

Using Reanalyses to assess 20th Century Changes in Climate Extremes

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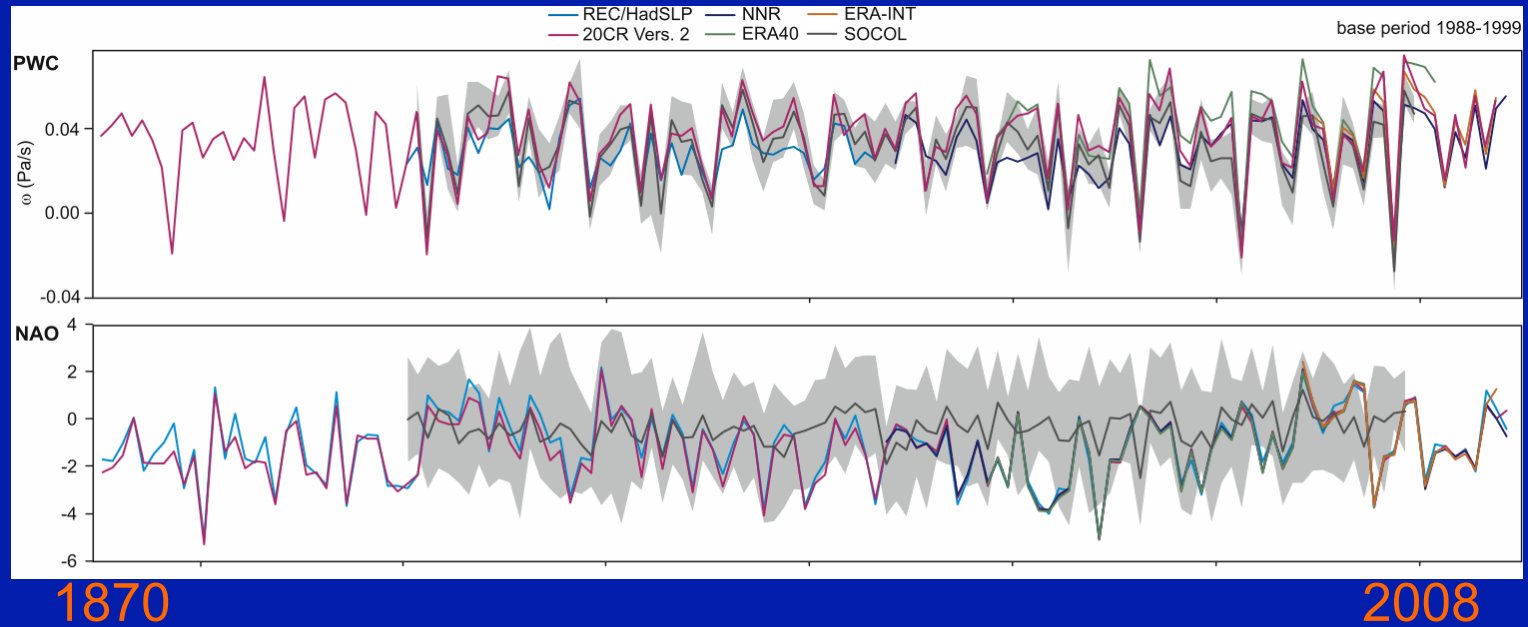
4th WCRP Reanalysis Conference May 2012

- 1) **We need the longest possible reanalysis datasets** to establish the significance of climate changes and to validate climate models. Several major circulation trends evident over the second half of the 20th century are weak or non-existent in century-long records.
- 2) **There is more to climate change than just a shift of the mean.** One also needs to consider the changes in variability. This has large implications for changes in extreme anomaly statistics.
- 3) **The PDFs of daily weather anomalies are not Gaussian.** Their skewed and heavy-tailed character make the detection and attribution of changes in extreme weather statistics even more difficult using relatively short (~ 50-yr) climate records.

Extreme weather events are often associated with variations in the major modes of atmospheric variability. Several of these modes do not show significant trends over the 1871-2008 period.

**Pacific Walker
Circulation**
(500 hPa vertical
velocity, SONDJ)

**North Atlantic
Oscillation**
(Sea Level
Pressure, DJF)



20th Century (20CR), ERA-40, NCEP-NCAR, ERA-Interim Reanalyses, and Statistical Reconstructions, and SST-forced GCM integrations

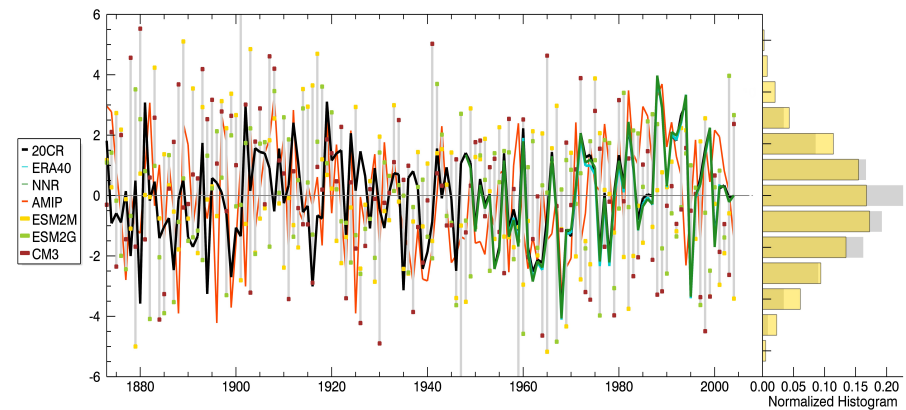
20th Century NAO variations in 20CR (BLACK) and other reanalyses, in an AMIP ensemble (RED) with prescribed observed SSTs and radiative forcings, and in 3 coupled model simulations with prescribed radiative forcings only.

Note that there are no significant long-term trends in the 20CR and AMIP series.

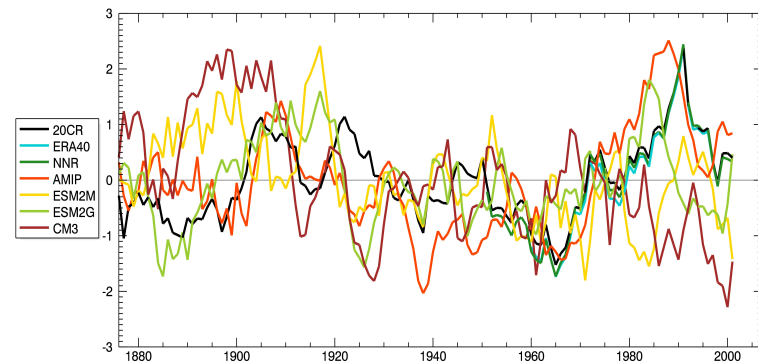
	20CR	ERA40	NNR	AMIP	ESM2M	ESM2G	CM3
20CR	1.00	1.00	1.00	0.30	-0.06	0.01	-0.05
ERA40		1.00	1.00	0.38	0.05	-0.07	0.02
NNR			1.00	0.37	0.01	-0.09	-0.02
AMIP				1.00	0.09	0.03	-0.03
ESM2M					1.00	0.04	-0.03
ESM2G						1.00	0.03
CM3							1.00

	20CR	ERA40	NNR	AMIP	ESM2M	ESM2G	CM3
20CR	1.00	0.99	0.99	0.65	-0.09	0.32	-0.22
ERA40		1.00	1.00	0.80	0.35	0.30	-0.35
NNR			1.00	0.80	0.24	0.29	-0.32
AMIP				1.00	-0.04	0.24	-0.16
ESM2M					1.00	0.06	0.41
ESM2G						1.00	0.24
CM3							1.00

NAO index



7-yr running mean NAO index



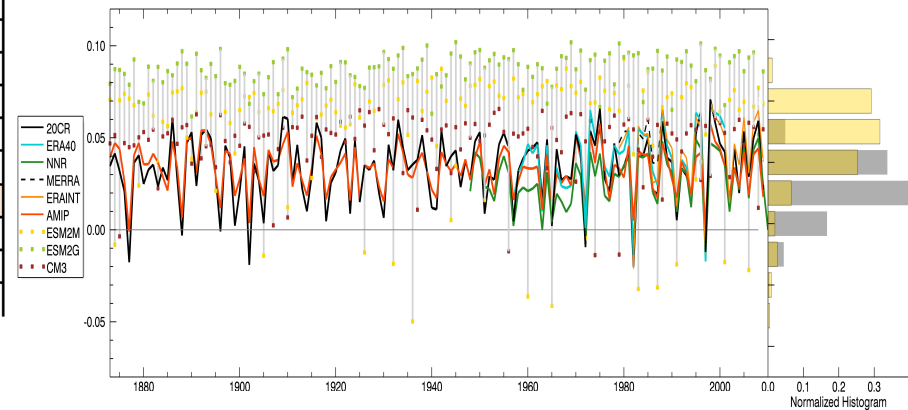
20th Century PWC (Pacific Walker Circulation) variations in 20CR (BLACK) and other reanalyses, in an AMIP ensemble (RED) with prescribed observed SSTs and radiative forcings, and in 3 coupled model simulations with prescribed radiative forcings only. There are no significant long-term trends in the 20CR and AMIP series.

PWC CORRELATIONS

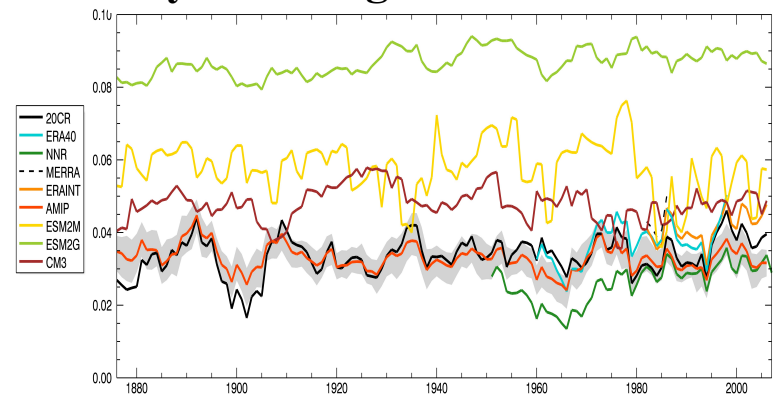
	20CR	ERA40	NNR	MERRA	ERAINT	AMIP	ESM2M	ESM2G	CM3
20CR	1.00	0.95	0.90	0.98	0.96	0.92	0.16	0.00	-0.18
ERA40		1.00	0.96	0.97	0.99	0.93	0.21	-0.08	-0.26
NNR			1.00	0.96	0.99	0.90	0.23	-0.15	-0.24
MERRA				1.00	0.98	0.88	0.26	-0.19	-0.19
ERAINT					1.00	0.94	0.24	-0.20	-0.22
AMIP						1.00	0.16	-0.04	-0.25
ESM2M							1.00	0.06	-0.01
ESM2G								1.00	0.03
CM3									1.00

PWC 7 y 20CR	ERA40	NNR	MERRA	ERAINT	AMIP	ESM2M	ESM2G	CM3	
20CR	1.00	0.76	0.58	0.99	0.88	0.68	-0.03	0.32	-0.17
ERA40		1.00	0.86	1.00	0.84	0.88	0.01	0.03	-0.60
NNR			1.00	0.97	0.97	0.66	-0.17	0.05	-0.20
MERRA				1.00	0.75	0.94	0.01	-0.33	-0.48
ERAINT					1.00	0.78	0.35	-0.32	0.06
AMIP						1.00	0.10	0.07	-0.31
ESM2M							1.00	0.11	0.05
ESM2G								1.00	0.16
CM3									1.00

PWC index



7-yr running mean PWC index



Several possible decompositions of climate variations

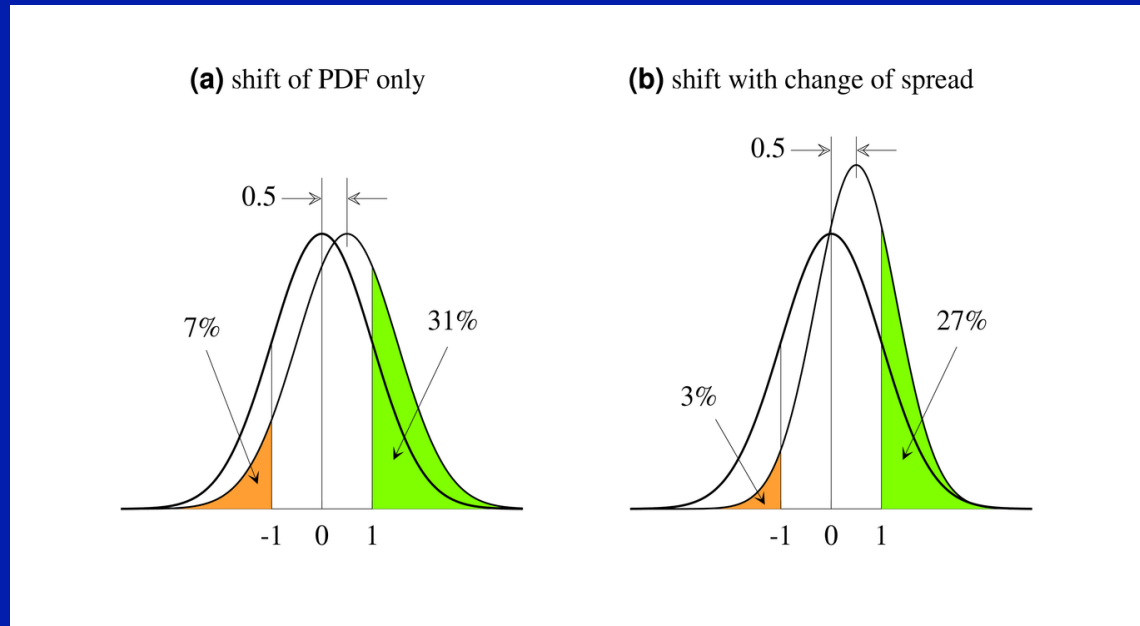
$$\begin{aligned} X(t) &= \text{Radiatively Forced} + \text{Unforced} \\ &= \text{Anthropogenic} + \text{Natural} \\ &= \text{Predictable} + \text{Unpredictable} \\ &= \text{ENSO-unrelated} + \text{ENSO-related} \end{aligned}$$

The **blue terms** complicate interpretation of discrepancies between observed and model simulated $X(t)$ over relatively short record lengths.

It might be more appropriate to consider the *statistics* of $X(t)$, specifically the PDF $p(X)$ of $X(t)$, and ask whether there have been significant changes in $p(X)$ over the 20th century and to what extent climate models have been able to capture them.

Considering observed and simulated long-term *trends* (i.e., changes in the first statistical moment of $p(X)$) is one way to do this, but it is not the only or even the most important way, **because climate change represents more than a shift of the mean.**

Even relatively minor changes of variability associated with a mean climate shift can have a large effect on the probability of extreme values



The right panel shows that if a mean positive shift of 0.5 is associated with a reduction in sigma from 1.0 to 0.8, the probability of extreme positive values (say $x > 1$) increases from 16% to 27%, which is smaller than the increase from 16% to 31% obtained if there is no change in sigma (left panel)

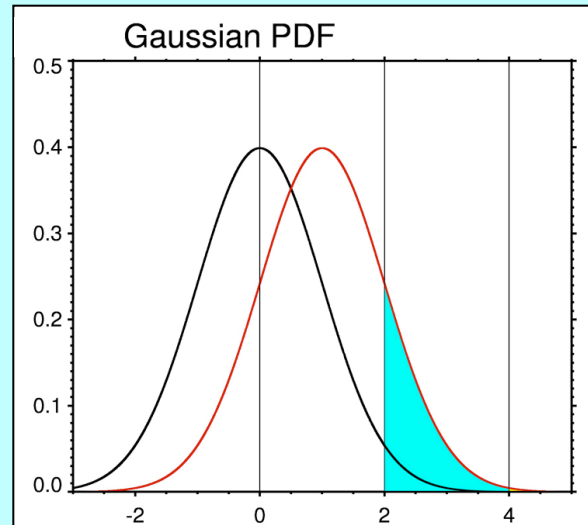
The probability of even more extreme anomalies ($x > 2.5$) actually decreases in this case.

In such a scenario global warming might actually **DECREASE** the risk of extreme heat waves !

It is also important to account for the non-Gaussian character of the PDFs of many climate variables of interest, which has large implications for the probabilities of extreme values and for our ability to estimate their changes using limited records

Consider Gaussian vs non-Gaussian PDFs, both $p(0,1)$, and shifted by 1 sigma

Gaussian PDFs

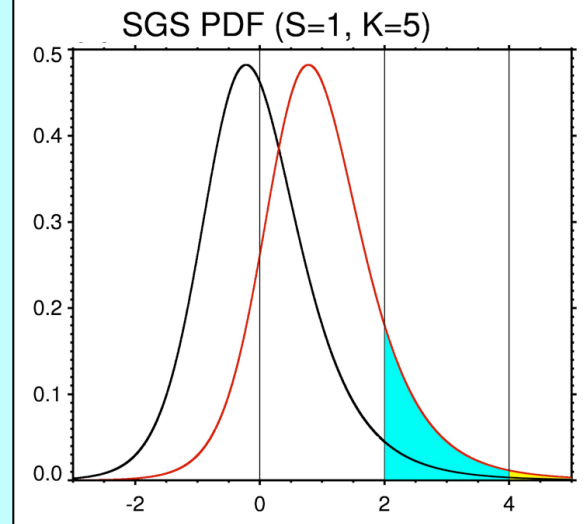


$P(x \geq 2) = 2.3\%$
and increases by
a factor of 7

$P(x \geq 4) = 0.003\%$
and increases by
a factor of 43

Non-Gaussian PDFs

skewed and heavy-tailed with
Skewness $S = 1$
Kurtosis $K = 5$

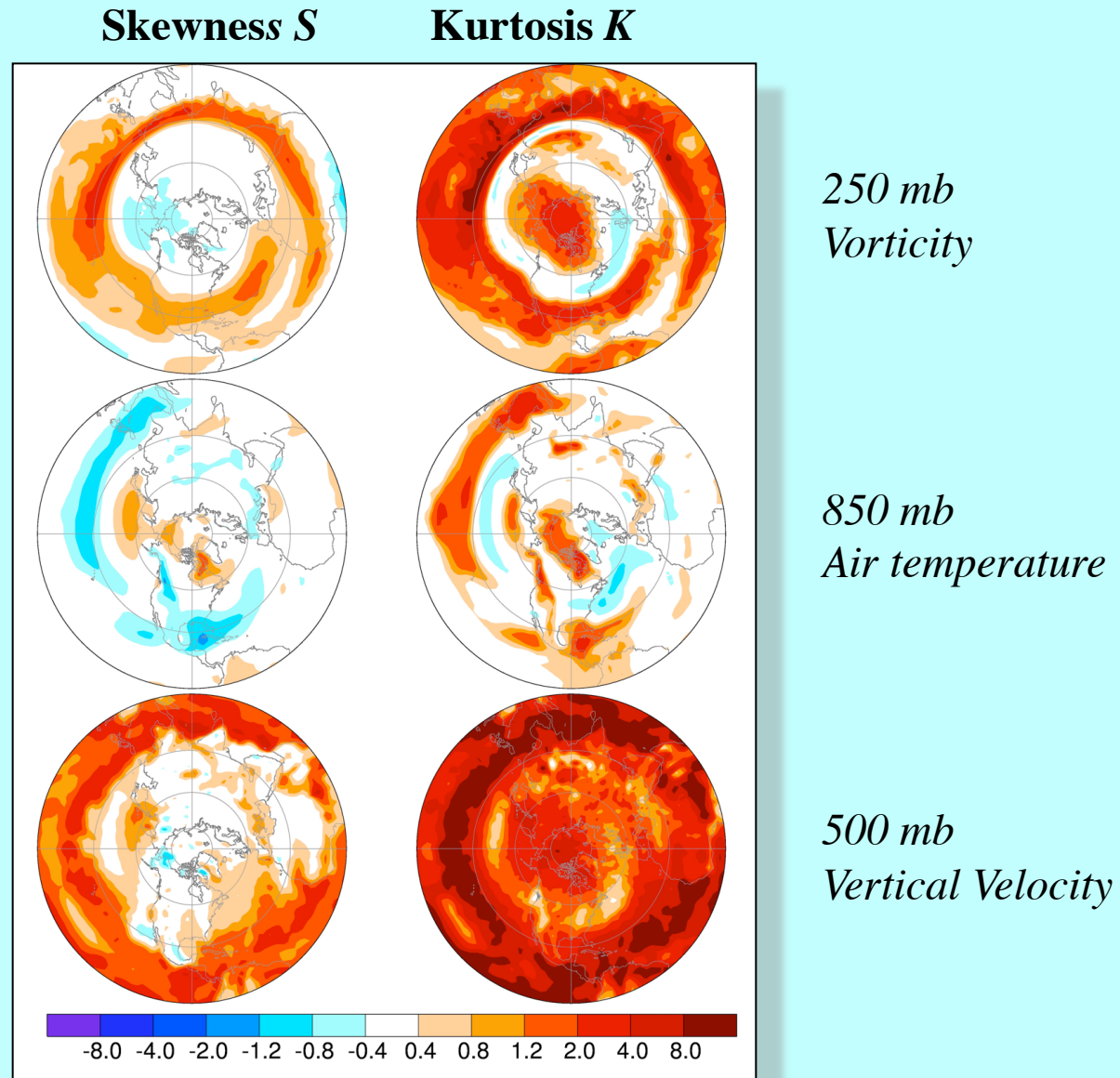


$P(x \geq 2) = 3.4\%$
and increases by
only a factor of 4

$P(x \geq 4) = 0.34\%$
and increases by
only factor of 3

From Sardeshmukh, Compo,
and Penland 2012

Skewness $S = \langle x^3 \rangle / \sigma^3$ and Kurtosis $K = \langle x^4 \rangle / \sigma^4 - 3$ of daily anomalies in winter computed over 137 winters (1871-2007) in the 20CR dataset (Compo et al 2011)

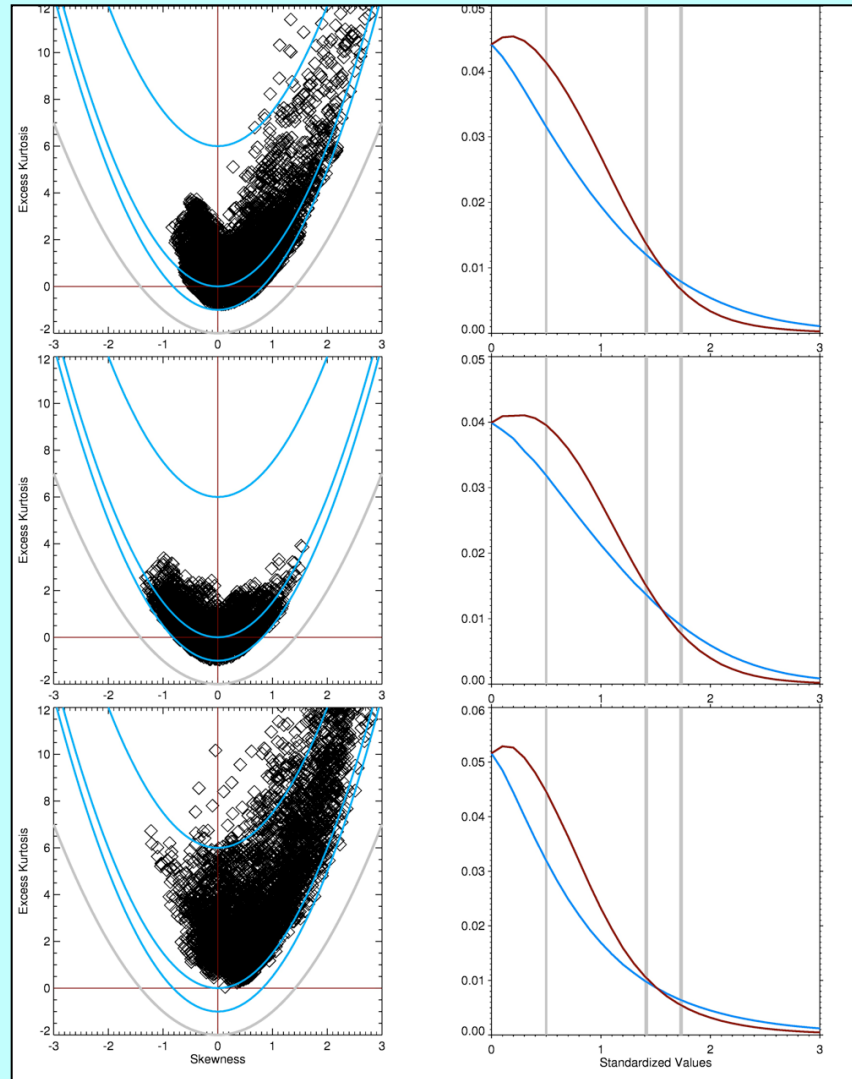


K vs S

Average Histograms

Some distinctive features of the non-Gaussianity of standardized daily anomalies at all Northern Hemisphere grid points

computed using 137 winters (1871-2007) of 20CR data



*250 mb
Vorticity*

*850 mb
Air temperature*

*500 mb
Vertical Velocity*

Note the parabolic inequality

$$K \geq 3/2 S^2$$

Note that the crossover point where $p(x) = p(-x)$ lies between 1.4σ and 1.7σ

A generic “Stochastically Generated Skewed” (SGS) probability density function (PDF) suitable for describing non-Gaussian climate variability (Sardeshmukh and Sura, *J. Clim.*, 2009)

$$p(x) = \frac{1}{\mathcal{N}} \left[(Ex + g)^2 + b^2 \right]^{-\left(1 + \frac{\lambda}{E^2}\right)} \exp \left[-\frac{2\lambda g}{E^2 b} \arctan \left(\frac{Ex + g}{b} \right) \right]$$

If $E \rightarrow 0$, then $p(x) \rightarrow$ a Gaussian PDF

$$\begin{aligned} \lambda &> 0 & b &\geq 0 \\ g &\geq 0 \text{ or } g < 0 \\ E &\geq 0 \end{aligned}$$

Such a PDF has power-law tails, its moments satisfy $K \geq (3/2) S^2$, and $p(x) = p(-x)$ at $\hat{x} \approx \sqrt{3} \sigma$

This PDF arises naturally as the PDF of the simplest 1-D damped linear Markov process that is perturbed by Correlated Additive and Multiplicative white noise (“CAM noise”)

$$\frac{dx}{dt} = - \left(\lambda + \frac{1}{2} E^2 \right) x + b \eta_1 + (Ex + g) \eta_2 - \frac{1}{2} Eg$$

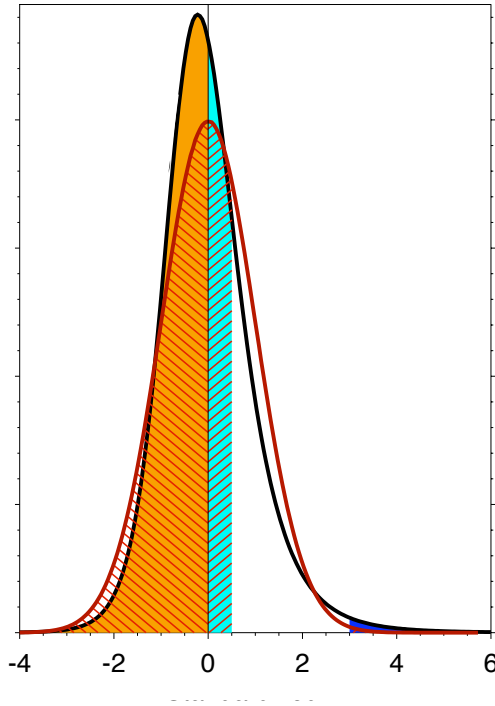
If $E \rightarrow 0$, this is just the evolution equation for Gaussian “red noise”

η_1 and η_2 are Gaussian white noises of unit amplitude.

The parameters of this model (and of the PDF) can be estimated using the first four moments of x and its correlation scale. **The model can then be run to generate Monte Carlo estimates of extreme statistics**

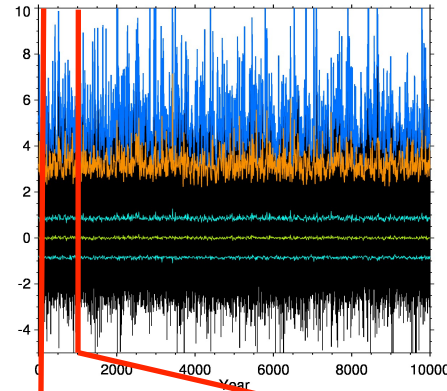
Sharply contrasting behavior of extreme w anomalies (and by implication, of extreme precipitation anomalies) obtained in 10^8 -day runs (equivalent to 10^6 100-day winters) of the Gaussian and non-Gaussian models

Gaussian (red) and non-Gaussian (black, $S=1$, $K=5$) PDFs with same mean and variance

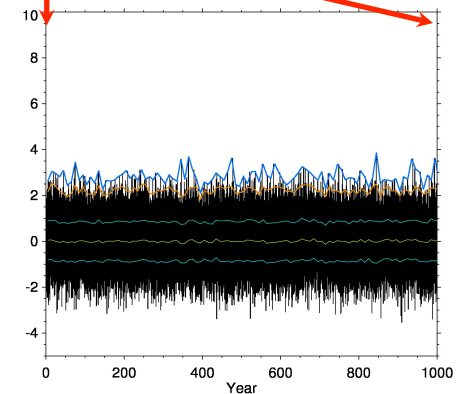
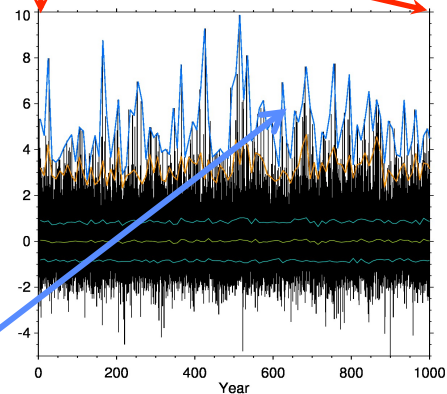
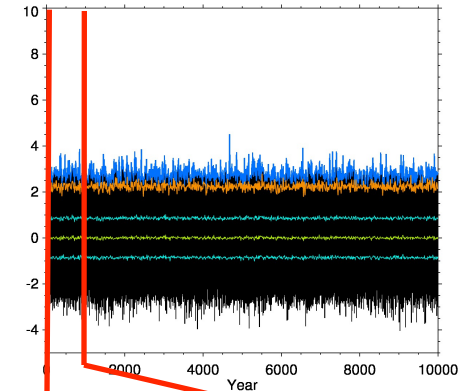


Note how one can obtain spurious 100-yr trends of decadal extremes in the non-Gaussian case *even in this statistically stationary world.*

Non-Gaussian ($S=1$, $K=5$)



Gaussian

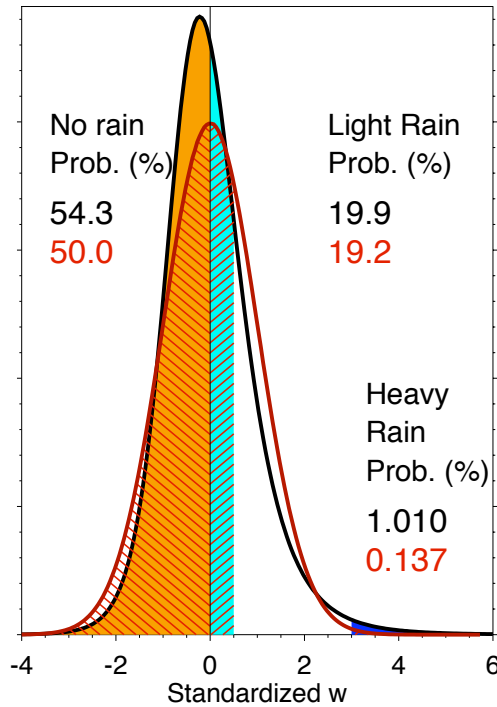


Blue curves: Time series of decadal maxima (i.e. the largest daily anomaly in each decade = 1000 days = 10 100-day winters)

Orange curves: Time series of 99.5th decadal percentile (i.e. the 5th largest daily anomaly in each decade)

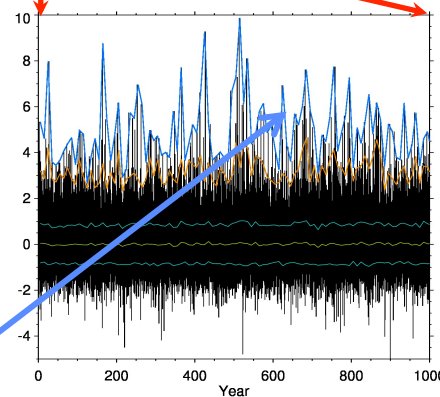
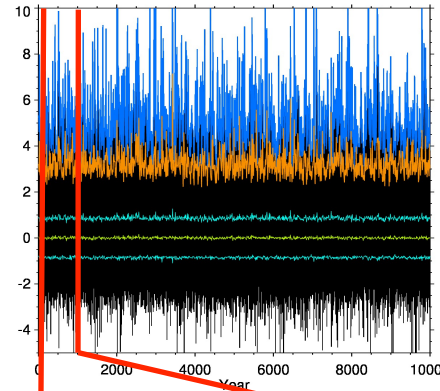
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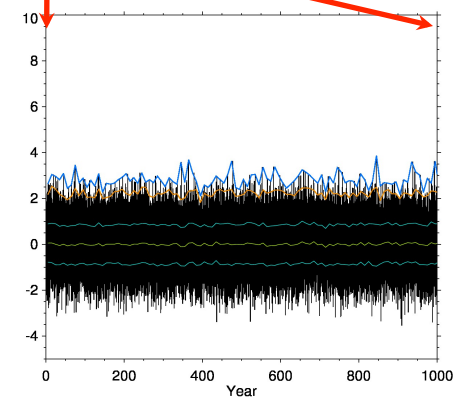
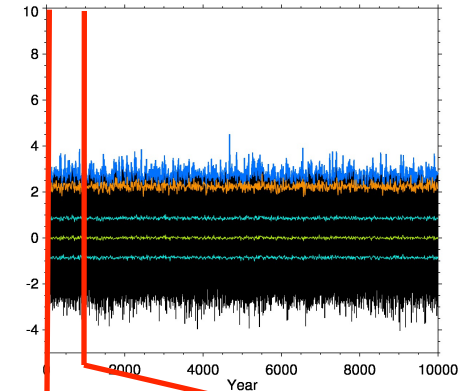


Note how one can obtain spurious 100-yr trends of decadal extremes in the non-Gaussian case *even in this statistically stationary world.*

Non-Gaussian ($S=1$, $K=5$)



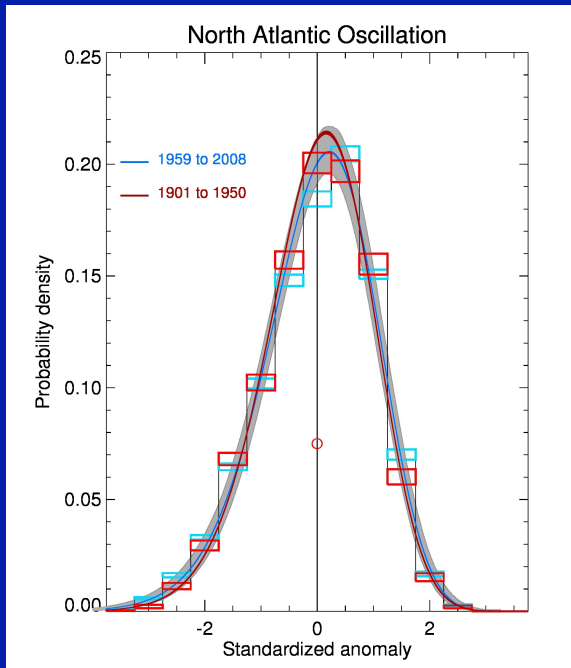
Gaussian



Blue curves: Time series of decadal maxima (i.e. the largest daily anomaly in each decade = 1000 days = 10 100-day winters)

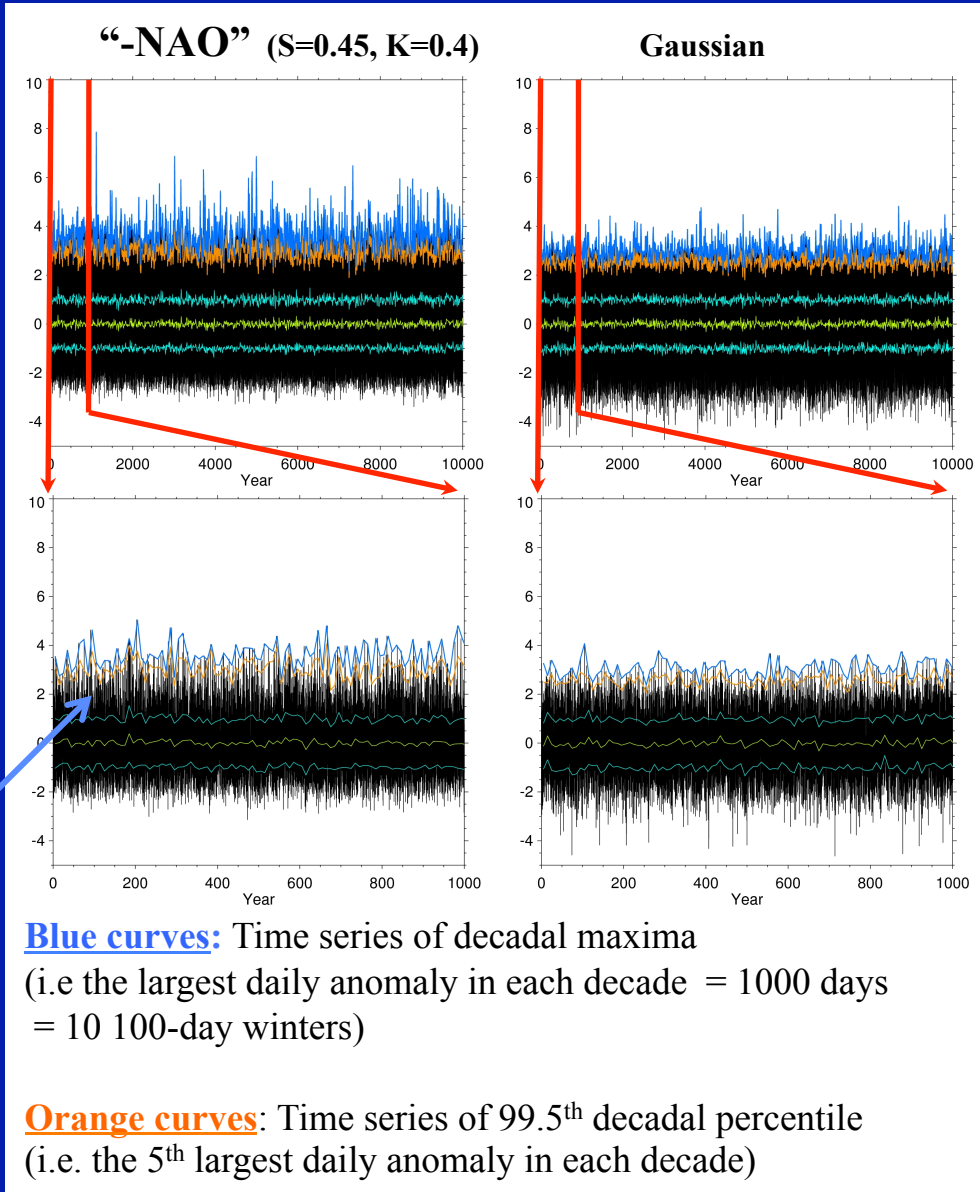
Orange curves: Time series of 99.5th decadal percentile (i.e. the 5th largest daily anomaly in each decade)

Sharply contrasting behavior of extreme “-NAO” anomalies (and by implication, of extreme weather) obtained in 10^8 -day runs (equivalent to 10^6 100-day winters) of the Gaussian and non-Gaussian models



Decorrelation time = 5.75 days

Note how one can obtain spurious 100-yr trends of decadal extremes in the non-Gaussian case *even in this statistically stationary world.*



Blue curves: Time series of decadal maxima (i.e. the largest daily anomaly in each decade = 1000 days = 10 100-day winters)

Orange curves: Time series of 99.5th decadal percentile (i.e. the 5th largest daily anomaly in each decade)

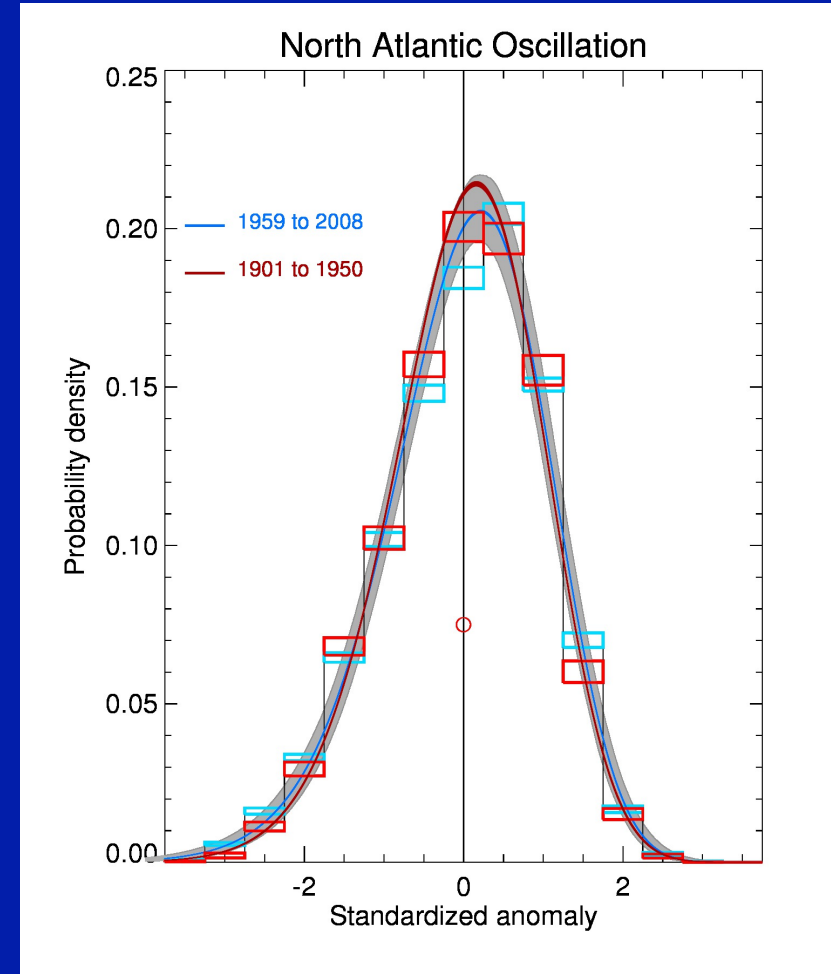
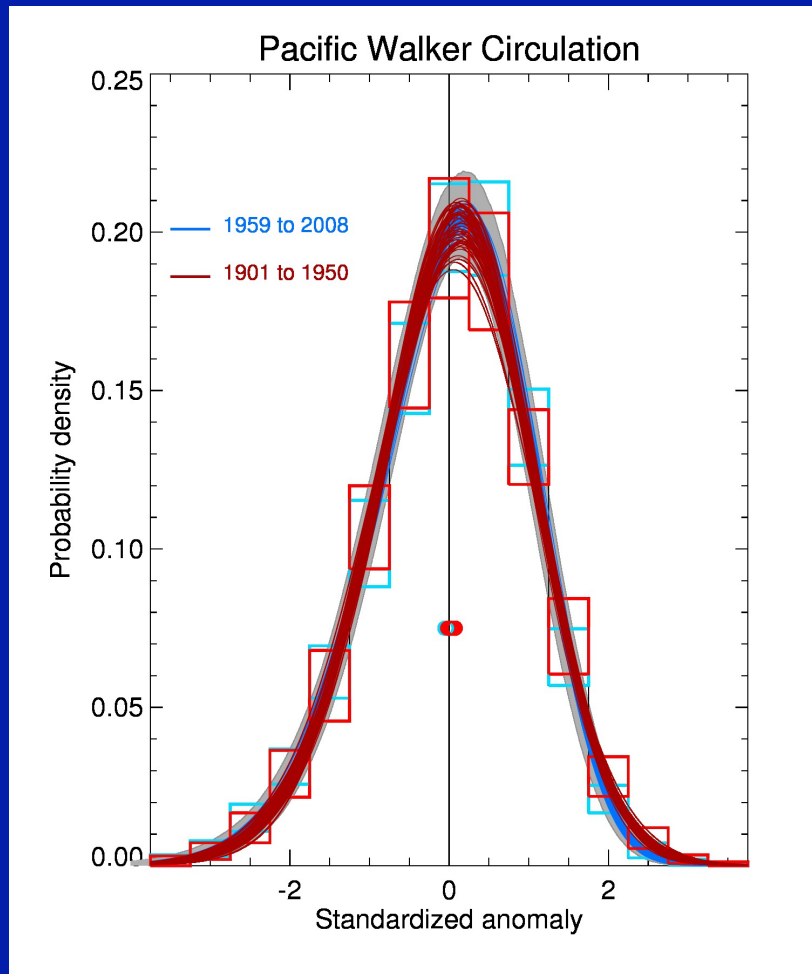
So, how do we assess 20th century changes in the NAO and PWC indices in light of these considerations ?

We estimated histograms from the December-March daily 20CRdata for these climate indices using each of the 56 reanalysis ensemble members, for two 50 year periods: **1901-1950** and **1959-2008**.

We also estimated SGS distributions for each index and ensemble member for **1901-1950** and **1959-2008**.

Using the ensemble-average SGS parameters, we generated a 1 million winter series to estimate the sampling uncertainty in the SGS distributions .

The Result : We find *no significant changes* between the first second halves of the reanalysis period in the PDFs of the PWC and the NAO.



Note again that the **blue** and **red** curves and boxes are a measure of observational uncertainty, whereas the grey swaths are a measure of sampling uncertainty.

Summary

1. **The PDFs of many climate variables are significantly skewed and heavy-tailed.** This fact has enormous implications both for the probabilities of extremes and for estimating changes in those probabilities using climate records or reanalyses of limited length.
2. **We have demonstrated the relevance of “stochastically generated skewed” (SGS) distributions** for describing daily atmospheric variability, that arise from simple extensions of a “red noise” process.
3. **The parameters of these SGS distributions, and of the associated linear Markov model, can be estimated from the first four moments** of the data (mean, variance, skewness, and kurtosis). The model can then be run to generate not only the appropriate SGS distribution, but also to estimate sampling uncertainties through Monte Carlo integrations.
4. **Using this model, we find that the variability of the NAO and the Pacific Walker Circulation has not changed significantly since 1901.**
5. **To accurately represent extreme weather statistics and their changes, it is necessary for climate models to accurately represent the first four moments of daily variability.**