Forced and unforced changes in the shape of summer temperature distributions

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27 April 2016
IMAGe ToY workshop: extremes
A method for diagnosing changes in temperature distributions

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IMAGe ToY workshop: extremes
Fearless collaborators

Andy Rhines
UW

Martin Tingley
IAG

Peter Huybers
Harvard
Recent high-impact summer heat waves in the NH

2003

http://www.history.com/

2010

http://i.telegraph.co.uk/

2012

https://www.blue-point-trading.com/
Many studies on changes in interannual variability...

The Hot Summer of 2010: Redrawing the Temperature Record Map of Europe

David Barriopedro, Erich M. Fischer, Jürg Luterbacher, Ricardo M. Trigo, Ricardo García-Herrera

European summer temperature

Frequency

-2 -1 0 1 2

European summer temperature: A 10-year smoothing is applied. Dotted line shows the frequency with temperature above the 95th percentile of the 1500 running decadal frequency of extreme summers, defined as those based European ([35°N, 70°N],...)
Perception of climate change

James Hansen\textsuperscript{a,1}, Makiko Sato\textsuperscript{a}, and Reto Ruedy\textsuperscript{b}

Many studies on changes in interannual variability

\textsuperscript{1}Visit http://sealevel.colorado.edu/ for more information.

\section*{Figure 1: Temperature Anomaly Distributions}

- Uses $\sigma$ for 1951–1980
- Uses Detrended $\sigma$ for 1981–2010
- Uses $\sigma$ for 1981–2010

- Normal Distribution
- 1951–1961
- 1961–1971
- 1971–1981
- 2001–2011

- Frequency of occurrence (\textit{y}) for $\text{-10} \leq \text{y} \leq 10$

\section*{Figure 2: Temperature Anomaly Distributions for 1981–2010}

- Normal Distribution
- 1951–1961
- 1961–1971
- 1971–1981
- 2001–2011

- Frequency of occurrence (\textit{y}) for $\text{-10} \leq \text{y} \leq 10$

\section*{Figure 3: Temperature Anomaly Distributions for 1981–2010}

- Normal Distribution
- 1951–1961
- 1961–1971
- 1971–1981
- 2001–2011

- Frequency of occurrence (\textit{y}) for $\text{-10} \leq \text{y} \leq 10$

\section*{Figure 4: Temperature Anomaly Distributions for 1981–2010}

- Normal Distribution
- 1951–1961
- 1961–1971
- 1971–1981
- 2001–2011

- Frequency of occurrence (\textit{y}) for $\text{-10} \leq \text{y} \leq 10$

\section*{Figure 5: Temperature Anomaly Distributions for 1981–2010}

- Normal Distribution
- 1951–1961
- 1961–1971
- 1971–1981
- 2001–2011

- Frequency of occurrence (\textit{y}) for $\text{-10} \leq \text{y} \leq 10$
Many studies on changes in **interannual** variability

**LETTER**

No increase in global temperature variability despite changing regional patterns

Chris Huntingford¹, Philip D. Jones²,³, Valerie N. Livina⁴,⁵, Timothy M. Lenton⁶ & Peter M. Cox⁷

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*Abstract*

Many studies on changes in interannual variability of...
…but a lot of information is lost when taking seasonal and/or spatial averages
Three sections of the talk

daily temperature data, non-normality, and quantile regression

changes in the shape of summer temperature distributions

comparison with the large ensemble
Three sections of the talk

daily temperature data, non-normality, and quantile regression

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Data source: global historical climatology network

Fraction of days with data

a) TMAX

Fraction of days with data
Daily temperature is usually non-normal

Boulder, CO

standard dev: 3.6
skewness: -0.66
excess kurtosis: 0.87
Globally, most stations have neg skewed TMAX.
Quantile regression: trends at different percentiles

Ordinary least squares (mean)

Quantile regression (median)

Quantile regression (other percentiles)
QR example: increased variance and skew

Roosevelt, AZ
Heterogeneous trends across space and percentile

nb: analysis for full NH in paper submitted to JGR-Atmospheres
Three sections of the talk

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Four basis functions explain 98.8% variance

b) PCA on T

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A graph showing the percentiles of the value of basis functions. The x-axis represents the percentile, ranging from 0 to 100. The y-axis shows the value of the basis functions. The graph includes lines for B0, B1, B2, and B3, each represented by different colors.
Results from PCA ~ trends from changing moments

a) Moments

Percentile

Value of basis function

Legendre
‘Quick and not-so-dirty’ PCA approx: Legendre polynomials

Gibson et al (1992), Physica D: Nonlinear Phenomena
Most of variance explained by mean shift

87%

d) Legendre
Mixed spatial pattern of sign of variance changes

- a) shift
- b) var
- c) skew
- d) kurt
Skewness locally, not globally, important

- a) shift
- b) var
- c) skew

- 87%
- 73%
- 13%

- a) shift
- b) var
- c) skew

- Skewness locally, not globally, important

Kurtosis locally, not globally, important.

4% locally significant
87%
72%
13%
Shape changes have a large impact on tails

- **Western US Tx**
  - Mean
  - Variance

- **Eastern Europe Tx**
  - Mean
  - Variance

- **Northeastern US Tn**
  - Skew
Three sections of the talk

daily temperature data, non-normality, and quantile regression

changes in the shape of summer temperature distributions

comparison with the large ensemble
Can models help us understand which of these changes are ‘forced’?
Comparison: observed and modeled shift
Comparison: observed and modeled shift

obs

ensemble mean
Comparison: observed and modeled shift

- shift
- var
- skew
- kurt

obs

ensemble mean

ensemble σ
Comparison: observed and modeled shift

for ensemble members, shift behavior explained between 56-84% of the variance in quantile trends, compared to 87% in the observations.
Comparison: observed and modeled shift

<table>
<thead>
<tr>
<th>obs</th>
<th>ensemble member</th>
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</table>
Comparison: observed and modeled variance change

obs
Comparison: observed and modeled variance change

obs

ensemble mean
Comparison: observed and modeled variance change

obs

ensemble mean

ensemble $\sigma$
Comparison: observed and modeled variance change

- **obs**
  - Map showing observed data with various symbols indicating different values.

- **ensemble member**
  - Map showing modeled ensemble member variance with color coding.

- **ensemble mean**
  - Map showing ensemble mean variance with color coding.

- **ensemble σ**
  - Map showing ensemble standard deviation variance with color coding.
Regions of greatest uncertainty are most variable

CESM LE
But model variability displaced from observed
Can models help us understand which of these changes are ‘forced’?

Probably not yet.
quantile regression can be used to quantify changes in the shape of temperature distributions.

The percentile trends can be summarized using Legendre polynomials, which can be interpreted (loosely) as changes in the first four statistical moments.

A large majority of the observed changes in summer temperature distributions can be explained by a positive shift. There is not a hemispherically-consistent signal for changes in shape.

The large ensemble shows a large range of behavior, some of which is related to its climatological variability, which has biases.

These methods are relatively general, and can be used in future studies for improved inter-comparability.
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despite these methods are relatively general, and can be used in future studies for improved inter-comparability