DETECTION AND ATTRIBUTION FOR SPATIAL EXTREMES

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Invited lecture at IMSI workshop on

Confronting Climate Change

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Acknowledgement and Co-Authors

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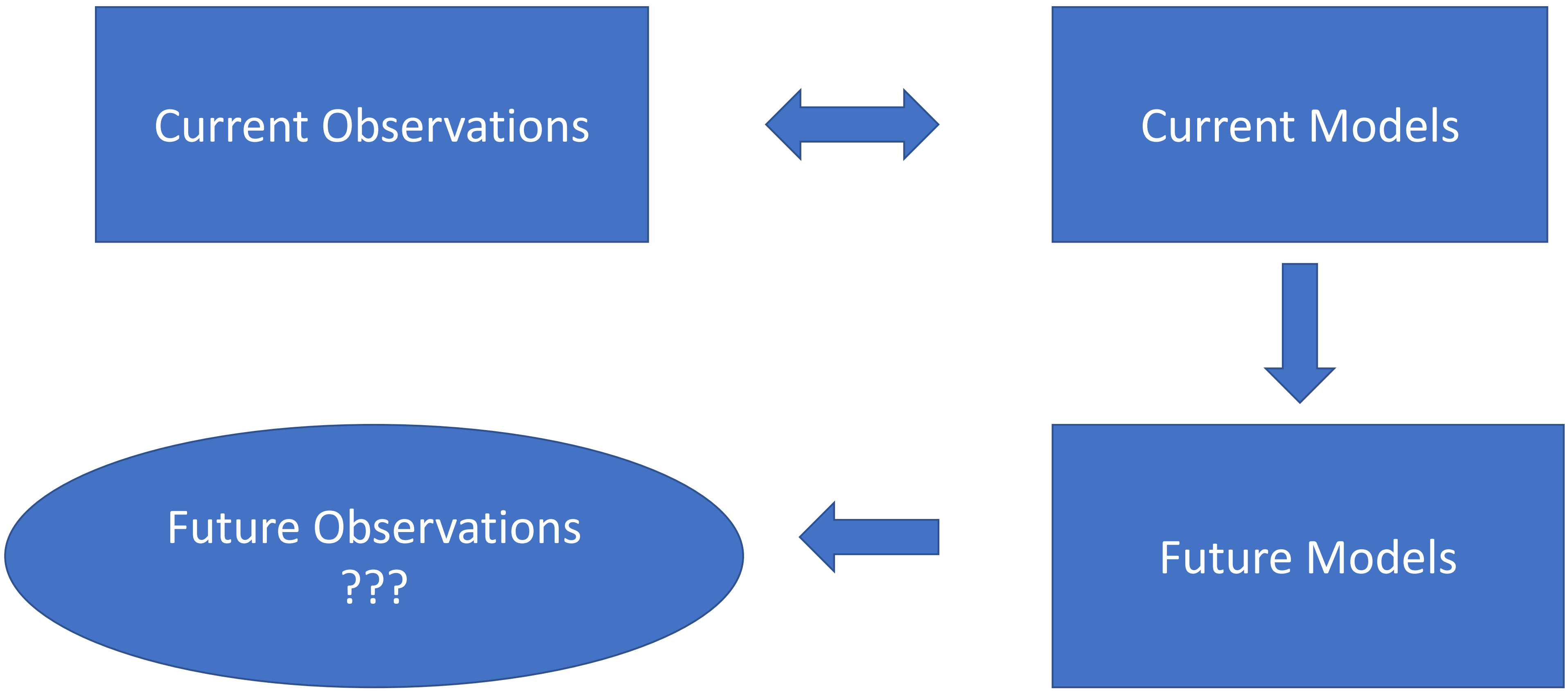
Conceptual Picture



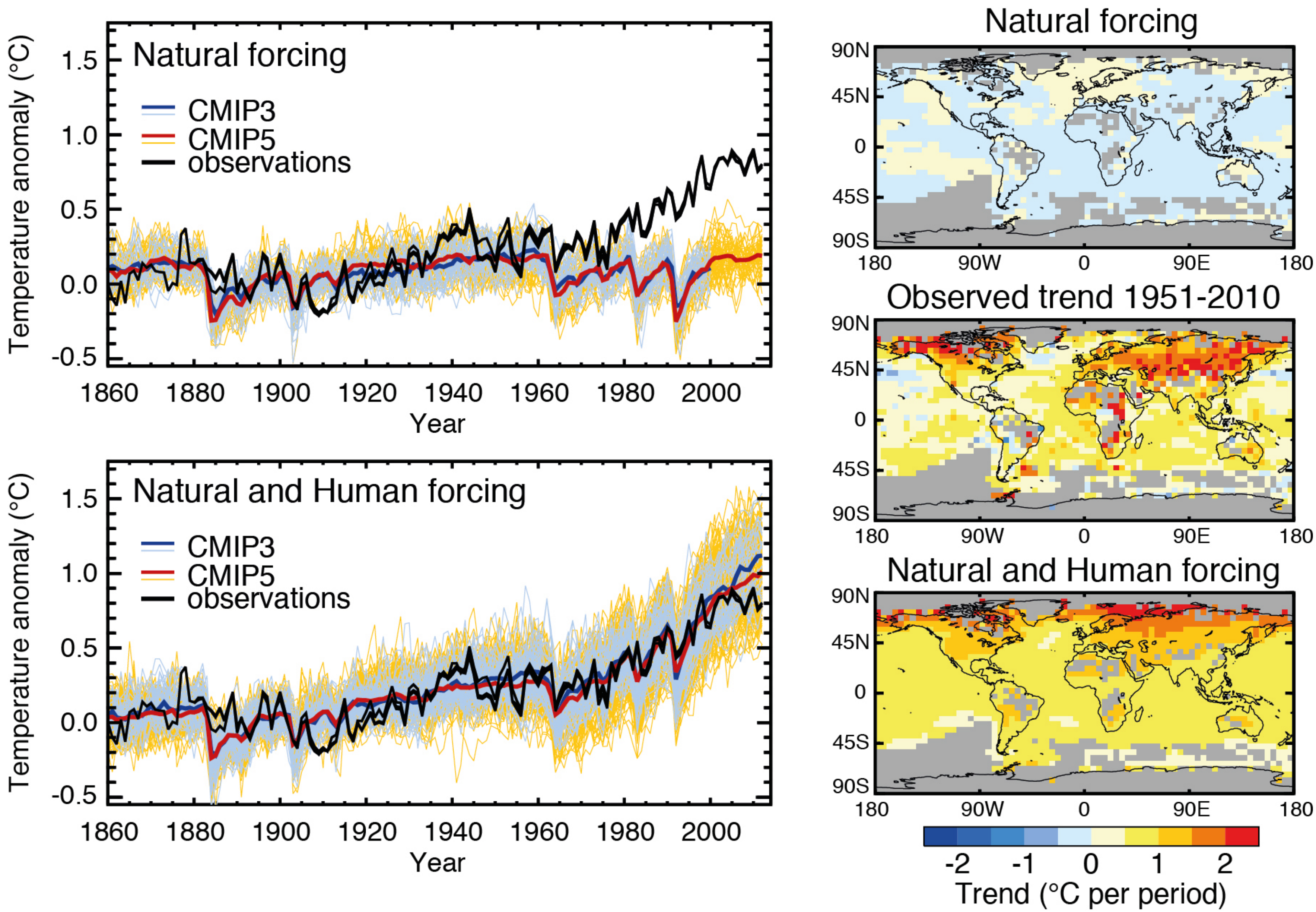
Outline of Talk

- Detection and attribution for climate means
- Detection and attribution for climate extremes
- Spatial extremes

What is "Detection and Attribution" all about?

- Climate scientists often make statements like "It is extremely likely* that human influence has been the dominant cause of the observed warming since the mid-20th century" (Fifth IPCC Report, 2013)
- How are such assessments made?
  - We can take any climate variable (simplest is global mean temperature) and plot its change over, say, 1950 to present day
  - A *climate model* can be used to simulate the same variable under *anthropogenic forcing* — taking into account changes in greenhouse gases, other pollutants including particulate matter, and other man-made effects such as land use change
  - However, we can also run the same climate model under *natural forcing* — just things like solar fluctuations, volcanic eruptions, changes in earth's orbit, and other things that could not possibly have a human cause
  - The anthropogenic signal is said to be *detected* if we can prove it has an influence on the observed pattern of climate change
  - Given that it is detected, an *attribution* is a statement showing what proportion of the observed change is due to human influence

*Greater than 95% probability



Natural forcing
CMIP3
CMIP5
observations
Temperature anomaly (°C)
1.5
1.0
0.5
0.0
-0.5
1860
1880
1900
1920
1940
1960
1980
2000
Year
Natural and Human forcing
CMIP3
CMIP5
observations
Temperature anomaly (°C)
Year
Natural forcing
Observed trend 1951-2010
Natural and Human forcing
90N
45N
0
45S
90S
180
90W
0
90E
180
-2
-1
0
1
2
Trend (°C per period)

Statistical Model
(Allen & Tett 1999; Allen & Stott 2003)

Observed trends $\mathbf{y}$; modeled trends $\mathbf{x}_1, \ldots \mathbf{x}_M$ corresponding to M climate models (e.g. $M = 2$; one anthropogenic, one natural)

Regression equation

$$\mathbf{y} \;=\; \sum_{j=1}^{M} \beta_j \mathbf{x}_j + \mathbf{u}, \;\; \mathbf{u} \sim N[\mathbf{0}, \mathbf{C}]$$

Writing $\mathbf{X} = \begin{pmatrix} \mathbf{x}_1 & \ldots & \mathbf{x}_M \end{pmatrix}$, $\boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_M \end{pmatrix}$, we have

$$\widehat{\boldsymbol{\beta}} \;=\; \left(\mathbf{X}^T\mathbf{C}^{-1}\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{C}^{-1}\mathbf{y} \text{ with Cov } \widehat{\boldsymbol{\beta}} \;=\; \left(\mathbf{X}^T\mathbf{C}^{-1}\mathbf{X}\right)^{-1}.$$

Extensions

- In practice $\mathbf{y}$ and $\mathbf{x}_1, \ldots \mathbf{x}_M$ are very high dimensional; $\mathbf{C}$ is ill-defined and $\mathbf{C}^{-1}$ even more so

- The traditional solution: use an *empirical orthogonal function* (also called *principal components*) decomposition to reduce the dimension to something manageable (e.g. 10 to 20).

- Another complication: unlike traditional regression analysis where the X's are treated as fixed, $\mathbf{x}_1, \ldots, \mathbf{x}_M$ are also random quantities. The most common solution involves *total least squares* analysis

- Numerous refinements over the past 5–10 years, but I'll mention just one here: Katzfuss, Hammerling and Smith (*GRL*, 2017) proposed a Bayesian algorithm.

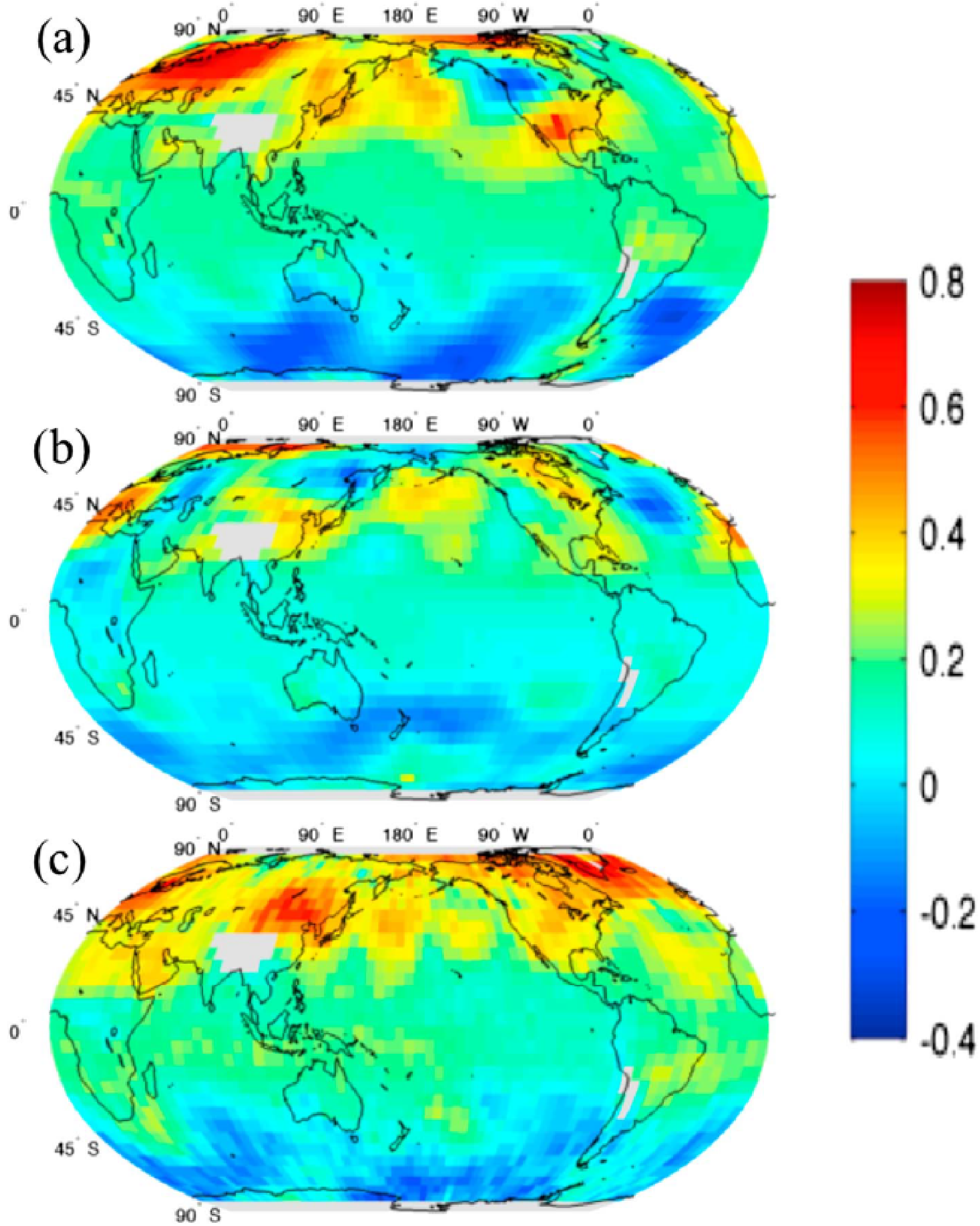


Figure 1. Linear tropospheric temperature trend (in °C per decade) for the period 1979–2005 for the giss e2 r p1 model run using (a) only anthropogenic forcing and (b) only natural forcing, and (c) the average of 396 observational ensemble members from RSS. Areas in grey were excluded from the analysis due to the absence of satellite observations.

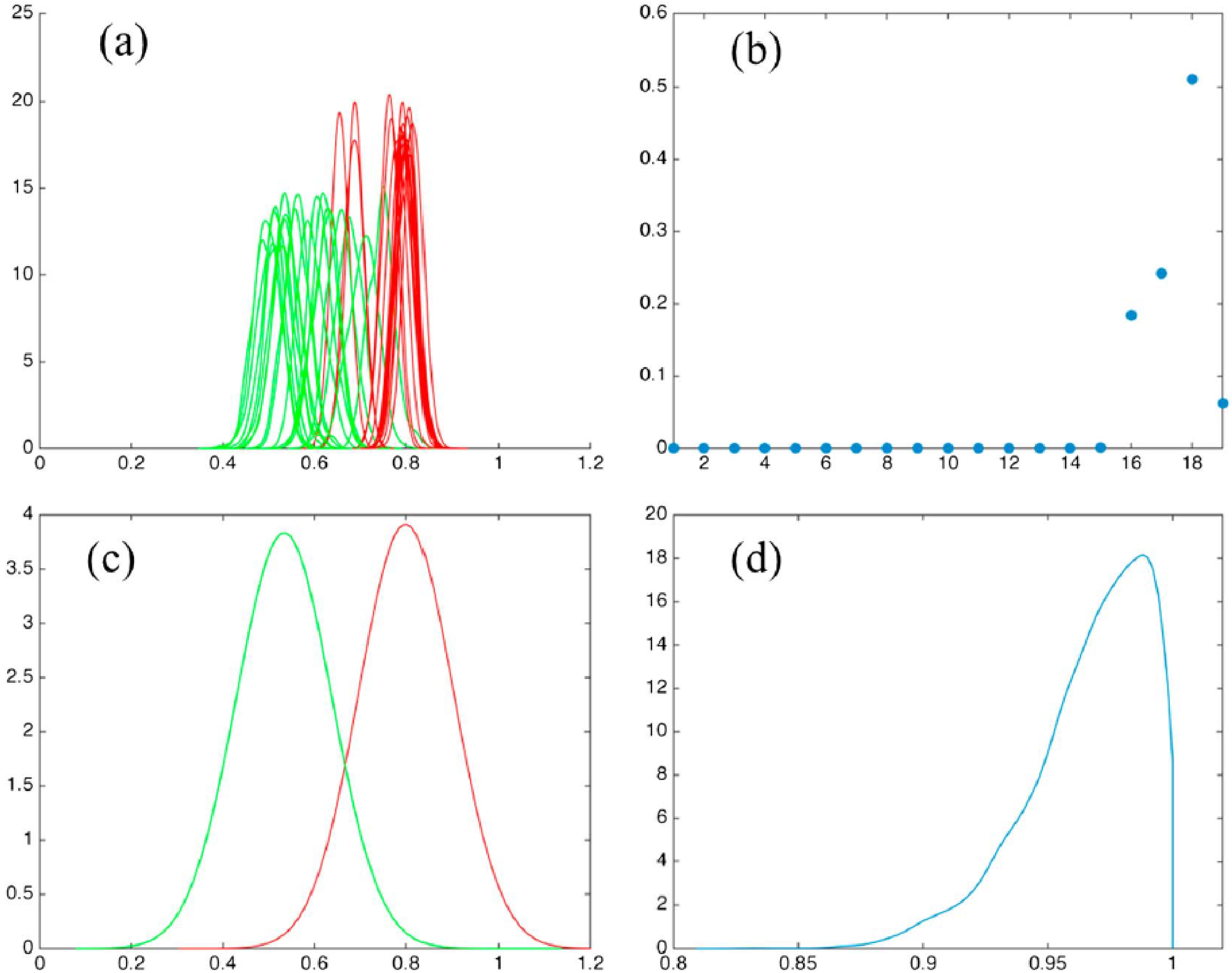


Figure 2. Results for the tropospheric temperature data analysis. (a) Posterior distributions of β_1 (anthropogenic forcing) in red and β_2 (natural forcing) in green for each EOF truncation $r \in \{1, \dots, 19\}$. (b) Posterior probabilities for different values of r. (c) Marginal posterior distributions of β_1 and β_2 obtained by Bayesian model averaging over r. (d) Posterior distribution of p values for the residual consistency test.

Detection and Attribution for Extreme Events

- Stott, Stone and Allen (*Nature*, 2004) — the original paper
- Annual issue of BAMS; NRC report (2016)
- Suppose we observe some extreme event. Using climate models, estimate the probability p_0 under natural forcings or p_1 under natural and anthropogenic forcings.
- The *fraction of attributable risk* is defined to be $1 - \frac{p_0}{p_1}$, assuming $p_0 < p_1$.
- Alternatively, use *risk ratio* $\frac{p_1}{p_0}$.
- It's still a challenge how to estimate p_0 and p_1. *Extreme value theory* is a class of statistical techniques for estimating extreme event probabilities under finite samples of data.

How Extreme was Hurricane Harvey?

- Hurricane Harvey hit the Houston area at the end of August 2017

- Very excessive precipitations led to major flooding

- Meteorologically, associated with a stalling of the storm system just off the Gulf coast, but recent work by Kossin and others has suggested such events are becoming more common overall

- Statistically, questions about (a) just how extreme an event this was, (b) whether such events will become more common in the future

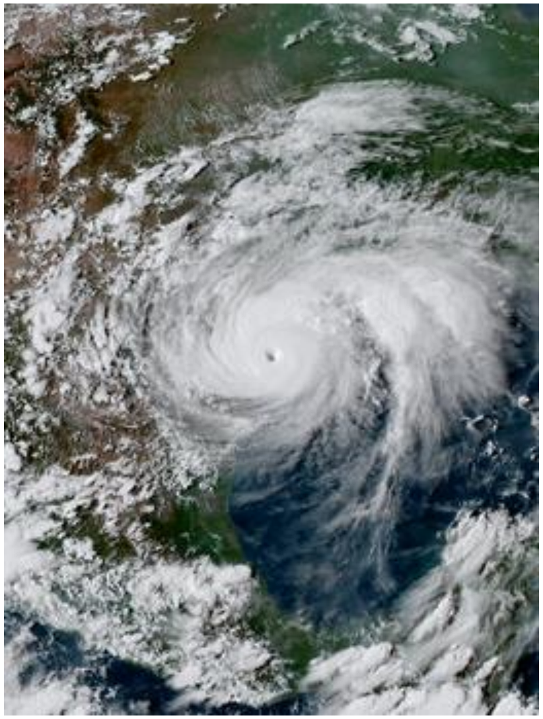


Photo Credits: NASA, CNN, Wikipedia, National Geographic

Scientific questions

1. How extreme was this event?
   - May be characterized as a once in N years event — but what is N?
   - What is the uncertainty of such a statement?

2. To what extent can the event be "attributed" to human influence?

3. What are the projected probabilities of a similar event in the future?

Other references on Hurricane Harvey:

- Van Oldenborgh et al, *Environmental Research Letters*, 2017
  - GEV applied to precipitation data from both observations and models, used global temperatures as a covariate
- Risser and Wehner, *GRL*, 2017
  - GEV applied to annual max 7-day precipitations, used Nino 3.4 and global CO_2 as covariates, no climate models
- Emanuel, *PNAS*, 2017
  - Not a statistical approach, used atmospheric model simulations under present-day and projected future conditions
- and others...

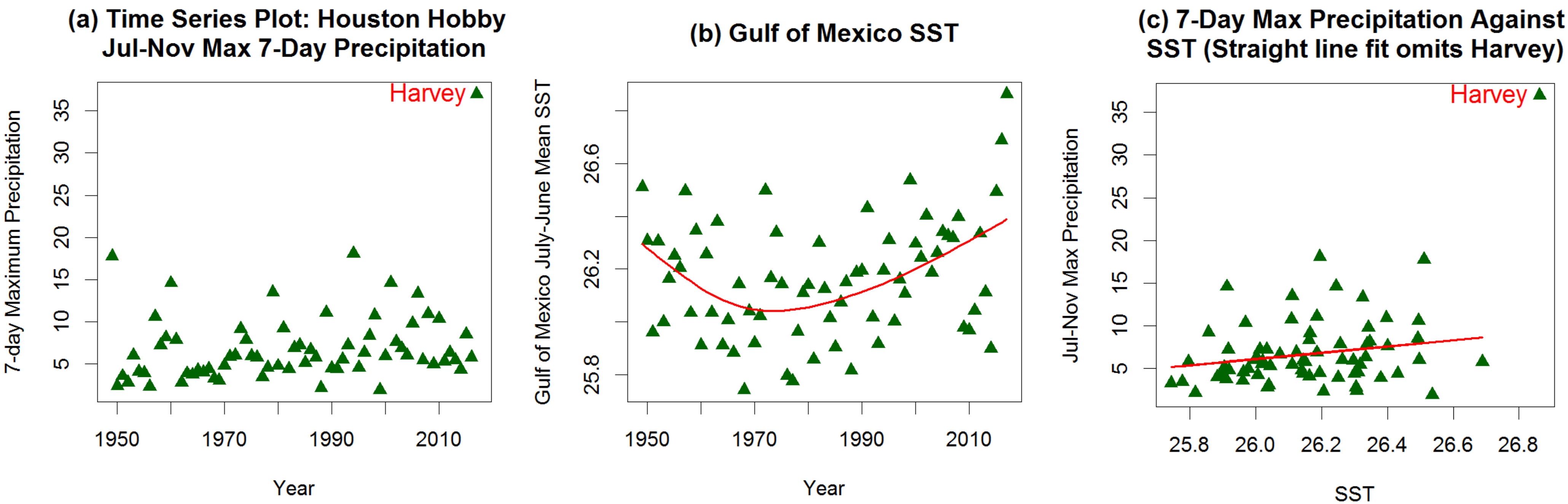
Analysis from a Single Station (Hammerling *et al.*, 2019)

- Precipitation data from Houston Hobby airport
- For each year, calculate max 7-day precipitation from June–November
- Also, mean Gulf of Mexico SST for year ending June 30
- Plotting the data suggests

(a) Steady increase in max precips. over $\sim$70 years, but Harvey a particular outlier

(b) SSTs have also risen slowly with 2016-7 largest in history

(c) Even excluding Harvey, there appears to be a positive relationship between the two



(a) Annual max 7-day precipitation in Houston, 1949–2016

(b) Annual mean Gulf of Mexico SST

(c) Plotting the annual 7-day max precipitation against the annual mean Gulf of Mexico SST

Statistical Methodology

- Annual maxima follow GEV:

$$\text{Pr}\{Y_t \le y\} = \exp\left[-\left\{1+\xi\left(\frac{y-\eta_t}{\tau_t}\right)\right\}_+^{-1/\xi}\right].$$

- Assume η_t and $\log\,\tau_t$ are linear functions of SST_t (Gulf of Mexico annual mean SST in year t) and $CO2_t$ (global mean CO_2 in year t).

- AIC chooses model:

$$\begin{aligned} \eta_t &= \theta_1 + \theta_4 SST_t + \theta_5 CO2_t, \\ \log\tau_t &= \theta_2 + \theta_6 SST_t, \\ \xi &= \theta_3. \end{aligned}$$

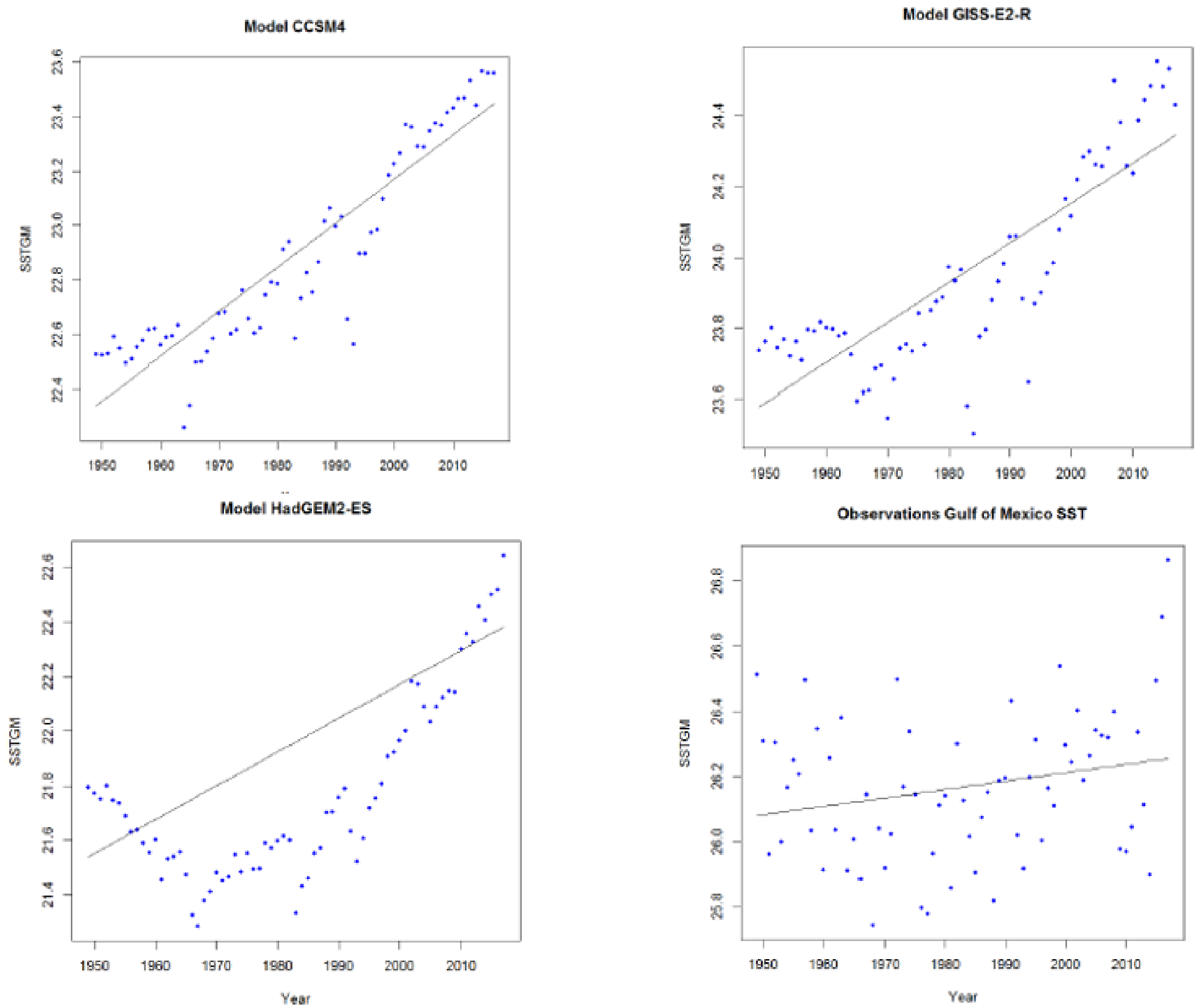
Parameter Estimates

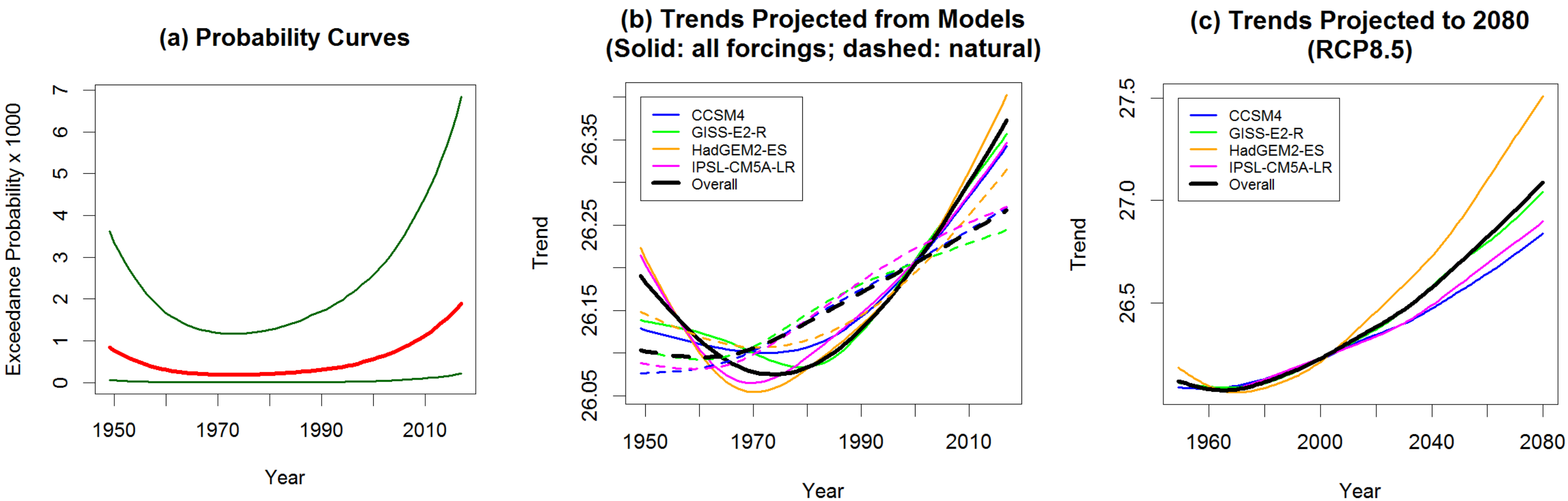
Parameter	Estimate	Standard error	t-statistic	p-value
θ_1	4.70	0.29	16.22	0.00
θ_2	0.56	0.13	4.25	0.00
θ_3	0.15	0.09	1.64	0.10
θ_4	3.06	1.49	2.06	0.04
θ_5	1.95	0.82	2.36	0.018
θ_6	1.24	0.50	2.48	0.013

Climate Model Projections

- Downloaded climate data from four climate models (part of CMIP5 archive)
- Computed GoM SSTs from three scenarios:
  - Historical data, all-forcings model
  - Historical data, natural forcings only
  - Future data (RCP8.5 scenario)
- Unfortunately, the historical data did not look much like the observational data
- To correct for this, a secondary detection and attribution analysis was performed on the SST data alone (regress observed SSTs on model values — either historical or natural)
- Hence, future projections...

GoM SST observations and models





(a) Estimated probability of a Harvey-sized event, as a function of SST, using EVT (66% confidence bands in green)

(b) Trends in SST from 4 climate models, under natural and natural+anthropogenic forcing

(c) Projected trends in SST through 2080, under "business as usual" emissions scenario

Relative Risks

Model	Present			Future		
	Lower	Mid	Upper	Lower	Mid	Upper
CCSM4	1.5	2.0	3.2	9.0	26.2	133
GISS-E2-R	1.8	2.5	4.8	13.5	43.5	244
HadGEM2-ES	1.6	2.1	3.5	23.6	73.3	415
IPSL-CM5A-LR	1.5	2.0	3.3	10.8	33.8	186
Combined	1.7	2.4	4.4	14.3	46.0	254

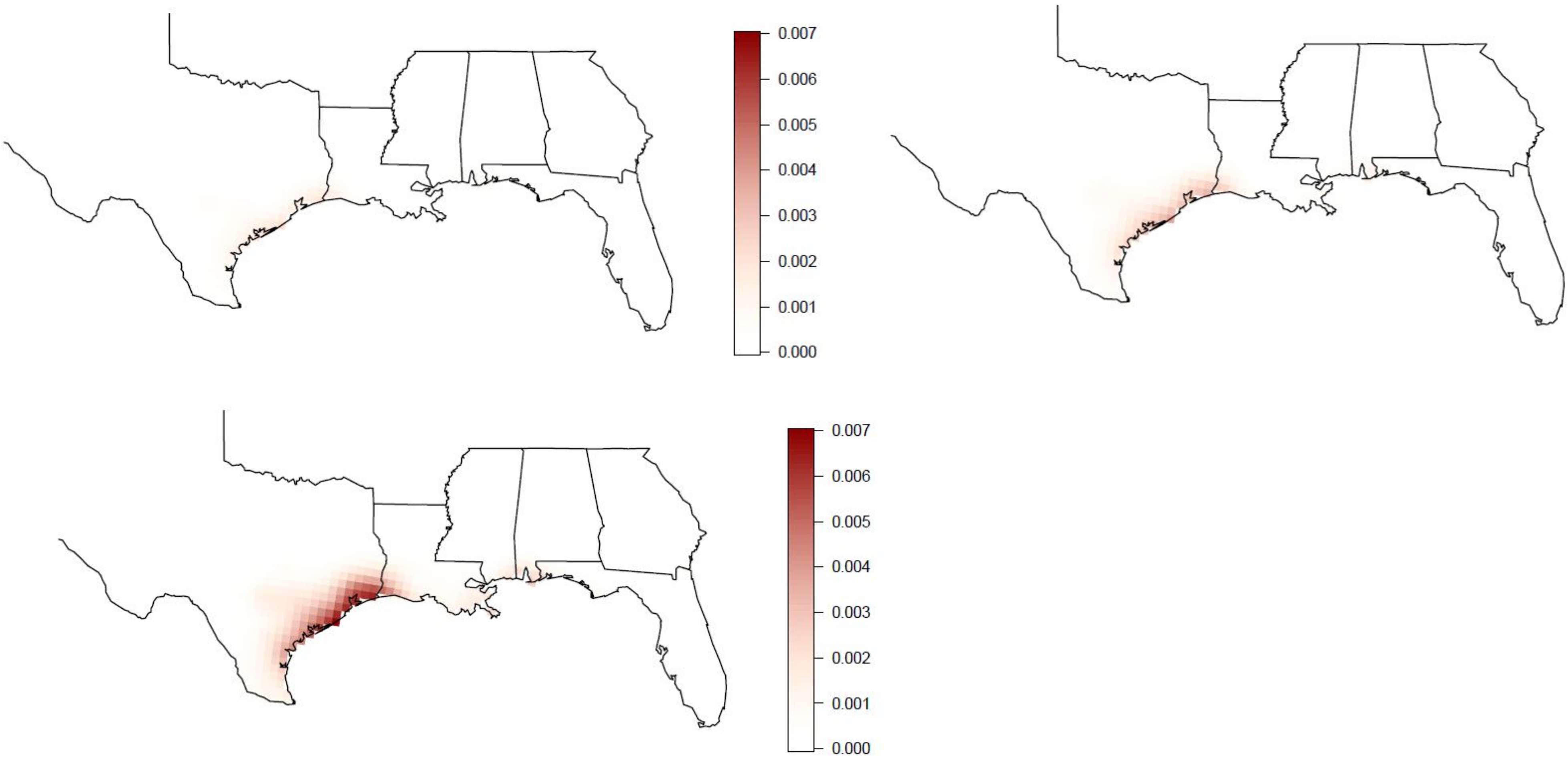
Relative risks. The columns labelled "Present" refer to relative risks for the 2017 event under an all-forcings scenario versus a natural-forcings scenario, computed under four climate models and with all four models combined. Lower, mid and upper bounds correspond to the 17th, 50th and 83rd percentiles of the posterior distribution. The columns labelled "Future" are relative risks for such an event in 2080 against 2017; same conventions regarding climate models and percentiles.

How Can We Extend This to a Spatial Field?

- Full “detection and attribution” not so far attempted, but this follows Russell *et al.* (*Environmetrics*, 2020)
- Precipitation data, 326 stations in 6 states bordering Gulf
- Model $\eta_t(\mathbf{s})$, $\tau_t(\mathbf{s})$, $\xi_t(\mathbf{s})$ in year t at station $\mathbf{s}$:

$$\begin{aligned} \eta_t(\mathbf{s}) &= \theta_1(\mathbf{s}) + \theta_2(\mathbf{s}) SST_t, \\ \log \tau_t(\mathbf{s}) &= \theta_3(\mathbf{s}) + \theta_4(\mathbf{s}) SST_t, \\ \xi_t(\mathbf{s}) &= \theta_5(\mathbf{s}), \end{aligned}$$

- $\boldsymbol{\theta}(\mathbf{s}) = \left(\begin{array}{ccc} \theta_1(\mathbf{s}) & \ldots & \theta_5(\mathbf{s}) \end{array} \right)^T$ modeled as a 5-dim spatial process based on *co-regionalization* (Wackernagel and many others)
- Two-stage estimation procedure allows also for spatial correlation among individual measurements



Estimated probability that the annual maximum seven-day rainfall event exceeds 70 cm. under three scenarios: low SST (top left); high SST (top right); 2017 SST (bottom). From Russell *et al.* (2020)

Summary

- Detection and attribution methods have played an important role in establishing the human role in climate change

- The more recent field of "detection and attribution for extremes" is less well defined despite a large literature — still many methods being used

- The literature on "spatial extremes" is still developing, but appears clearly relevant to the modeling of large-scale climate events

- CMIP6 is projected to generate about 20 PB of data

- Many possibilities for ambitious data science!!

References

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