidecadal Oscillation (AMO) are associated with alternating trans-decadal regimes in precipitation and drought frequency, which appear to be sensitive to small but persistent changes in the prevalent atmospheric circulation patterns over the continental regions adjacent to the oceans that mediate the oscillations. They have also been shown to modulate (render nonstationary) the rainfall signatures of El Niño-Southern Oscillation (ENSO) in the United States and they are reflected in the multidecadal changes in North Pacific fisheries. Of concern for climate applications is the fact that — unlike El Niño-Southern Oscillation (ENSO) — numerical models have proven incapable of predicting future phase shifts of D2M climate modes in a deterministic manner.

The alternatives to such predictions are probability-based projections, but these are hampered because the instrumentally based time series are limited to the last 130-150 years, which yield too few realizations of D2M cycles for conventional statistical approaches to deal with. There are two ways to approach the lack of suitable observational data sets; (1) applying Monte Carlo-style resampling techniques to the climate index data and (2) analyzing longer, multi-century proxy reconstructions, based mostly on tree rings. To illustrate this, we apply both approaches to the problem of projecting the risk of a future shift in the AMO. By then adjusting a probability model to the distribution of resampled AMO phase intervals, we extract a practical method for determining the risk of a future departure from the current AMO regime. In lieu of nonexistent deterministic predictions, this method provides an essential element for the development of decision support tools for managers and stakeholders in sectors affected by D2M climate modes, such as agriculture, water, energy, health and disaster risk.

To illustrate the methods, we use the unsmoothed 424-year annualized index of the AMO reconstructed from tree rings in North America and Europe (Gray et al. 2004), calibrated against the AMO index suggested by Enfield et al. (2001). To eliminate unwanted short-interval variability, the time series are then smoothed with a Butterworth filter of order 8 and a half-amplitude response cutoff at 15 years. To increase the sample size we randomly resample the index multiple times, each time transforming the original time series into the frequency domain, randomizing the Fourier phases, and reverse transforming back to the time domain. Unlike most randomizations in the time domain, this method preserves the original power spectrum, but still produces resampled series whose temporal correlations with each other and the original series are expected to be zero on average. Fig. 1 (top panel) shows the smoothed AMO reconstruction, annotated with the regime intervals between zero crossings, plus similar plots for three randomly resampled versions of the data. The assumption implicit in this resampling is that the original series is extracted from a larger population (longer duration) with time-invariant statistics (stationary).

The histogram of Fig. 2 (top) illustrates a typical empirical distribution of AMO regime intervals produced by extracting five new time series from the original Gray et al. (2004) spectrum. The distribution is fit by the smooth curve, which corresponds to a gamma pdf whose shape (A) and scale (B) parameters are adjusted to the data by maximum likelihood estimation (MLE). As in the example shown, a Kolmogorov-Smirnov (KS) goodness-of-fit test is applied to the cumulative distribution (cdf, lower panel) and usually shows the fit to be acceptable at the 95% level of significance. Each new fivefold resampling results in varied but similar parameter estimates. To obtain a stable estimate of the gamma distribution for the 424-year period, we average the parameter estimates from 50 resamplings, obtaining $A = 1.93$ and $B = 10.3$. These values are later used to project the risk of future regime shifts.

If we divide the longer index series into three segments of 141 years each and repeat the above procedure, we find that the distribution parameters differ significantly from one segment to another, which means that the AMO process is not stationary. This does not invalidate the estimation procedure, but it means that the distribution parameters are more uncertain than implied by the 50-member spread for the longer 424-year estimation. By pooling the 150 parameter pairs for the three segments, we can estimate the uncertainty of the underlying distribution more realistically. We will return to this in a later section.

Making the projections

If we let $P(\rho)$ represent the probability of a realization ρ within the population space of the stochastic regime intervals (T), we can then construct useful probability projections for future realizations, based on the estimated gamma parameters. For example, the conditional probability that a future regime shift will occur within t_2 years, given that t_1 years have elapsed since the last, opposite regime shift, may be expressed as

$$P(T > t_1 \cap T \le t_1 + t_2 \mid T > t_1) = P(T > t_1 \cap T \le t_1 + t_2)/P(T > t_1)$$

$$= P(t_1 < T \le t_1 + t_2)/P(T > t_1)$$

$$= (\Gamma[t_1 + t_2] - \Gamma[t_1])/(1 - \Gamma[t_1]) \qquad \text{Eq. 1}$$

where $t = t_1 + t_2$ is the current climate regime interval and $\Gamma[t]$ is the estimated gamma cdf. A reasonable, further refinement of this statement is to ignore the probability space for very short intervals (five years or less) that would normally be ignored in practice in retrospective analysis. This is accomplished by using a truncated gamma in Eq. 1, $\Gamma\square[t] = \Gamma\,[t]/\square\square\square\,\Gamma\,[5])$, where $t > 5$.

Fig. 3 shows the probability $P(\rho)$ as a function of t_1 (abscissa) and t_2 (ordinate). An example of using this calculation is as follows. It is generally thought that the AMO switched from cool to warm during the 1994-95 time frame. If we use Fig. 3 with $t_1 = 10$ years, i.e., the number of years that have elapsed since that time, we find a rather low probability (< 30%) that the AMO will switch back to its cool phase in less than $t_2 = 5$ years from now. For $t_2 = 10$ and 15 years, the risk increases to ~51% and ~70%, respectively, while a regime shift within 20 years is highly likely (~86%). Based on current research, such a shift would be associated with a return to more frequent droughts in Florida, fewer droughts in the Colorado River basin, and less frequent severe hurricanes in the tropical Atlantic. As expected, Fig. 3 shows that the risk for any of these t_2 values increases as time advances and the last regime shift recedes further into the past (t_1 increases).

The uncertainty of such estimates can be derived from the parameter estimates of the three Gray et al. (2004) time segments, which collectively have a considerably larger spread than those of the 424-year estimation used for Fig. 3. This is primarily due to the nonstationarity of the intervals over the last half millennium. Pooling the 3x50 segment estimates of A and B, we randomly select a large number of parameter values within their overall 1-α confidence intervals and generate the corresponding rms uncertainty in $P(\rho)$ over the domain of Fig. 3. The uncertainty is fairly uniform over the $[t_1,t_2]$ domain shown. For confidence intervals between 95% and 99%, the uncertainty ranges between ±2% ($\alpha = 0.05$) and ±5% ($\alpha = 0.01$), respectively.

We have not fully explored the uncertainties that attend such projections. Besides the uncertainty associated with natural nonstationarity, it is also desirable to consider how the quality of the reconstruction will affect the distribution parameters. Where multiple reconstructions of the same climate index are available (at least four exist for the PDO) the uncertainty due to the inability of the reconstructions to perfectly emulate the climate process can be estimated by applying the above methods to the multiple reconstructions, rather than to segments of a single reconstruction. Only one reconstruction yet exists for the AMO, so we have not done this.

Fig. 3 is only one example of a potentially useful climate risk projection tool. Thus for any given year in which decisions are made, one can also construct a graph showing the distribution for $P(t_a < T \le t_b)$, where t_a (abscissa) and t_b (ordinate) define a time range, e.g. 10-15 years into the future. The risk of an AMO shift between $t_a = 2015$ AD and $t_b = 2020$ AD is about 19%.

Other, more esoteric projections can be developed. McCabe et al. (2004) have shown how the uncorrelated +/- phases of the PDO and AMO have juxtaposed since the mid-19th century in ways that plausibly explain mega droughts in the southwestern and Midwestern U.S. If both oscillations can be statistically modeled as we have done here only for the AMO, it is possible to develop joint probability projections for the four possible phase-phase scenarios (+/+. +/-. -/-. -/+), under the assumption that the climate oscillations are mutually independent. It is also possible to query the conditional probability for regime interval magnitude or intensity — based on the index area subtended between zero crossings — given an interval of a certain length.

Summary and discussion

We have shown how a multi-century proxy reconstruction of a climate index may be used to estimate the pdf of climate regime intervals, thus providing a basis for the projection of climate risk and the eventual development of useful decision support tools. The spectrum preserving resampling of the time series provides sufficient sample sizes for pdf estimation using the gamma distribution. We have given a detailed example of a derived climate risk projection and have suggested others that can be developed.

Consider the situation in 1990, more than 20 years into a period of cool North Atlantic sea surface temperatures (AMO) associated with dry conditions in Florida, wet conditions in the southwestern region and less frequent hurricanes. It is not difficult to imagine management decisions that could have been made then as an AMO reversal became imminent within operational time horizons. Where water was expected to become more plentiful, flood control measures could have been implemented and development on flood plains discouraged. Where more persistent and/or frequent droughts were expected, more water could have been shunted to aquifer storage, water access leases shortened, reservoir withdrawals reduced, conservation measures implemented and agricultural practices modified. Underwriting associations could have increased the funding of windstorm contingency pools in anticipation of more frequent, destructive hurricanes.

D2M climate risk assessment is not useful only when a climate shift becomes imminent. In general, for any policy or measure that can be adopted in anticipation of a change, there exists an alternative to be followed if the probability of change is low. Policies may be reviewed periodically in light of changing probabilities and the spectrum and effectiveness of available mitigation measures can be revised on a regular basis. Cognizance of the changing nature of climate and its impacts is a relatively recent development and it has taught us that effective management should not be based on static policies. Perhaps the best example of this lesson is the recent increase in destructive hurricane potential related to the change in the AMO climate regime and its impact on the insurance industry.

It is important to point out that the usefulness of these methods for actual applications will depend on the nature of the application, the strength of the connection between the climate mode and the target variable, and managers' ability to utilize the projections in making operational decisions. In general, the closer the relationships of the modeled index to the decision-triggering target variables, the better. Thus, if a proxy reconstruction of stream flow exists, this may be more useful to model than the climate mode whose association with the stream flow is less than perfect. However, projections based on a climate mode have the advantage of being appropriate over a wider range of applications and geographic regions.

Finally, the ultimate uncertainty for which there is no sure remedy at present, is the effect that global climate change will have on future climate regime characteristics. However, it is worth noting that if the true future distribution parameters are different from those in the past, the effect on risk projection (as shown in Fig. 3) is to shift all probabilities in the same direction and by similar amounts. Hence, the relative change in probability from one part of the domain to another is little affected by a parameter discrepancy. Arguably, the evolving *change* in risk is more likely to influence management and policy adjustments, than is the absolute risk at a given position, as long as the errors are within reasonable bounds. In fact this principle applies to all sources of uncertainty.

References

Enfield, D. B., A. M. Mestas-Nuñez, and P. J. Trimble, 2001: The Atlantic multidecadal oscillation and its relation to rainfall and river flows in the continental U.S. Geophys. Res. Lett., 28, 2077-2080.

Gray, S. T., J. L. Graumlich, J. L. Betancourt, and G. T. Pederson, 2004: A tree-ring based reconstruction of the Atlantic Multidecadal Oscillation since 1567 A.D. Geophys. Res. Lett., 31, L12205, doi:10.1029/2004GL019932.

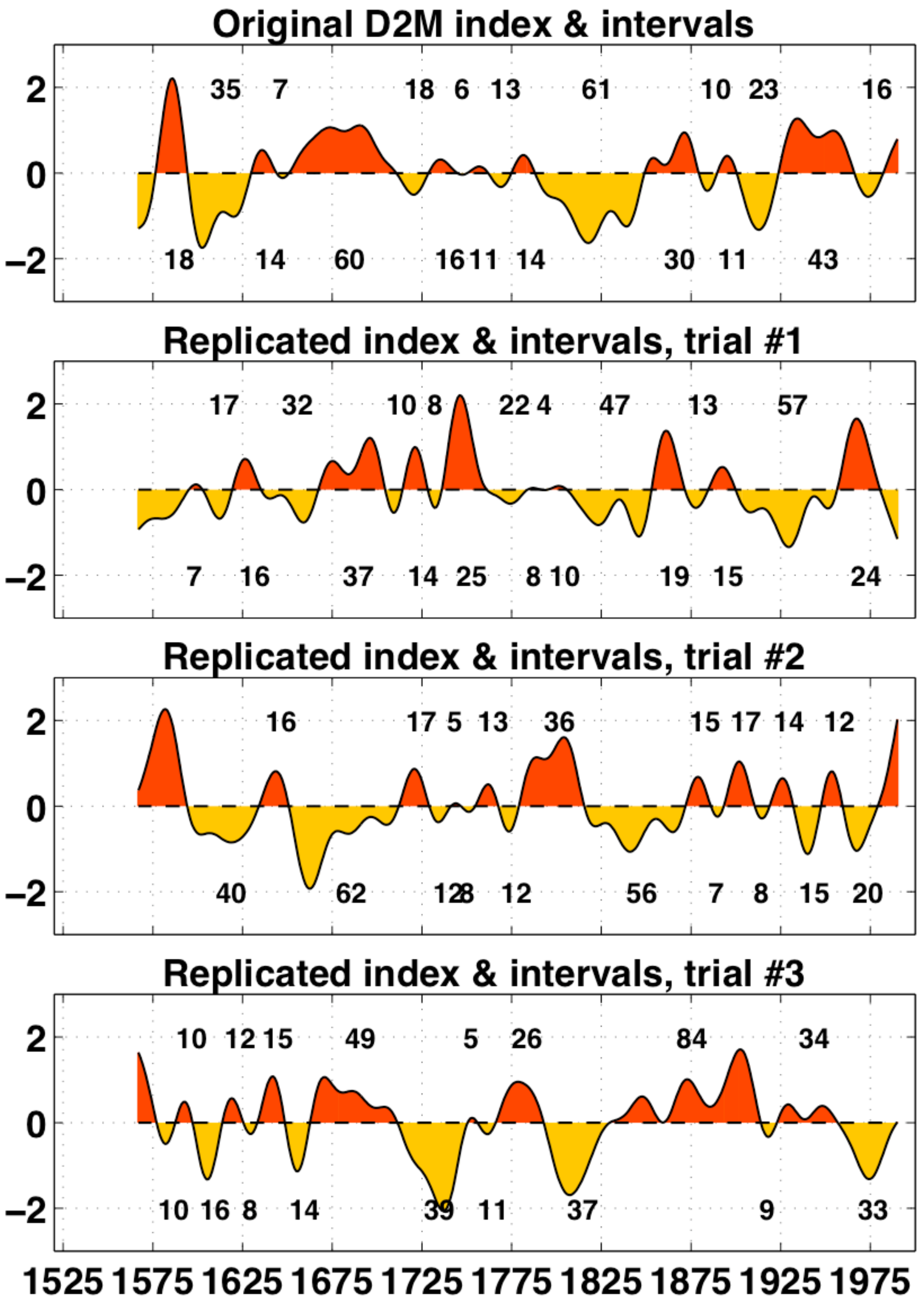
McCabe, G. J., M. A. Palecki, and J. L. Betancourt, 2004: Pacific and Atlantic Ocean influences on multidecadal drought frequency in the United States. Proc. Nat. Acad. Sci., 101, 4136-4141.

Figure captions

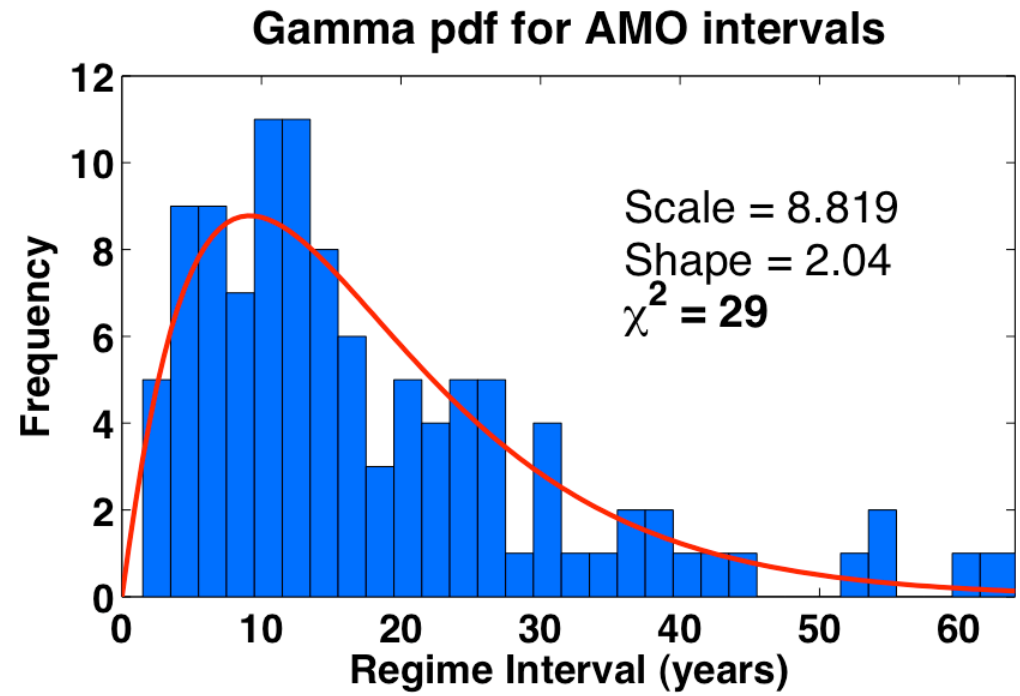
Fig. 1. Upper panel: Smoothed annual tree ring reconstruction of the Atlantic multidecadal oscillation (AMO) index by Gray et al. (2004). Lower panels: Smoothed resampled versions of the Gray et al. index using randomization in the frequency domain (Ebisuzaki 1997). Numeric annotations are the intervals (years) between zero crossings.

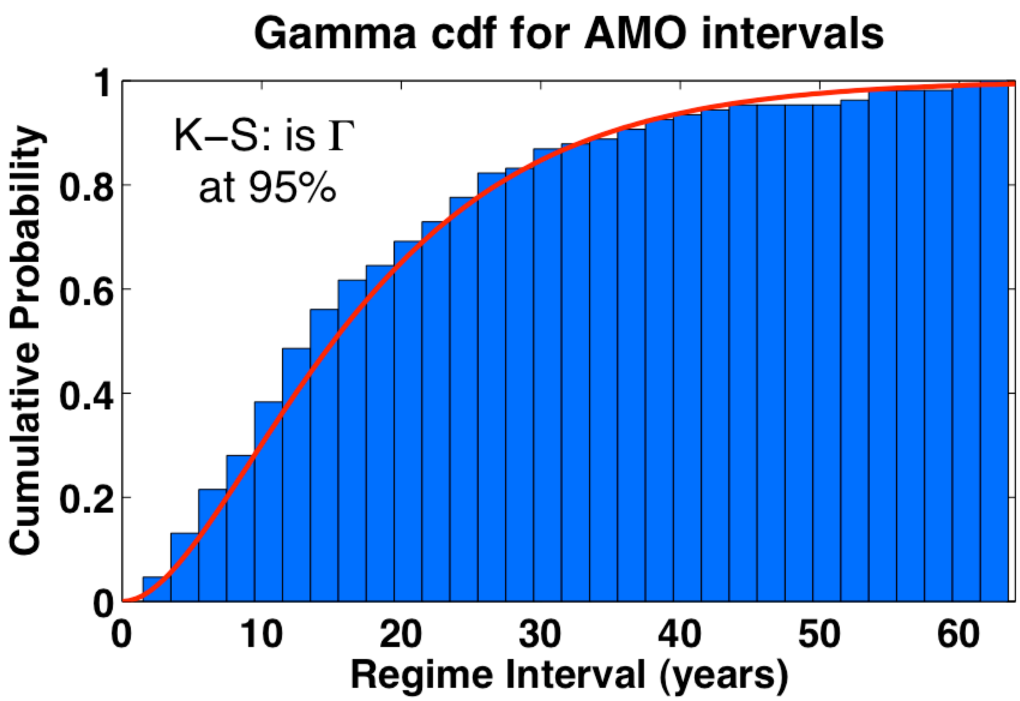
Fig. 2. Upper panel: histogram (vertical bars) of zero crossing intervals from a set of five resampled and smoothed versions of the Gray et al. (2004) index and the maximum likelihood (MLE) gamma probability distribution (solid curve) fit to the histogram. Lower panel: cumulative empirical distribution (vertical bars) and gamma cumulative distribution function (solid curve), indicating that the Kolmogorov-Smirnov goodness-of-fit criterion is satisfied at the 95% significance level.

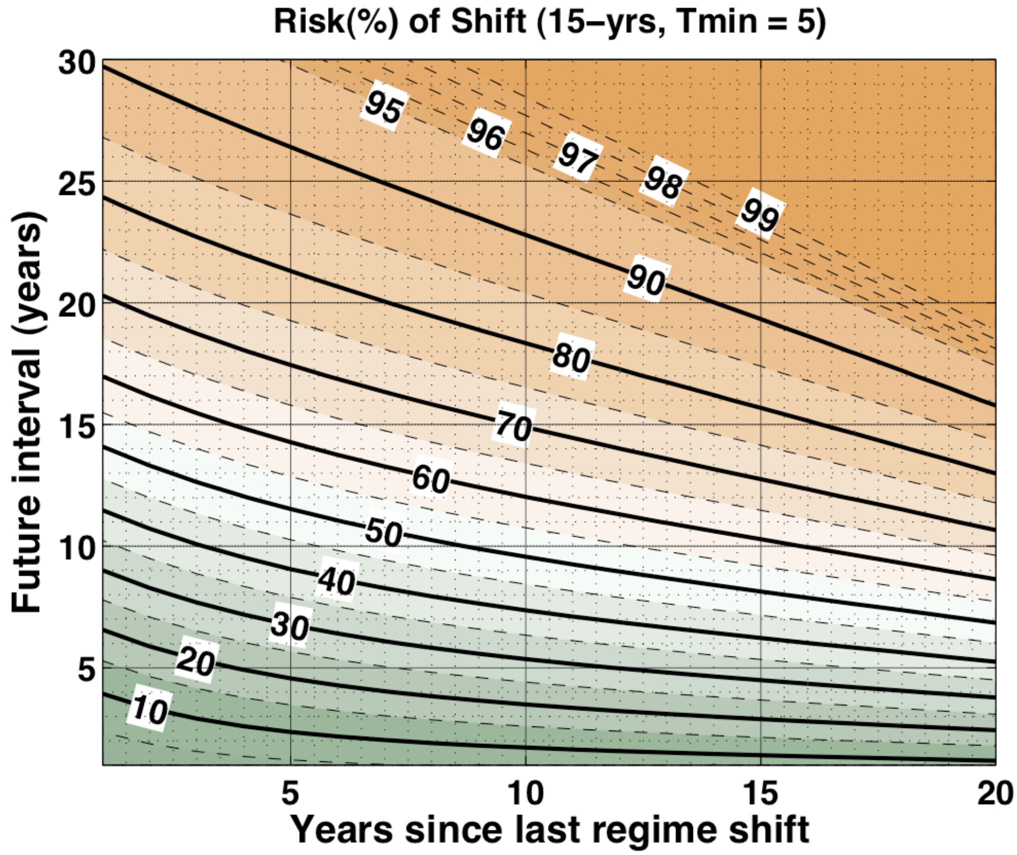
Fig. 3. Distribution of the probability of an AMO regime shift occurring wthin t_2 future years (ordinate) given that t_1 years (abscissa) have elapsed since the last regime shift. Based on the gamma distribution with scale and shape parameters of 10.3 years and 1.93, truncated for $t_1 + t_2 > 5$ years (see text).



Original D2M index & intervals
Replicated index & intervals, trial #1
Replicated index & intervals, trial #2
Replicated index & intervals, trial #3
2
0
−2
1525 1575 1625 1675 1725 1775 1825 1875 1925 1975


Gamma pdf for AMO intervals
Scale = 8.819
Shape = 2.04
χ² = 29
Frequency
Regime Interval (years)
0
2
4
6
8
10
12
0
10
20
30
40
50
60


Gamma cdf for AMO intervals
K–S: is Γ
at 95%
Cumulative Probability
Regime Interval (years)
0
0.2
0.4
0.6
0.8
1
0
10
20
30
40
50
60


Risk(%) of Shift (15−yrs, Tmin = 5)
Future interval (years)
Years since last regime shift
30
25
20
15
10
5
5
10
15
20
95
96
97
98
99
90
80
70
60
50
40
30
20
10