A HIERARCHICAL MODEL FOR REGRESSION-BASED CLIMATE CHANGE DETECTION AND ATTRIBUTION

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www.unc.edu/~rls

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I. THE PUBLIC POLICY CONTEXT

II. HISTORY

III. OUTLINE OF STATISTICAL APPROACH

IV. NEW HIERARCHICAL MODELING APPROACH

V. CONCLUSIONS

I. THE PUBLIC POLICY CONTEXT

From the Fourth Assessment Report of IPCC —

Warming of the climate system is unequivocal, as is now evident from observations of increases in average air and ocean temperatures, widespread melting of snow and ice, and rising global average sea level

Most of the observed increase in global average temperatures since the mid-20th century is *very likely** **due to the observed increase in anthropogenic greenhouse gas concentrations**

*Greater than 90% chance

ASA Activities

- ASA has an *Advisory Committee on Climate Change Policy* (principal sponsor of this session)
  - Rick Katz (NCAR) — current chair

- ASA members have been included in three *climate science days* on Capitol Hill (thanks to Steve Pierson)

- Joint activities with other societies
  - I organized a symposium on *Communicating Uncertainty in Climate Change Science* at the AAAS meeting last February (Murali Haran, Mark Berliner, Lenny Smith speakers; Andy Revkin discussant)

II. HISTORY

On the signal-to-noise problem in atmospheric response studies

By KLAUS HASSELMANN
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SUMMARY

The problem of identifying the mean atmospheric response to external forcing in the presence of the natural variability of the atmosphere is treated as a pattern-detection problem. It is shown that without application of filtering techniques to reduce the number of degrees of freedom of the response pattern the atmospheric response inferred from data or model experiments will normally fail a multi-variate significance test. A step-wise pattern construction method is proposed which avoids these difficulties. Starting from a

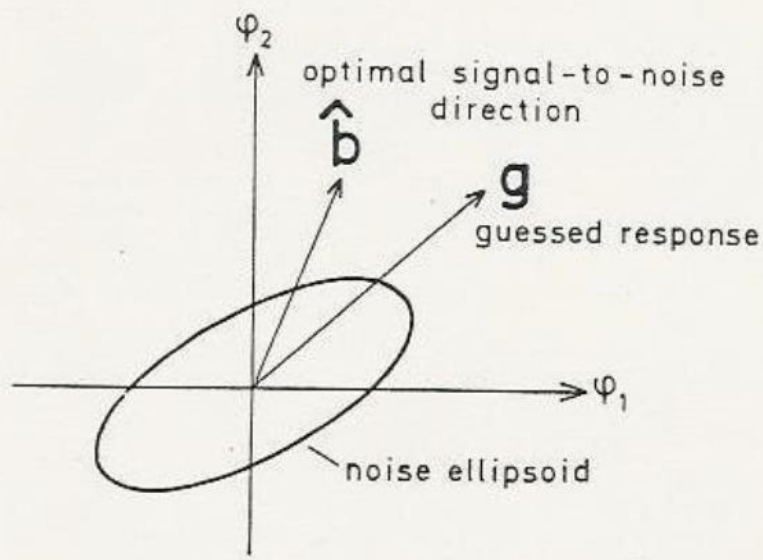

Figure 1. Relation between guessed response pattern vector g and maximal significance direction $\hat{\mathbf{b}}$ relative to error ellipsoid, see Eq. (27).

Detecting Greenhouse-Gas-Induced Climate Change with an Optimal Fingerprint Method

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ABSTRACT

A strategy using statistically optimal fingerprints to detect anthropogenic climate change is outlined and applied to near-surface temperature trends. The components of this strategy include observations, information about natural climate variability, and a "guess pattern" representing the expected time–space pattern of anthropogenic climate change. The expected anthropogenic climate change is identified through projection of the observations onto an appropriate optimal fingerprint, yielding a scalar-detection variable. The statistically optimal

Climate Dynamics (1999) 15:419–434

M. R. Allen · S. F. B. Tett

Checking for model consistency in optimal fingerprinting

Abstract Current approaches to the detection and attribution of an anthropogenic influence on climate involve quantifying the level of agreement between model-predicted patterns of externally forced change and observed changes in the recent climate record. Analyses of uncertainty rely on simulated variability from a climate model. Any numerical representation of the climate is likely to display too little variance on small spatial scales, leading to a risk of spurious detection results. The risk is particularly severe if the detection strategy involves optimisation of signal-to-noise because unrealistic aspects of model variability may automatically be given high weight through the optimisation. The solution is to confine attention to aspects of the model and of the real climate system in which the model simulation of internal climate variability is adequate, or, more accurately, cannot be shown to be deficient. We propose a simple consistency check based on standard linear regression which can be applied to ... model response are correct, and neglecting the possibility of non-linear feedbacks, the amplitude of the observed signal suggests a climate sensitivity range of 1.2–3.4 K, although the upper end of this range may be underestimated by up to 25% due to uncertainty in model-predicted response patterns.

1 Introduction

A common overall approach has emerged to the detection of anthropogenic climate change. A detection statistic is defined and evaluated in an observational dataset. This might be a global mean quantity (e.g. Stouffer et al. 1994); a model versus observation pattern correlation (Mitchell et al. 1995a; Tett et al. 1996); the observed trend in pattern correlation (Santer et al. 1996); or some form of "optimised fingerprint" (Hasselmann 1979; Hannoschöck and Frankignoul 1985; Bell

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M. R. Allen · P. A. Stott

Estimating signal amplitudes in optimal fingerprinting, part I: theory

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Abstract There is increasingly clear evidence that human influence has contributed substantially to the large-scale climatic changes that have occurred over the past few decades. Attention is now turning to the physical implications of the emerging anthropogenic signal. Of particular interest is the question of whether current climate models may be over- or under-estimating the amplitude of the climate system's response to external forcing, including anthropogenic. Evidence of a signifi-

1 Introduction

This study describes a variant of the regression-based technique of climate change detection and attribution that is generally known as "optimal fingerprinting" (see, e.g. Hasselmann 1979, 1993, 1997; Bell 1986; North et al. 1995; Leroy 1998; Allen and Tett 1999). The finger-printing approach is to define a pattern of response to

Statistical Principles for Climate Change Studies

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ABSTRACT

Statistical principles underlying "fingerprint" methods for detecting a climate change signal above natural climate variations and attributing the potential signal to specific anthropogenic forcings are discussed. The climate change problem is introduced through an exposition of statistical issues in modeling the climate signal and natural climate variability. The fingerprint approach is shown to be analogous to optimal hypothesis testing procedures from the classical statistics literature. The statistical formulation of the fingerprint scheme suggests new insights into the implementation of the techniques for climate change studies. In particular, the statistical testing ideas are exploited to introduce alternative procedures within the fingerprint model for attribution of climate change and to shed light on practical issues in applying the fingerprint detection strategies.

Bayesian Climate Change Assessment

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(Manuscript received 20 September 1999, in final form 10 January 2000)

ABSTRACT

A Bayesian fingerprinting methodology for assessing anthropogenic impacts on climate was developed. This analysis considers the effect of increased CO_2 on near-surface temperatures. A spatial CO_2 fingerprint based on control and forced model output from the National Center for Atmospheric Research Climate System Model was developed. The Bayesian approach is distinguished by several new facets. First, the prior model for the amplitude of the fingerprint is a mixture of two distributions: one reflects prior uncertainty in the anticipated value of the amplitude under the hypothesis of "no climate change." The second reflects behavior assuming "climate change forced by CO_2." Second, within the Bayesian framework, a new formulation of detection and attribution analyses based on practical significance of impacts rather than traditional statistical significance was presented. Third, since Bayesian analyses can be very sensitive to prior inputs, a robust Bayesian approach, which investigates the ranges of posterior inferences as prior inputs are varied, was used. Following presentation of numerical results that enforce the claim of changes in temperature patterns due to anthropogenic CO_2 forcing, the article concludes with a comparative analysis for another CO_2 fingerprint and selected discussion.

Bayesian Design and Analysis for Superensemble-Based Climate Forecasting

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ABSTRACT

The authors develop statistical data models to combine ensembles from multiple climate models in a fashion that accounts for uncertainty. This formulation enables treatment of model specific means, biases, and covariance matrices of the ensembles. In addition, the authors model the uncertainty in using computer model results to estimate true states of nature. Based on these models and principles of decision making in the presence of uncertainty, this paper poses the problem of superensemble experimental design in a quantitative fashion. Simple examples of the resulting optimal designs are presented. The authors also provide a Bayesian climate modeling and forecasting analysis. The climate variables of interest are Northern and Southern Hemispheric monthly averaged surface temperatures. A Bayesian hierarchical model for these quantities is constructed, including time-varying parameters that are modeled as random variables with distributions depending in part on atmospheric CO_2 levels. This allows the authors to do Bayesian forecasting of temperatures under different Special Report on Emissions Scenarios (SRES). These forecasts are based on Bayesian posterior distributions of the unknowns conditional on observational data for 1882–2001 and climate system model output for 2002–97. The latter dataset is a small superensemble from the Parallel Climate Model (PCM) and the Community Climate System Model (CCSM). After summarizing the results, the paper concludes with discussion of potential generalizations of the authors' strategies.

GEOPHYSICAL RESEARCH LETTERS, VOL. 33, L05710, doi:10.1029/2005GL024831, 2006

Incorporating model uncertainty into attribution of observed temperature change

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[1] Optimal detection analyses have been used to determine the causes of past global warming, leading to the conclusion by the Third Assessment Report of the IPCC that "most of the observed warming over the last 50 years is likely to have been due to the increase in greenhouse gas concentrations". To date however, these analyses have not taken full account of uncertainty in the modelled patterns of climate response due to differences in basic model formulation. To address this current "perfect model" assumption, we extend the optimal detection method to include, simultaneously, output from more than one GCM

such as methane, nitrous oxides and CFC effect of increased atmospheric aerosols (m and natural factors (including changes in and stratospheric aerosols following volc These forcings, which we refer to hencefortl and NAT respectively, have distinct spatia "fingerprints" on surface climate, which al entiation. Optimal detection methods [*Has* utilise these contrasting responses to isolate influence of different forcings by compar (atmosphere-ocean) General Circulation

Identifying human influences on atmospheric temperature

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Contributed by Benjamin D. Santer, June 22, 2012

III. OUTLINE OF STATISTICAL APPROACH

Basic Idea of Detection and Attribution Analysis:

$$y = \sum_{j=1}^{m} \beta_j x_j + u = X\beta + u$$

where

- y: observed signal
- $x_1, ..., x_m$: climate projections due to m forcing factors (e.g. greenhouse gases, aerosols, solar, volcanic)
- u: noise, assumed normally distributed with mean 0 and covariance matrix C

GLS solution:

$$\widehat{\beta} = (X^T C^{-1} X)^{-1} X^T C^{-1} y$$

If a particular coefficient β_j is statistically significantly different from 0, we say that the jth forcing factor has been *detected*

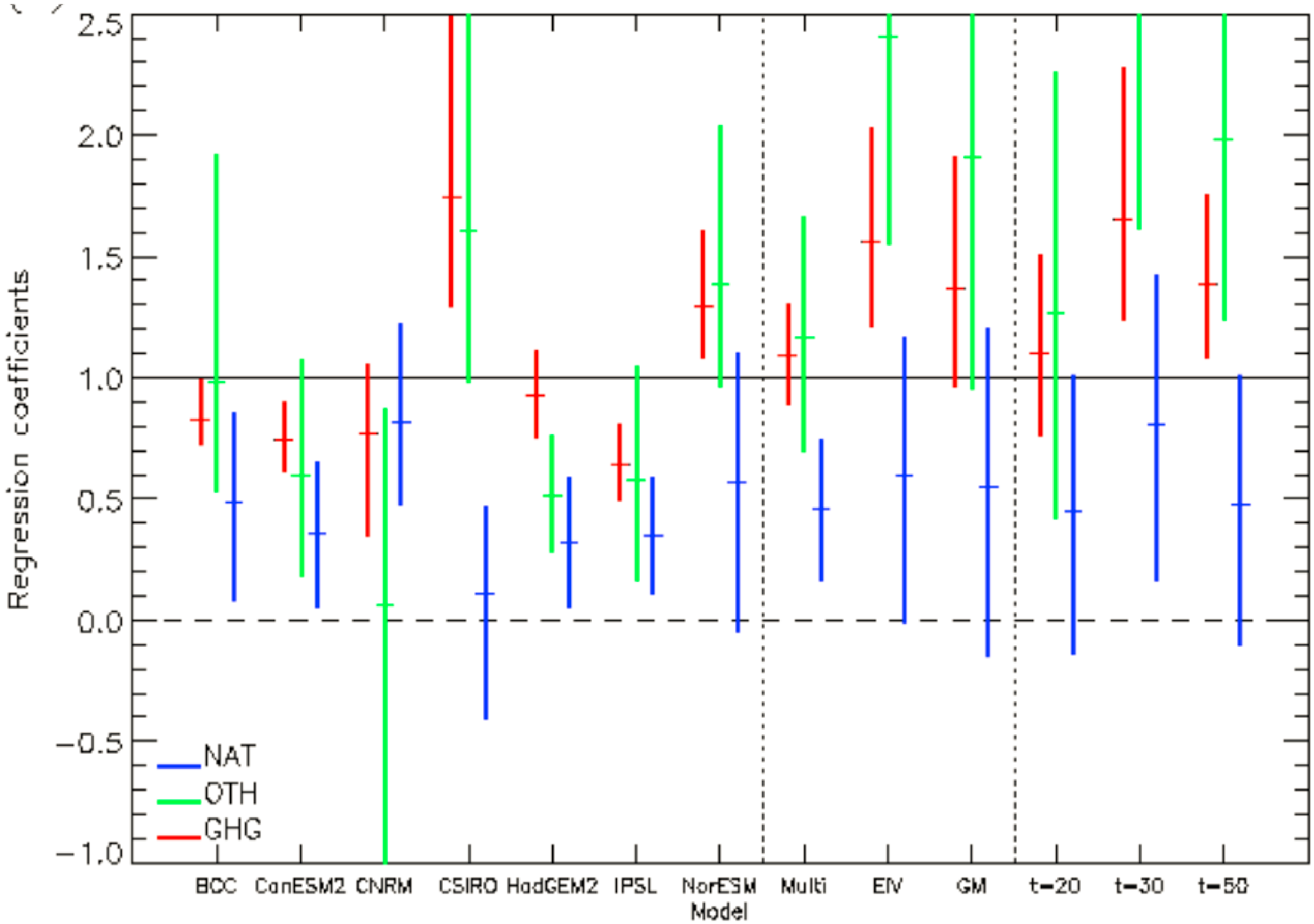
Among those forcing factors that are detected, the corresponding β_js are then interpreted as the *attribution* of the observational signal to the different forcing factors

Workshop at Banff International Research Station last year, see

http://www.birs.ca/events/2012/5-day-workshops/12w5037

http://da-frontiers-birs-2012.wikispaces.com/BIRS+Workshop+Papers

From a recent presentation by Nathan Gillett -



Complications

y and $x_1, ..., x_m$ are very high dimensional (typically thousands) but the number of independent observations is very small. This makes estimation of C difficult

Solutions used by climate scientists:

- Estimate C from *control runs* of the climate model
- Expand in *empirical orthogonal functions* (principal components) and then truncate

Are there better ways of estimating a covariance matrix in high dimensions?

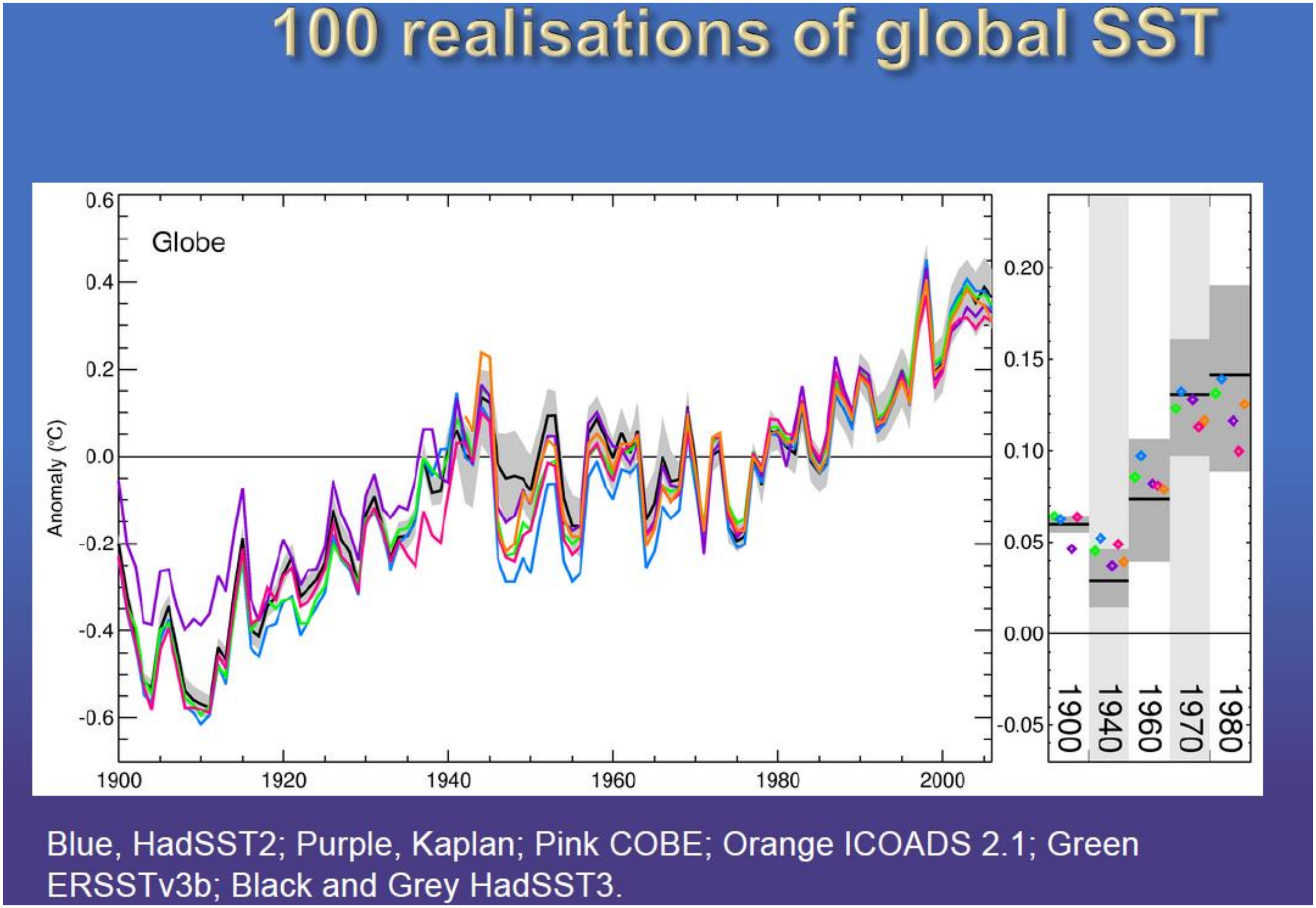
More Complications

- The x_js are not actually known (errors in variables problem) — climate scientists have addressed this using the *total least squares* algorithm (Allen and Stott 2003) but the sampling properties of this appear to be unknown
  - Connection with math stat work on errors in variables, e.g. Gleser, *Annals of Statistics*, 1982 (but Gleser's asymptotics won't apply in the D&A setting)

- Recently, climate scientists have started to realize that the ys aren't actually known either — use of *ensembles of observational data realizations* (Peter Thorne, Carl Mears)

- There are additional issues about how to incorporate model uncertainty

From a slide by Peter Thorne (Banff Workshop) –



Sources of Uncertainty for MSU Satellite Reconstructions (Carl Mears, Banff Workshop) –

- Instrument noise
- Spatial/Temporal Sampling
- Errors in measurement time (diurnal) adjustment
- The effect of these on the merging process
  - merging parameters are deduced from intersatellite differences
  - Errors in differences can lead to errors in merging parameters
- Other, unknown errors, some of which would be difficult to detect.

Producing Ensembles (Carl Mears, Banff Workshop) –

1. Start with a gridded monthly dataset of all zeros. Each satellite's data is valid only for months when that satellite was actually observing. (144x72x408x13)
2. For each valid satellite/month, add in a random realization of the sampling uncertainty.
3. Then add is a realization of the diurnal uncertainty.

$$s_{Diur} = a_1(Diur_1 - \langle Diur \rangle) + a_2(Diur_2 - \langle Diur \rangle) + \ldots$$

4. Perform merge using same method as we use for the real data.
5. Repeat a large number (right now 400) of times to get numerous realizations of the expected errors.

   (144x72x408x400) ~ 6.5 GB – large but manageable.

From Santer et al. (2012) –

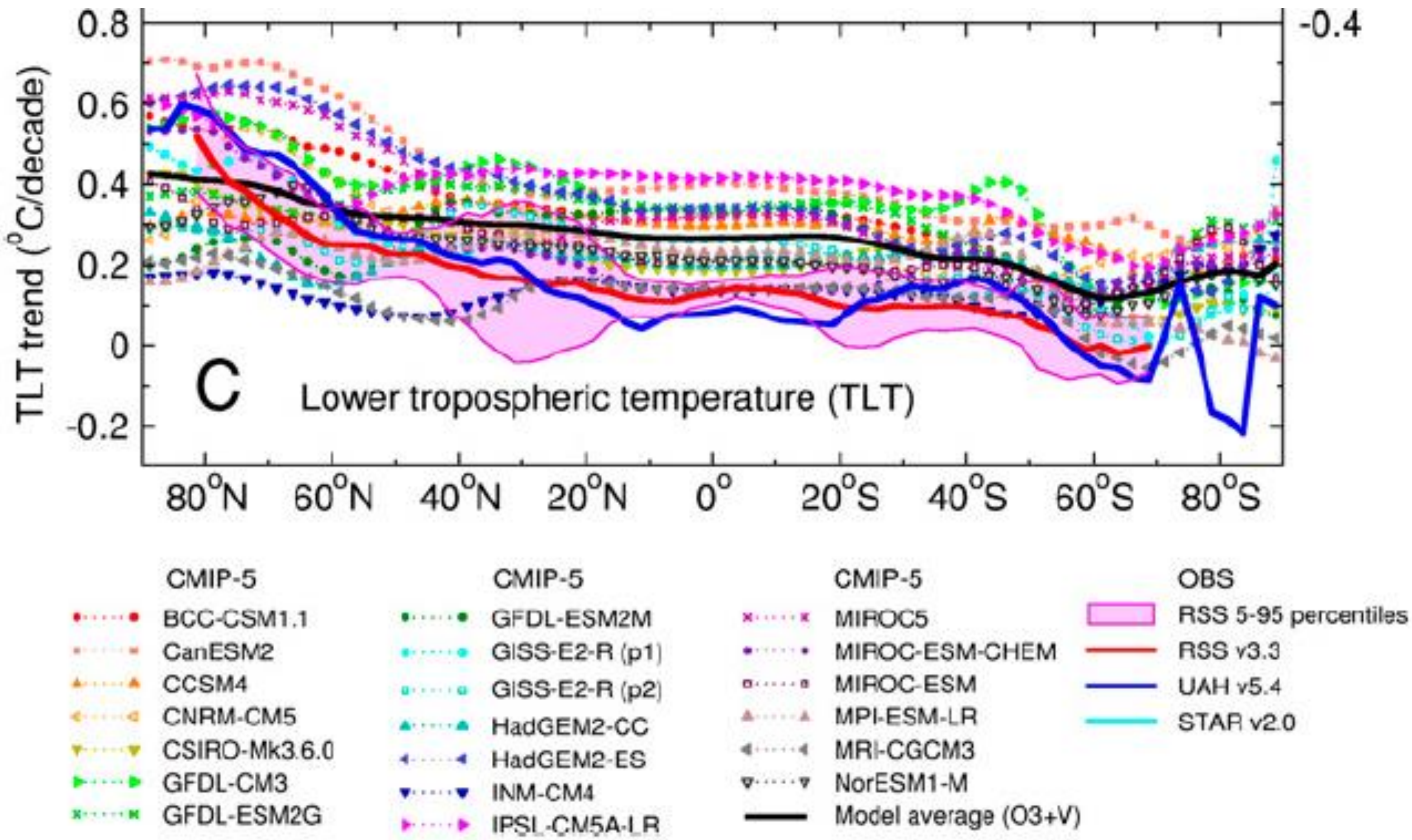


Fig. 3. Zonal mean trends in observed and synthetic (*A*) TLS, (*B*) TMT, and (*C*) TLT between 1979 and 2011. Observational results are from UAH, STAR, version 3.3 of the RSS dataset, and the 11 RSS percentile realizations. Model

IV. NEW HIERARCHICAL MODELING APPROACH
(joint with Dorit and Matthias)

Statistical Model

True temperature change is unknown, but we have an ensemble of N temperatures changes. We assume that

$$\mathbf{y}^{(i)}|\mathbf{y},\mathbf{W} \overset{iid}{\sim} N_n(\mathbf{y},\mathbf{W}), \quad i = 1,\ldots,N,$$

where $\mathbf{W}$ is a covariance matrix describing the variability of the ensemble members around the true temperature change

Assume that GCM output can be written as the sum of the (true) temperature change due to forcing plus the internal climate variability with covariance matrix $\mathbf{C}$:

$$\mathbf{x}_j^{(l)}|\mathbf{x}_j,\mathbf{C} \overset{ind}{\sim} N_n(\mathbf{x}_j,\mathbf{C}), \quad l = 1,\ldots,L_j,\ j = 1,\ldots,m,$$

where L_j is the number is the number of GCM runs under the jth forcing scenario

Statistical Model (continued)

- Internal climate variability: $\mathbf{C} = \mathbf{BKB}'$, where $\mathbf{B}$ contains the first r principal components estimated from control runs (EOFs), $\mathbf{K} = diag\{e^{\lambda_1}, \ldots, e^{\lambda_r}\}$, and $r << n$

- Observation uncertainty: $\mathbf{W} = \sigma^2 \widetilde{\mathbf{W}}(\gamma)$, where $\widetilde{\mathbf{W}}$ is a correlation matrix based on a Gaussian Markov random field (i.e., $\widetilde{\mathbf{W}}^{-1}$ is sparse).

- Priors:

  - Noninformative priors for $\boldsymbol{\beta}$ and σ

  - Vaguely informative priors for the λ_i

  - Discrete uniform prior on $\{\gamma_1, \ldots, \gamma_{n_\gamma}\}$ for γ

Bayesian Fitting Procedure

Gibbs sampler with adaptive Metropolis-Hastings updates

High-dimensional problem $\rightarrow$ Integrate out $\mathbf{y}$ and $\mathbf{X}$:

$$\mathbf{y}^{(i)} = \bar{\mathbf{X}}\boldsymbol{\beta} + g(\boldsymbol{\beta})\mathbf{B}\boldsymbol{\eta} + \boldsymbol{\epsilon}^{(i)},\ i = 1, \ldots, N$$

where $\bar{\mathbf{X}}$ has jth column $\sum_{l=1}^{L_j} \mathbf{x}_j^{(l)}/L_j$, $g(\boldsymbol{\beta}) = (1+\sum_{j=1}^{m} \beta_j^2/L_j)^{1/2}$, $\boldsymbol{\eta} \sim N_r(\mathbf{0}, \mathbf{K})$, and $\boldsymbol{\epsilon}^{(i)} \overset{iid}{\sim} N_n(\mathbf{0}, \mathbf{W})$

After precomputing certain quantities for all possible values of $\gamma \in \{\gamma_1, \ldots, \gamma_{n_\gamma}\}$, the number of computations required to evaluate the likelihood in the MCMC algorithm does not depend on n or N anymore

Proposed Application

Observational and Model temperature data:

- Climate Model Intercomparison project (CMIP5) models: suite of 19 models
- Remote Sensing Systems temperature retrievals based on microwave sounding units (MSUs): 400 realizations
- Temperature at different layers of the atmosphere
  - lower stratosphere (TLS)
  - mid– to upper troposphere sphere (TMT)
  - lower troposphere (TLT)

$\Rightarrow$ Same setup as was used by Santer et al.(2012).

V. CONCLUSIONS

- The field of detection and attribution is important for public policy about uncertainty in climate change projections

- Well established statistical methodology largely developed by climate scientists

- But, there are opportunities for more sophisticated statistical analyses — this presentation has outlined some possibilities

- There is a whole other set of techniques based on *paleoclimatology* (Bo Li, later in this session)

- Many possibilities for the future!