Detection, attribution of long-term change, and event attribution

Francis Zwiers
PCIC, University of Victoria
BIRS, 14 June 2016

Photo: F. Zwiers (Strait of Juan de Fuca)

Introduction

- Enormous interest in event attribution
  - Event and media driven (eg, Calgary floods, Fort McMurray fires)
  - Questions are mostly retrospective
- Requires “rapid response” science
  - Recently assessed by US National Academies of Science (2016)
- Topics for this talk
  - Detection and attribution of long-term change
  - Event attribution
  - Discussion

Detection and Attribution of long term change

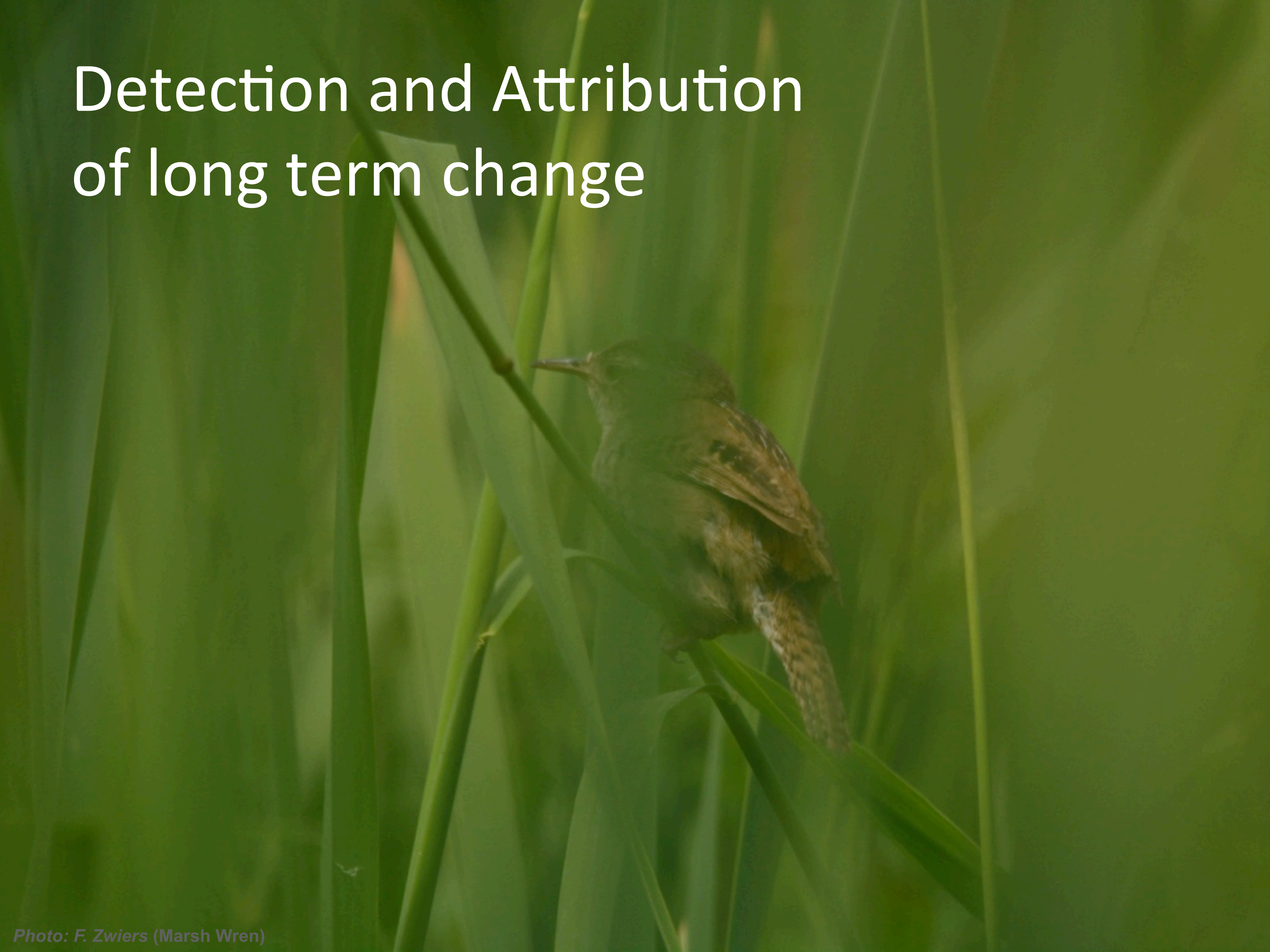


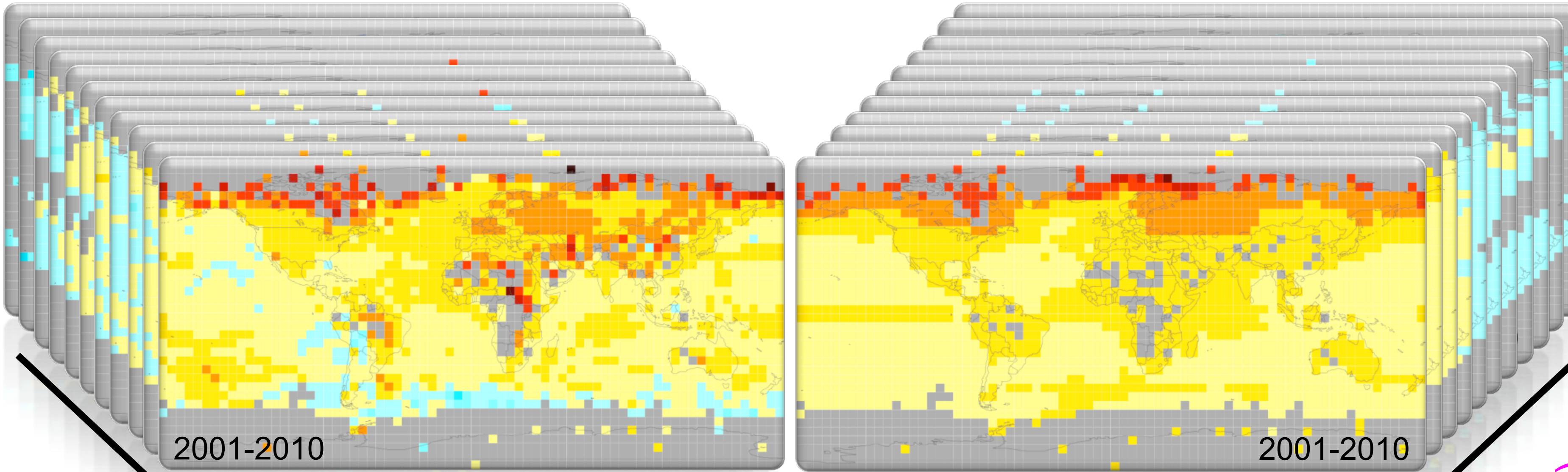
Photo: F. Zwiers (Marsh Wren)

D&A of long-term change

- Definitions
  - *Detection* – identifying that a change has occurred
  - *Attribution* – evaluating contributions from causal factors
- Methods
  - Involve simple statistical models
  - Complex implementation due to data volumes (which are both small and large)
- Usual assumptions
  - Key forcings have been identified
  - Signals and noise are additive
  - Climate models simulate large-scale patterns of response correctly
- Leads to a regression formulation

Observations (HadCRUT4)

Multi-model mean (ALL forcings)



11 decades (1901-1911 to 2001-2011)

$\mathbf{Y}$

$\mathbf{X}$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

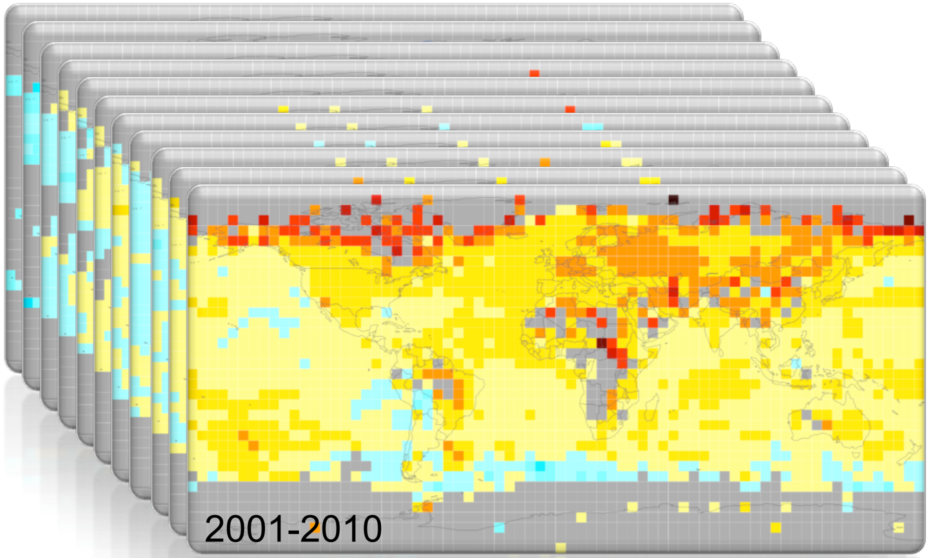
Evaluate scaling factors $\leftarrow \widehat{\boldsymbol{\beta}}$

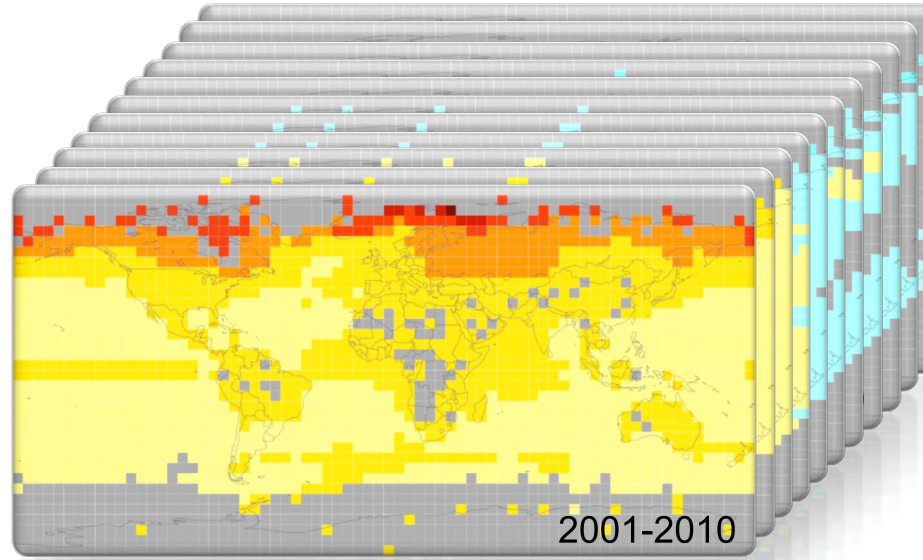
$\hat{\boldsymbol{\varepsilon}} \rightarrow$ Evaluate residuals

After Weaver and Zwiers (2000)

Observations (HadCRUT4)

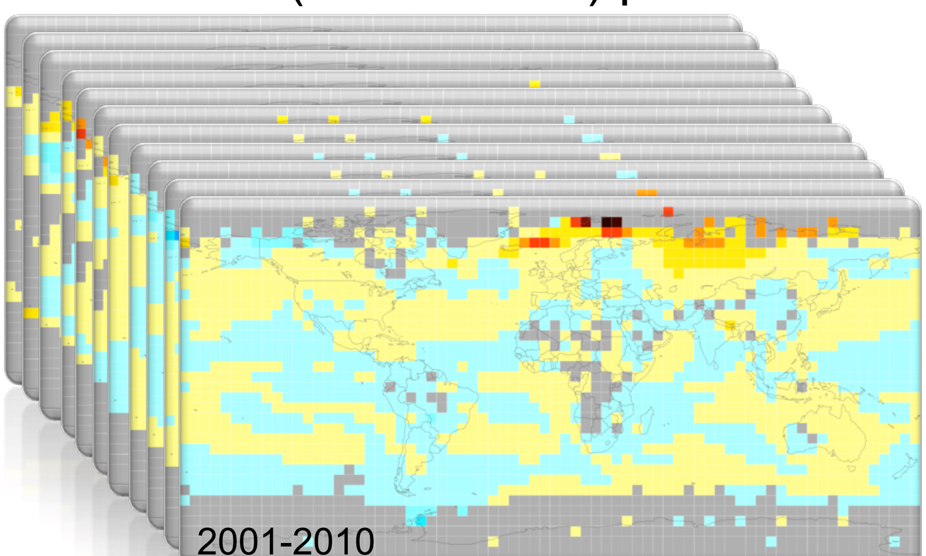
Multi-model mean (ALL forcings)

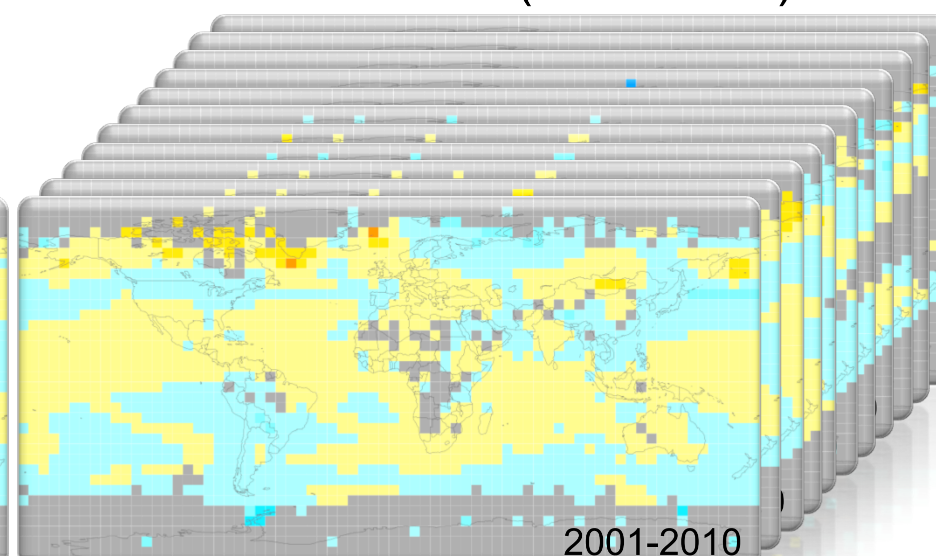




11 decades (1901-1911 to 2001-2011)

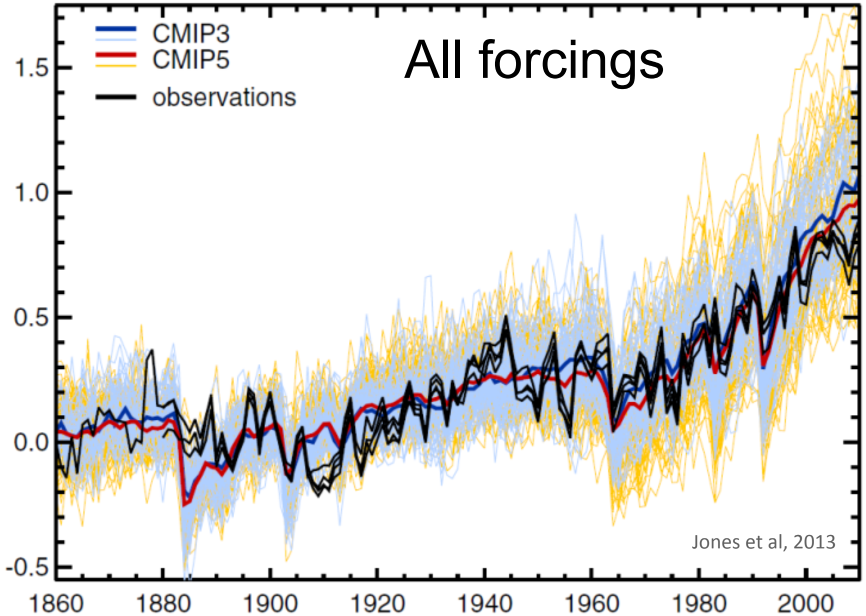
Two (of hundreds) pre-industrial control run “chunks” (CanESM2)





Global warming attribution

Global mean temperature relative to 1880-1919



See also Figure 10.1, IPCC WG1 AR5

Trend in global surface temperature (1951-2010)

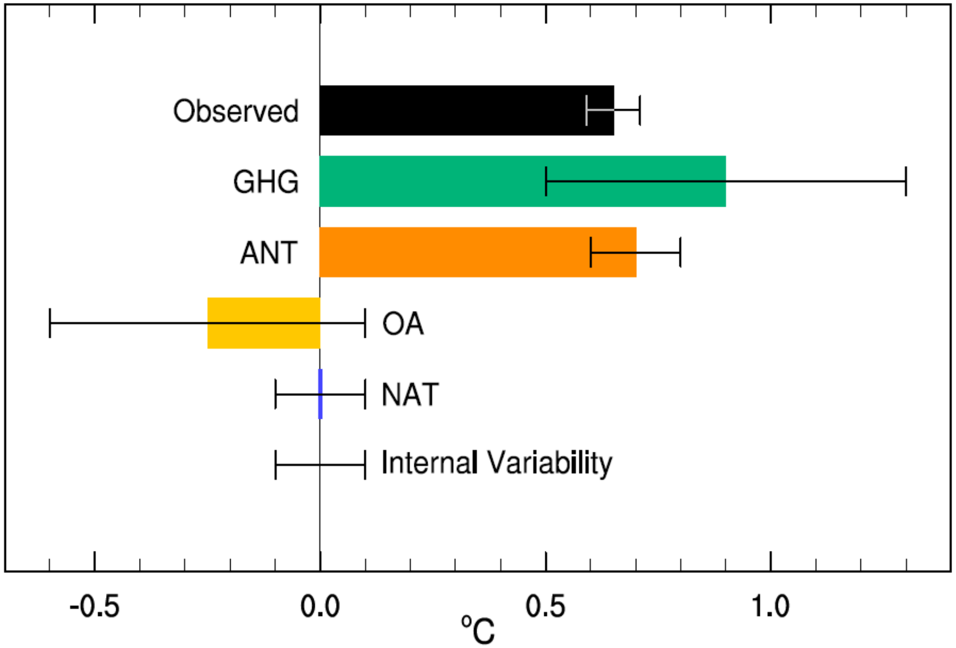


Figure TS.10, IPCC WG1 AR5

It is *extremely likely* that human influence has been the dominant cause of the observed warming since the mid-20th century.

Detection and Attribution Summary

- Concerned with long term change
- Quantifies how the mean state (or some other statistic) has changed over time due to forcing

- Examples
  - Global and regional mean temperature
    - Large body of literature, very high confidence
  - Temperature extremes
    - Growing literature, high confidence
  - Precipitation extremes
    - Emerging evidence, medium or lower confidence

Some concerns

- Most studies implicitly assume Gaussian noise (generally not a large concern)
- Sampling variability in the estimation of the noise covariance matrix is not accounted for well
  - Hannart (2016) proposes a solution
- Most studies treat inter-model differences as sampling variability equivalent to internal variability
  - Hannart et al (2014) proposes a partial solution
  - Ribes et al (2016) propose an alternative approach
  - In reality, we do not have a comprehensive statistical framework that allows us to describe how the available ensembles of opportunity have been obtained

Some concerns …

- Many studies still use ad-hoc methods for covariance matrix regularization (e.g., EOF-truncation)
  - Some now use better approaches (e.g., the Ledoit-Wolf (2004) estimator) following Ribes et al (2013a, 2013b)

- Many studies do not discuss basic assumptions
  - Key forcings have been identified (and thus there are no other confounding influences)
  - Additivity of signals and noise, independence of noise on mean state
- Tendency to attribute based only on statistical evidence (see discussion in Mitchell et al., 2001)

D&A of changes in extremes
- a temperature example

Photo: F. Zwiers (Lanzhou)

See WCRP summer school on extremes, ICTP, July, 2014

An approach to D&A on extremes using EV theory

- Several available indices are "block maxima"
  - Temperature: TNn, TXn, TNx, TXx
  - Precipitation: RX1day, RX5day
- Suggests using the "Generalized Extreme Value" (GEV) distribution, and incorporating the effects of forcing via its parameters
- An example is Zwiers et al, 2011

GEV distribution

- Based on limit theory which predicts that the distribution of block maxima will converge to a *Generalized Extreme Value* distribution 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-block return value (blocks are often years)

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

- Density function

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

Working assumption

- External forcing affects only the GEV location parameter μ

- Parallel to the regression approach
  - Estimates the conditional mean (“location parameter”) of the Gaussian distribution

How do we get the expected pattern of change in μ?

- For a given climate model and forcing, assume M runs
- 10M years of output for each decade

→ 10M block maxima x_{tlk} for decade t at grid box k

$t=1, \ldots, N$ decades

$l=1, \ldots, 10M$ simulated years for decade t

- Use these 10M block maxima to estimate GEV parameters for decade t at grid box k

→ estimate N+2 parameters μ_{tk}, σ_k and ξ_k at each grid box

- Do this via maximum likelihood

Maximum likelihood estimation of μ_{tk}, σ_k and ξ_k

Maximize the joint likelihood

$$
\begin{aligned}
&L\left(\mu_{1k}, \ldots, \mu_{Nk}, \sigma_{k,} \xi_k \middle| x_{tlk}, t = 1, \ldots, N, l = 1, \ldots, 10M\right) \\
&\quad = \prod_{t=1}^{N} \prod_{l=1}^{10M} f\left(x_{tlk} \middle| \mu_{tk}, \sigma_{k,} \xi_k\right) \\
&\quad = \prod_{t=1}^{N} \prod_{l=1}^{10M} \frac{1}{\sigma_k} \left[1 + \xi_k \left(\frac{x_{tlk} - \mu_{tk}}{\sigma_k}\right)\right]^{-1-1/\xi_k} \exp\left\{-\left[1 + \xi_k \left(\frac{x_{tlk} - \mu_{tk}}{\sigma_k}\right)\right]^{-\frac{1}{\xi_k}}\right\}
\end{aligned}
$$

Equivalently, minimize the negative log-likelihood

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

Do this at individual grid boxes k

How do we model the observed extremes?

- Use the GEV distribution
  - we have observed block maxima $y_{tk}, t = 1961, \ldots, 2000$
- Make the location parameter signal-dependent as follows

$$\mu_{tk}^{o} = \mu_{t_0 k}^{o} + \beta(\tilde{\mu}_{tk}^{m} - \tilde{\mu}_{t_0 k}^{m})$$

$$\text{where} \begin{cases} t = t_0, \cdots, 2000, t_0 = 1961 \\ \mu'\text{s constant within decades} \end{cases}$$

  and $\tilde{\mu}_{tk}^{m}$ is the multi-model ensemble mean of the location parameter estimates for grid box k in decade t from the forced simulations
- Parameters to be estimated from obs are $\mu_{t_0 k}^{o}, \sigma_{k}^{o}, \xi_{k}^{o}, \beta$
- Note that β is the same at all locations k

Fit the GEV distribution to observations at all grid boxes simultaneously by minimizing

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

where

$$\begin{aligned} -\ln(L_k) &= (T - t_0 + 1)\ln(\sigma_k^o) \\ &+ \left(1 + \frac{1}{\xi_k^o}\right) \sum_{t=t_0}^{T} \ln\left[1 + \xi_k^o \left(\frac{y_{tk} - \mu_{t_0k}^o - \beta\Delta\tilde{\mu}_{tk}^m}{\sigma_k^o}\right)\right] \\ &+ \sum_{t=t_0}^{T} \left[1 + \xi_k^o \left(\frac{y_{tk} - \mu_{t_0k}^o - \beta\Delta\tilde{\mu}_{tk}^m}{\sigma_k^o}\right)\right]^{-1/\xi_k^o} \end{aligned}$$

Do this using the profile likelihood technique

Parallels with standard D&A

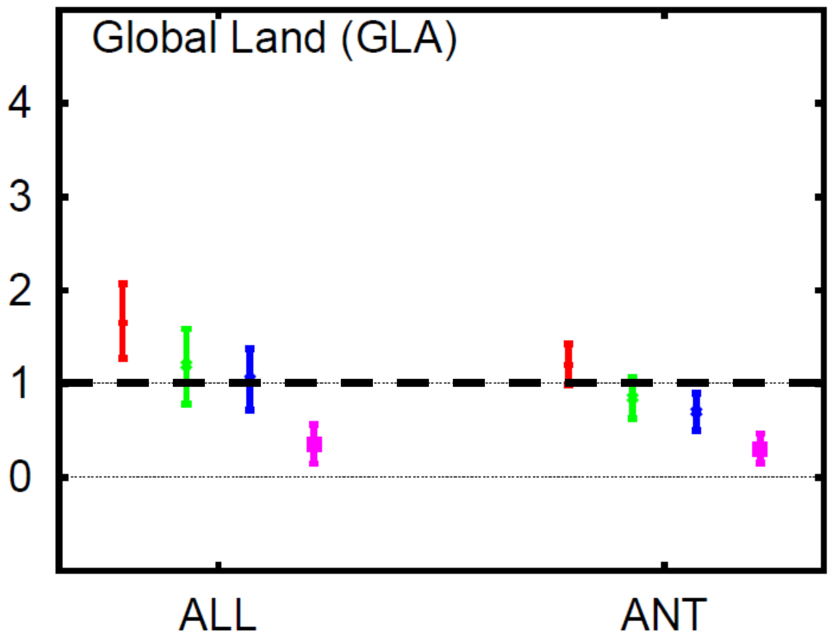
- Single scaling factor to modify the space-time pattern of change in model simulated location parameters
- Like OLS rather than TLS because we don’t take uncertainty in model derived location factors into account
- Non-optimized because the likelihood function does not represent dependence between extremes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

Unlike standard D&A

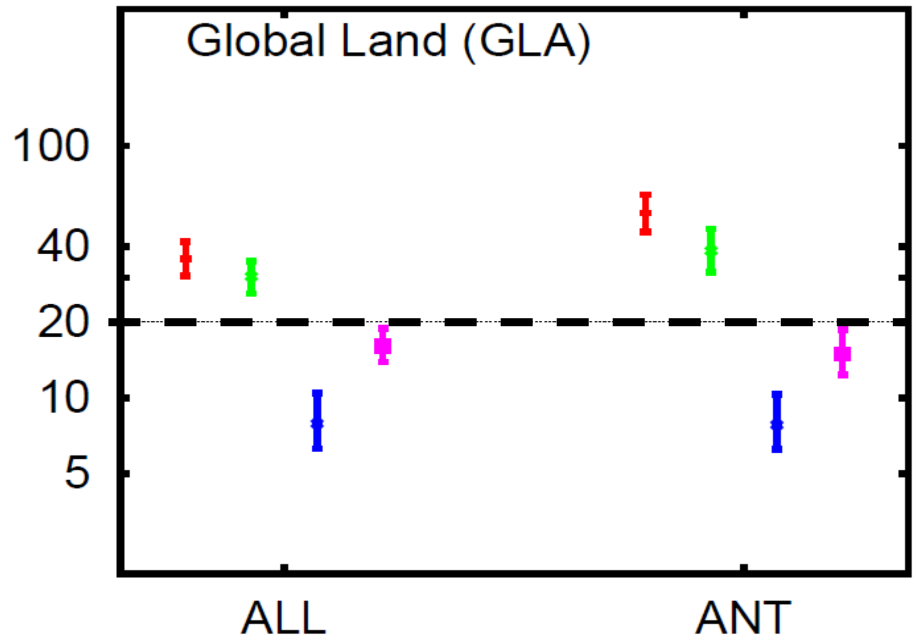
- Uncertainty analysis was not based on control variability because daily output was not available from CMIP3 control runs – used a block bootstrap approach instead

Global Results

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

Event attribution

Calgary East Village (June 25, 2013), courtesy [Ryan L.C. Quan]

Event attribution

- The public asks: Did human influence on the climate system …
  - Cause the event?
- Most studies ask: Did it …
  - Affect its odds?
  - Alter its magnitude?
- Some think we should reframe the question …
  - Rather than “Did human influence …” (which requires comparison with a counterfactual world)
  - Ask “How much (eg, of a given storm’s precipitation) is due to the attributed warming (eg, in the storm’s moisture source area)” (after Trenberth et al, 2015)

Most studies

- Compare factual and "counterfactual" climates
  - Counterfactual → the world that might have been if we had not emitted the ~600GtC that have been emitted since preindustrial
- These studies almost always
  - Define a class of events rather than a single event
  - Use a probabilistic approach
- Shepherd (2016) defines this as "risk based"
  - Contrasts it with a "storyline" based approach
  - i.e., analysis of the specific event that occurred

"Framing" event attribution studies

- Event type
  - Class vs individual
- Analysis approach and approach
  - "risk based" or "storyline"
- Event definition
  - What spatial scale, duration, etc
- Which risk-based question
  - Did climate change alter the odds, or the magnitude?
- What factors should be taken into account
  - "Conditioning"
  - e.g., coincident SST anomaly pattern

The NAS Report (2016) struggled with these distinctions

“Conditioning” examples

- Did human influence alter its likelihood

$$Prob(E|forcing) \;\; vs \;\; Prob(E|\neg forcing)$$

$$Prob(E|forcing, SST) \;\; vs \;\; Prob(E|\neg forcing, \widetilde{SST})$$

- Did human influence alter its magnitude

$$f(M|E, forcing) \;\; vs \;\; f(M|E, \neg forcing)$$

$$f(M|E, forcing, SST) \;\; vs \;\; f(M|E, \neg forcing, \widetilde{SST})$$

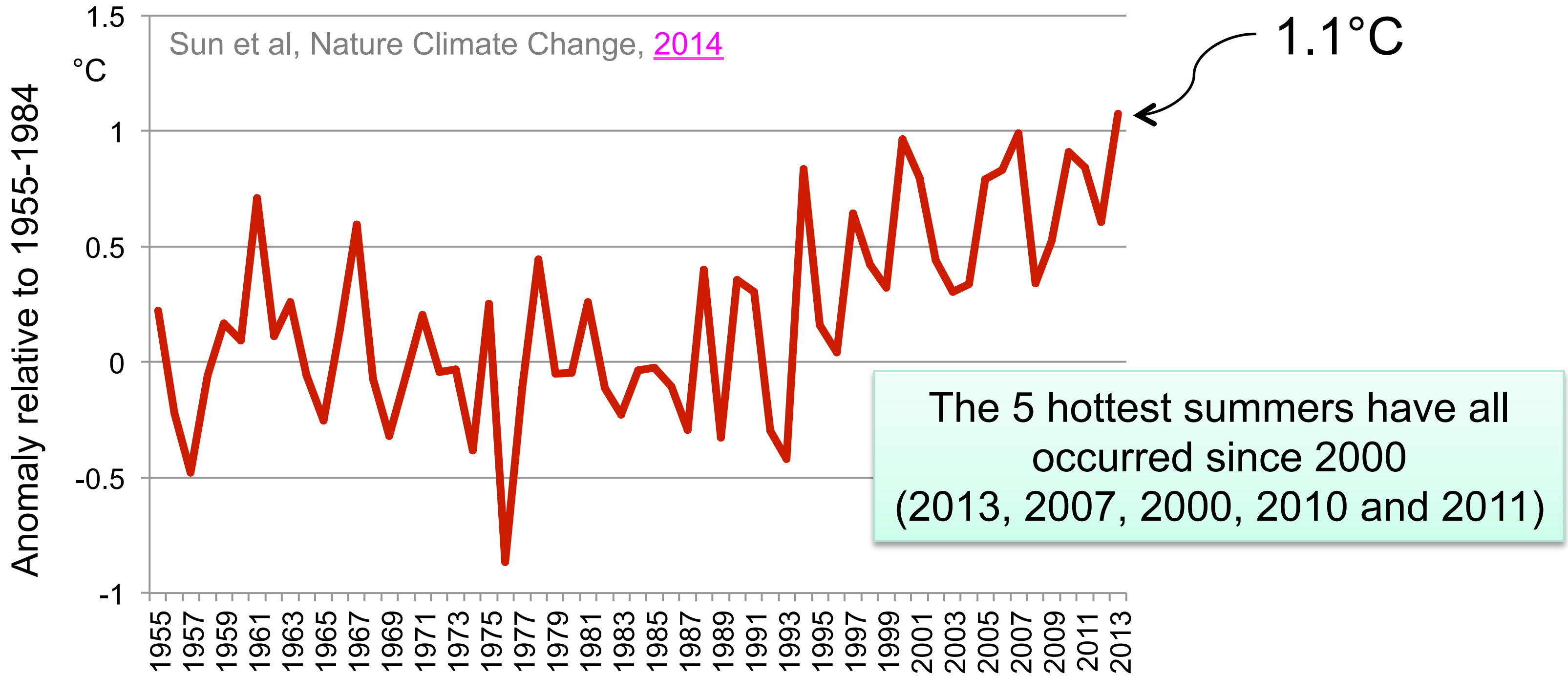
Recent examples

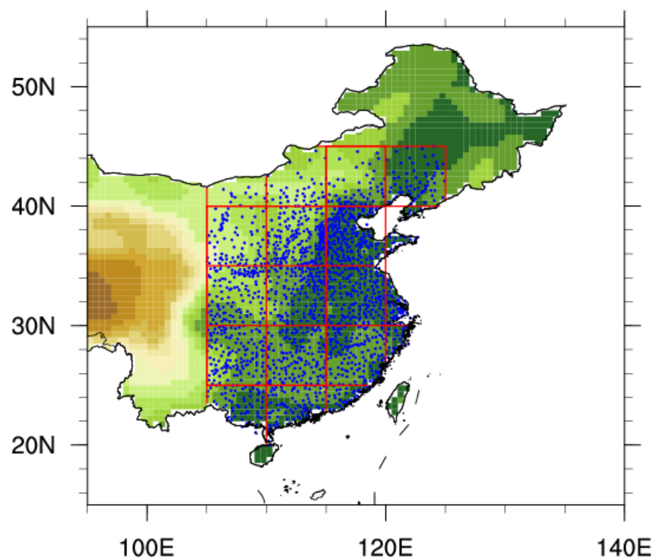
- China's very hot summer of 2013
  - Sun et al. (2014)
  - Condition only on anthropogenic forcing
- Calgary floods
  - Teufel et al (accepted, Clim Dyn)
  - Condition on anthropogenic forcing and SSTs
  - Uses both risk based and storyline approaches
- Arctic low sea-ice extent events
  - Kirchmeier-Young et al (submitted, J Climate)
  - Extreme low summer minimum of Sept, 2012
  - Extreme low winter maximum of March, 2015

China’s Summer of 2013

Photo: F. Zwiers **(Lijiang – Black Dragon Pool)**

JJA mean temperature in Eastern China

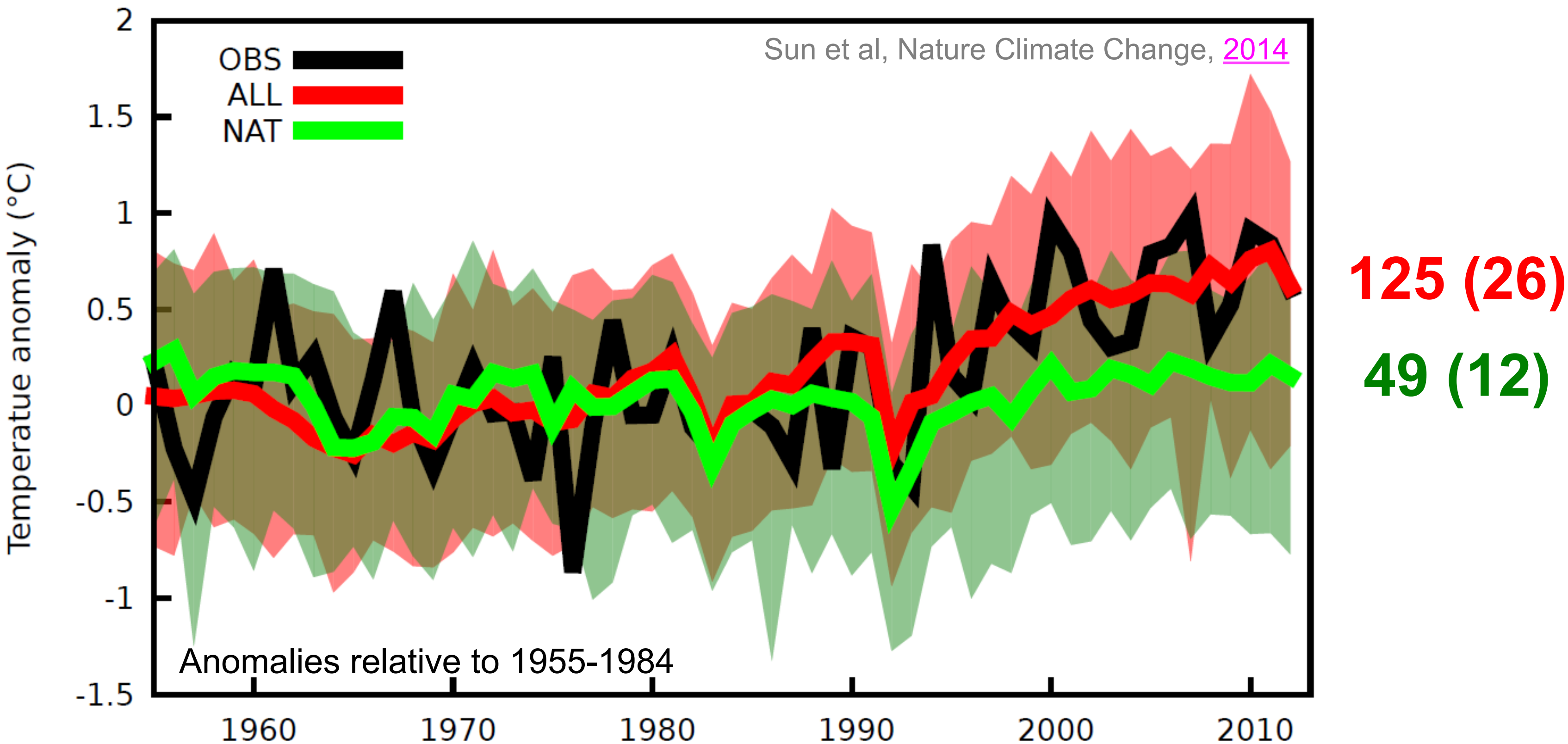




Eastern China is densely observed

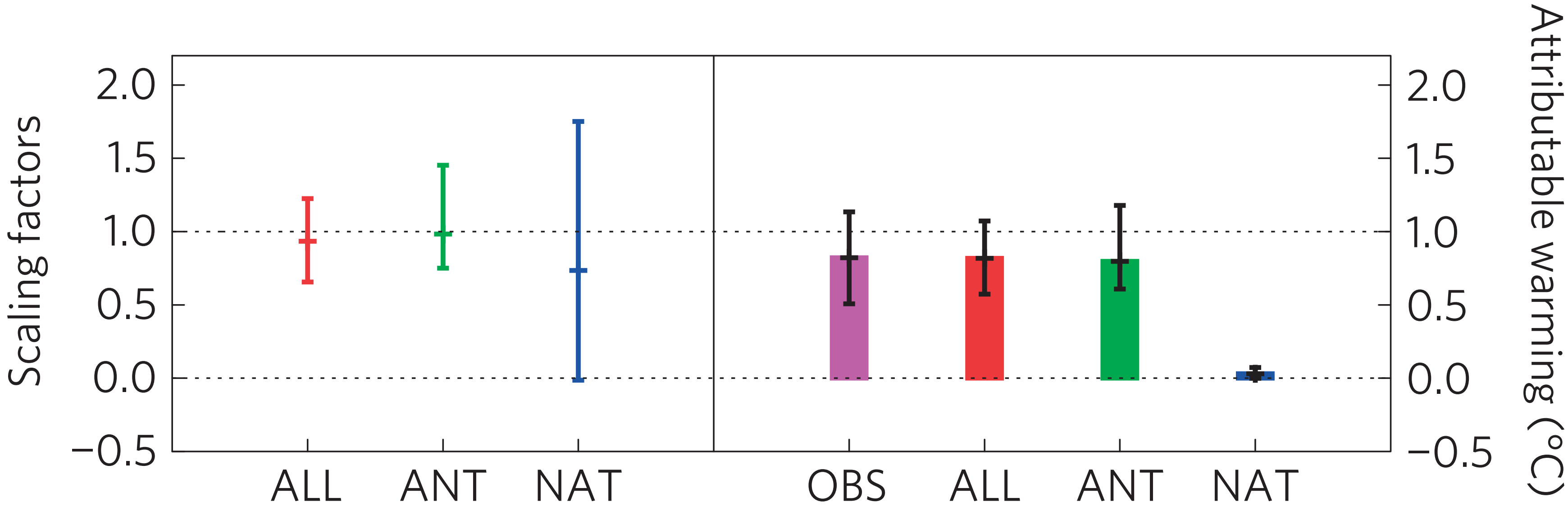
- 1749 stations (1955 onwards)
- JJA mean temperature increased 0.82°C over 1955-2013
- records were broken at more than 45% of stations in JJA 2013

Observed and simulated JJA mean temperature in Eastern China (1955-2012)



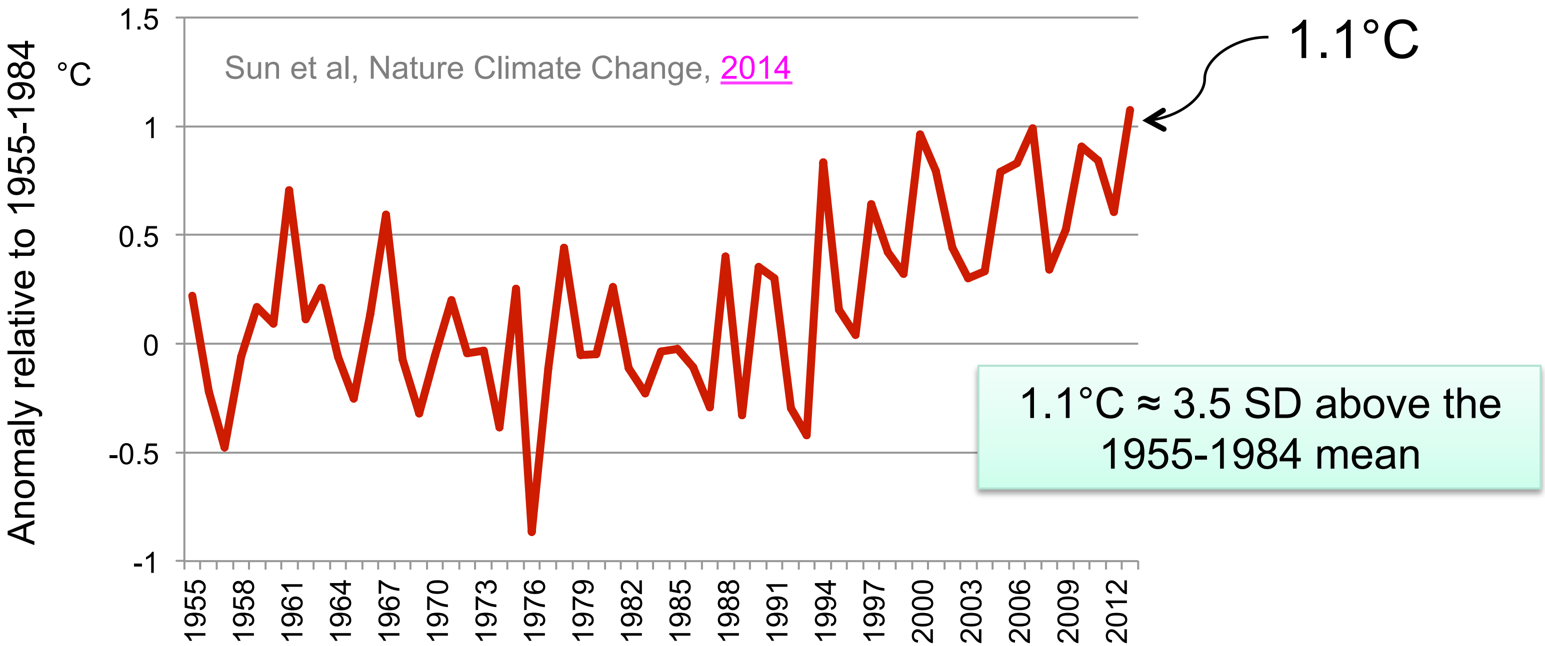
The multi-model ensemble mean (ALL forcing) well simulates the observed temperature record.

Detection and attribution results for change JJA climate over 1955-2012



- ALL forcing → 0.82°C (0.57°C, 1.07°C)
- NAT forcing → 0.03°C (-0.00°C, 0.07°C)
- Urban warming may be responsible for part of the “ALL” attributed warming - possibly 0.21°C (0.16°C, 0.26°C)

How rare was JJA of 2013?



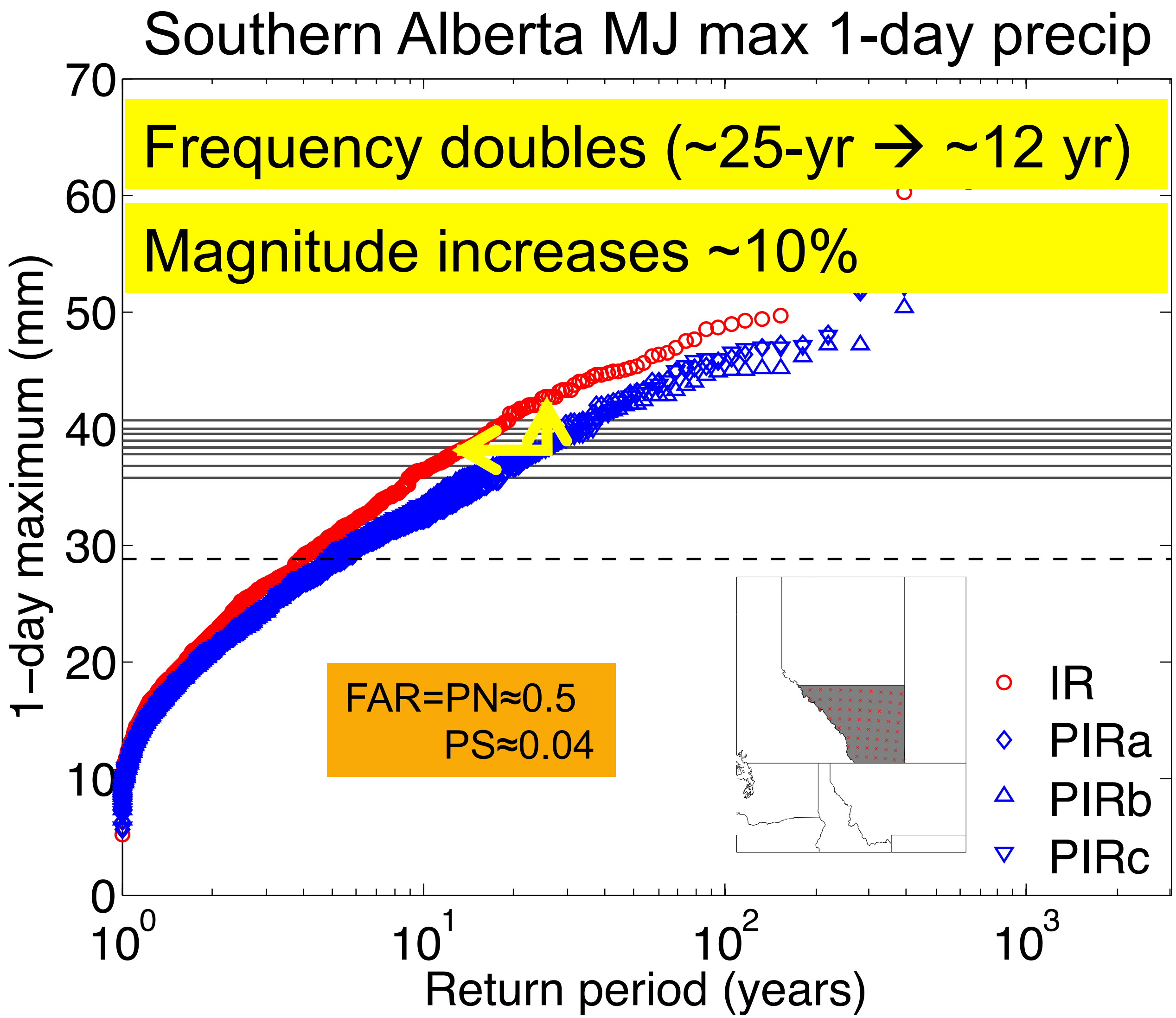
- Estimated event frequency
  - once in 270-years in control simulations
  - once in 29-years in “reconstructed” observations
  - once in 4.3 years relative to the climate of 2013
- Fraction of Attributable Risk in 2013: $(p_1 - p_0)/p_1 \approx 0.984$
- Prob of “sufficient causation”: $PS=1-((1-p_1)/(1-p_0)) \approx 0.23$

Calgary flood, 2013

Looking towards downtown Calgary from Riverfront Avenue (June 21, 2013), courtesy [Ryan L.C. Quan]

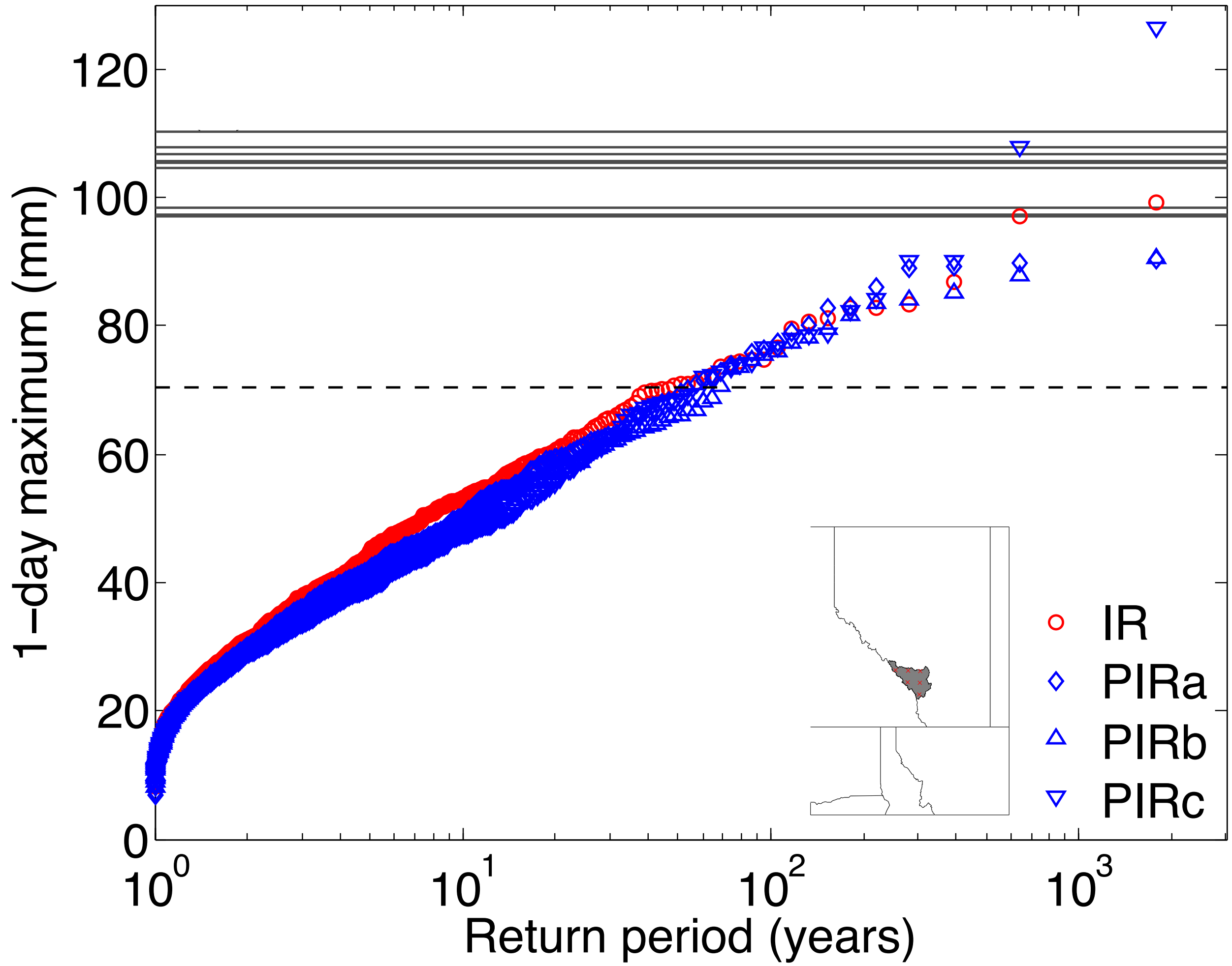
Calgary floods (Teufel et al, accepted)

Distribution of annual May-June maximum 1-day southern-Alberta precipitation in CRCM5 under factual and counter-factual conditions (conditional on prevailing global pattern of SST anomalies)



Calgary floods (Teufel et al, accepted)

Distribution of annual May-June maximum 1-day Bow River Basin precipitation in CRCM5 under factual and counter-factual conditions (conditional on prevailing global pattern of SST anomalies)

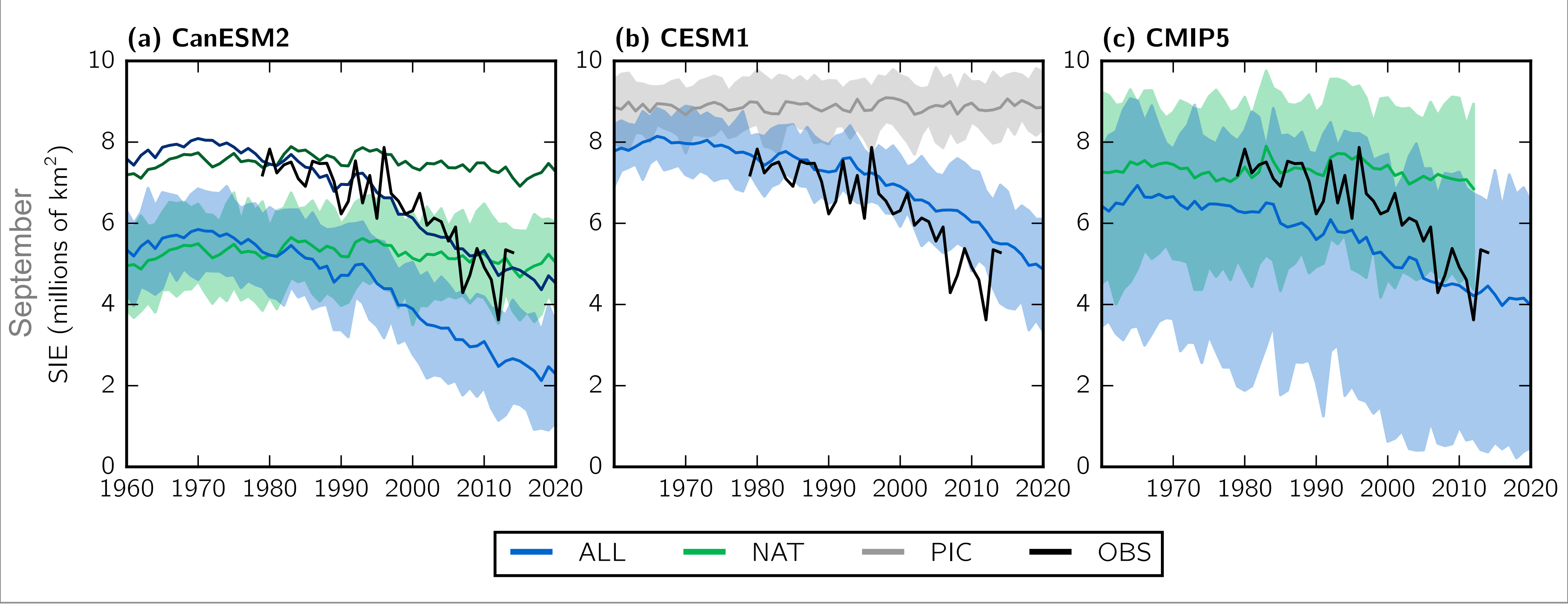


Arctic sea-ice extent extremes

Photo: F. Zwiers **(approach to Alert, Aug., 2009)**

Ensembles of ALL and NAT Forcing

Simulate Arctic sea ice extent (SIE) under anthropogenic + natural forcings (ALL) and only natural forcings (NAT) and compare the probabilities of occurrence of a particular extreme event under each forcing.



N = 50 N = 30 N = 35

Internal Variability Comparison

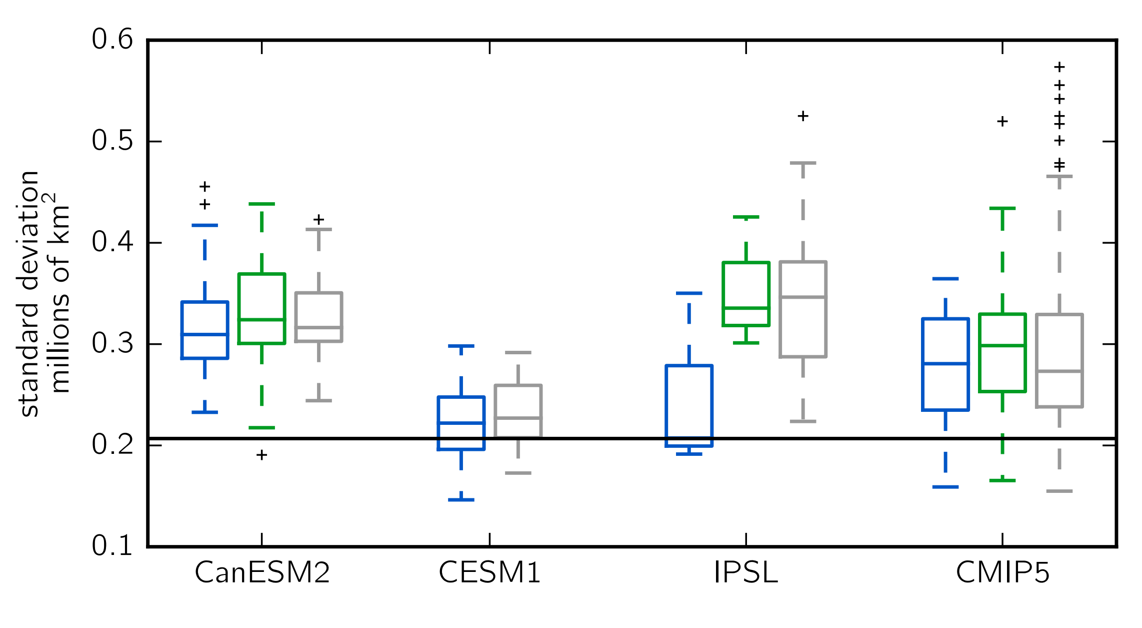
How does model internal variability compare to observations?

Compare standard deviation of each annual SIE time series with observed (black line).

ALL **NAT** **PIC**

A linear trend has been removed from ALL and OBS before the standard deviation is computed.

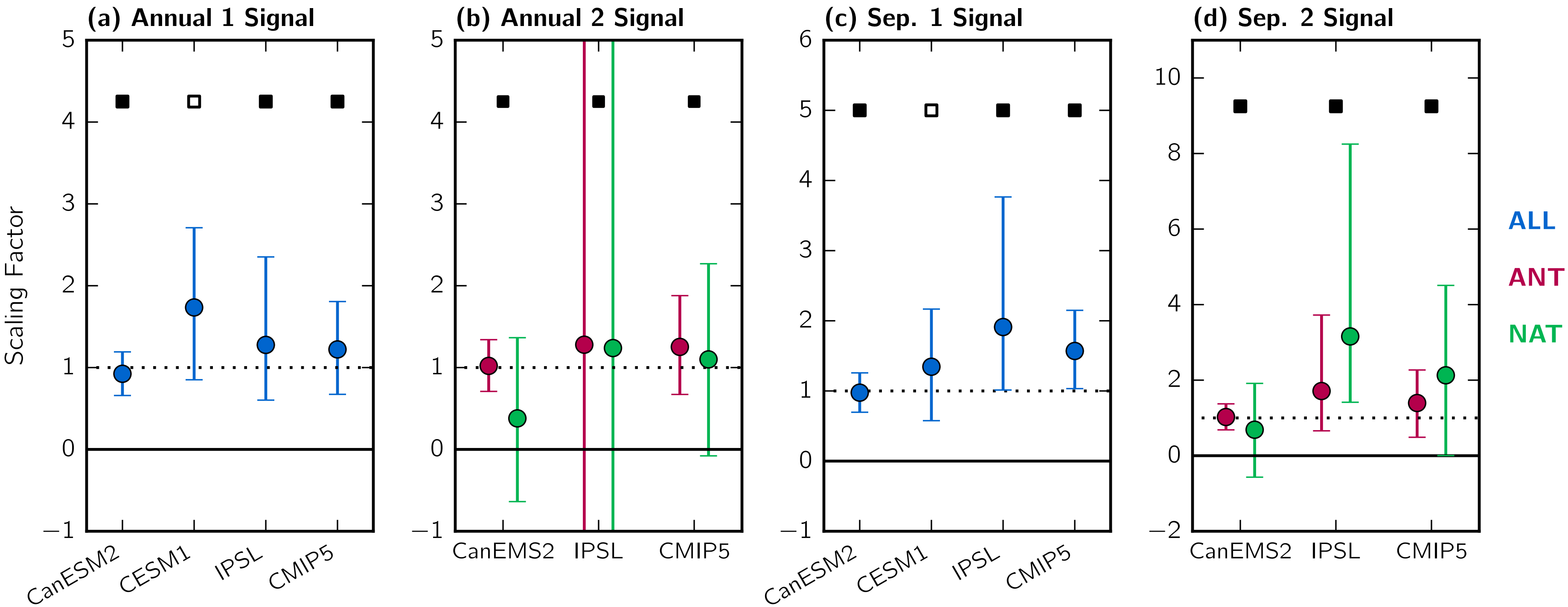
Standard Deviation of annual mean SIE after trend removal



- Most models show more variability than observations
- Generally good agreement between forcing scenarios
- CESM1 underestimates variability in Sep.

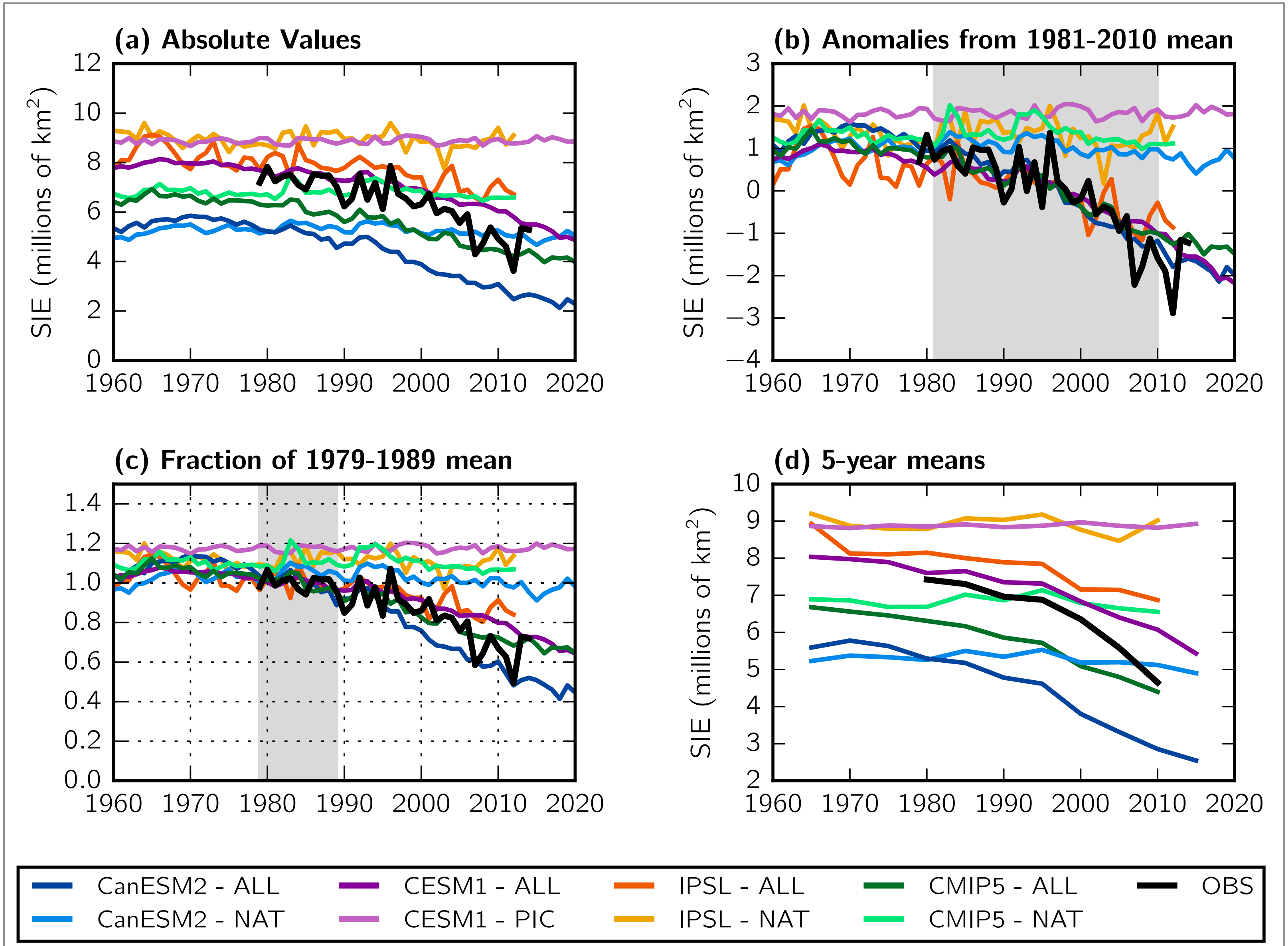
Detection/Attribution Results

How much of the observed temporal pattern in SIE can be explained by the ALL and NAT responses?



ALL and ANT forcing signals detected with almost all models for both annual and Sep. and are generally consistent in magnitude with observations

Defining SIE Extreme Events



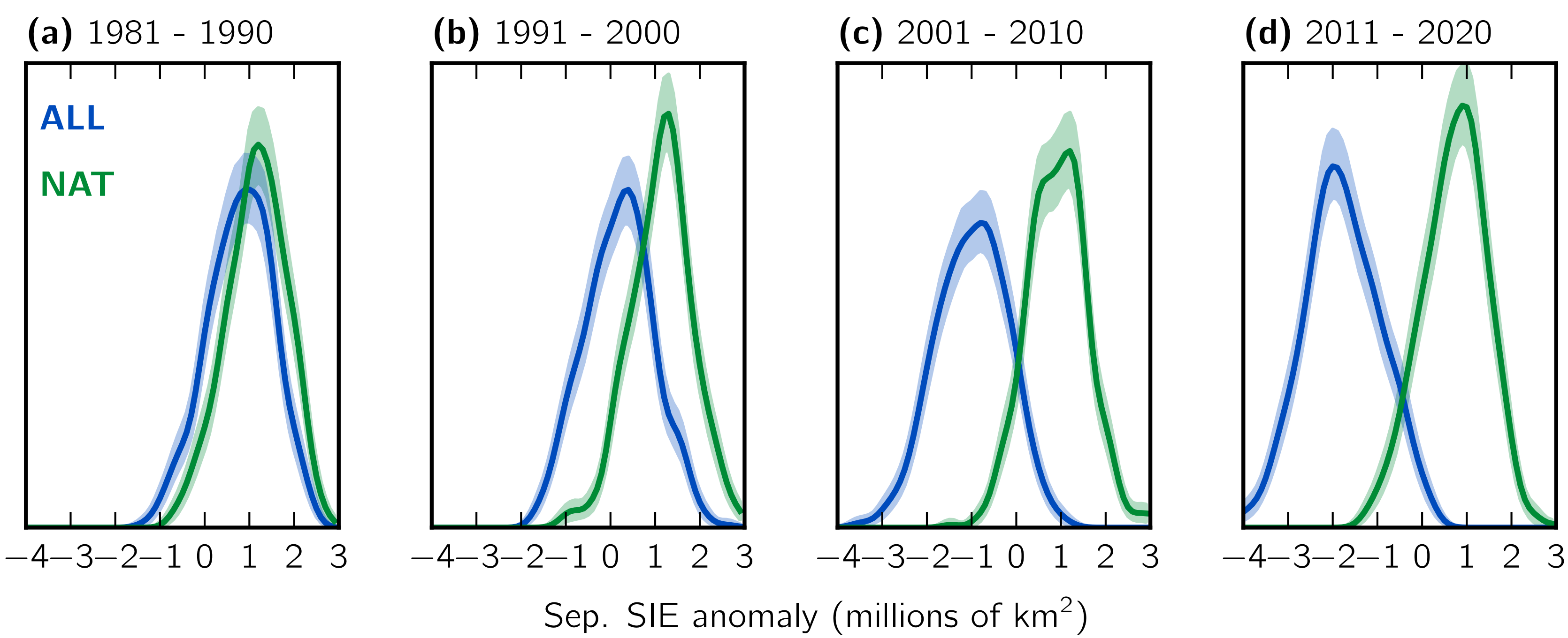
Event Attribution Methods

(1) Pool data from all ensemble members for each decade

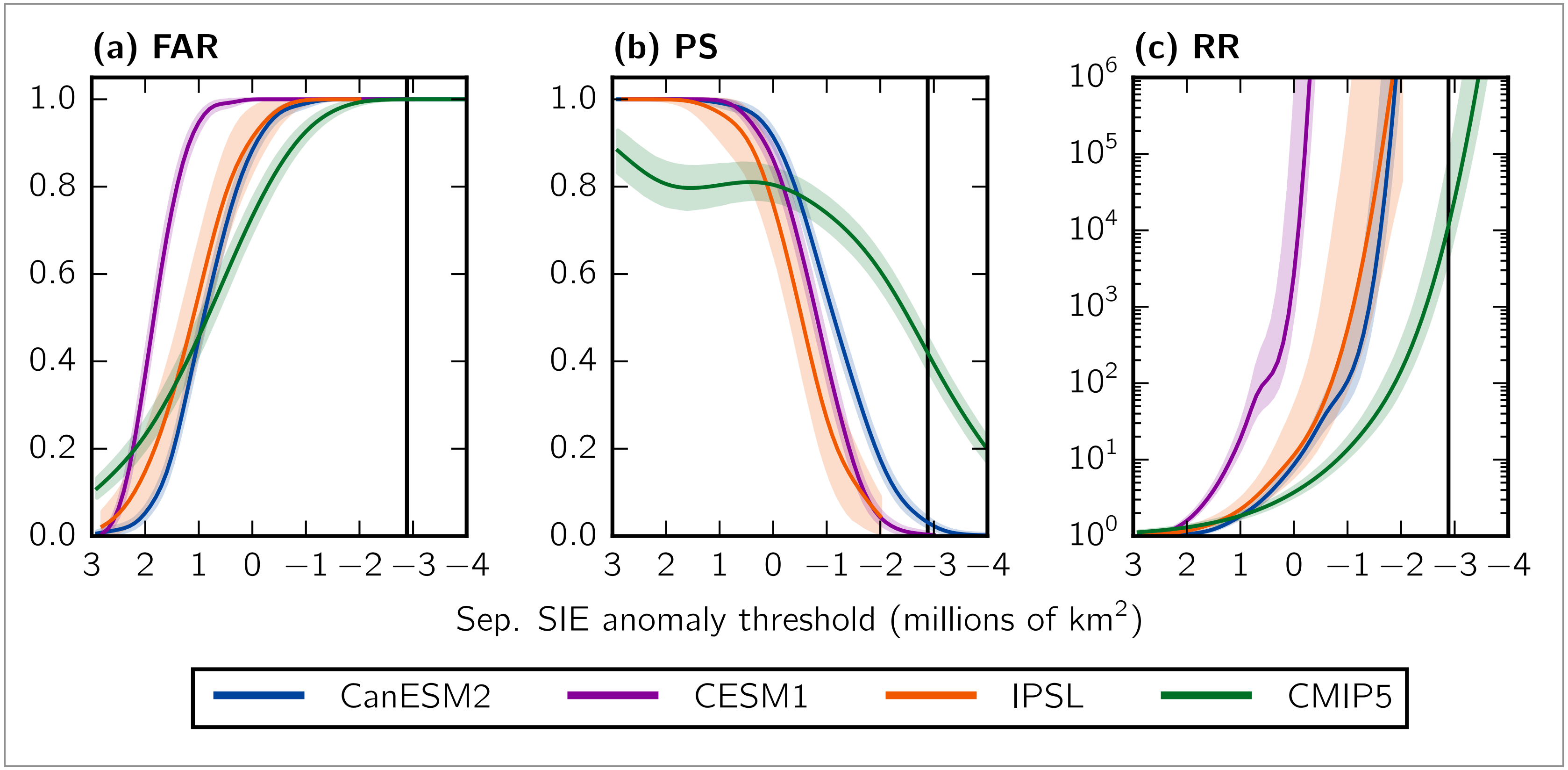
(2) Fit density curves

(3) Integrate to determine probability of an event more extreme than each anomaly threshold

(4) Compare probability of event under ALL forcing with the probability of the same event under NAT forcing

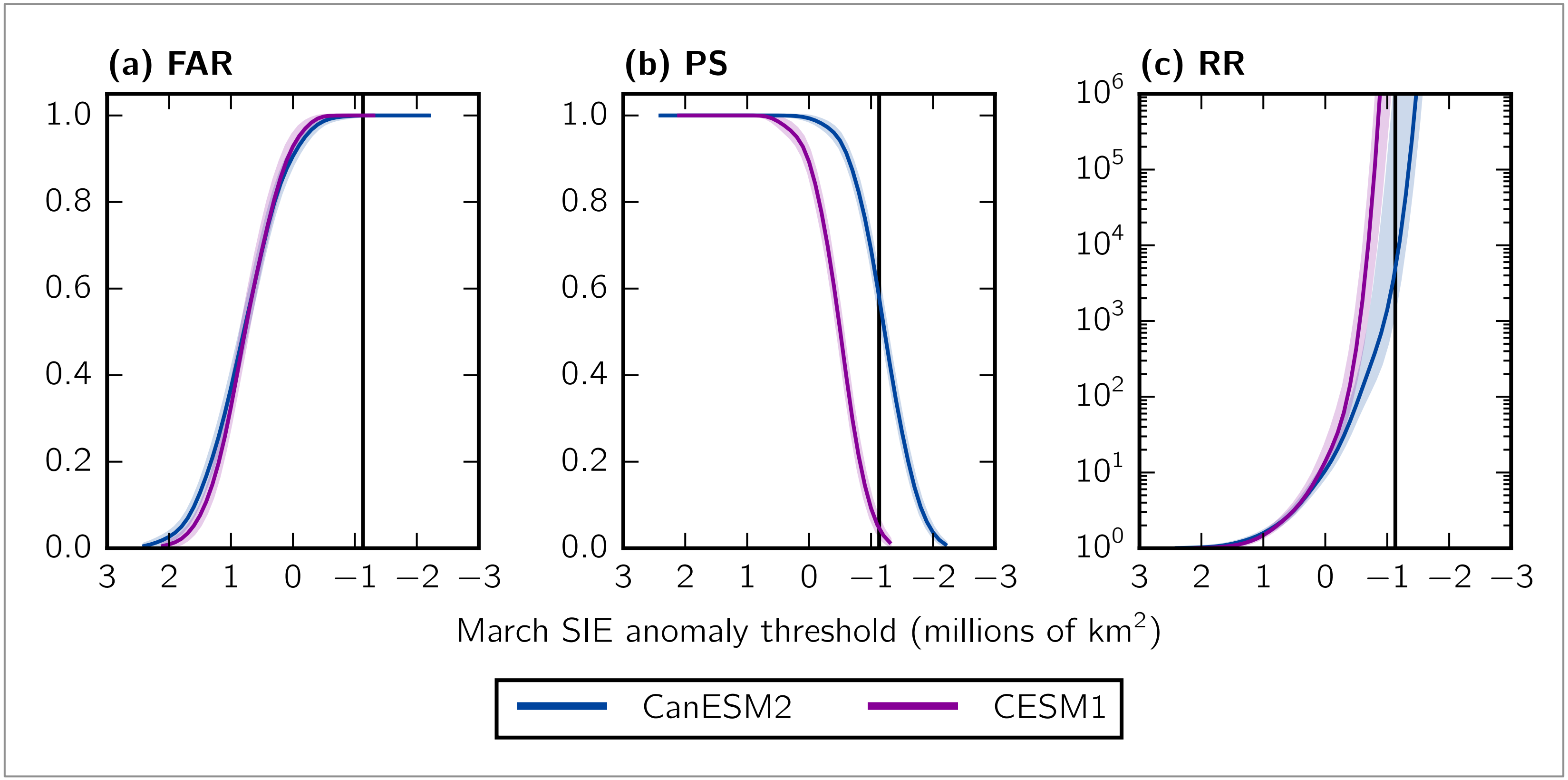


Event Attribution Results – Sep.



All models indicate an event of a magnitude equal to or more extreme than the 2012 record minimum would be *exceptionally unlikely* to occur under natural forcing alone. ALL forcing is a necessary, but not sufficient cause.

Event Attribution Results – Mar.

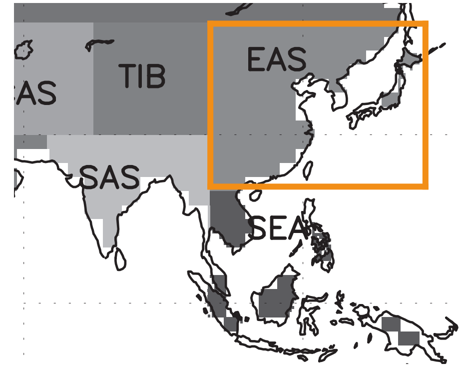


Both models indicate ALL forcing is a necessary condition for the 2015 event. In CanESM2 it is also almost a sufficient condition.

Some unresolved issues

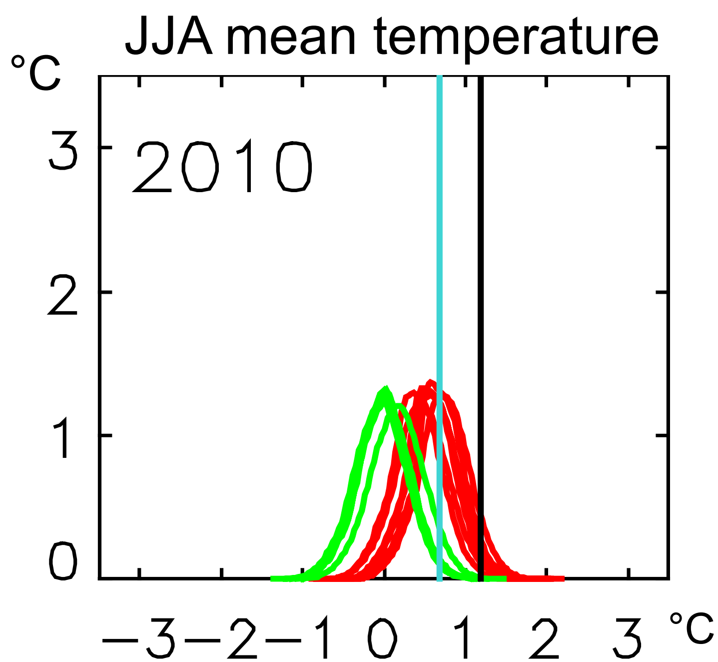
Photo: F. Zwiers

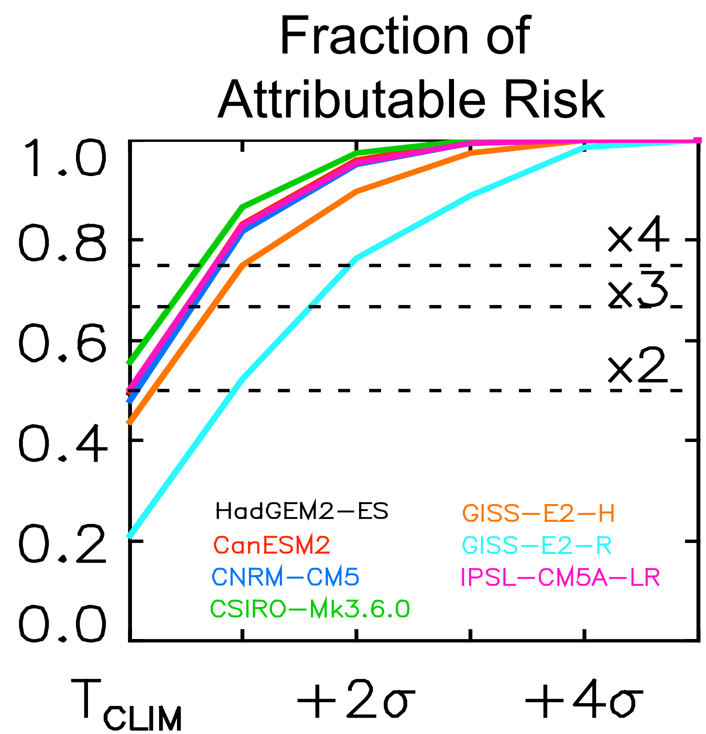
Retrospective vs prospective



- Most studies are prompted by specific events
- Alternatively, could study pre-defined events

Distribution of annualJJA temperature in the 2000's relative to 1961-90 in East Asia with and without ANT forcing





Christidis et al, 2014

Some unresolved issues

- Event characterization
  - Class vs individual, risk-based vs storyline
  - Individual is not synonymous with storyline
  - Data assimilation approach of Hannart et al (2016)
- Event definition
- Dependence on models
- Counterfactual state specification uncertainty when conditional approach is used
- Selection bias
  - Need objective event selection criteria
- Communications
  - At each stage media and response/recovery cycle


Questions?
Photo: F. Zwiers