Detection and attribution

Approaches for climate and weather extremes

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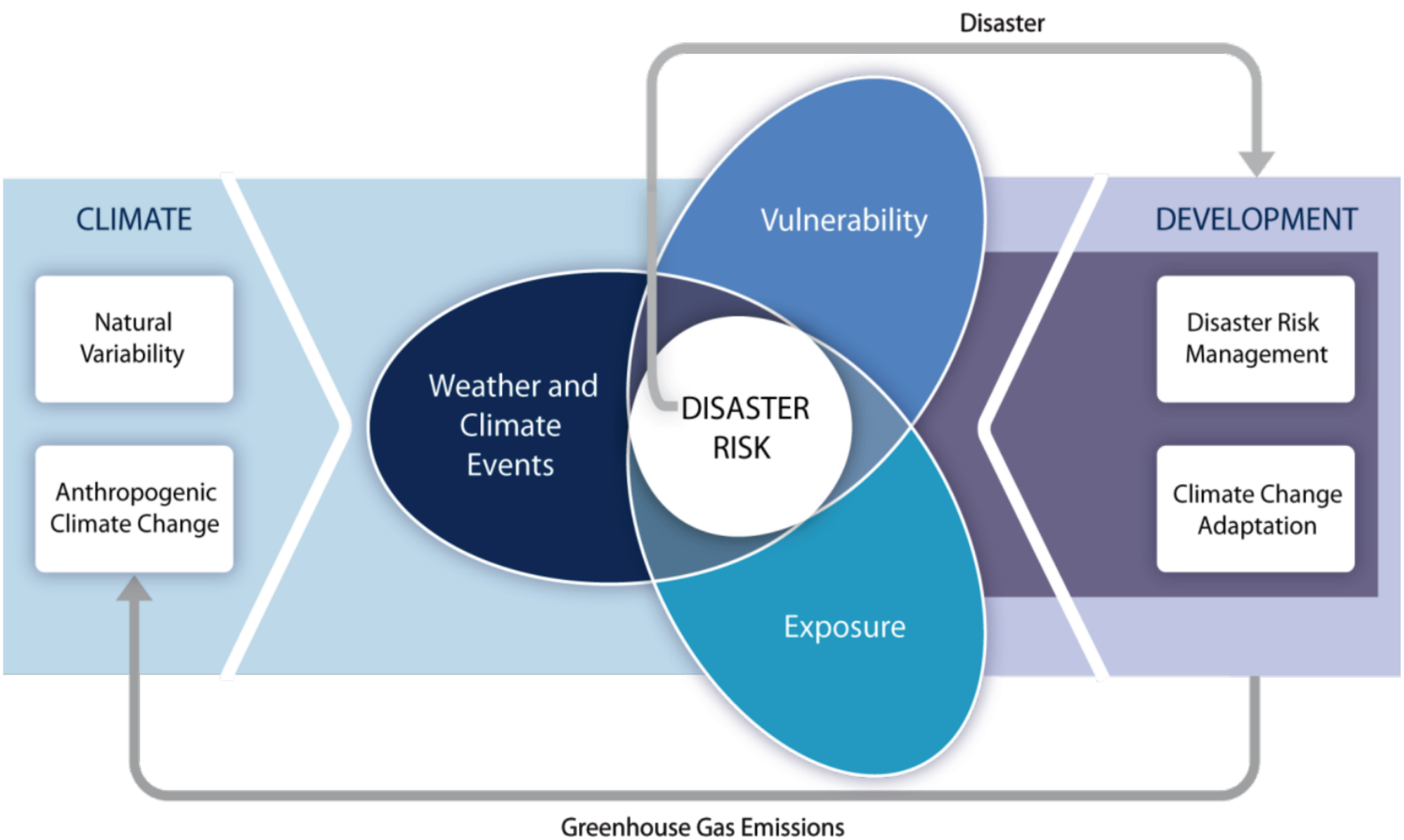
Introduction

Extremes in climate science …

- Very wide range of space and time scales
- Range from very small scale short duration (tornadoes) to large scale long duration (eg drought)

- Language used in climate science is not very precise
  - High impact (but not really extreme)
  - Exceedance over a relatively low threshold
    - e.g., 90^{th} percentile of daily precipitation amounts
  - Rare events (long return period)
  - Unprecedented events (in the available record)

Increasing vulnerability, exposure, or severity and frequency of climate events increases disaster risk

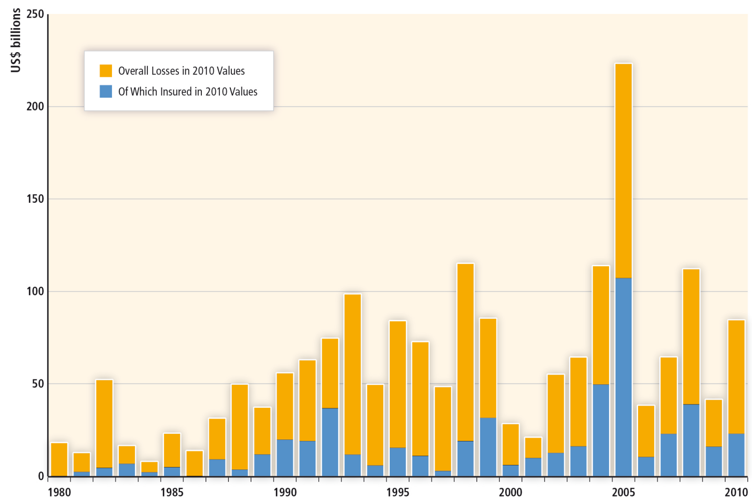


*Disaster risk management and climate change adaptation can influence the degree to which **extreme events translate into impacts** and **disasters***

IPCC SREX, Fig SPM.1

ipcc
INTERGOVERNMENTAL PANEL ON climate change

Economic losses from climate-related disasters have increased, with large spatial and interannual variations

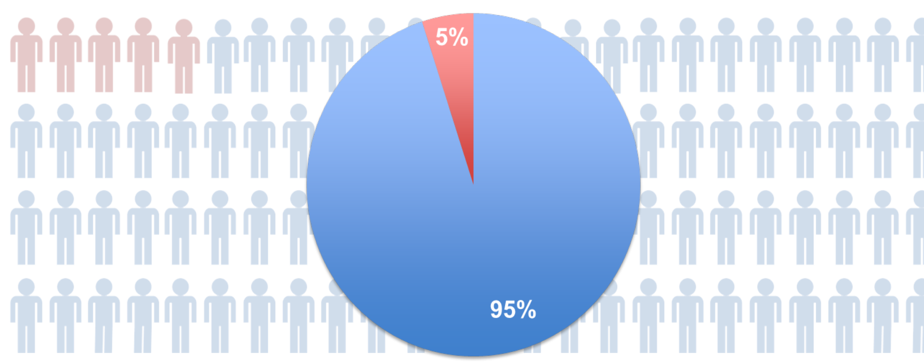


Data from Munich Re, 2011

Increasing exposure of people and assets has been the major cause of changes in disaster losses

Economic disaster losses are higher in developed countries

Fatalities are higher in developing countries



From 1970-2008, over **95%** of natural-disaster-related deaths occurred in developing countries

Effective risk management and adaptation are tailored to local and regional needs and circumstances

- changes in climate extremes vary across regions
- each region has unique vulnerabilities and exposure to hazards
- effective risk management and adaptation address the factors contributing to exposure and vulnerability

INTERGOVERNMENTAL PANEL ON climate change

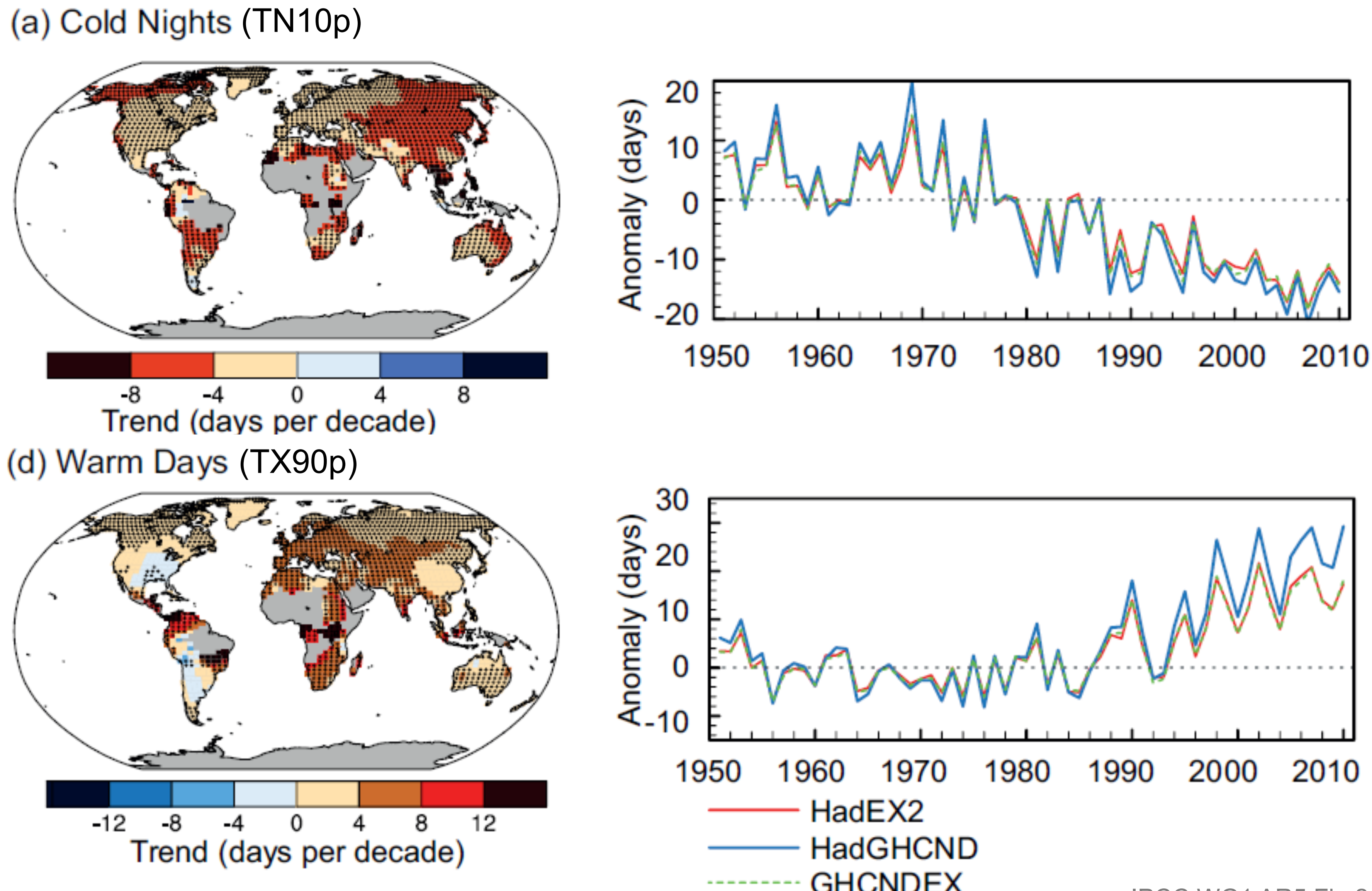
Observed changes

Summary of Observed Changes

- Changes in many extreme weather and climate events have been observed since about 1950
- Cold days and nights: Frequency has ***very likely*** decreased globally
- Heat waves: Frequency has ***likely*** increased in some regions.
- Heavy precipitation: Frequency has ***likely*** increased in more land regions than where it has decreased.
- Intensity of heavy precipitation: Confidence varies regionally, ***very likely*** has intensified in North America.

IPCC WG1 AR5 Table SPM-1

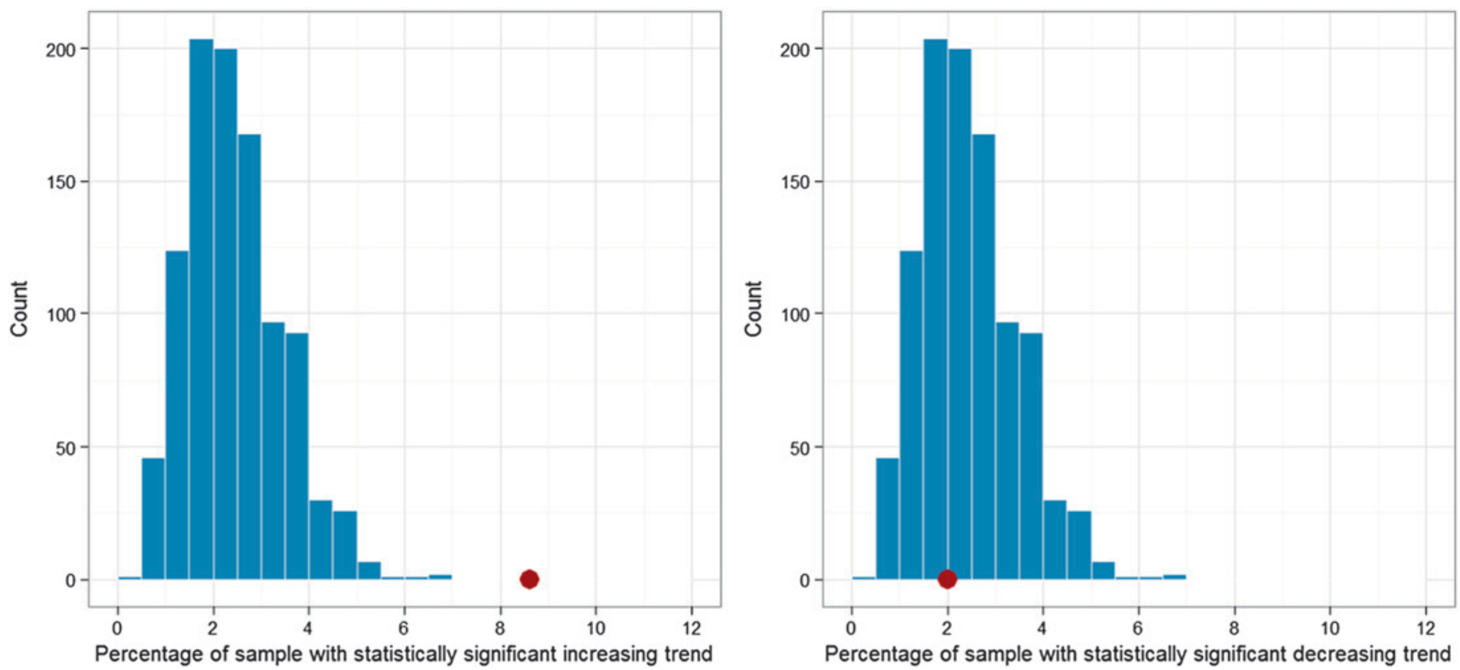
Temperature extremes – 1951-2010



IPCC WG1 AR5 Fig 2.32

Annual maximum 1-day precipitation trends, 1900-2009

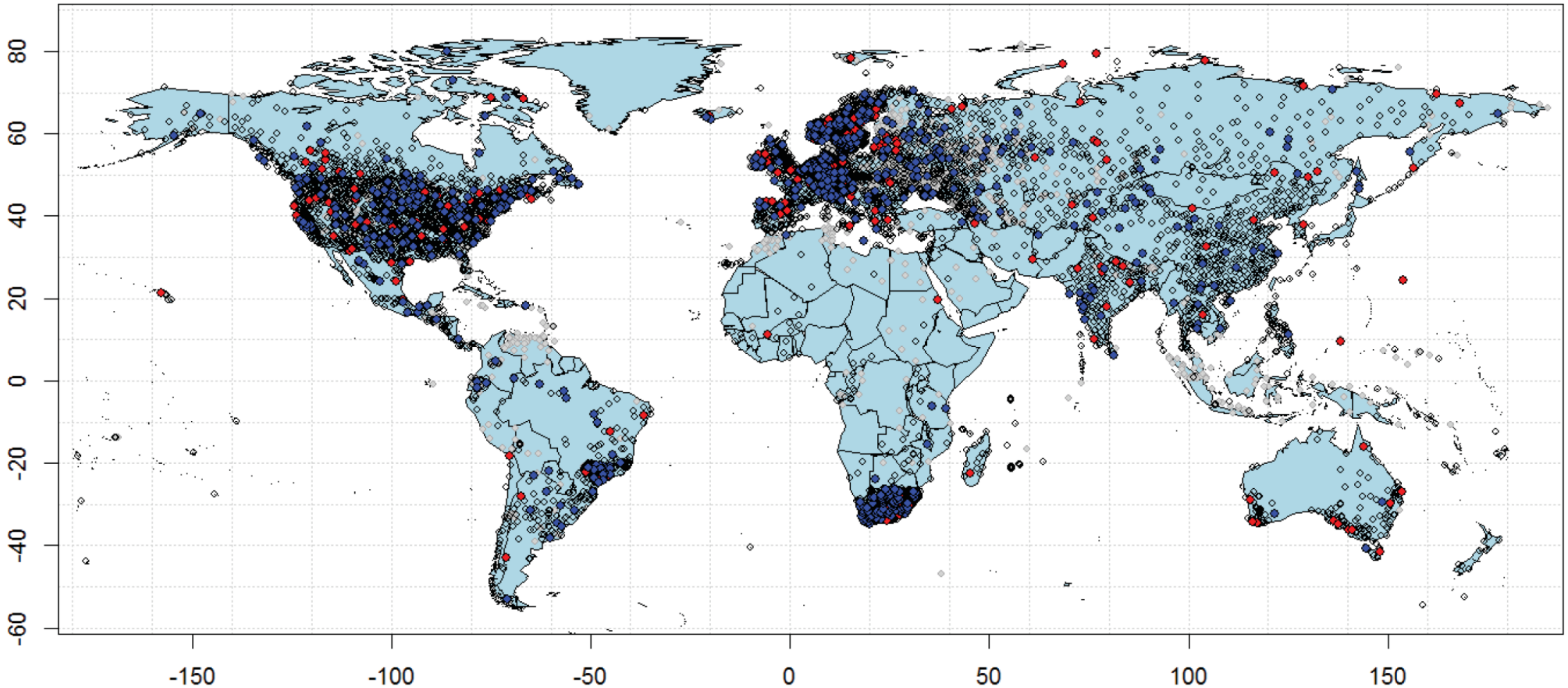
Percentage of significant Mann-Kendall trend tests based on 8376 GHCN-D stations with 30-years or more data (median length 53 years)



Westra et al 2013, Fig. 3

- Tests conducted at the 5% level (two sided)
- 8.6% showed significant increasing trends (red dot, left)
- 2.0% showed significant decreasing trends (red dot, right)
- Increasing trends substantially more frequent than expected by random chance (blue bootstrap distributions for rejection rate).

Assessment of association between annual maximum 1-day precipitation and global mean temperature



- **8376 stations with > 30 yrs data, median length 53 yrs**
- **Significant positive (10.0% of stations, expect 2.5%)**
- **Significant negative (2.2% of stations, expect 2.5%)**
- **Rejection rate similar everywhere**

Westra et al (2013, Fig. 5)

AR5 attribution assessments for the 2nd half of the 20th century

- Daily temperature extremes: ***very likely*** that anthropogenic forcing has contributed to changes in frequency and intensity
- Heavy precipitation: ***medium confidence*** that anthropogenic forcing has contributed to intensification in global land regions
- Drought and tropical cyclones: ***low confidence*** in attributing changes
- Some of the supporting evidence, and underlying methods, will be presented in the remainder of this talk

IPCC WG1 AR5 Table SPM-1

Rest of this lecture: approaches for D&A on extremes

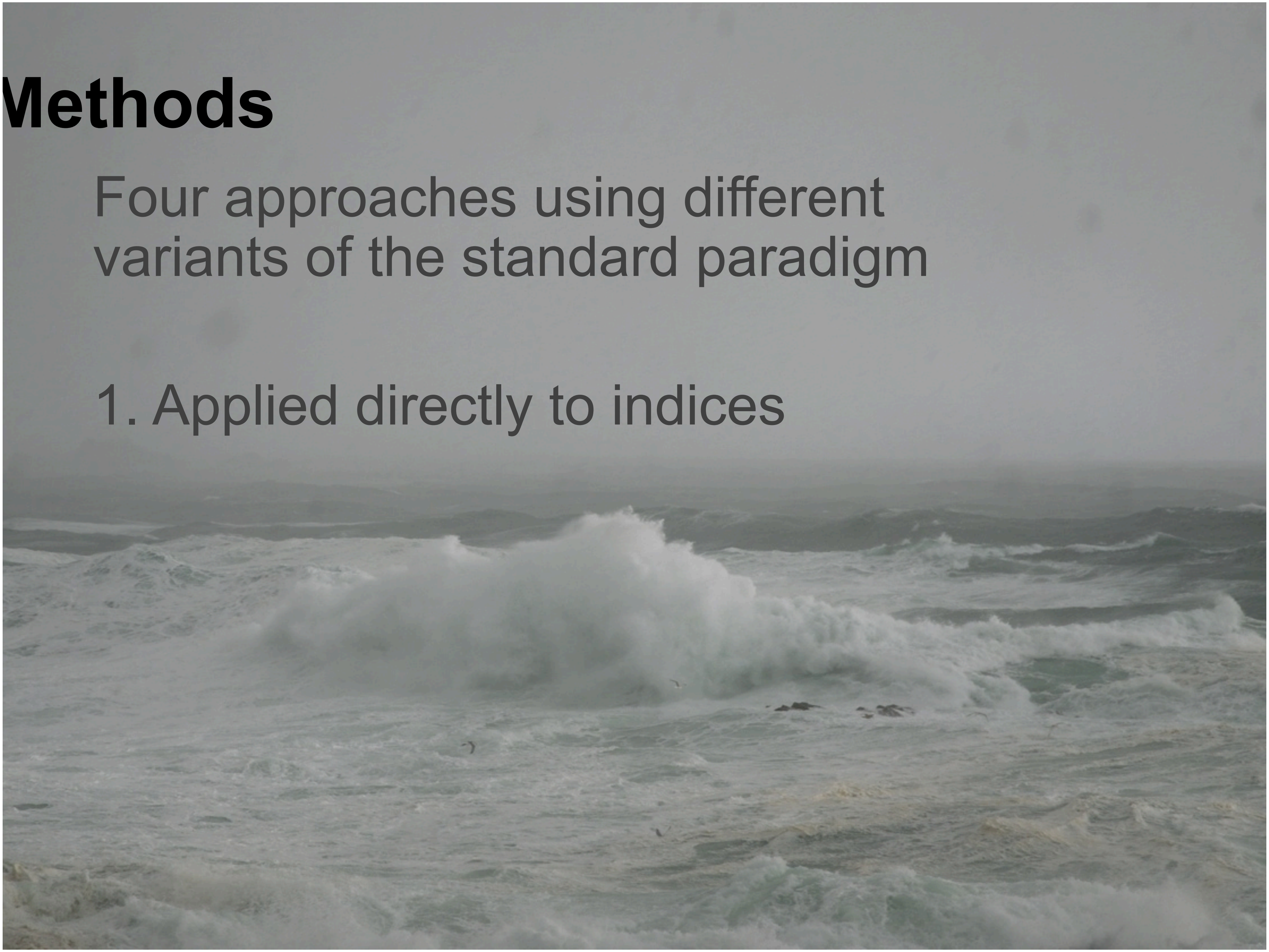
1. Indices + standard paradigm
   - Hegerl et al 2004, J Climate, Christidis et al 2005, GRL, Wen et al., 2013, GRL
2. Transformation of variable + standard paradigm
   - Fit GEV distribution locally
   - Apply probability integral transform

   Min et al 2011, Nature, Zhang et al., 2013, GRL
3. Standard paradigm applied to EV distribution parameters
   - Brown et al 2008, JGR, Christidis et al 2011, J Climate
4. Cast problem directly within framework of extreme value theory
   - Zwiers et al, 2011, J. Climate

Methods

Four approaches using different variants of the standard paradigm

1. Applied directly to indices



1. D&A applied directly to indices

- Extreme values or indices averaged over space and time such that Gaussian assumption is valid due to central limit theorem
- Originally proposed by Hegerl et al, 2004
  - Model-model assessment of potential detectability based on temperature and precipitation
  - Response in indices of temperature extremes seen to be different from that in means, but S/N ratio nearly as large
  - Forced changes in moderately extreme precipitation may be more detectable than change in mean precipitation
- First application to annual temperature extremes by Christidis et al, 2005

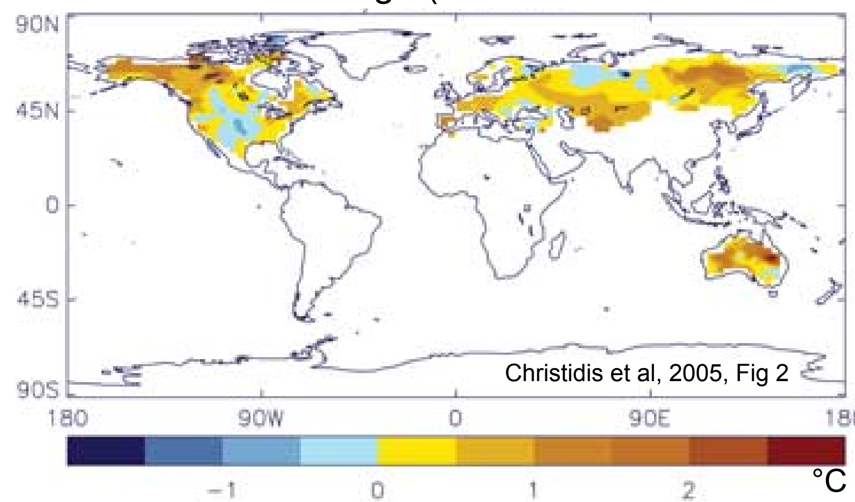
Possible figure??

- Some subsequent studies include
    - Christidis et al, 2010
        - Temperature of the warmest night of the year (1950-1997)
    - Morak et al, 2011
        - Frequency of warm nights (1951-1999)
    - Morak et al, 2013
        - Frequency of warm and cold days and nights (1951-2003)
    - Wen et al., 2013
        - Annual temperature extremes over China
- There is also a literature on extreme seasonal temperature that uses the standard paradigm
    - Jones et al, 2008
        - Frequency of warm NH summers (1900-2006) – 2 step
    - Stott et al, 2011
        - Frequency of extremely warm summer seasons (1909-2008) – 1 step
    - Christidis et al, 2014 (submitted)
        - Odds of very warm annual and seasonal mean temperatures (1950-2012)

D&A applied directly to indices

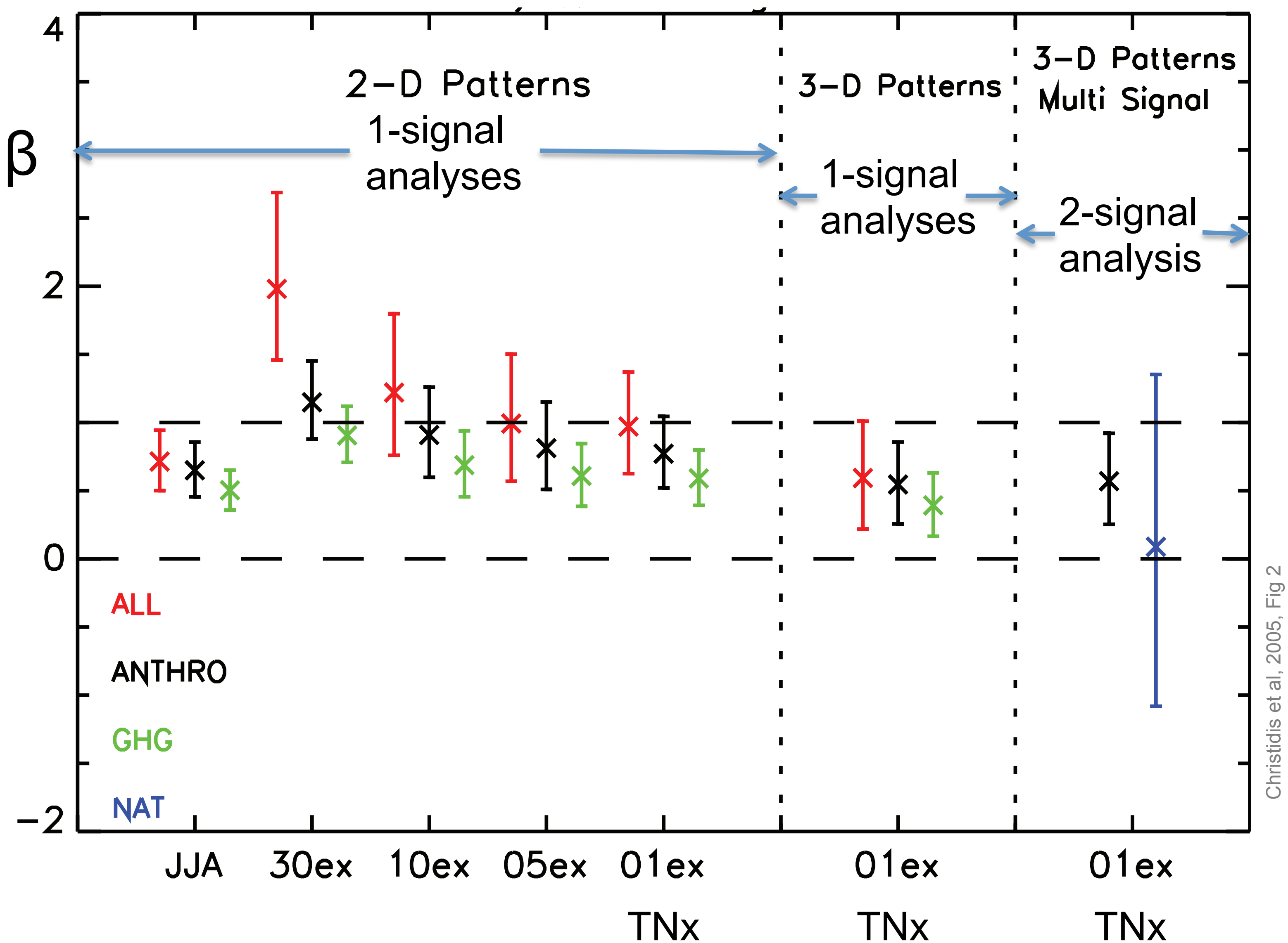
- Christidis et al, 2005
- Consider N warmest days, warmest nights, coldest days and coldest nights of the year (N = 30, 10, 5 and 1)
- Observations from Caesar et al, 2005
- Signals and control runs from HadCM3
- 2-D spatial patterns and 3-D space-time patterns considered
- TLS, truncate at EOF 20

Observed TNx change (1980-1999 vs 1950-1969)

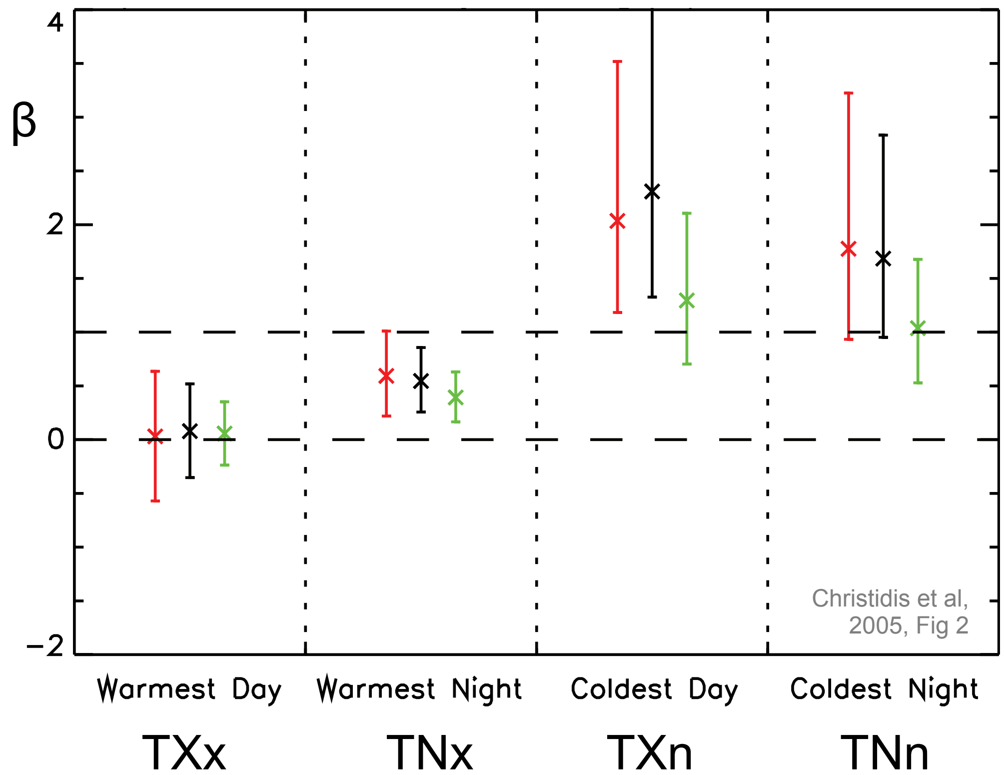


$$\mathbf{Y} = \mathbf{Y}^{Forced} + \boldsymbol{\varepsilon}$$
$$\widetilde{\mathbf{X}} = \mathbf{X}^{Forced} + \boldsymbol{\Delta}$$
$$\mathbf{Y}^{Forced} = \mathbf{X}^{Forced}\boldsymbol{\beta}$$

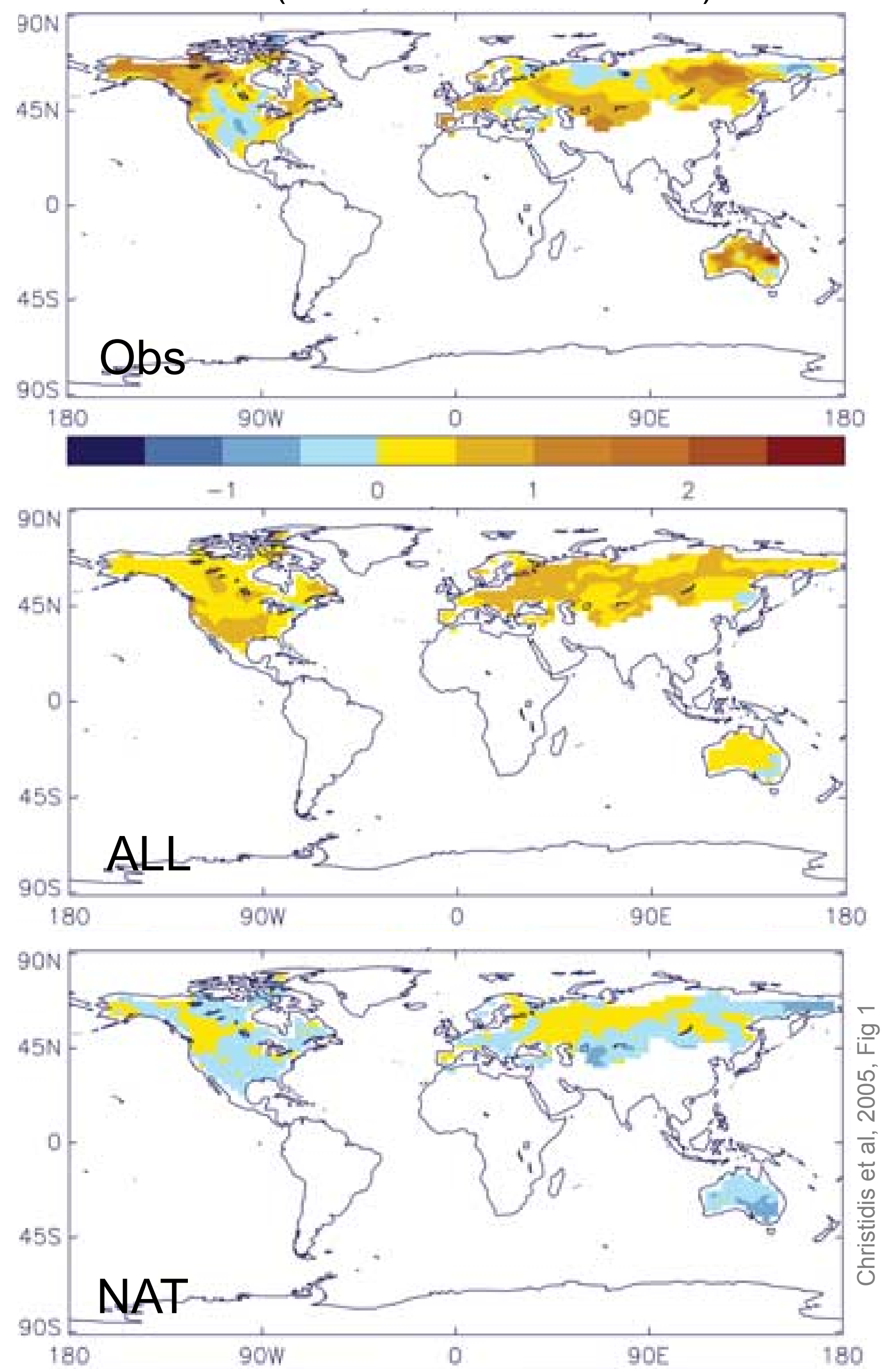
Scaling factor on model simulated change in temp. of warm nights, 1950-1999



Scaling factor on HadCM3 **ALL**, **ANT**, and **GHG** responses fitted to observed temperature extremes (1-signal analyses, 1950-1999)



TNx (1980-1999 vs 1950-1969)

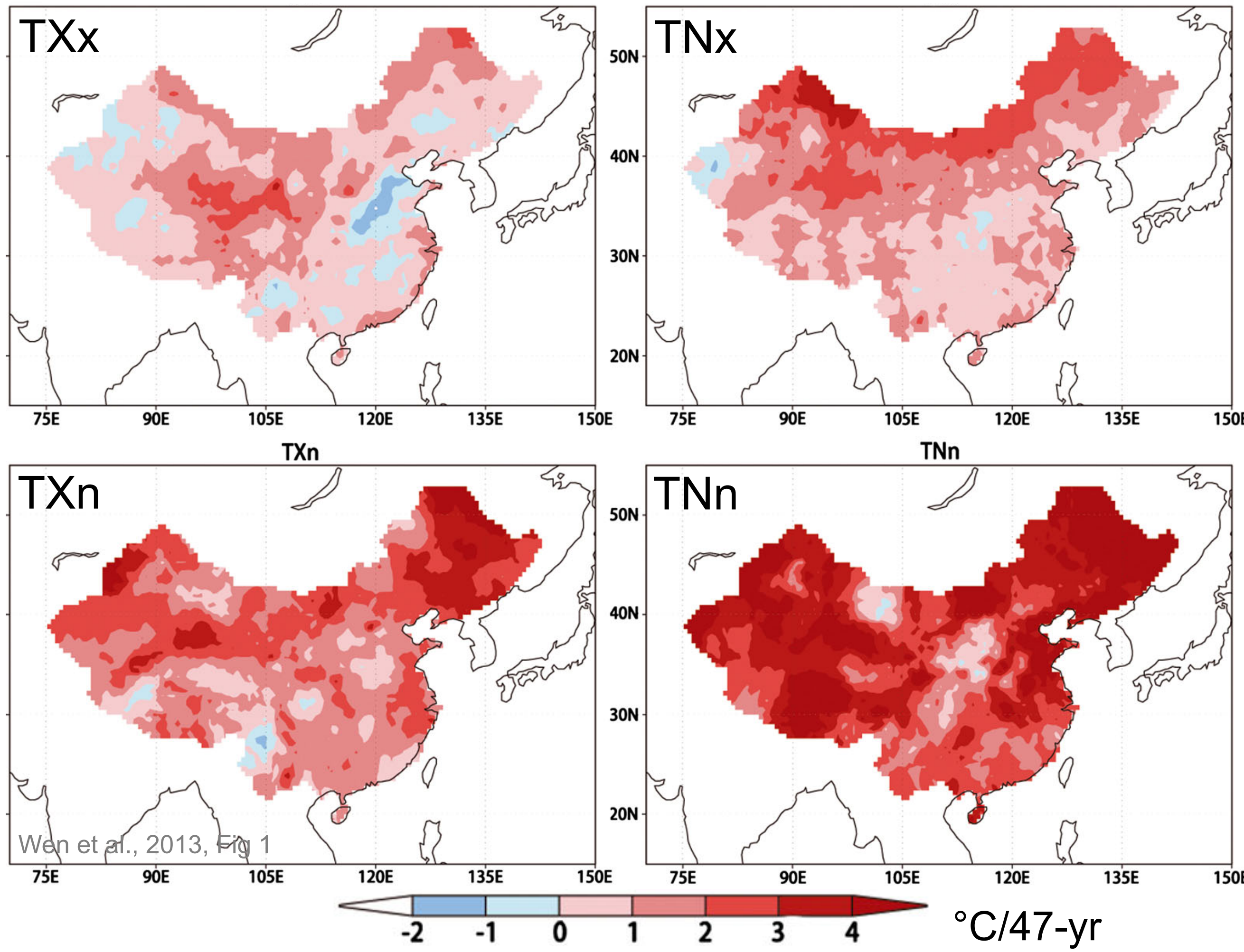


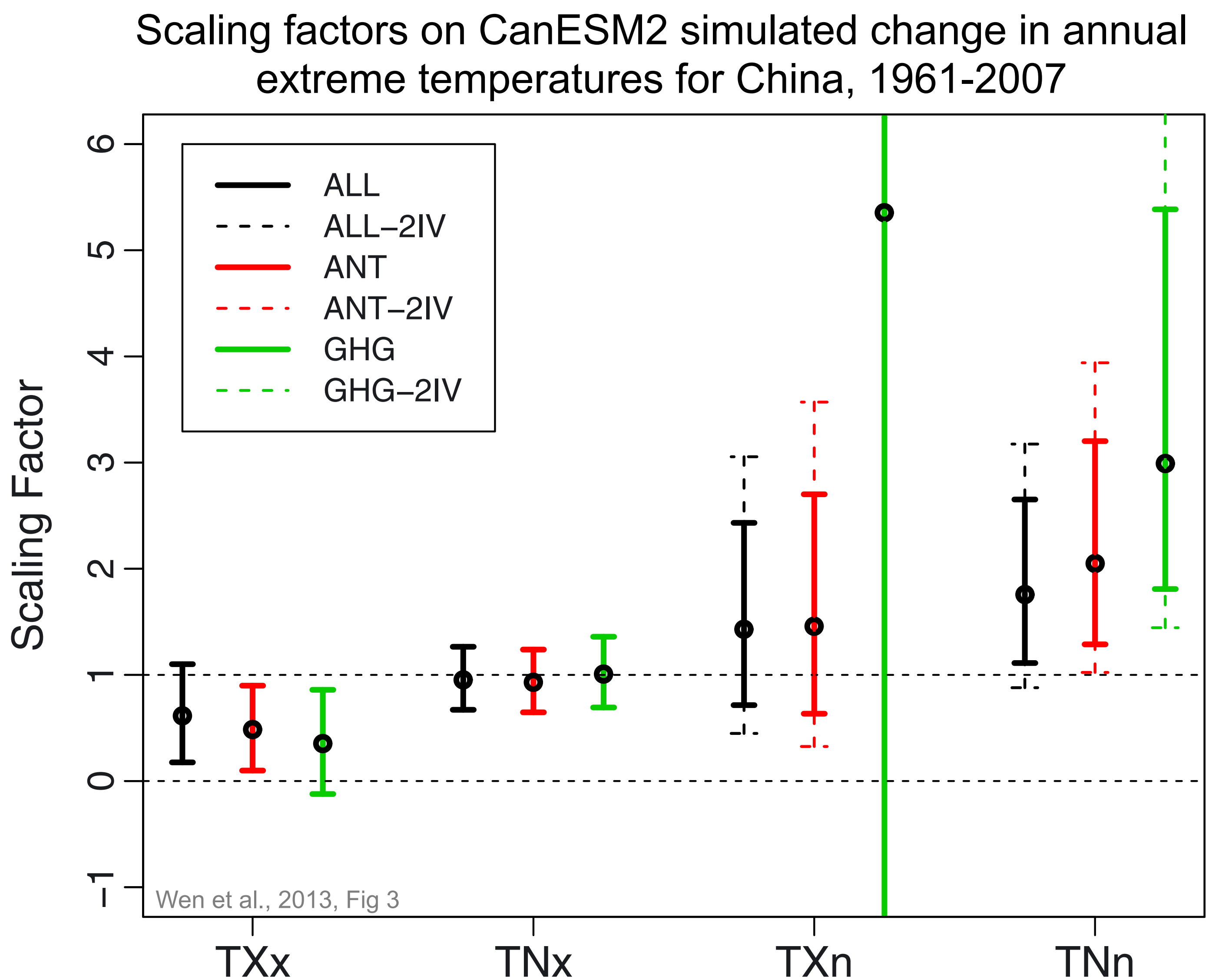
Note that HadCM3 simulated change in TXx not detected

D&A applied directly to indices

- Wen et al, 2013
- China, 1961-2007, annual extremes (TNn, TNx, TXn, TXx)
- Observations from Wu and Gao (2012), based on 2416 stations
- Signals and control runs from CanESM2
- Space-time analysis (decadal averages, 7-subregions)
- TLS, truncate at EOF 15 or 20 depending upon index used

Observed 47-year trend in annual temperature extremes

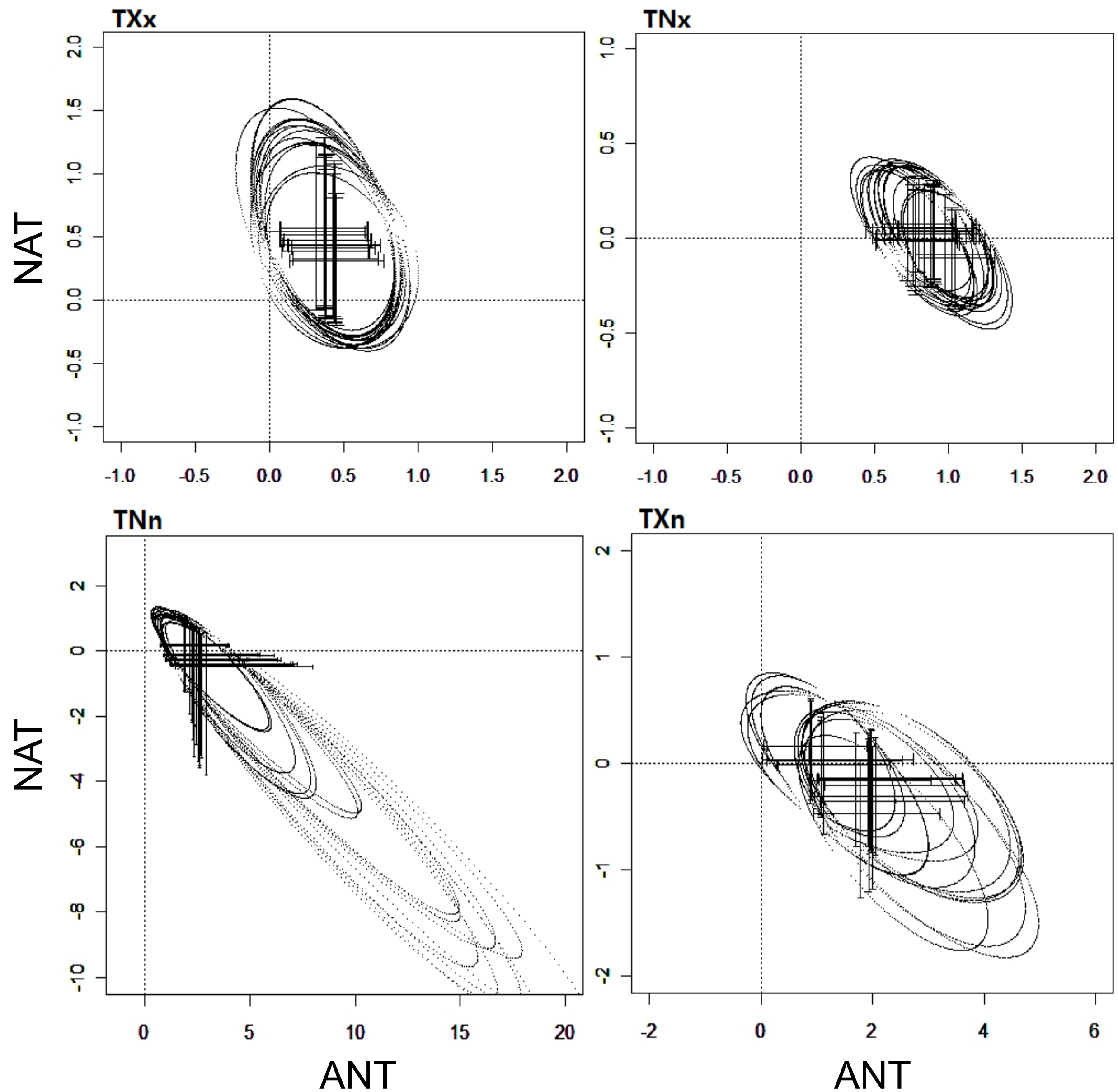



Scaling factors on CanESM2 simulated change in annual extreme temperatures for China, 1961-2007
Scaling Factor
ALL
ALL–2IV
ANT
ANT–2IV
GHG
GHG–2IV
-1
0
1
2
3
4
5
6
TXx
TNx
TXn
TNn
Wen et al., 2013, Fig 3

Scaling factors on CanESM2 simulated change in annual extreme temperatures for China, 1961-2007

90% confidence regions and marginal confidence intervals based on a 2-signal analysis

Sensitivity to EOF truncation, using 15-30 EOFs



Wen et al., 2013, Fig S5

D&A applied directly to indices

- Advantages
  - Simple
  - Tries to optimize signal to noise ratio by accounting for spatial covariance structure of extremes indices
- But
  - Residuals might still have a skewed distribution
  - Potential losses in efficiency of estimators, bias, etc.

Methods

2. Standard paradigm applied to transformed extremes

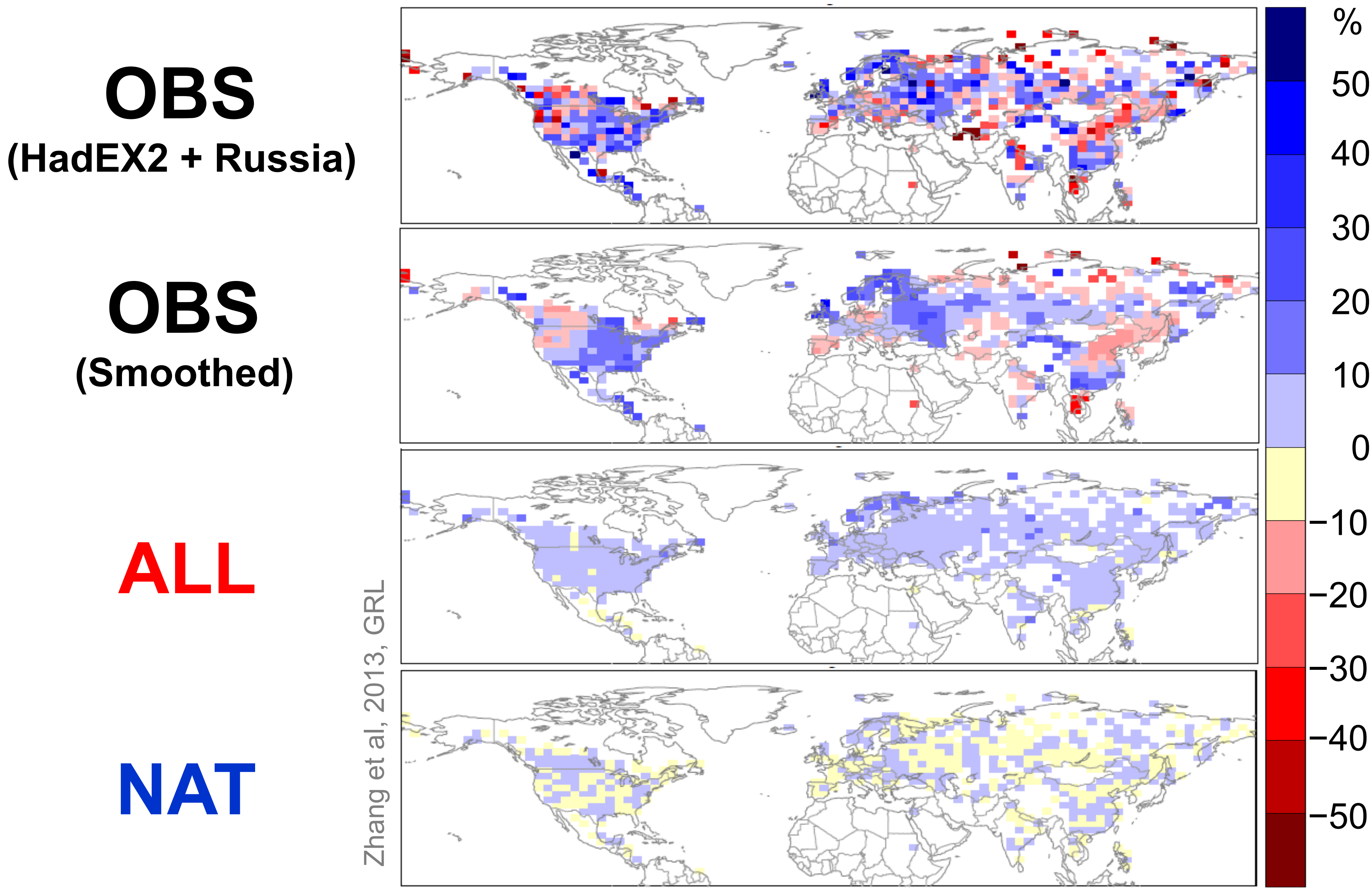
2. D&A on transformed extremes

- Transform to a probability index
  - Fit an extreme value distribution locally
  - Apply probability integral transform
  - Transformed values have approximately the uniform distribution
  - Time and area averaging produces Gaussian values
  - Could use simpler transforms
- Apply standard D&A paradigm
- Examples include
  - Min et al 2011, 2013, Zhang et al, 2013.

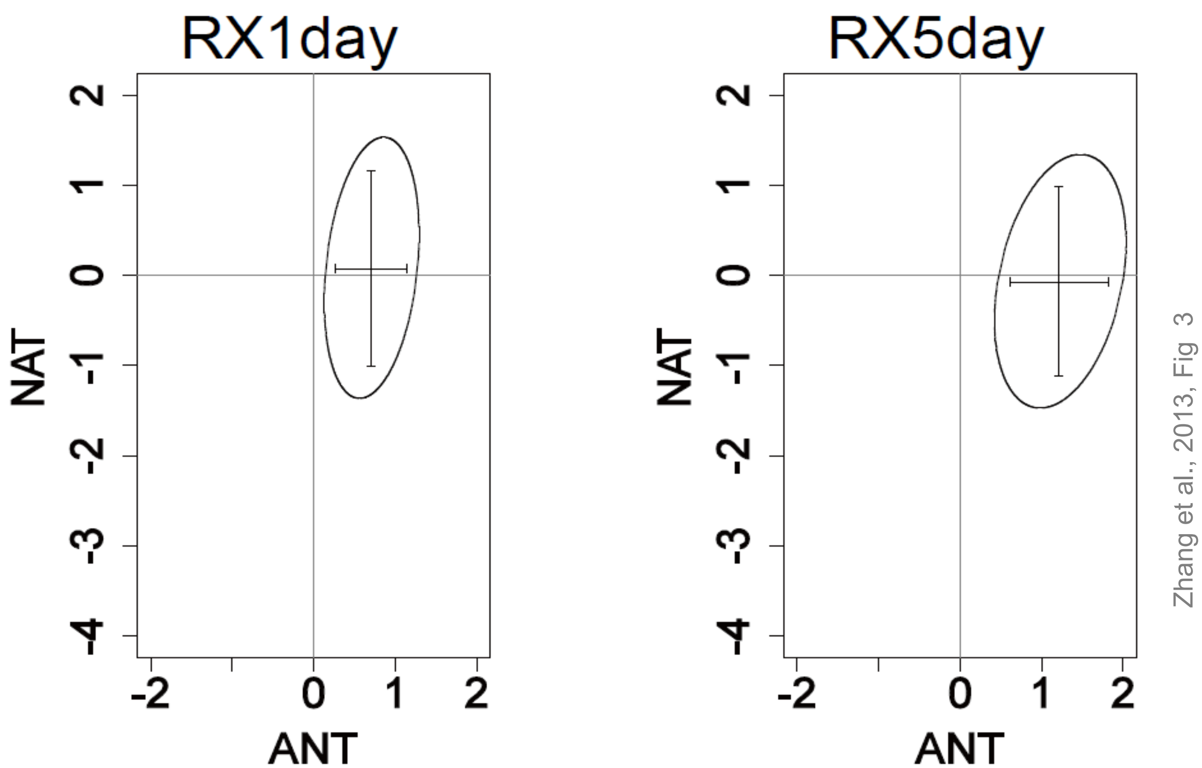
Zhang et al, 2013

- RX1day, RX5day, 1951-2005
- HadEX2 (Donat et al, 2012) augmented with Russian station data, transformed
- Multi-model signals and control runs (54 ALL runs, 14 GCMs; 34 NAT runs, 9 GCMs; >15K years control, 31 GCMs)
- Time evolution only (5-year means, domain averaged) and space-time evolution (5-year means, regionally averaged, 2 or 3 regions)
- TLS, no EOF truncation (except when considering 1-year means); total of 460 chunks to estimate internal variability

PI Trends (RX1D; 1951-2005)



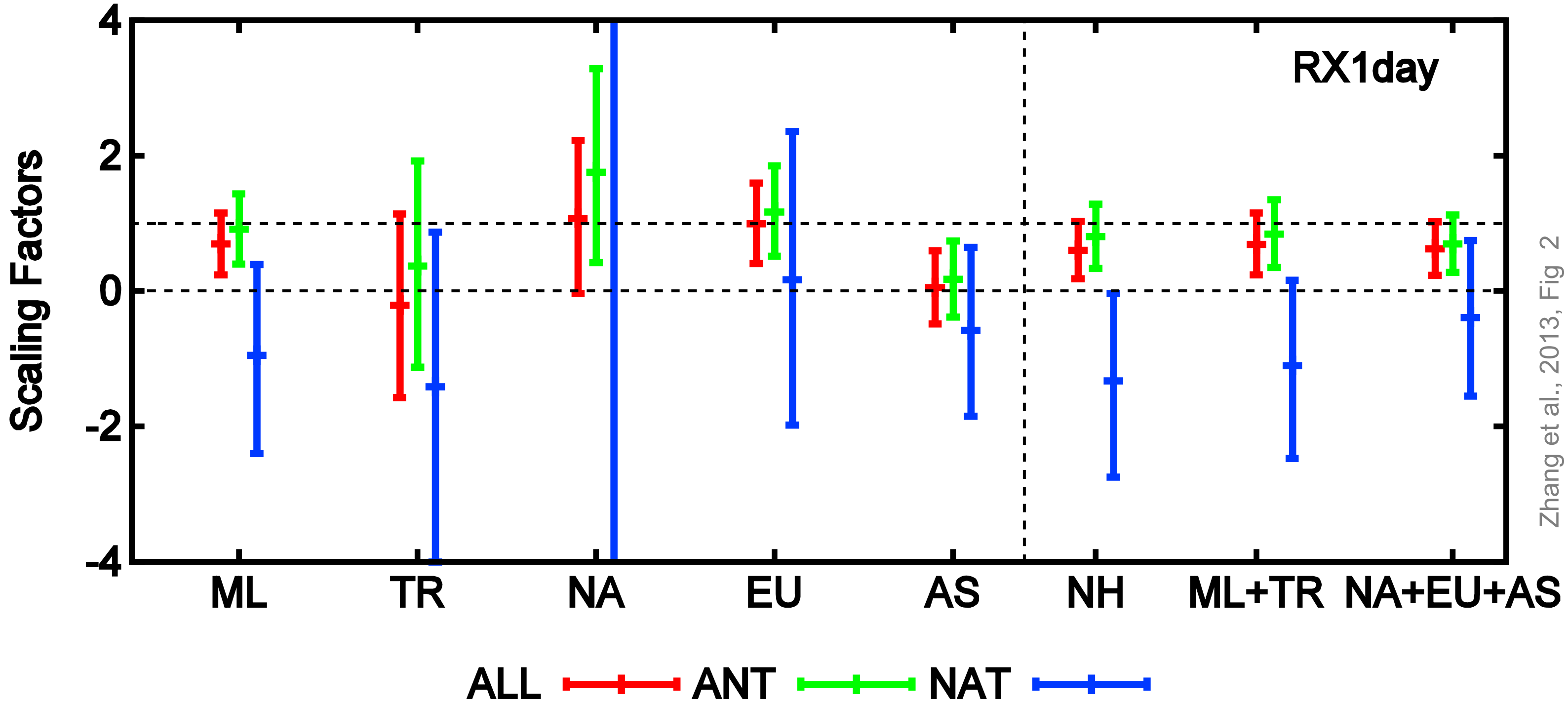
Detection results – 1951-2005



- Space-time (3 regions, 5 year means → 33-dim problem)
- 54 ALL runs (14 models), 34 NAT runs (9 models)
- No dimension reduction (>15000 years control, 31 models)
- 460 “chunks” for internal variability

Detection results – 1951-2005

5-95% uncertainty intervals on scaling factors
1-signal analyses, 5-year regional means with 1, 2 or 3 regions



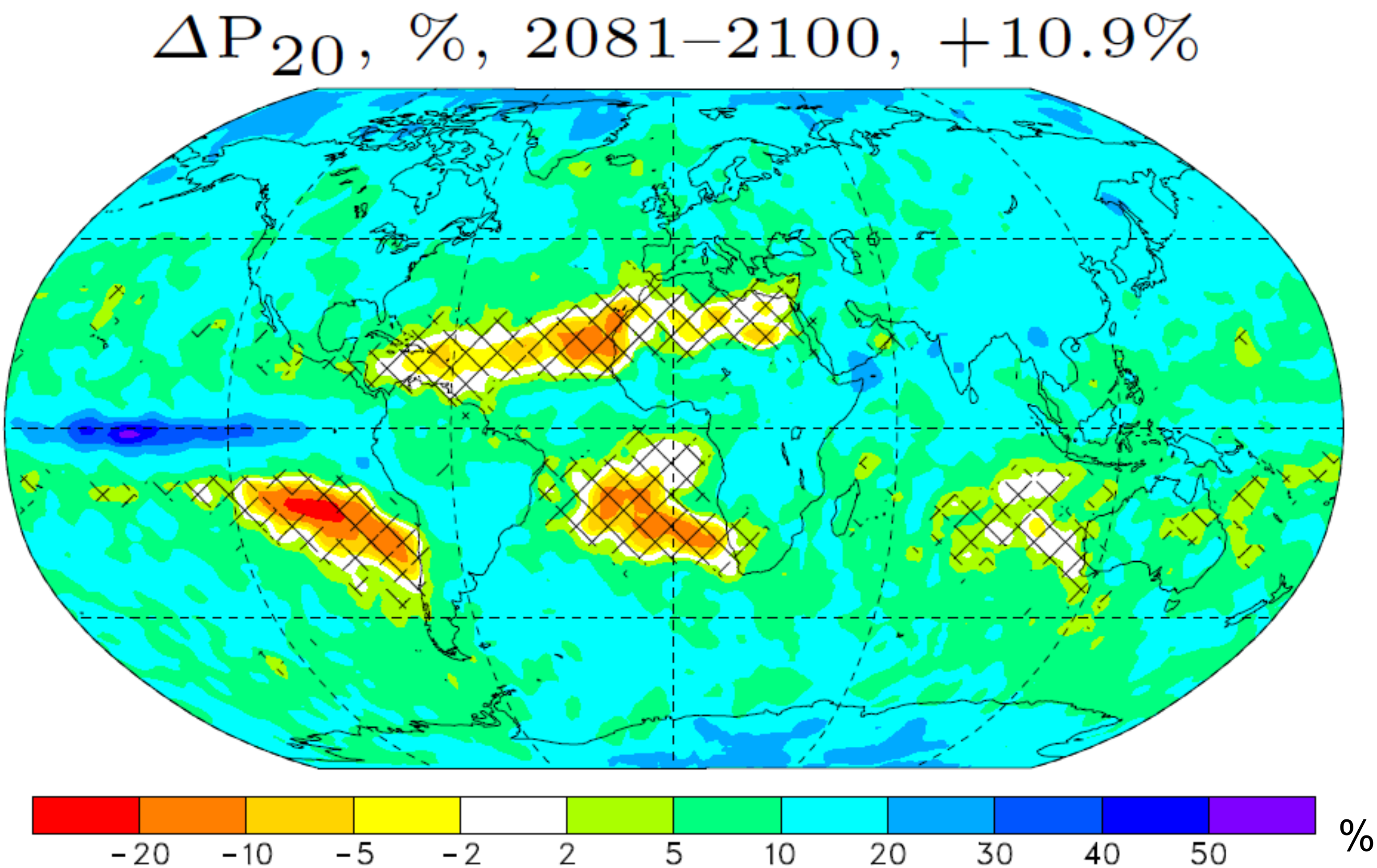
ML – mid-latitudes, TR – tropics, NA – North America, EU – Europe, AS - Asia

Implications

- PI for RX1day increased 4.0 [1.4 – 6.8] % over 1951-2005 due to ANT forcing
- Implies
  - RX1day intensification of 3.3 [1.1 – 5.8] %
  - Sensitivity of 5.2 [1.3 – 9.3] %/K
  - Waiting time for early 1950's 20-year event reduced to ~15 years
  - Fraction of Attributable Risk ≈ 25%
- For extremes
  - Primary response appears to be thermodynamic
  - Station data do not allow us to see a dynamic response
  - Offsetting effects of GHGs and aerosols may be too subtle to detect with current methods

CMIP5 RCP4.5 precipitation projections

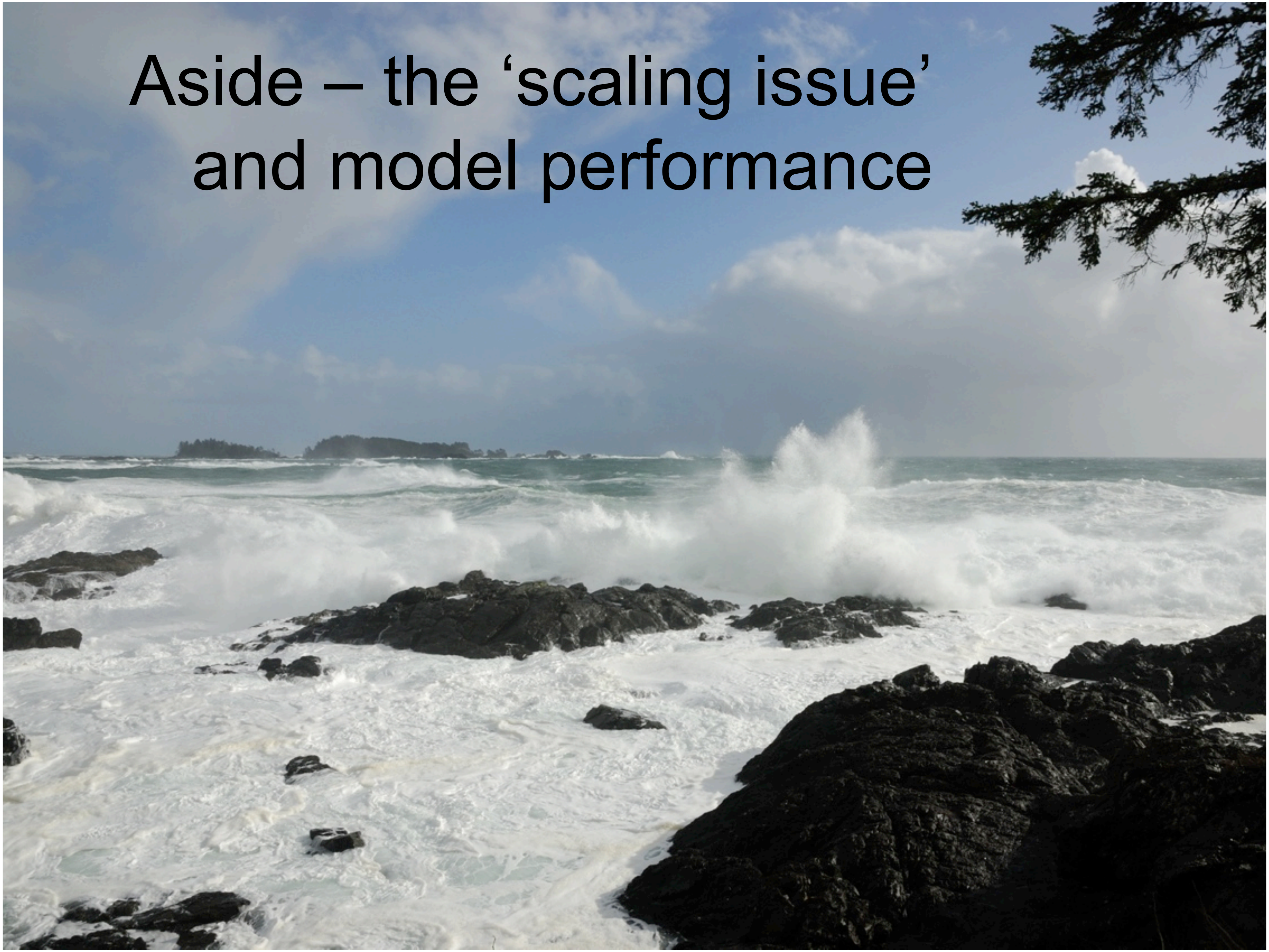
Change in 20-yr extremes relative to 1986-2005



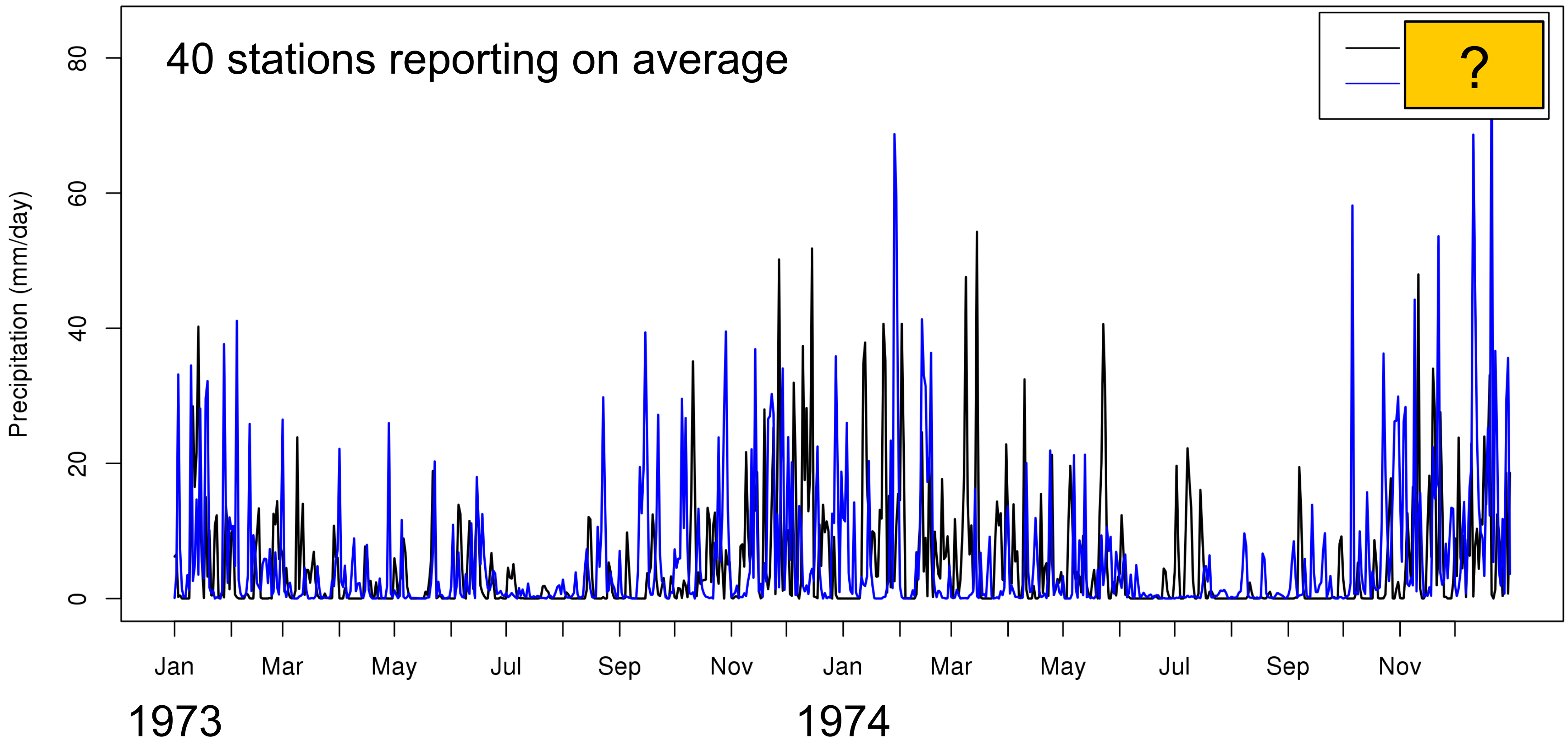
Kharin et al (2013, Fig. 4)

D&A on transformed extremes

- Advantages
  - Partial solution to scaling issue for variables like precipitation
    - Allow extreme events at difference locations to be more comparable
  - Can optimize signal to noise ratio by accounting for spatial covariance structure of extremes
  - Can use model output to estimate uncertainties
- Disadvantages
  - Results can be difficult to interpret physically

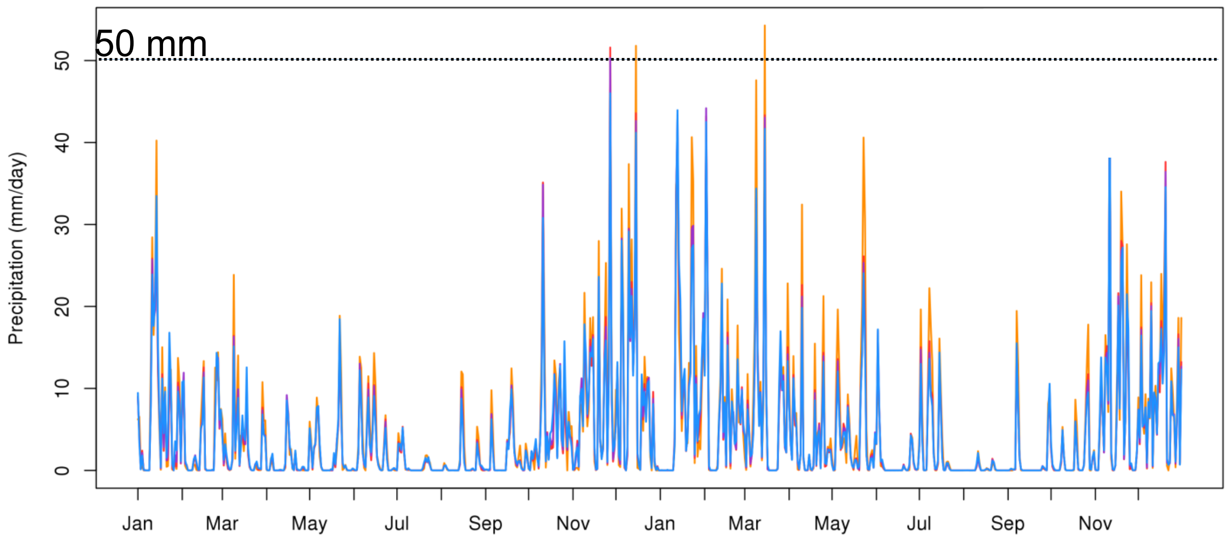

Aside – the ‘scaling issue’
and model performance

Mean daily precipitation in the MIROC4h
grid box centered on 49.1N, 123.2W (Vancouver)

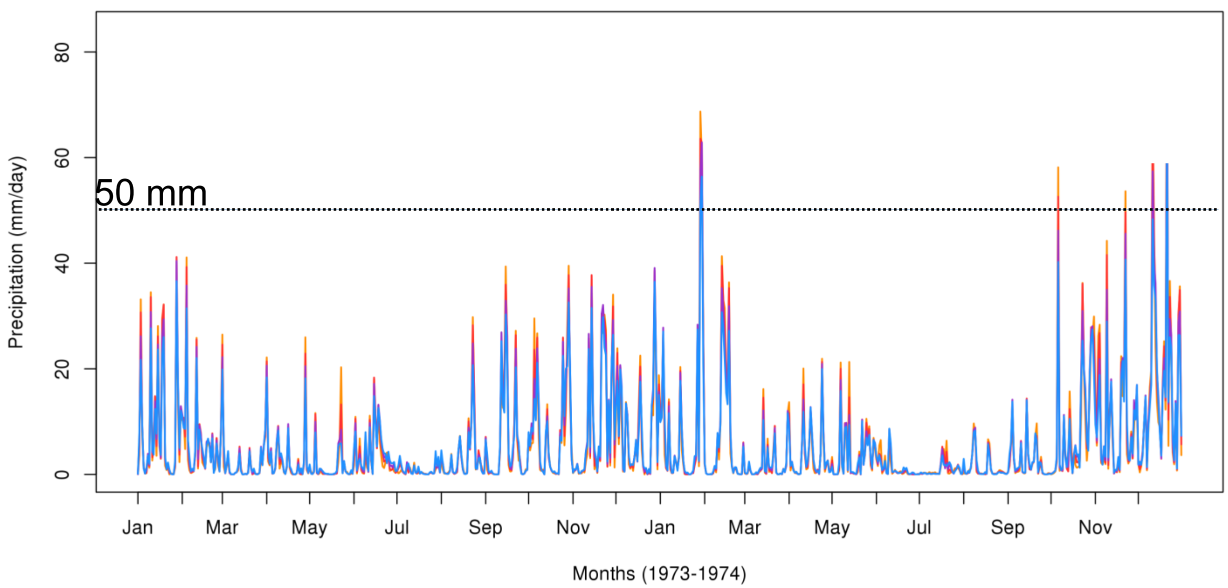


Courtesy B. Veerman, PCIC

Observed



MIROC4h



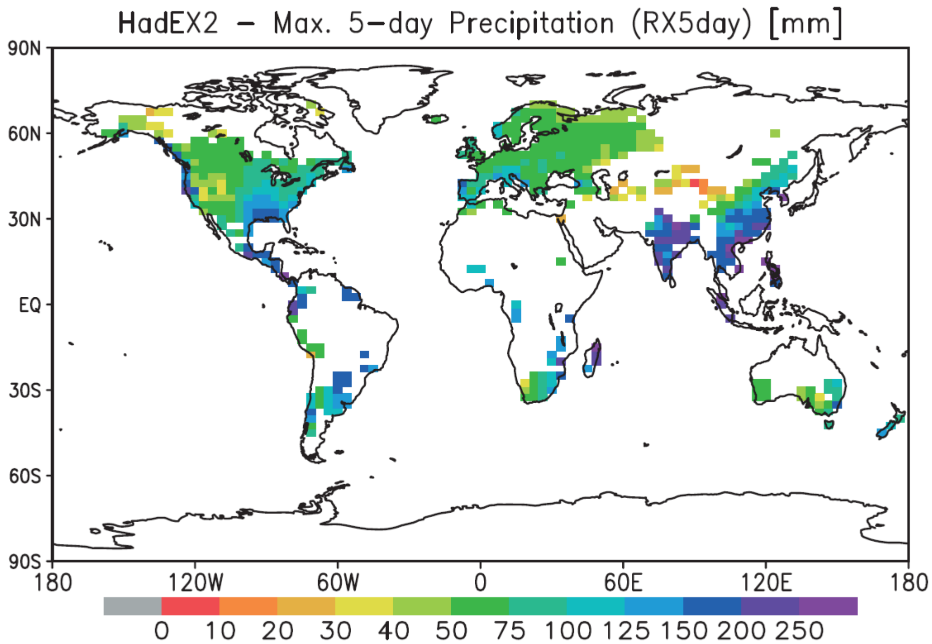
45km x 60km
(40 stations)
135km x 180km
(133 stations)
225km x 300km
(160 stations)
315km x 420km
(196 stations)

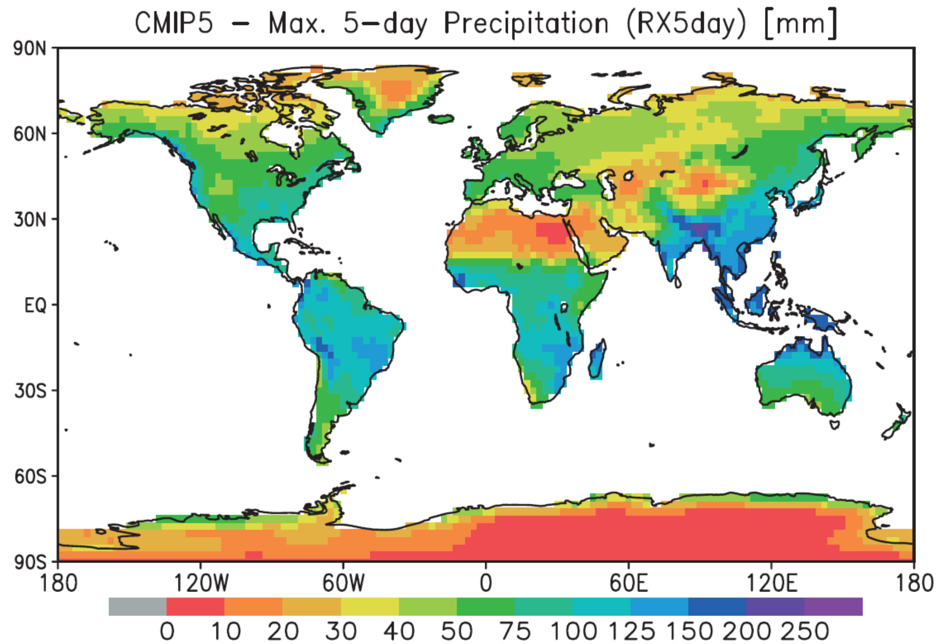
Courtesy B. Veerman, PCIC

5-day precip extremes (1981-2000)

HadEX2

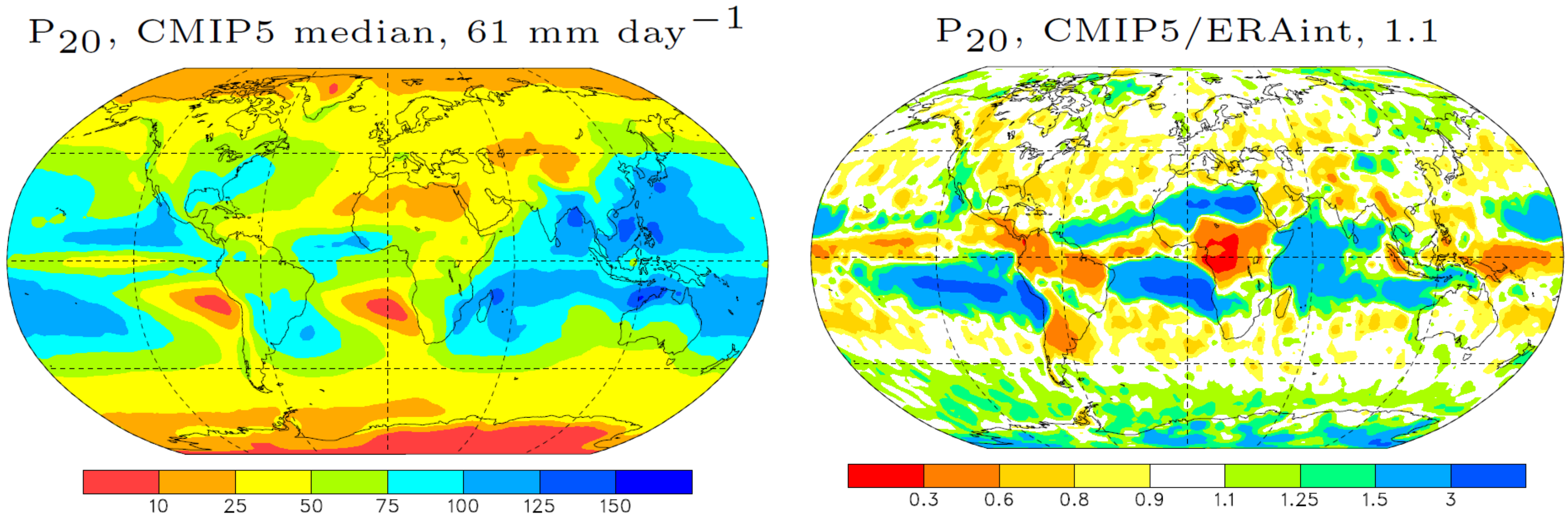
CMIP5 – 31 models





Sillmann et al (2013a, Fig. 6)

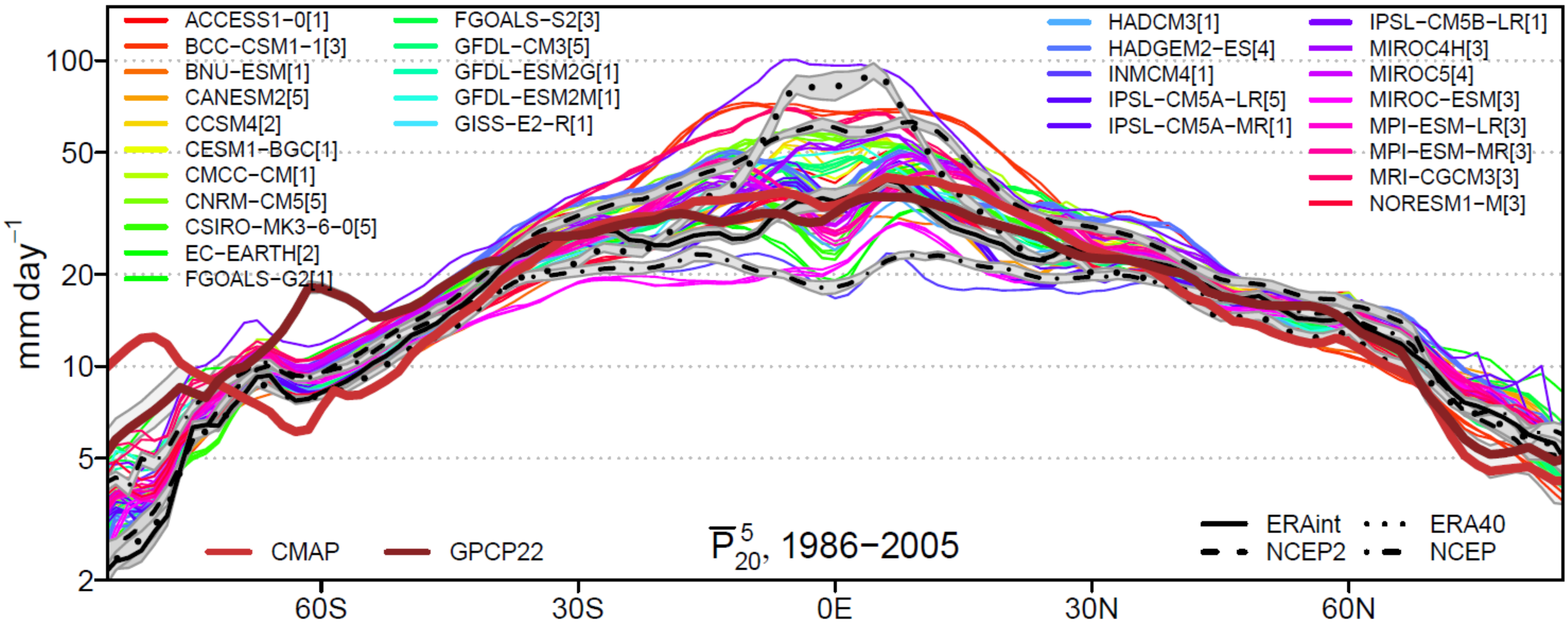
20-year 1-day precip events (1986-2005)



- Models compare reasonably well with reanalyses in mid-latitudes
- Great uncertainty in the tropics
- Note that precipitation is a “Type C” reanalysis product (i.e., no direct observational constraints and thus reanalysed values are predominately determined by the model)

Kharin et al (2013, Fig. 1)

Zonal means of 20-yr 5-day events

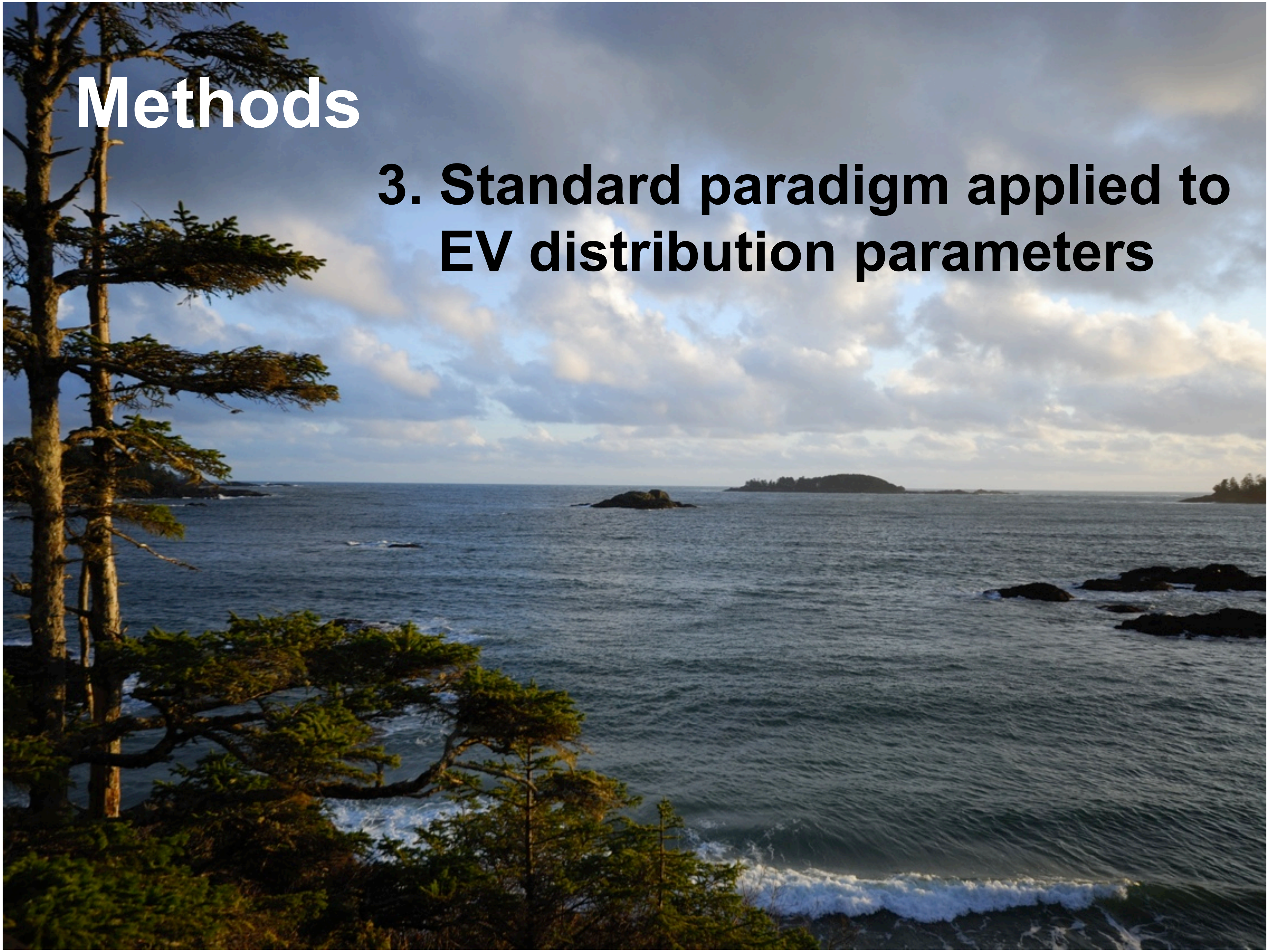


- Median model (not shown) compares quite well with GPCP and CMAP
- Models compare reasonably well with reanalyses at mid-latitudes
- Question of whether models reproduce precip correctly on resolved scales remains open

Kharin et al (2013, Fig. S5)

Methods

3. Standard paradigm applied to EV distribution parameters



3. D&A on EV distribution parameters

- Fit an extreme value distribution to observed extreme values and conduct D&A on the space-time pattern of extreme value distribution parameter estimates

Brown et al, 2008

- Evaluate observed temperatures for evidence of non-stationarity in extremes using a peaks-over-threshold approach
- Based on a limit theory which predicts that exceedances above a high threshold will behave like a Poisson process (in the limit), and that the distribution of the exceedances will converge to the Generalized Pareto distribution
- Conditional on $x > u$ the expected number of exceedances above x per year is given by

$$[1 + \xi\left(\frac{x-\mu}{\sigma}\right)]^{-1/\xi}$$

and the expected magnitude of an exceedance occurring, on average, once every m years is

$$z_m = \begin{cases} \mu - (\sigma/\xi)\left\{1 - \left[-\ln\left(1 - \frac{1}{m}\right)\right]^{-\xi}\right\} & \xi \neq 0 \\ \mu - \sigma\ln\left[-\ln\left(1 - \frac{1}{m}\right)\right] & \xi = 0 \end{cases}$$

Brown et al, 2008

- Use Caesar et al (2006) gridded daily max and min temperatures
- Location, scale and shape parameters are made functions of time

$$
\begin{aligned}
\mu_t &= \alpha_0 + \alpha_1 t \\
\sigma_t &= \exp(\beta_0 + \beta_1 t) \\
\xi_t &= \gamma_0 + \gamma_1 t
\end{aligned}
$$

- Threshold u made a function of time by fitting a trend to local temperature anomalies, and then shifting the trend line up or down such that exceedance frequency is 1.5%
- Since anomalies are used, the threshold effectively follows the local annual cycle.

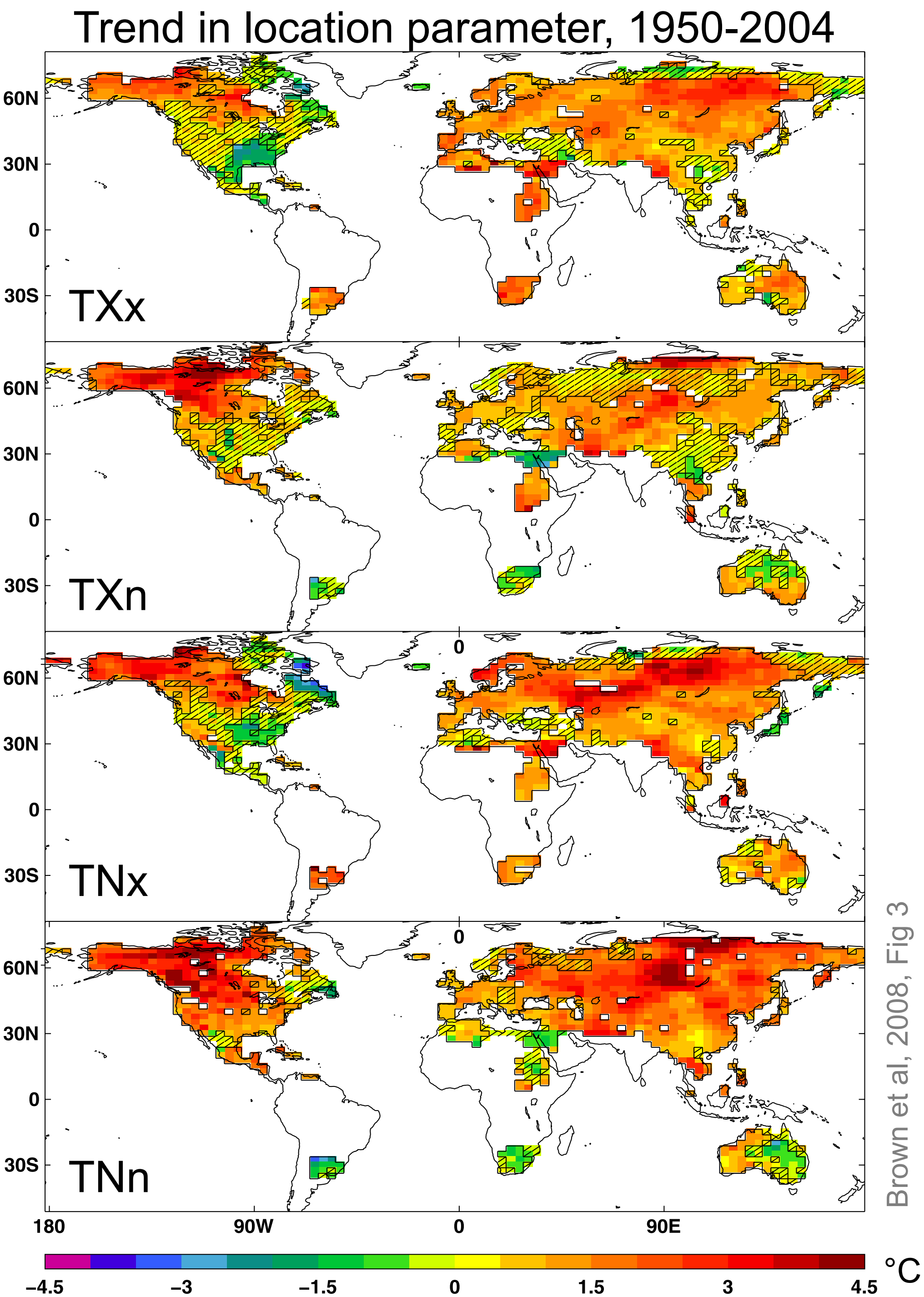
Results

- A change in the behaviour of extremes is detected (the location parameter is non-stationary)
- Daily temperature extremes warm 1-3°C over 1950-2004
- Greater warming in the cold tail.
- Trends in extremes are not found to be significantly different from trends in means for most of the land surface with data
- NAO modulates winter temperature extremes across much of the Northern Hemisphere
- Argument for using POT approach is that data are used more efficiently

Evaluation of trends in location parameter:

- Cross-hatching indicates that the estimated trend is *not* significant at 10% level based on a likelihood-ratio test

- Locations masked missing are points where Kolmogorov-Smirnov test fails at the 1% level



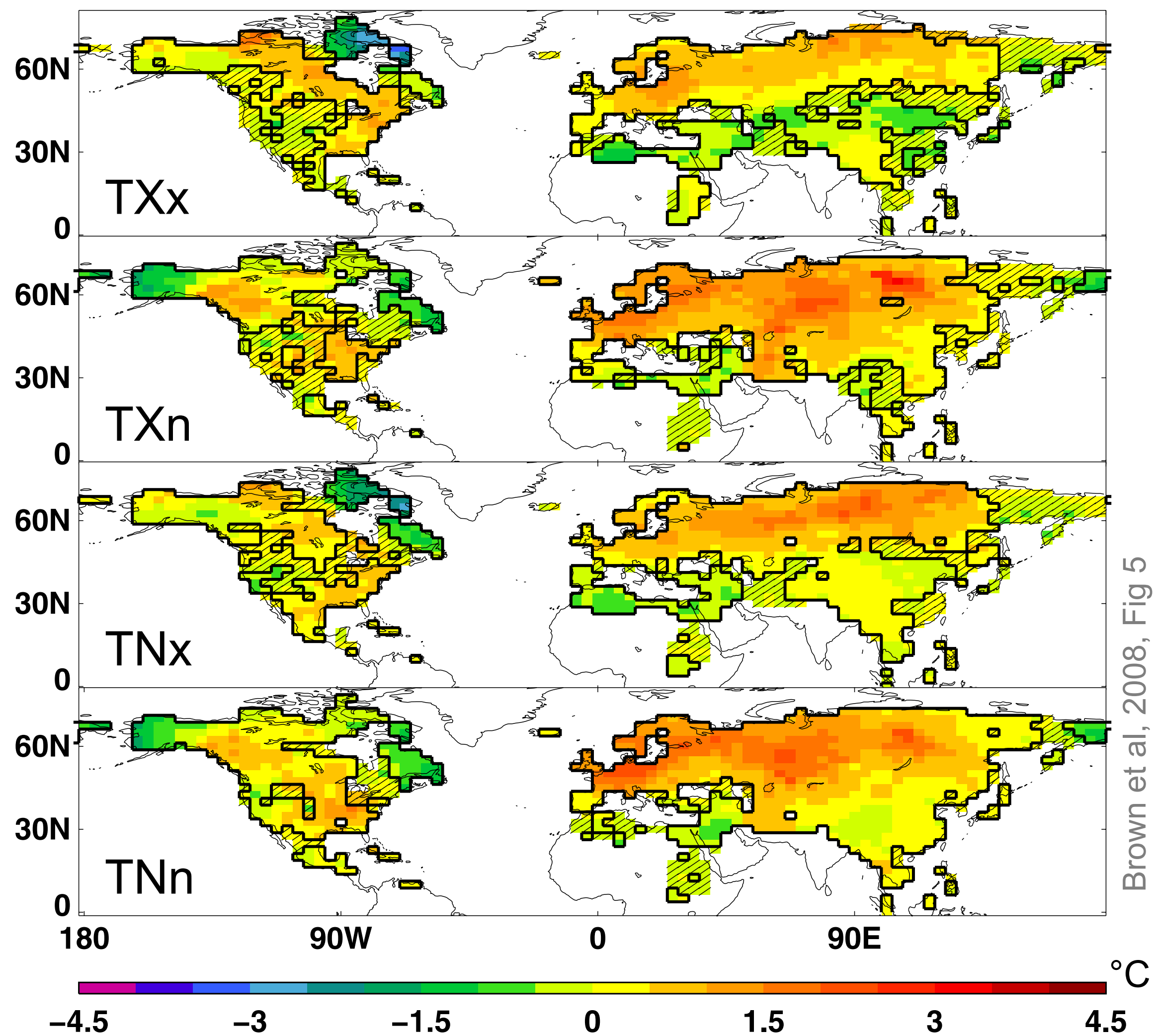
Brown et al, 2008, Fig 3

Evaluation of effect of NAO on location parameter:

$$\mu_t = \alpha_0 + \alpha_1 t + \alpha_2 \mathrm{NOA}_t$$

- Lack of cross-hatching indicates that both time and the NAO index are significant at 10% level based on a likelihood-ratio test
- Locations masked missing are points where Kolmogorov-Smirnov test fails at the 1% level

Range of variation in location parameter for winter temperature extremes due to NAO, 1950-2004



Brown et al, 2008, Fig 5

Some other studies that have used covariates in extreme value distributions include −

- Kharin et al, 2007, 2013
  - Block maximum approach
  - Use time as a covariate in analyses of projected temperature and precipitation extremes
- Zhang et al, 2010
  - Block maximum approach
  - Use SO, PDO and NAO indices as covariates in analysis of North American precipitation extremes
- Sillmann et al, 2011
  - Block maximum approach
  - Use a blocking index in an analysis of European winter cold temperature extremes

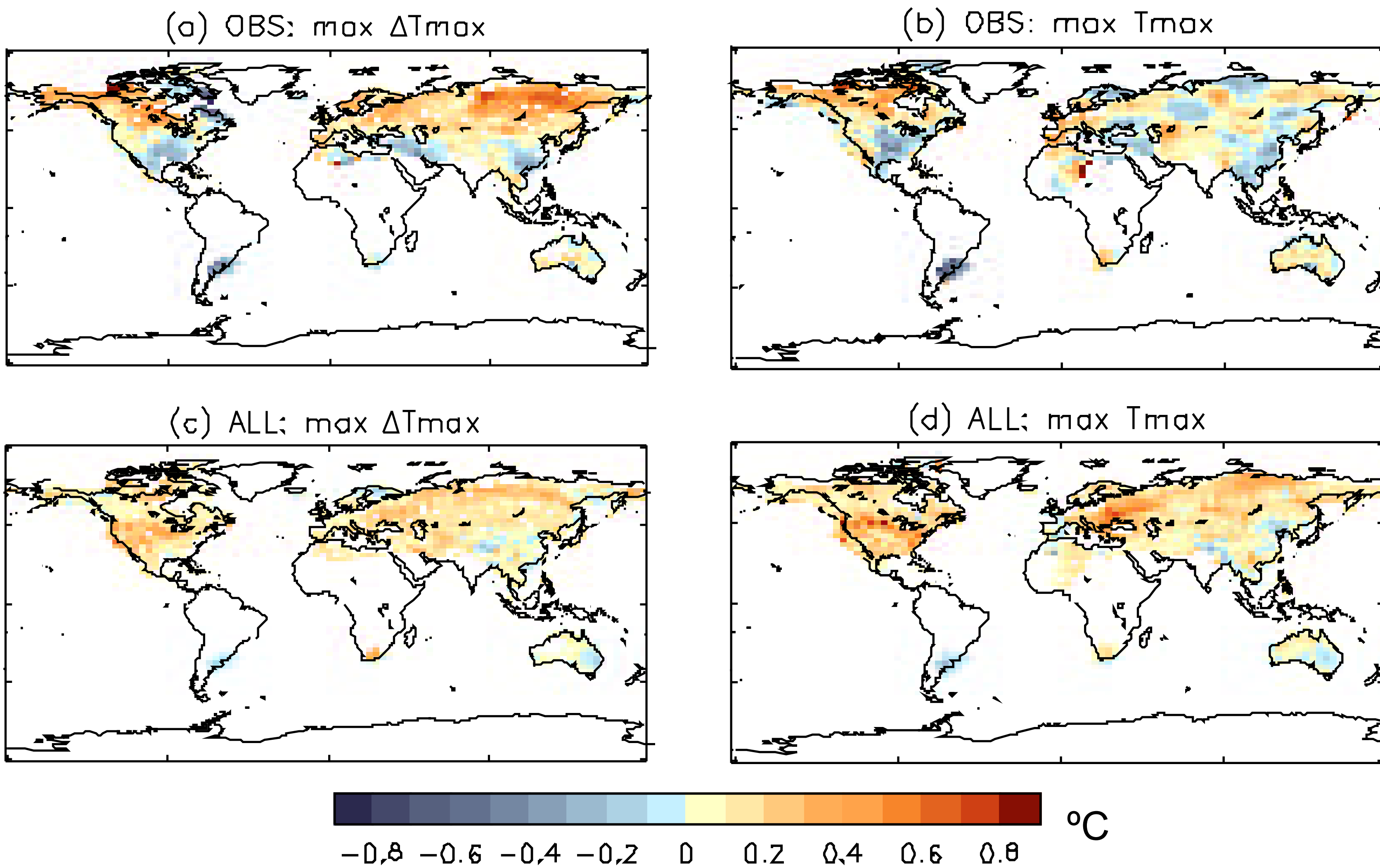
Christidis et al, 2011

- Application to D&A of change in TXx
- Observations: Caesar et al, 2006, 1950-1999
- Models: HadCM3 with ANT, NAT and ALL (4 member ensembles) + 3500 years of control simulations

Data processing

- Separately consider
  - $\max T_{max}$ (TXx), and
  - $\max \Delta T_{max}$ (anomalies of daily T_{max} relative to its climatology)
- For each 50-year segment, at each grid point that is not masked as missing …
  - Perform a PP-POT extreme value analysis with threshold u set so that daily $T_{max} > u$ less than 2% of days
  - Retain the decadal location parameters for further analysis

Trends in location parameters, 1950-1999

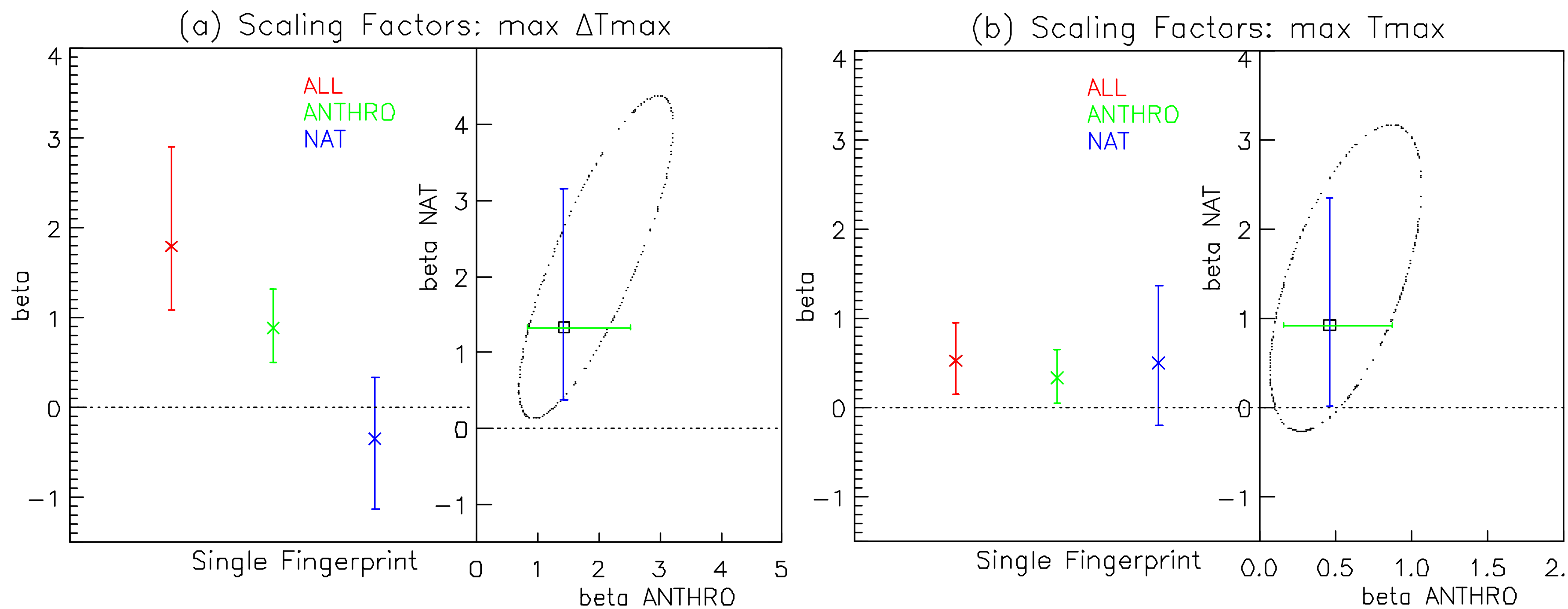


Christidis et al, 2011, Fig 1

D&A analysis approach

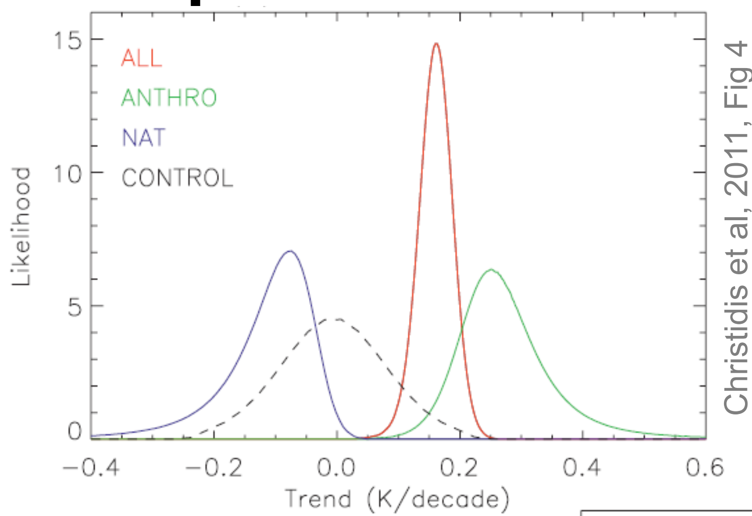
- For both maxT_{max} and maxΔT_{max}
- Do a standard TLS based D&A analysis where the analysis is on decadally varying and “T8” spatially filtered location parameter estimates derived from
  - observations
  - forced runs (and then ensemble averaged)
  - control simulations
- Detect ANT in both maxT_{max} and maxΔT_{max}

One- and two-signal detection results for change in the GPD location parameter of extreme warm daily T_{max} over the period 1950-1999 based on data with the annual cycle removed (left) and retained (right)



Christidis et al, 2011, Fig 3

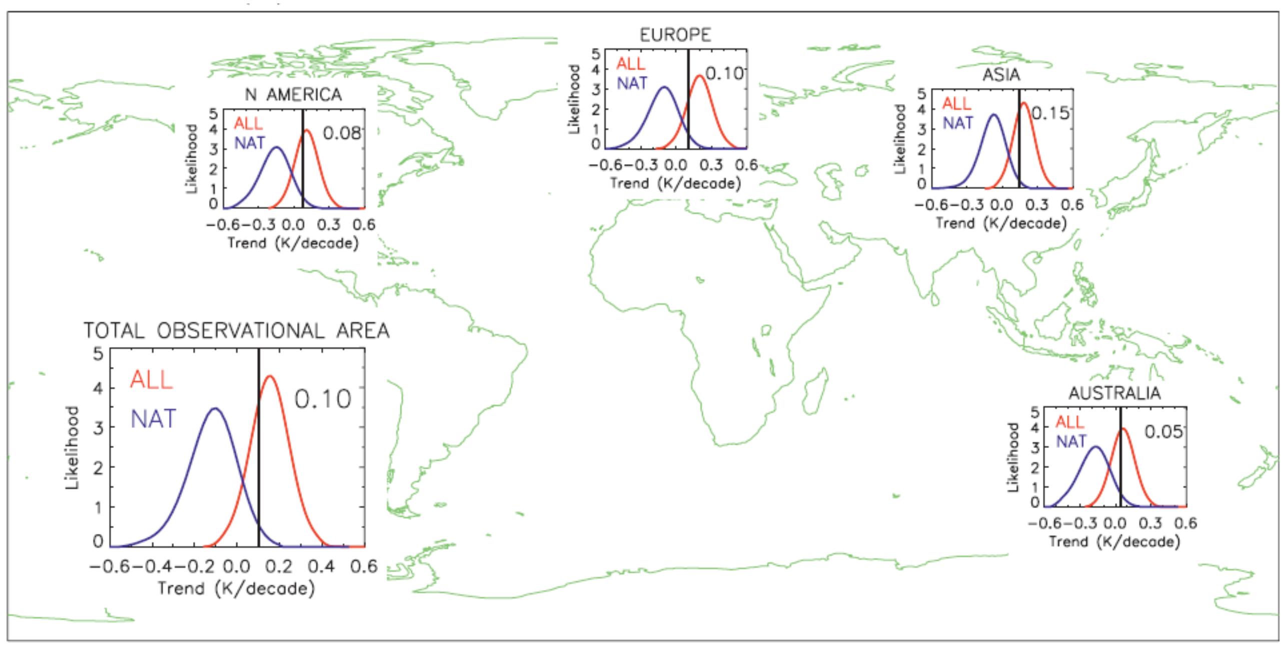
Estimate PDF of trend in location parameters using scaling factors



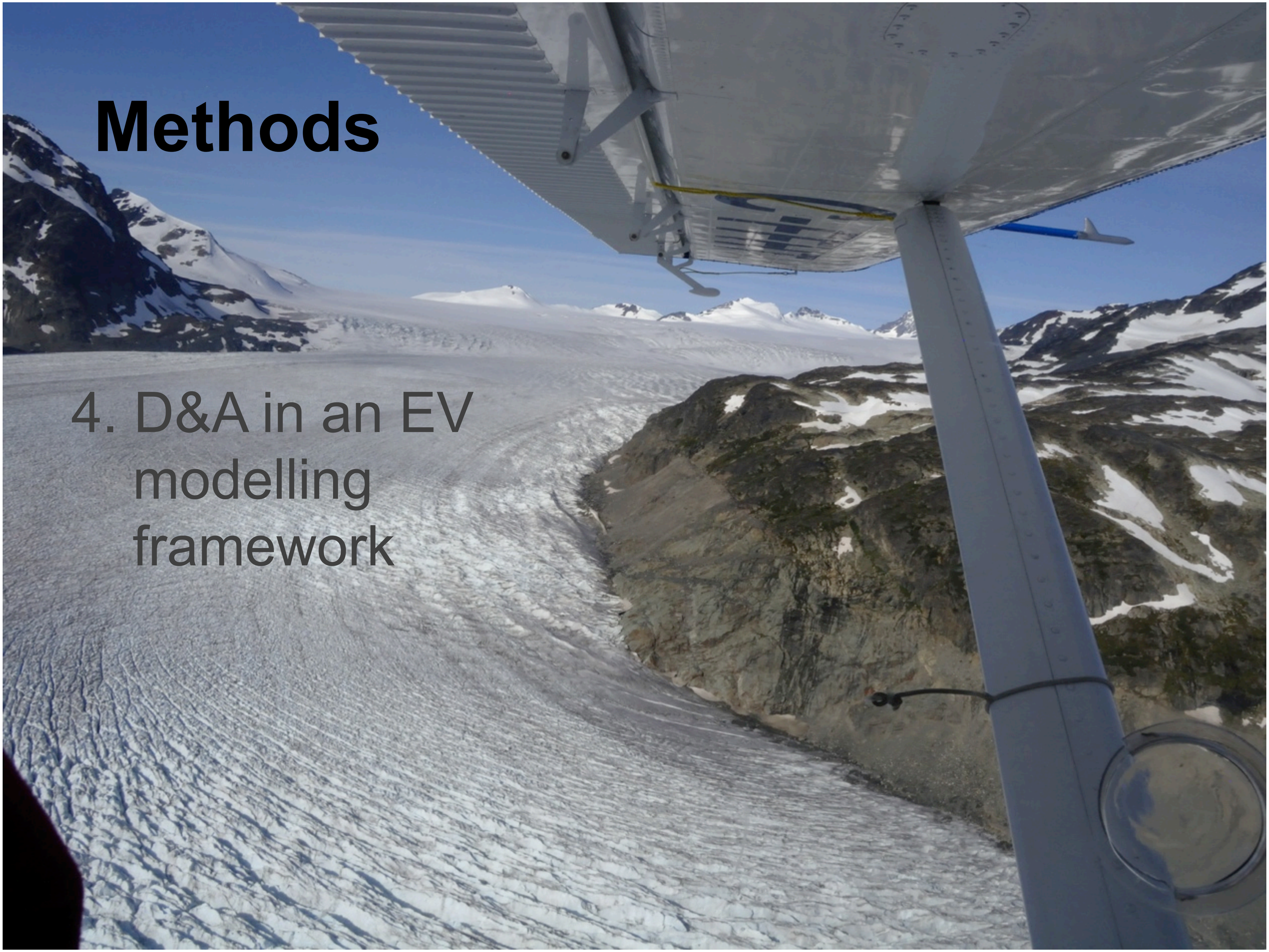
Christidis et al, 2011, Fig 4

Global Scale

Continental Scale



Christidis et al, 2011, Fig 5


Methods
4. D&A in an EV modelling framework

4. D&A on extremes using an EV distribution

- Zwiers et al, 2011
  - D&A on the extremes themselves using the block maximum approach
  - Fit a GEV distribution to observed extremes , with “signal” described in terms of expected changes in the location parameter
  - Consider TNn, TNx, TXn, TXx, 1961-2000 (annual cycle not removed)
  - Observations from HadEX (Alexander et al, 2006)
  - Model simulations from 7 CMIP3 models that provided daily data (hence 1961-2000, rather than another period)
- Approach is similar to Christidis et al, 2011, except that estimated location parameter changes are not analysed separately with a linear regression model

Recall GEV distribution

- Asymptotic distribution of block maxima
- Based on a limit theory which predicts that block maxima will have a Generalized Extreme Value distribution, in the limit, as blocks become large
- Distribution function

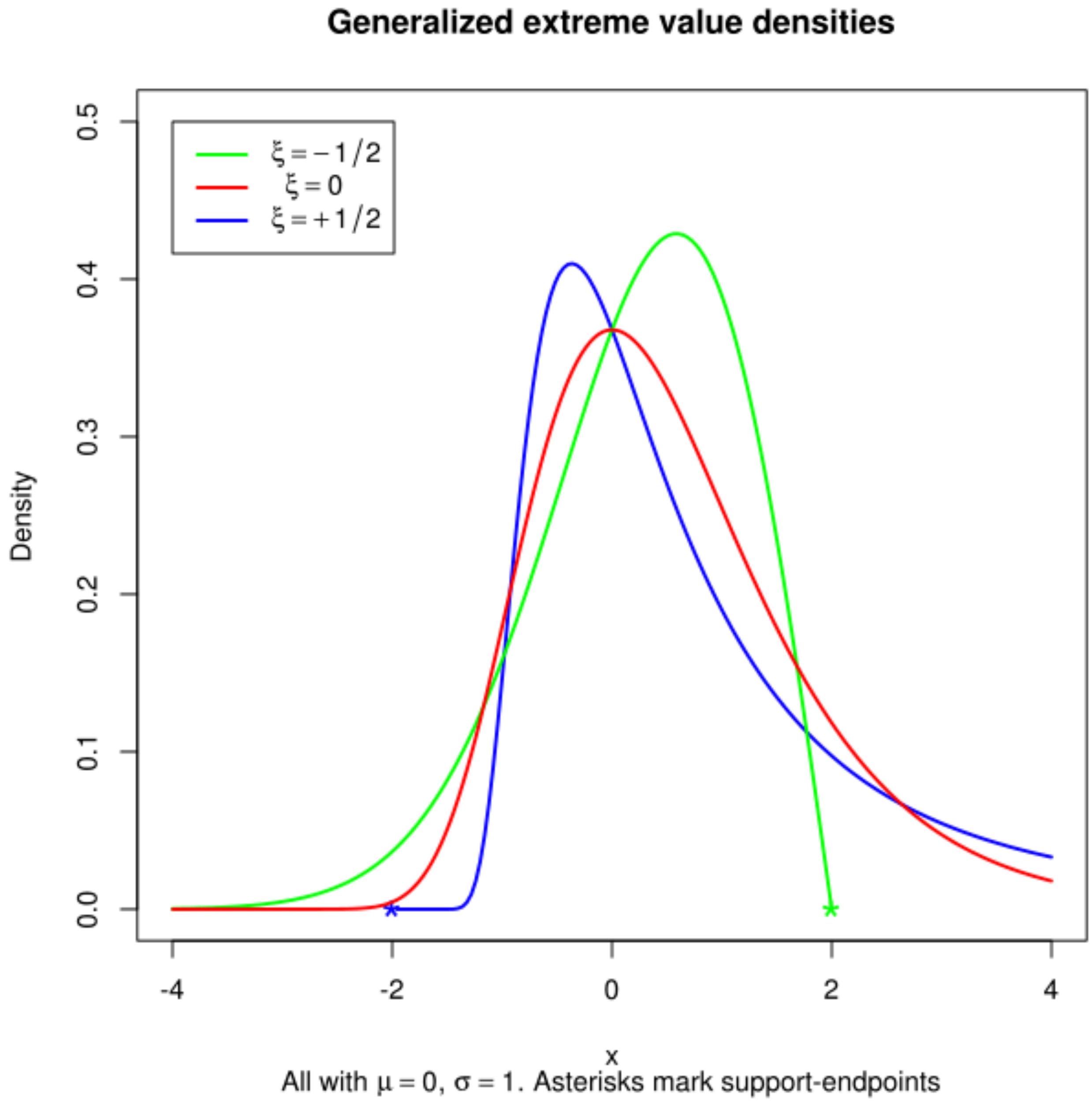
$$F(y|\mu,\sigma,\xi) = \begin{cases} \exp\left[-\,exp\left\{-\dfrac{y-\mu}{\sigma}\right\}\right], \; \xi = 0 \\ \exp\left[-\left\{1+\xi\dfrac{y-\mu}{\sigma}\right\}^{-1/\xi}\right], \;\; \xi \neq 0, 1+\xi\dfrac{y-\mu}{\sigma} > 0 \end{cases}$$

- m year return value

$$y_m = \begin{cases} \mu - (\sigma/\xi)\left\{1 - \left[-\ln\left(1-\dfrac{1}{m}\right)\right]^{-\xi}\right\} & \xi \neq 0 \\ \mu - \sigma\ln\left[-\ln\left(1-\dfrac{1}{m}\right)\right] & \xi = 0 \end{cases}$$

- Density function

$$f(y|\mu,\sigma,\xi) = \begin{cases} \dfrac{1}{\sigma}\exp\left[-\dfrac{y-\mu}{\sigma} - \exp\left(-\dfrac{y-\mu}{\sigma}\right)\right], \; \xi = 0 \\ \dfrac{1}{\sigma}\left(1+\xi\dfrac{y-\mu}{\sigma}\right)^{-1-1/\xi}\exp\left[-\left(1+\xi\dfrac{y-\mu}{\sigma}\right)^{-1/\xi}\right], \;\; \xi \neq 0, 1+\xi\dfrac{y-\mu}{\sigma} > 0 \end{cases}$$



Weibull $\xi<0$
Gumbel $\xi=0$
Fréchet $\xi>0$

Recall idea

- Fit the GEV to the observed block maxima at individual grid boxes
- Allow the location parameter μ to vary with time
- But impose the pattern of change in μ that is predicted by climate models forced with ALL or ANT forcing

How do we get the pattern of change in μ?

- Assume an ensemble of M runs from a given model for a given forcing
- Provides 10M years of output for each decade, and thus a sample of l=1,…, 10M block maxima x_{ilk} for decade i=1, …, N at grid box k
- For grid box k, we estimate the location parameters μ_{ik} i=1, …, N decades, scale parameter σ_k and shape parameter ξ_k by maximizing the joint likelihood of these N+2 parameters

$$L = \prod_{\substack{i=1,\ldots,N \\ l=1,\ldots 10M}} \frac{1}{\sigma_k}\left[1+\xi_k\left(\frac{x_{ilk}-\mu_{ik}}{\sigma_k}\right)\right]^{-1-1/\xi_k} \exp\left\{-\left[1+\xi_k\left(\frac{x_{ilk}-\mu_{ik}}{\sigma_k}\right)\right]^{-\frac{1}{\xi_k}}\right\}$$

Equivalently, minimize the negative log-likelihood

$$-\ln(L) = \sum_{\substack{i=1,\ldots,N \\ l=1,\ldots,10M}} \left\{\ln(\sigma_k) + \left(1+\frac{1}{\xi_k}\right)\ln\left[1+\xi_k\left(\frac{x_{ilk}-\mu_{ik}}{\sigma_k}\right)\right] + \left[1+\xi_k\left(\frac{x_{ilk}-\mu_{ik}}{\sigma_k}\right)\right]^{-\frac{1}{\xi_k}}\right\}$$

How do we represent the observed extremes statistically?

- Use the GEV distribution (we have block maxima)
- Make location parameter signal-dependent as follows

$$\mu_{t,k} = \mu_{t_0,k} + \beta \Delta\tilde{\mu}_{t,k}$$

$$\Delta\tilde{\mu}_{t,k} = \tilde{\mu}_{t,k} - \tilde{\mu}_{t_0,k}, \qquad t_0 = 1961$$

- The μ's are constant within decades
- $\tilde{\mu}_{t,k}$ is the ensemble mean of the location estimates for grid box k in decade t from the forced simulations
- Parameters to be estimated from observations are $\mu_{1961,k}, \sigma_k, \xi_k, \beta$
- Note that β is the same at all locations k

→ We fit the GEV distribution at all grid boxes simultaneously by minimizing

$$-\ln(L) = -\sum_{\boldsymbol{k}} \ln(L_k)$$

Where

$$\begin{aligned} -\ln(L_k) &\\ &= (T - t + 1)\ln(\sigma_k) \\ &+ \left(1 + \frac{1}{\xi_k}\right) \sum_{t=t_0}^{T} \ln\left[1 + \xi_k \left(\frac{y_{t,k} - \mu_{t_0,k} - \beta \Delta\tilde{\mu}_{t,k}}{\sigma_k}\right)\right] \\ &+ \sum_{t=t_0}^{T} \left[1 + \xi_k \left(\frac{y_{t,k} - \mu_{t_0,k} - \beta \Delta\tilde{\mu}_{tk}}{\sigma_k}\right)\right]^{-1/\xi_k} \end{aligned}$$

$$t_0 = 1961, \qquad T = 2000$$

- Do this using the profile likelihood technique

Parallels with standard D&A

- Single scaling factor to modify the space-time pattern of change in model simulated location parameters
- Like OLS rather than TLS because we don’t take uncertainty in model derived location factors into account (could think about how to do that as an exercise)
- Non-optimized because the likelihood function does not represent dependence between extremes at different locations

Unlike standard D&A

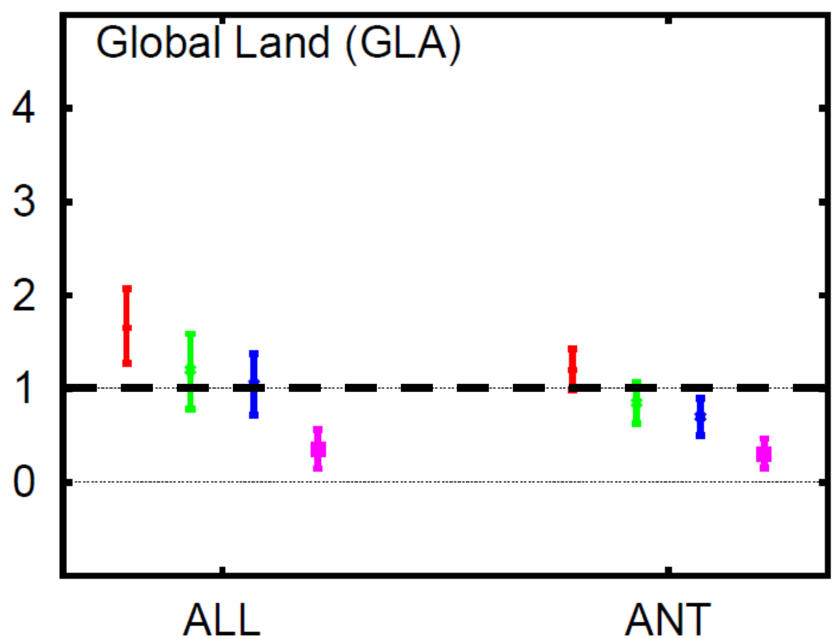
- Uncertainty analysis (next slide) was not based on control variability because daily output was not available from CMIP3 control runs

Approach used for uncertainty analysis

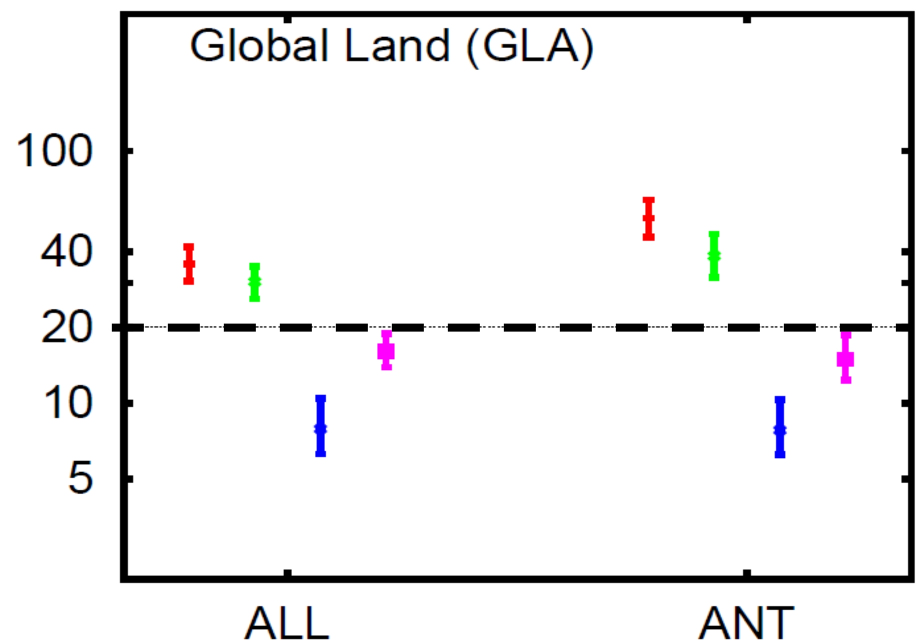
- Daily output from control runs not available for CMIP3
- Used a resampling process instead
  1. Remove scaled signal from observed extremes
  2. Randomly reorder residuals in 5-year blocks
  3. Add scaled signal back
  4. Re-estimate scaling factor
  5. Repeat 1-4 many times to build a sampling distribution for β
- This process accounts for spatial dependence and temporal dependence up to ~5-year time scale only, but is conditional upon the estimated signals (changes in location parameter due to forcing that are estimated from models)
- We also used a resampling process to estimate signal uncertainty

Results: Global

Scaling factors and bootstrapped 5-95% uncertainty ranges



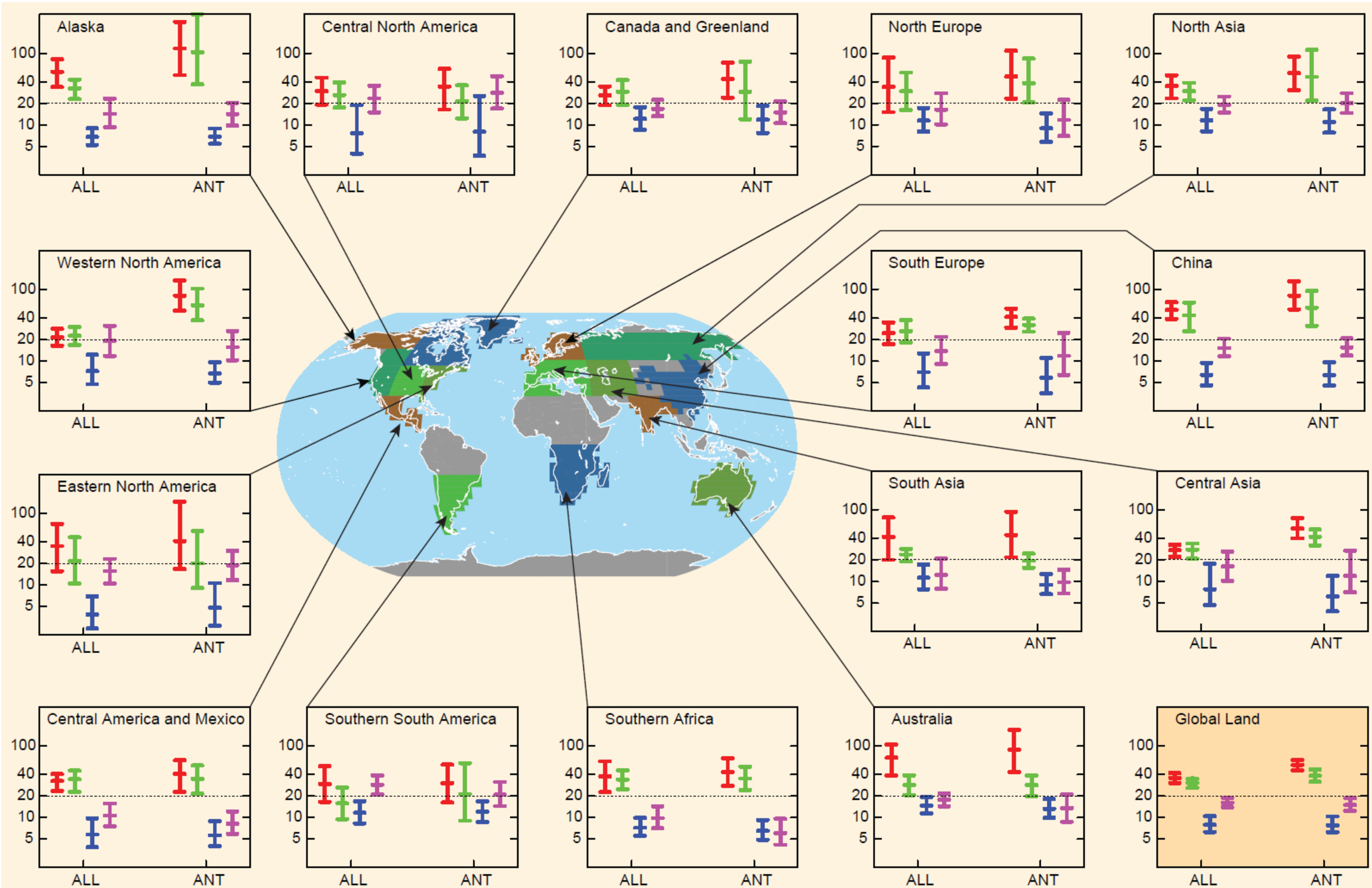
Implied change in waiting times for 20-year event (1990's vs 1960's)



Zwiers, et al., 2011, *J Climate*

TNn, TXn, TNx, TXx

Implied changes in waiting times (1990’s vs 1960’s)



Discussion

5. Discussion

- Considered several approaches
- Have not assessed which approach results in most efficient detection
- Ability to model spatial dependence in extremes remains limited
- Thus detection on suitably transformed data or on EV distribution parameters currently remains preferable
- Nevertheless, advantages to further developing detection approaches within EVT framework
- Should be able to calculate FAR directly
- Potentially a constraint on projections of future extremes

Discussion

- "Extremes" is a much broader topic, not all of which is amenable to extreme value theory
  - Tornadoes
  - Tropical cycles
  - Drought
  - ...


Thank you!

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