Dealing with Uncertainties in Climate Projection

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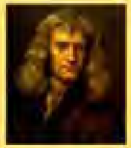

Isaac Newton Institute for Mathematical Sciences

Mathematical and Statistical Approaches to Climate Modelling and Prediction

11 August - 22 December 2010

Organisers: Dr R Chandler *(UCL)*, Dr M Collins *(Exeter)*, Professor P Cox *(Exeter)*, Dr K Horsburgh *(National Oceanography Centre, Liverpool)*, Professor JM Huthnance *(National Oceanography Centre, Liverpool)*, Dr JC Rougier *(Bristol)*, Professor DB Stephenson *(Exeter)* and Professor J Thuburn *(Exeter)*

Programme Theme

Our best estimates of future climate are based on the use of complex computer models that do not explicitly resolve the wide variety of spatio-temporal scales making up Earth's climate system. The non-linearity of the governing physical processes allows energy transfer between different scales, and many aspects of this complex behaviour can be represented by stochastic models. However, the theoretical basis for so doing is far from complete. Many uncertainties remain in predictions derived from climate models, yet governments are increasingly reliant on model predictions to inform mitigation and adaptation strategies. An overarching aim of climate scientists is to reduce the uncertainty in climate predictions and produce credible assessments of model accuracy. This programme focuses on two key themes that both require the close collaboration of mathematicians, statisticians and climate scientists in order to improve climate models and the interpretation of their output.

The first theme is the development of improved stochastic sub-grid-scale physics models, which have the potential to improve the variability of ensemble climate simulations. Progress can be made by establishing frameworks for relating models of different resolutions and for combining stochastic Earth System Models of Intermediate Complexity (EMICs) with global climate models (GCMs). Stochastic approaches to climate modelling will benefit from improving the connection between deterministic models and statistical tools such as downscaling, emulation, reified modelling and dimensional reduction.

The second aspect of the programme concerns the use of statistical techniques to create a theoretically sound basis for probabilistic climate prediction. The vast amount of data produced by climate models needs synthesis in order to provide the predictions, and credible error estimates, required by policy makers. This theme will provide an environment in which to seek quantitative answers to fundamental questions of interpreting probabilistic output, and the reliability of climate predictions at varying space and time scales. It will also consider what measurements can be used to assess the quality of climate model predictions.

This programme will bring together world-leading researchers in climate modelling, mathematics and statistics in order to make progress in solving some of the major issues facing climate prediction.

Notation

$$c = M(p, R)$$

M = model/function
c = climate variable
p = model parameters/inputs
R = radiative forcing
Subscript h=historical, f=future
o = observations

$$c_h = M(p, R_h)$$
$$c_f = M(p, R_f)$$

General Algorithm:

- Run model/evaluate function at many different input parameters for historical radiative forcing
- Compute metric of fit between model output and observations
- Weight future projections according to the value of the metric

$$m = (c_h - o)^T (c_h - o) = \sum (c_h - o)^2$$

$$w = \exp\left(-\frac{1}{2}\sum (c_h - o)^2\right)$$

Issues

$$c = M(p, R)$$

- Validity of the model/function, M
- Sampling of model/functional parameters, p
- What observations to use to compute metric/weights
- Uncertainties in observations
- Physical understanding of projections

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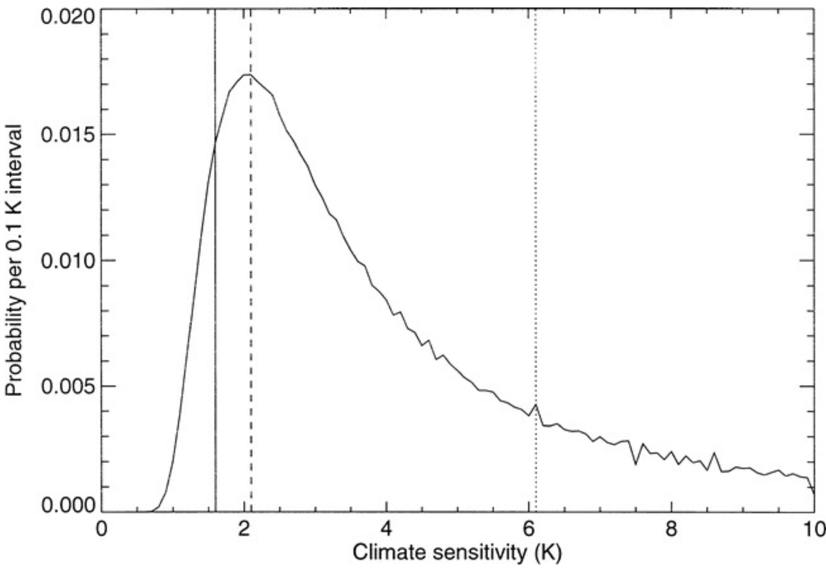
Estimating Climate Sensitivity

$$\lambda = \frac{R_{2X}}{\Delta T_{2X}} = \frac{F_h + R_h}{\Delta T_h} = M([F_h, \Delta T_h], R_h)$$

Feedback parameter, λ, is a function, M, of the observed historical TOA flux, F_h (equivalent to the ocean heat uptake), the observed temperature change, ΔT_h and the radiative forcing, R_h.

All these quantities can be estimated from observations or can be calculated but are all uncertain.

Produce large sample of parameter space and weight parameters according to observations (equivalent to specifying priors in this case).



Gregory, J. M.; Stouffer, R. J.; Raper, S. C. B.; Stott, P. A.; Rayner, N. A.; An observationally based estimate of the climate sensitivity. Journal Of Climate, 15, 3117-3121, 2002

Techniques for Projections

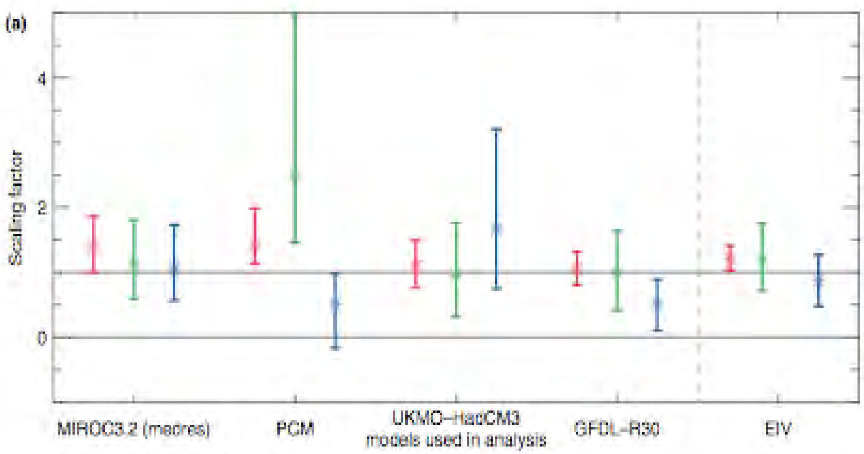
(projection = dependent on emissions scenario)

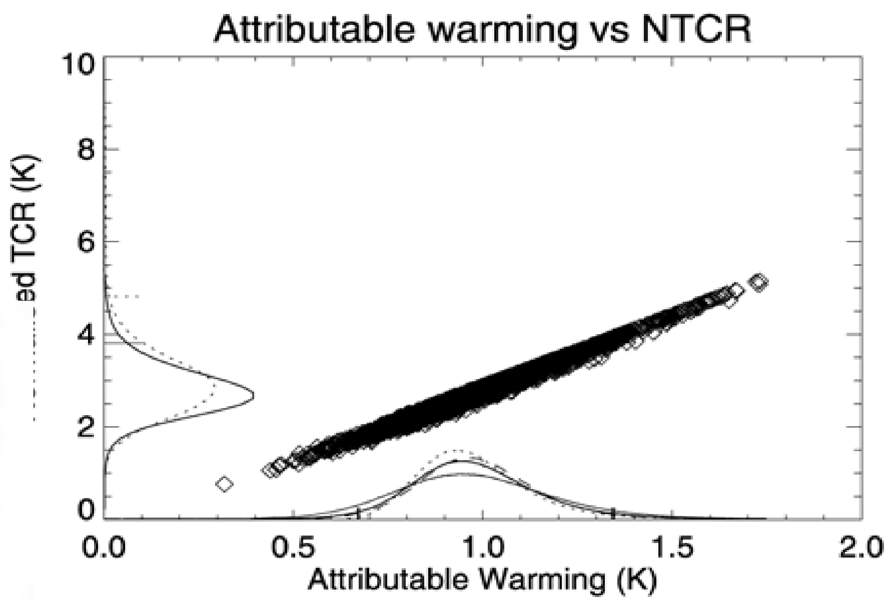
- Extrapolation of signals (ASK)
- Interpreting the multi-model ensemble
- Emergent constraints
- Single-model Bayesian approaches
- Process-based constraints

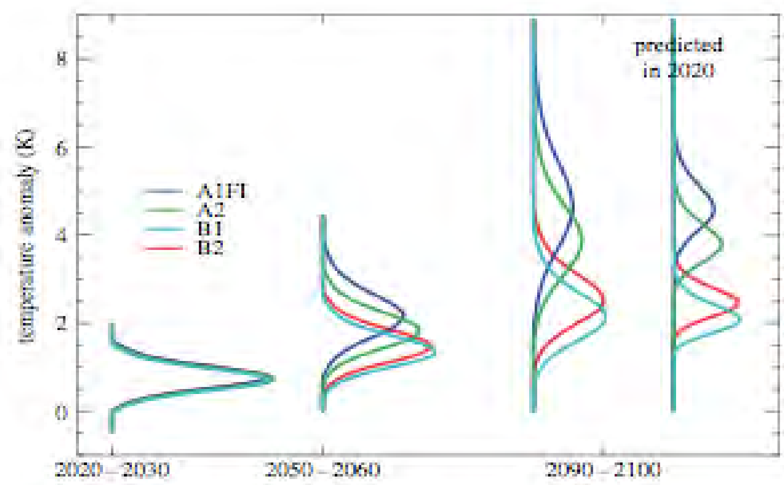
Extrapolation of Signals: ASK

$$\Delta T_f = M(\Delta T_h, R_f)$$

$$\Delta T_f = \alpha \Delta T_h^{CO2} + \beta \Delta T_h^{aer} + \ldots$$





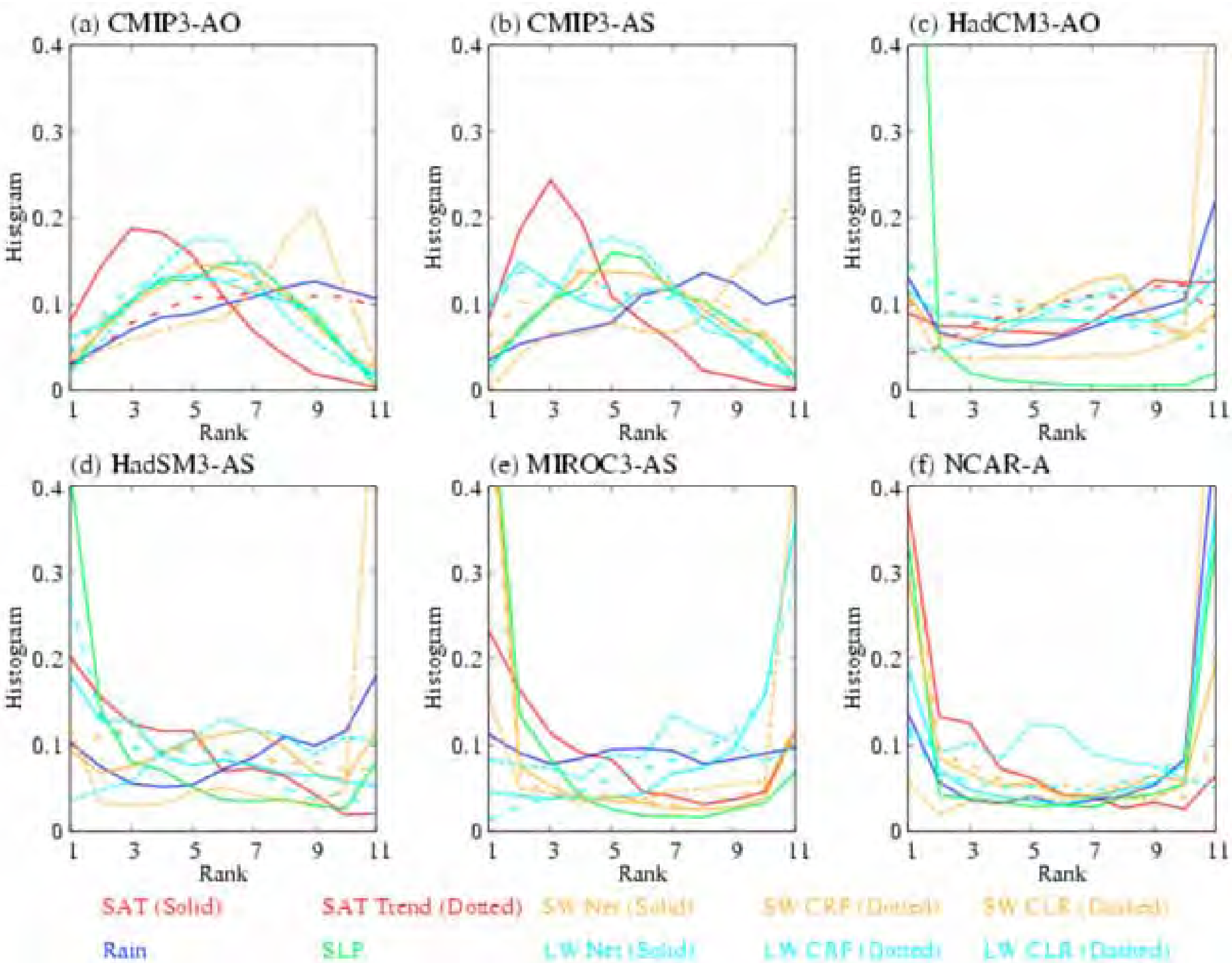


Peter Stott & Jamie Kettleborough, Origins and estimates of uncertainty in predictions of twenty-first century temperature rise, Nature, 416, pp.719-723, 18 April 2002.

Interpreting the Multi-Model Ensemble

- The multi-model ensemble is an ad-hoc collection of non-independent models of varying complexity and quality
- Not easy to write down a rule for interpreting the ensemble using simple statistics
- Perhaps that doesn't matter if the ensemble outputs are *reliable* i.e. the observations and the ensemble members are interchangable

Interpreting the Multi-Model Ensemble



Rank histograms from ensemble output

Loop over grid points and rank the observation w.r.t. ensemble members, compute histogram

Uniform histogram is desirable

U-shaped = too narrow

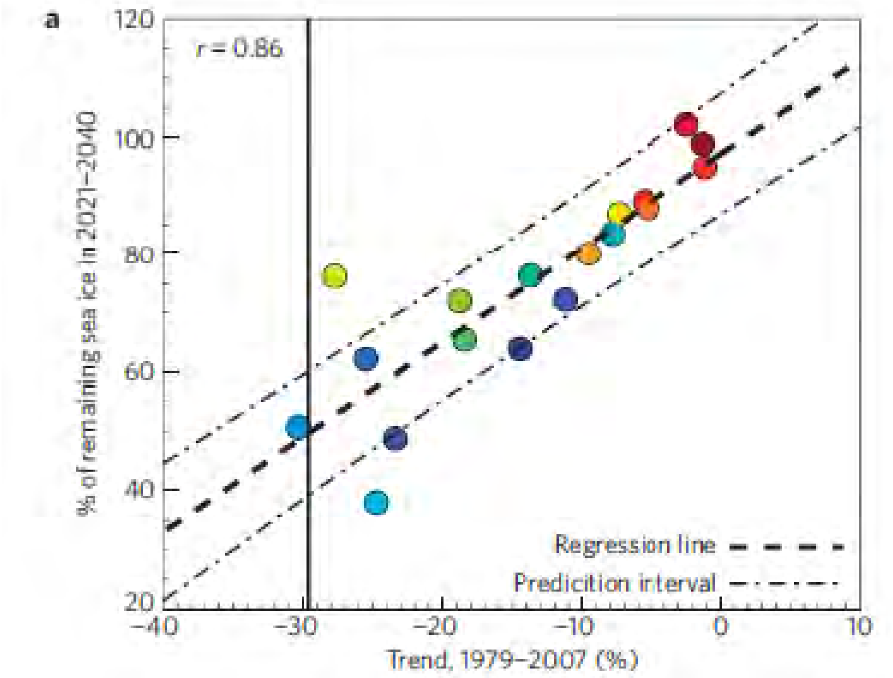
Domed = too wide

Yokohata T, Annan JD, Hargreaves JC, Jackson CS, Tobis M, Webb MJ, Collins M 2011: Reliability of multi-model and structurally different single-model ensembles. Submitted to Climate Dynamics.

Emergent Constraints

$$c_f = M(p,R) = f(c_h) = \alpha c_h + \beta$$

- Future sea-ice trends can be expressed as a simple linear function of historical/observed sea ice trends
- Emergent constraint derived from multi-model ensemble but also consistent with physical reasoning
- Use observed trend (with uncertainties) to constrain future projections

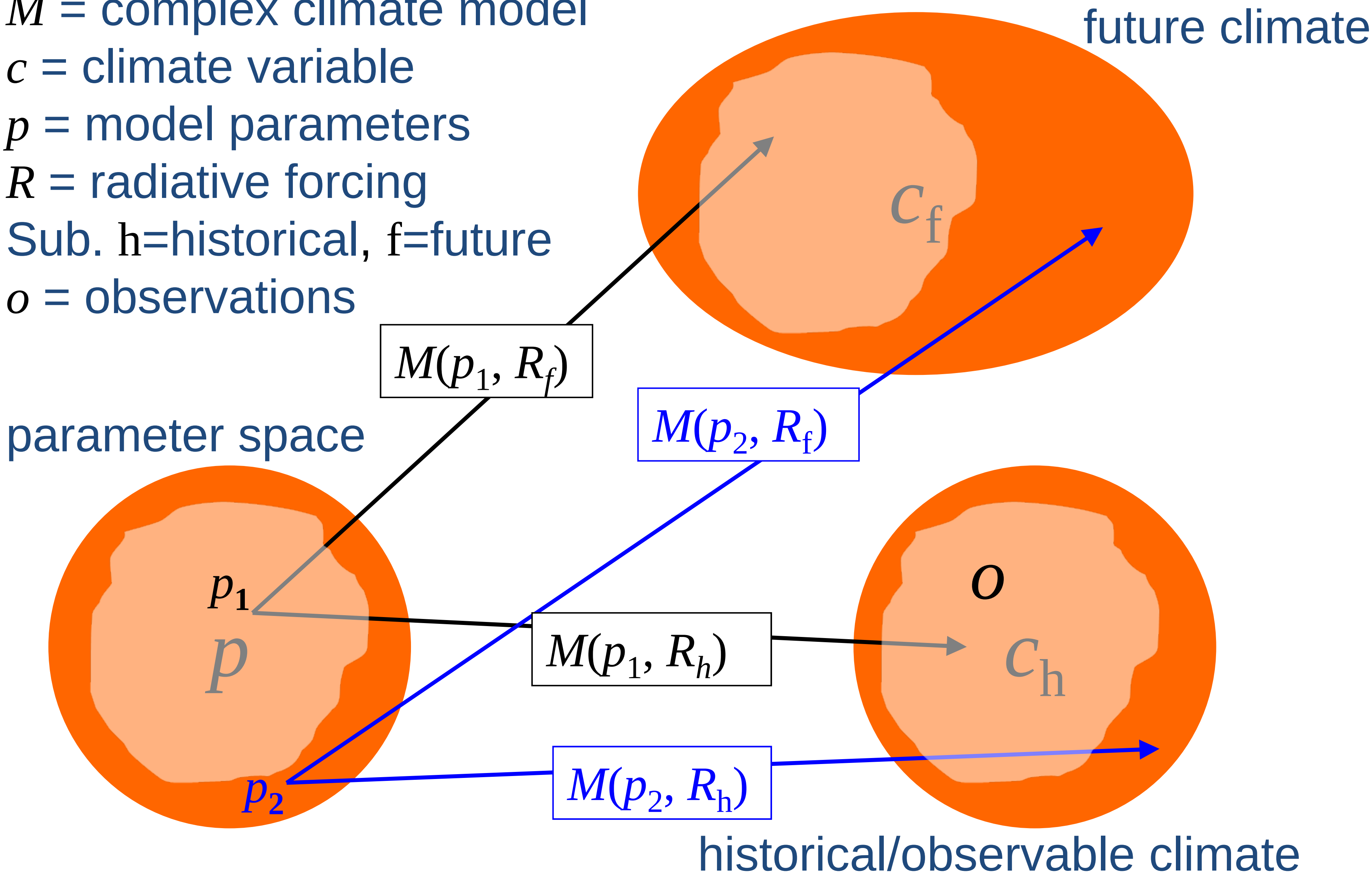


Hall A, Qu X (2006) Using the current seasonal cycle to constrain snow albedo feedback in future climate change. Geophys. Res. Lett., 33, L03502

Rougier Bayesian Approach

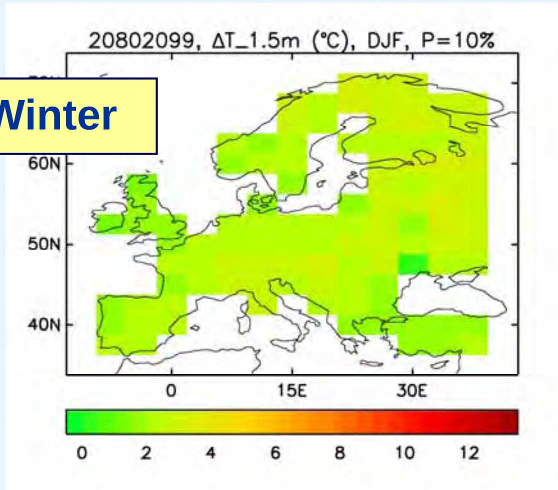
$$c = M(p, R)$$

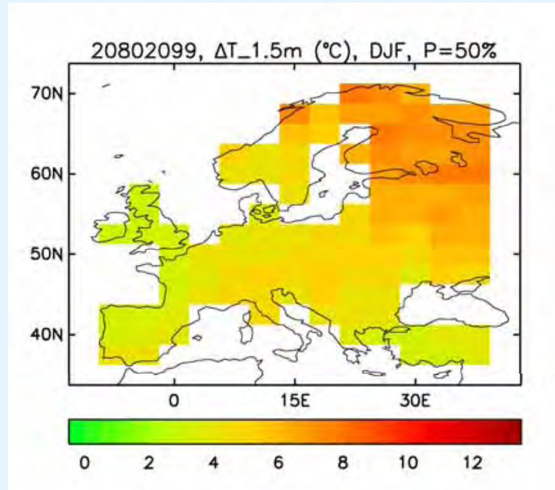
M = complex climate model
c = climate variable
p = model parameters
R = radiative forcing
Sub. h=historical, f=future
o = observations

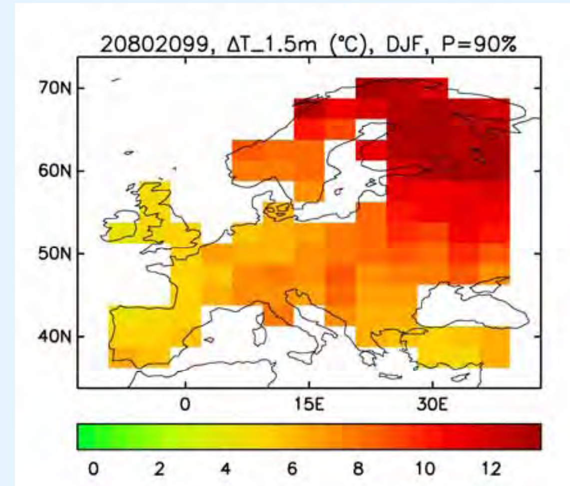


Surface temperature changes for the 2080s

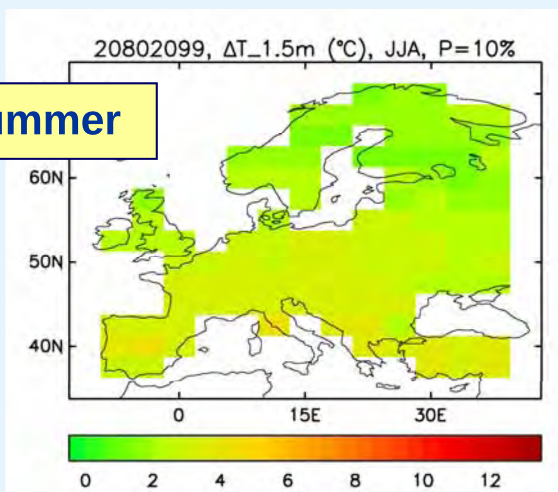
Winter

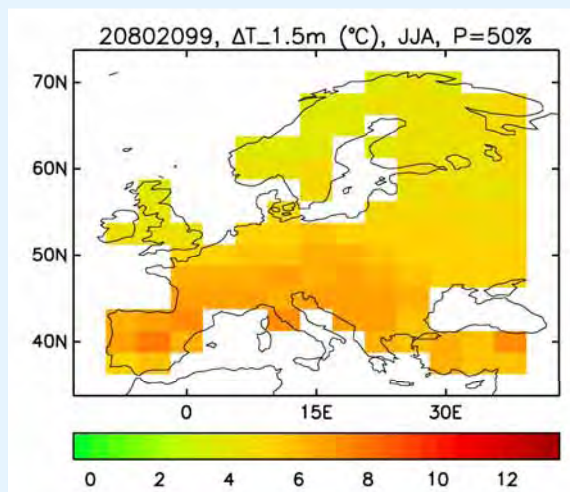


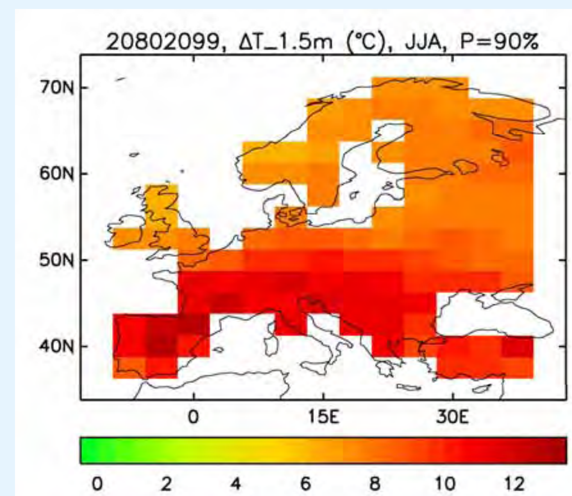




Summer







10th percentile | **Median** | **90th percentile**

Process-Based Evaluation and Constraints

$$c = M(p, R)$$

M = model/function
c = climate variable
p = process variables
R = radiative forcing
Subscript h=historical, f=future
o = observations

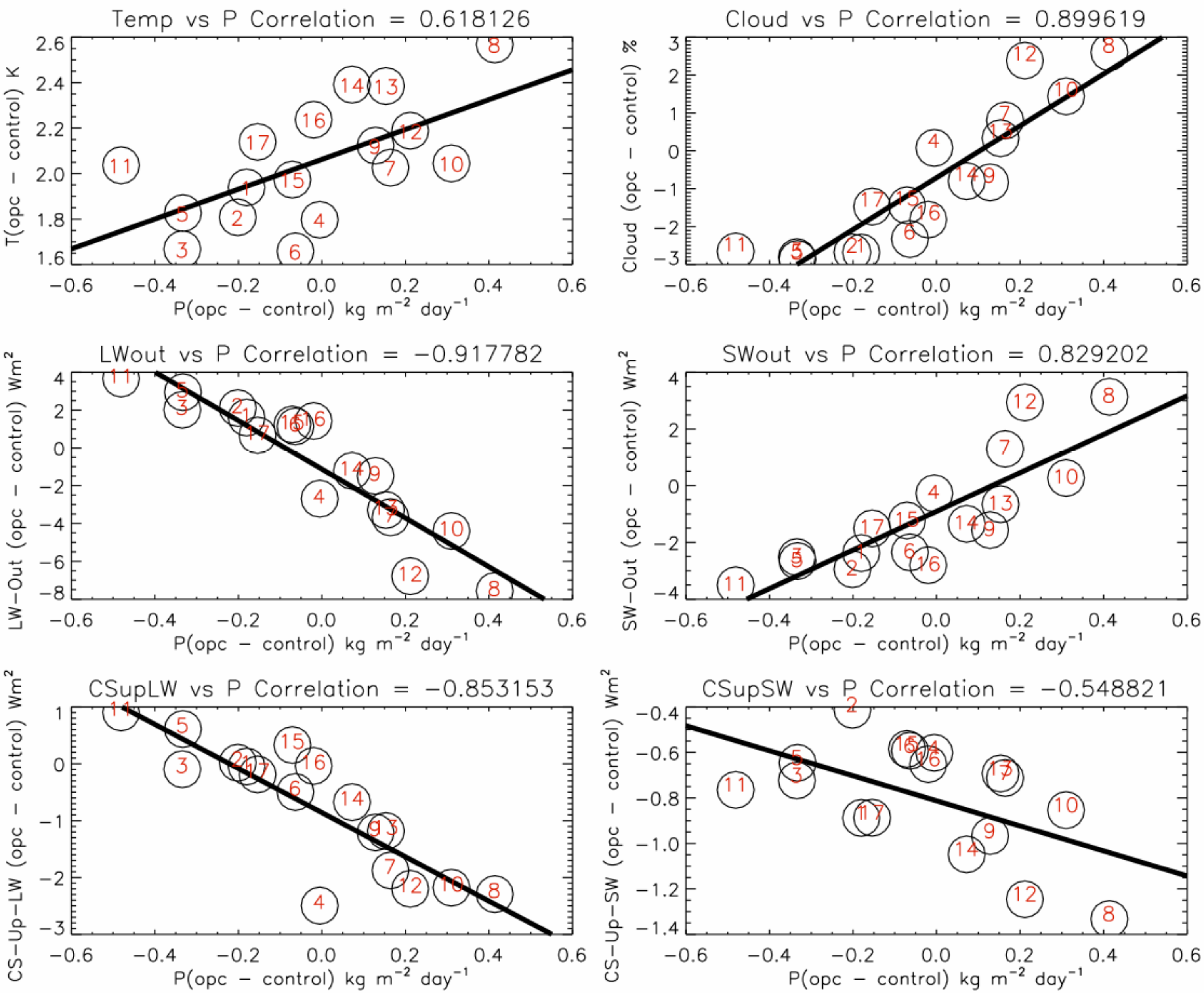
$$c_h = M(p, R_h)$$

$$c_f = M(p, R_f)$$

Examples of process variables:

- Time average fluxes, moisture convergence, cloud regimes, …
- Trends/Interannual variability/seasonal cycle
- “Sensitivities” or “emergent process”, dP/dT, dF/dT, dF/dP, …

Correlation Plots: India: 0 S to 30 N, 60 to 90 E: March-April-May



NERC Pagoda Project – Collins, Long, Stephenson, Yip

Summary and Future Work

- Generic framework of defining a model/function, perturbing uncertain parameters and constraining those parameters using observations
- Need to be clear about the framework we are using in publications
- Potential review/perspectives paper for Nature Climate Change
- CMIP5 analysis
- Formulate process-based approach better and implement to look at changes in the global hydrological cycle, ENSO, …

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Rougier Bayesian Approach

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Subscript h=historical, f=future
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$$c_h = M(p, R_h)$$

$$c_f = M(p, R_f)$$

Metric: $$m = (c_h - o)^T (c_h - o) = \sum (c_h - o)^2$$

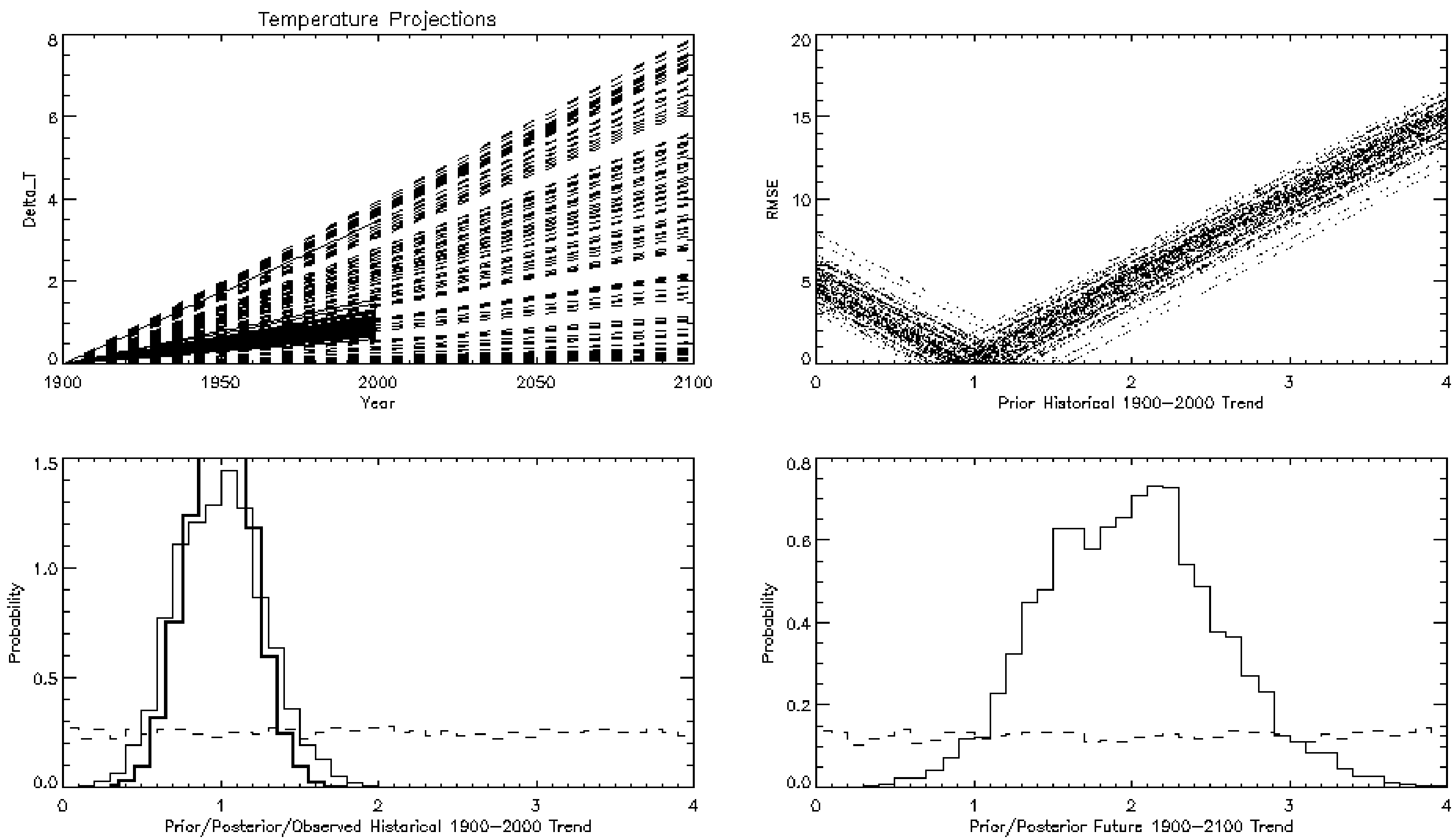
Weights: $$w = \exp\left(-\frac{1}{2}\sum (c_h - o)^2\right)$$

Simple Example

Global mean temperature in the past and the future is a simple linear trend with unknown slope, α. We have observations, o, of past trends which suggest 1K/century warming with a standard deviation of 0.2 K/century.

$$\Delta T = \alpha t$$

$$w = \exp\left(-\frac{1}{2} \frac{(\alpha - o)^2}{\sigma^2} \right)$$



ASK: Strengths and Weaknesses

- Conceptually simple for “near-term” (linear) climate change
- Useful for global and large-scale temperature projections, untested for other variables
- Implementation made more complex by the use of attributable warming

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Strengths and Weaknesses

- Consistent with current practice (e.g. IPCC)
- Can only be tested for historical climate variables, not future projections
- Inconsistent with the idea of errors-common-to-all-models (e.g.split ITCZ)
- Perhaps a zeroth-order test

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Strengths and Weaknesses

- Strength in simplicity and physical understanding
- Relies on model relationships
- Will not work for all variables (e.g. climate sensitivity)
- Consistency of projections of different variables?

Strengths and Weaknesses

- Rigorous statistical approach
- Can be implemented for “exotic” variables
- Weak observational constrains
- Estimating discrepancy
- Very expensive to implement