Assessing perturbed parameter ensembles as a tool for sampling model uncertainties and making climate projections

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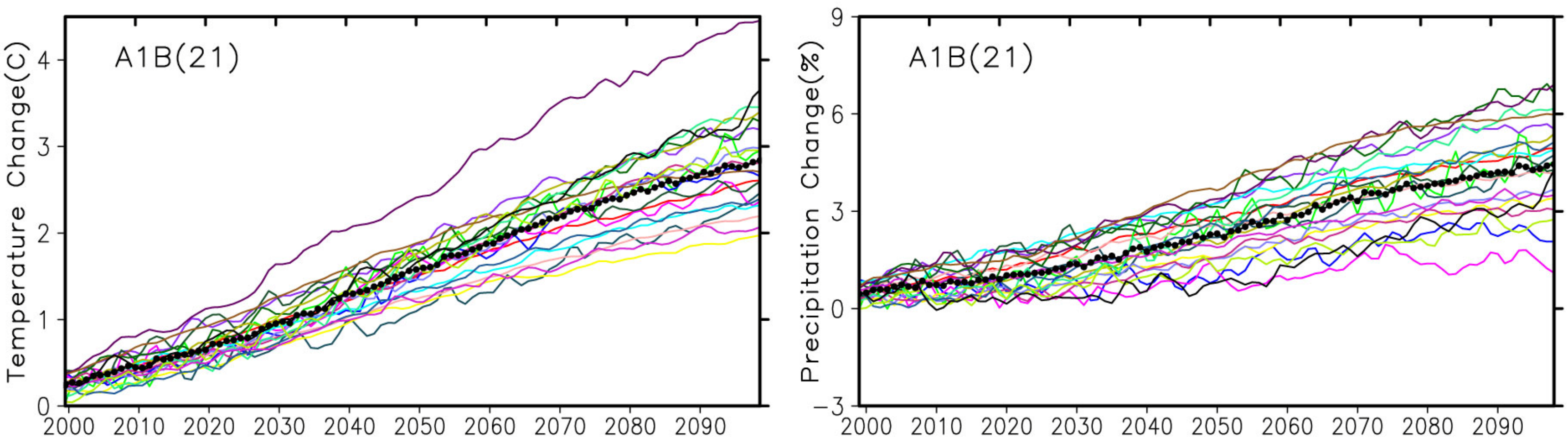
Contents

- Motivation and purposes
- Illustrations of uses from international studies using different base models
- Making climate projections using perturbed parameter ensembles
- Summary and outlook

Modelling Uncertainties

Most commonly characterised by the spread in a multi-model ensemble of climate projections run at different international centres, and collected in a common archive.



Responses of annual mean surface temperature (left) and precipitation (right) to SRES A1B emissions, in 21 coupled AOGCMs contributed to IPCC AR4.

Multi-model ensembles (MMEs)

Key Strengths

• Each member extensively tested – credibility derived from tuning and validation against a wide range of observables

• Constructed from a large pool of alternative components – samples different structural assumptions

• The source of much of our knowledge of projected future climate changes

Some Limitations

• Not designed to sample modelling uncertainties in a systematic fashion ("ensemble of opportunity")

• Rather small. Difficult to get robust estimates of most likely changes, or associated uncertainties, especially for regional changes and extreme events

• Difficult to use MMEs to assess climate risks as there is no obvious "best" way of determining the distribution of possible changes of which the MME is a sample.

Perturbed physics ensembles (PPEs)

- **Designed to sample uncertainties systematically within a single model framework**

- **Executed by perturbing poorly constrained model parameters within expert-specified ranges**

- **Samples uncertainties in the [assumed] deterministic outputs of bulk formulae parameterisations**

- **Key strength: Allows greater control over experimental design cf "ensembles of opportunity"**

- **Key limitation: does not sample structural or stochastic modelling uncertainties**

Perturbed physics ensembles using different models

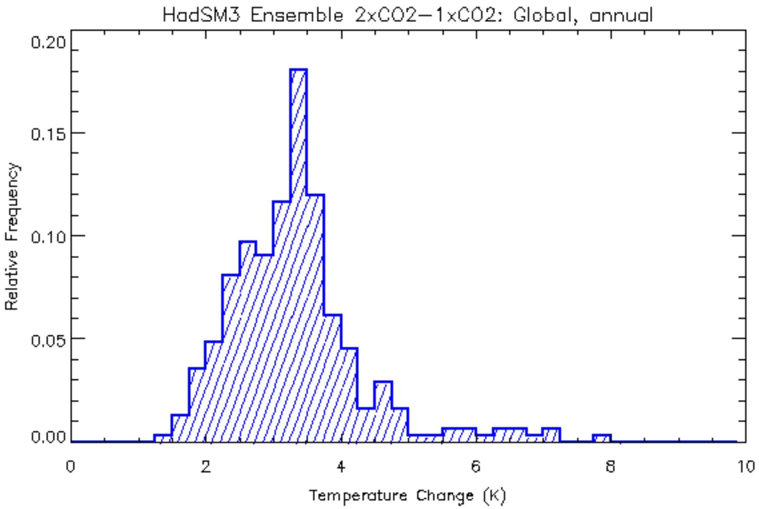
- HadCM3: Widely studied via climate*prediction*.net (Oxford Univ.) and QUMP (Met Office) projects in various model configurations

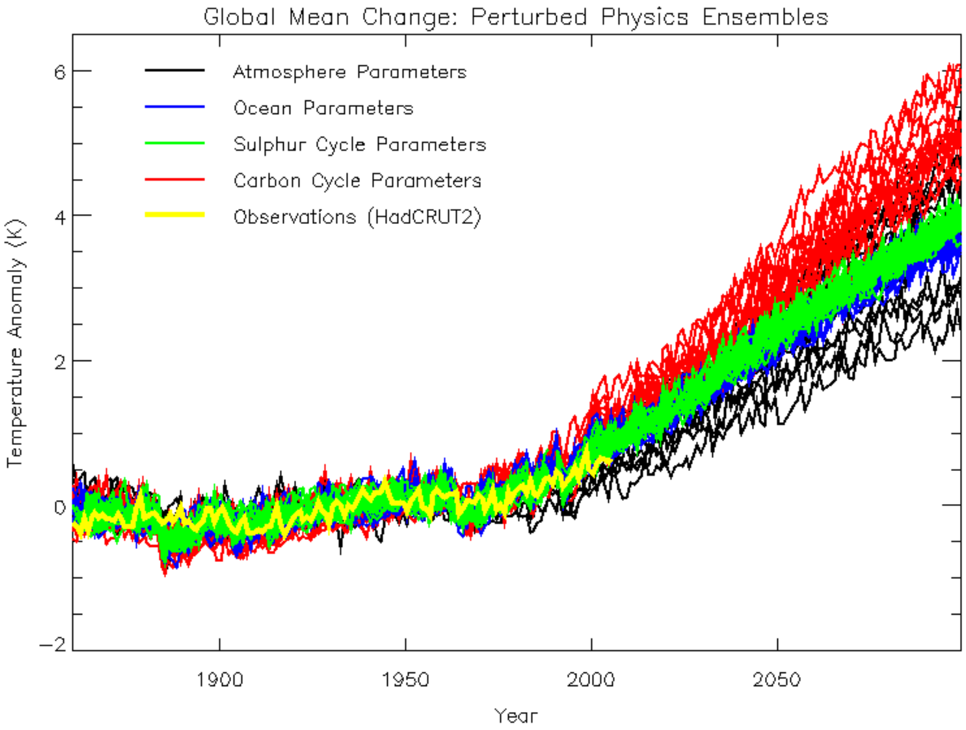
- NCAR CAM3.x, 4: Several projects (Jackson et al., Sanderson, Covey et al.)

- MIROC3.2: (JUMP project, Yokohata et al., 2010)

- EGMAM (Free Univ. Berlin (Niehorster))

Perturbed parameter ensembles looking at different parts of the earth system





- **Much work focused on atmosphere parameters (understanding drivers of uncertainty in climate sensitivity and regional climate change)**
- **But also simulations looking at ocean, sulphur cycle, carbon cycle: Important if a more comprehensive sampling of uncertainties is needed to provide robust information on risks.**

Murphy et al. 2004, Webb et al. 2006, Harris et al. 2006, Rougier et al. 2009, Collins et al 2006, 2010

Atmosphere Parameters (HadCM3 QUMP experiments)

Large Scale Cloud

Ice fall speed

Critical relative humidity for formation

Cloud droplet to rain: conversion rate and threshold

Cloud fraction calculation

Convection

Entrainment rate

Intensity of mass flux

Shape of cloud (anvils) (*)

Cloud water seen by radiation (*)

Radiation

Ice particle size/shape

Cloud overlap assumptions

Water vapour continuum absorption (*)

Boundary layer

Turbulent mixing coefficients: stability-dependence, neutral mixing length

Roughness length over sea: Charnock constant, free convective value

Dynamics

Diffusion: order and e-folding time

Gravity wave drag: surface and trapped lee wave constants

Gravity wave drag start level

Land surface processes

Root depths

Forest roughness lengths

Surface-canopy coupling

CO_2 dependence of stomatal conductance (*)

Sea ice

Albedo dependence on temperature

Ocean-ice heat transfer

Different experiments choose different parameter sets, and have different aims

TABLE 1. Varied parameters in JUMP experiment (MIROC3.2 ensemble).

No.	Variables	Description	Unit
1	vice0	Ice fall speed factor	$m\ s^{-1}$
2	b1	Efficiency factor for liquid precipitation	$m^3\ kg^{-1}\ s^{-1}$
3	prctau	*e*-folding time for ice precipitation	s
4	alp	Gravity wave drag factor	$rad\ m^{-1}$
5	tefold	*e*-folding time for horizontal diffusion	day
6	snrfrs	Snow amount required for refreshing snow albedo	$kg\ m^{-2}$
7	elamin	Minimum entrainment factor of cumulus convection	m^{-1}
8	rddr	Downdraft factor	$m\ s^2\ K^{-1}\ kg^{-1}$
9	dffmin	Minimum vertical diffusion coefficient	$m^2\ s^{-1}$
10	rhmcrt	Critical relative humidity for cumulus convection	—
11	ray0	Rayleigh friction *e*-folding time	day
12	usminm	Minimum scalar wind for vertical diffusion	$m\ s^{-1}$

Yokohata et al (2010), MIROC3.2

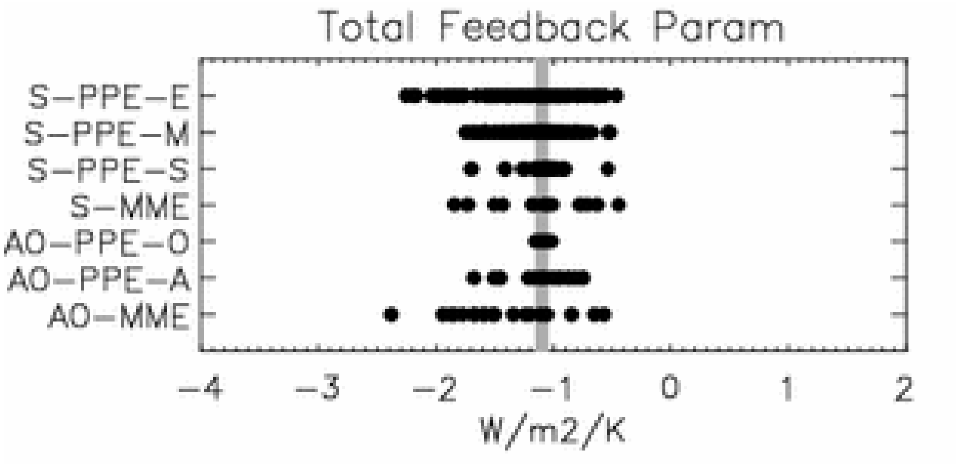
TABLE 1. Underconstrained CAM3.1 parameters with default values (asterisk) and ranges of prior distributions and posterior uncertainties represented by the best-performing models within each of the six independent convergence chains (1–6).

Parameter	Definition	Value Ranges
RHMINL [%/100]	Low cloud critical relative humidity	0.80 * 6 5 4 3 2 0.95
RHMINH [%/100]	High cloud critical relative humidity	0.60 2 5 3 4 * 6 1 0.90
ALFA [fraction]	Initial cloud downdraft mass flux	0.05 6 4 * 2 5 1 3 0.60
TAU [hours]	Consumption rate of CAPE	0.5 * 3 5 1 6 2 4 8.0
ke $[(kg\ m^{-2}\ s^{-1})^{-1/2} s^{-1}]$	Environmental air entrainment rate	3.0e-6 2 3 4 1 * 6 5 10.0e-6
c0 $[m^{-1}]$	Precipitation efficiency	3.0e-3 * 5 6 3 2 4 1 6.0e-3

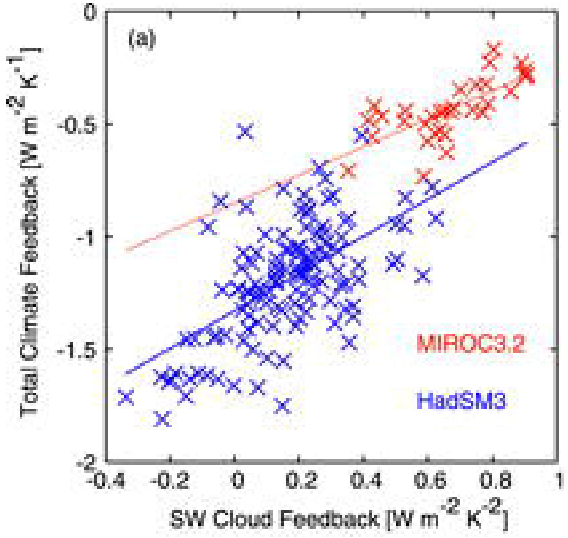
Jackson et al (2008), CAM3.1

- **Results will depend on the design of the perturbation strategy, as well as on the base model used for the PPE.**
- **Study of climate sensitivity and cloud feedbacks has been a major (though not exclusive) focus**

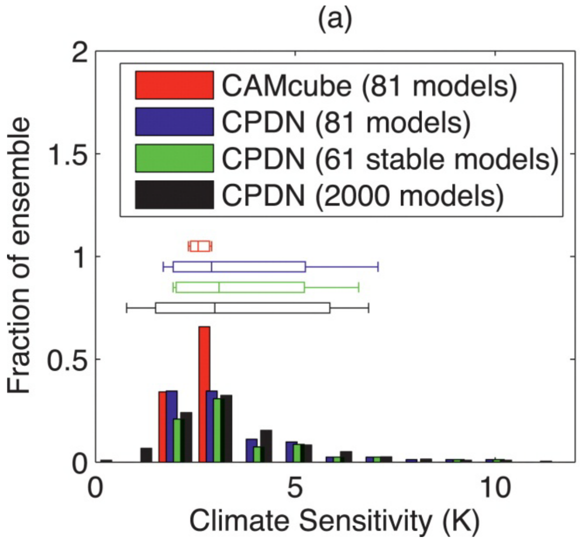
Comparison of global climate feedbacks between ensembles



Different Met Office HadCM3 PPEs cf CMIP3 multi-model ensembles (Collins et al., 2010)



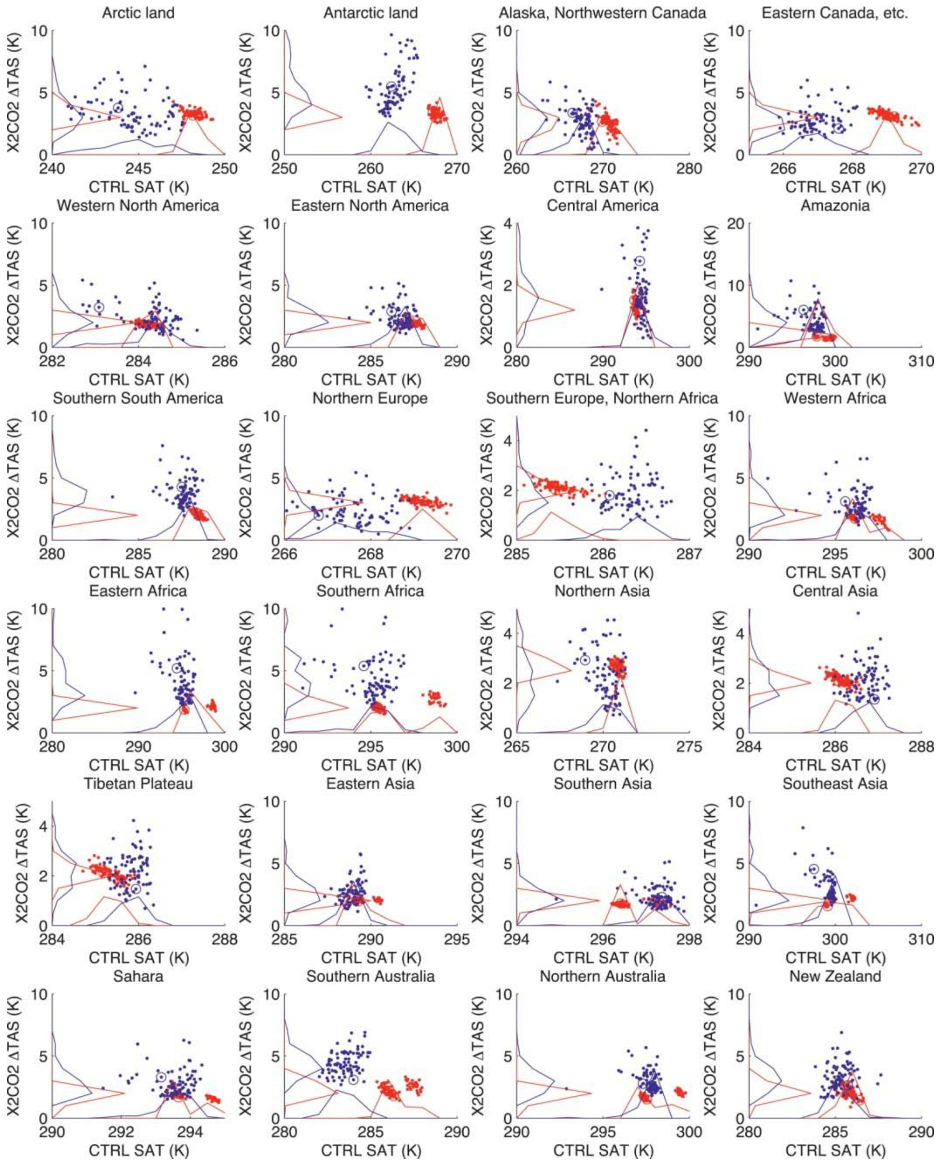
MIROC PPE cf HadCM3 PPE (Yokohata et al., 2010)



Climateprediction.net HadCM3 PPEs cf CAMcube PPE (Sanderson, 2010)

- **PPEs sample a spread of global climate feedbacks, in some cases comparable to CMIP3**

PPEs also simulate a range of regional outcomes for present climate, and greenhouse-gas forced changes

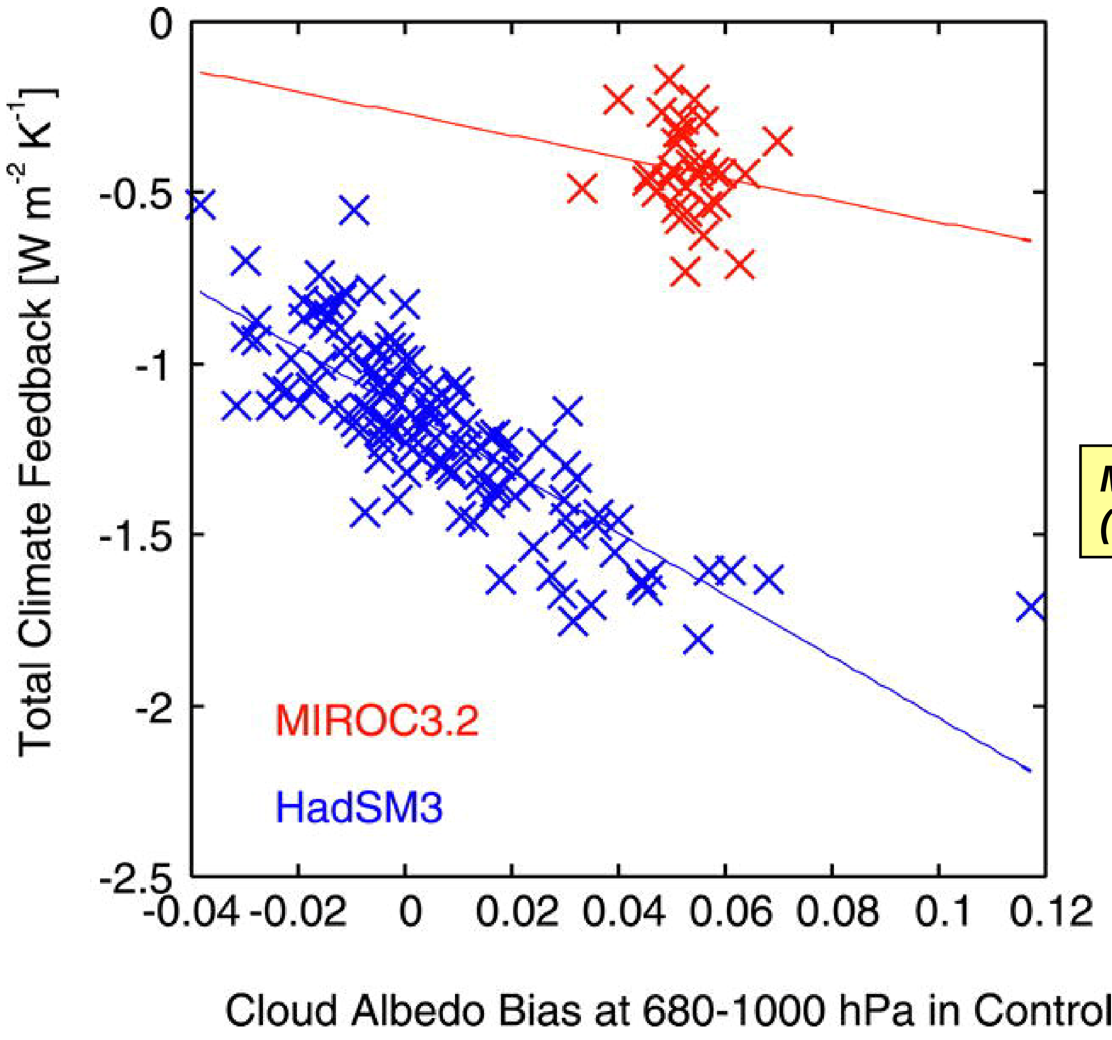


Climate*prediction.net* *PPE*

CAMcube PPE

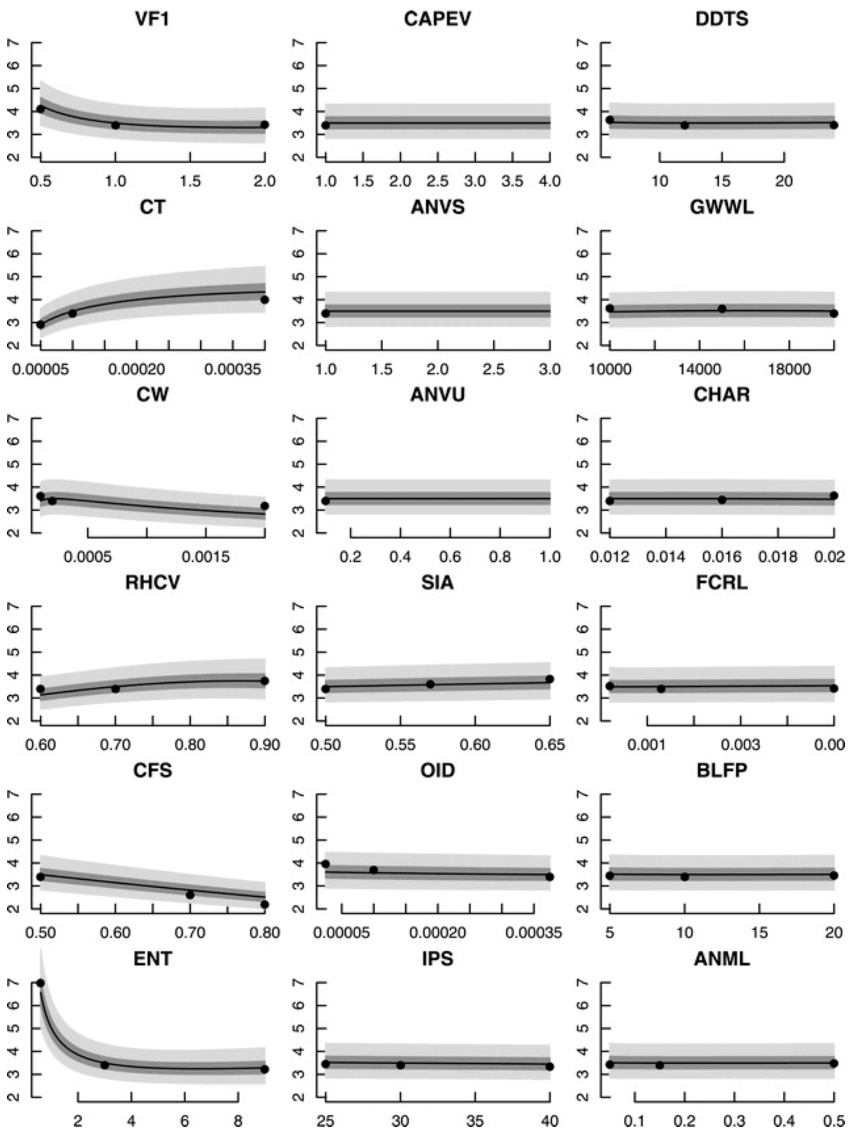
Sanderson (2010)

Understanding how parameter-driven uncertainties in PPEs depend on structural properties of the model



MIROC PPE cf HadCM3 PPE (Yokohata et al., 2010)

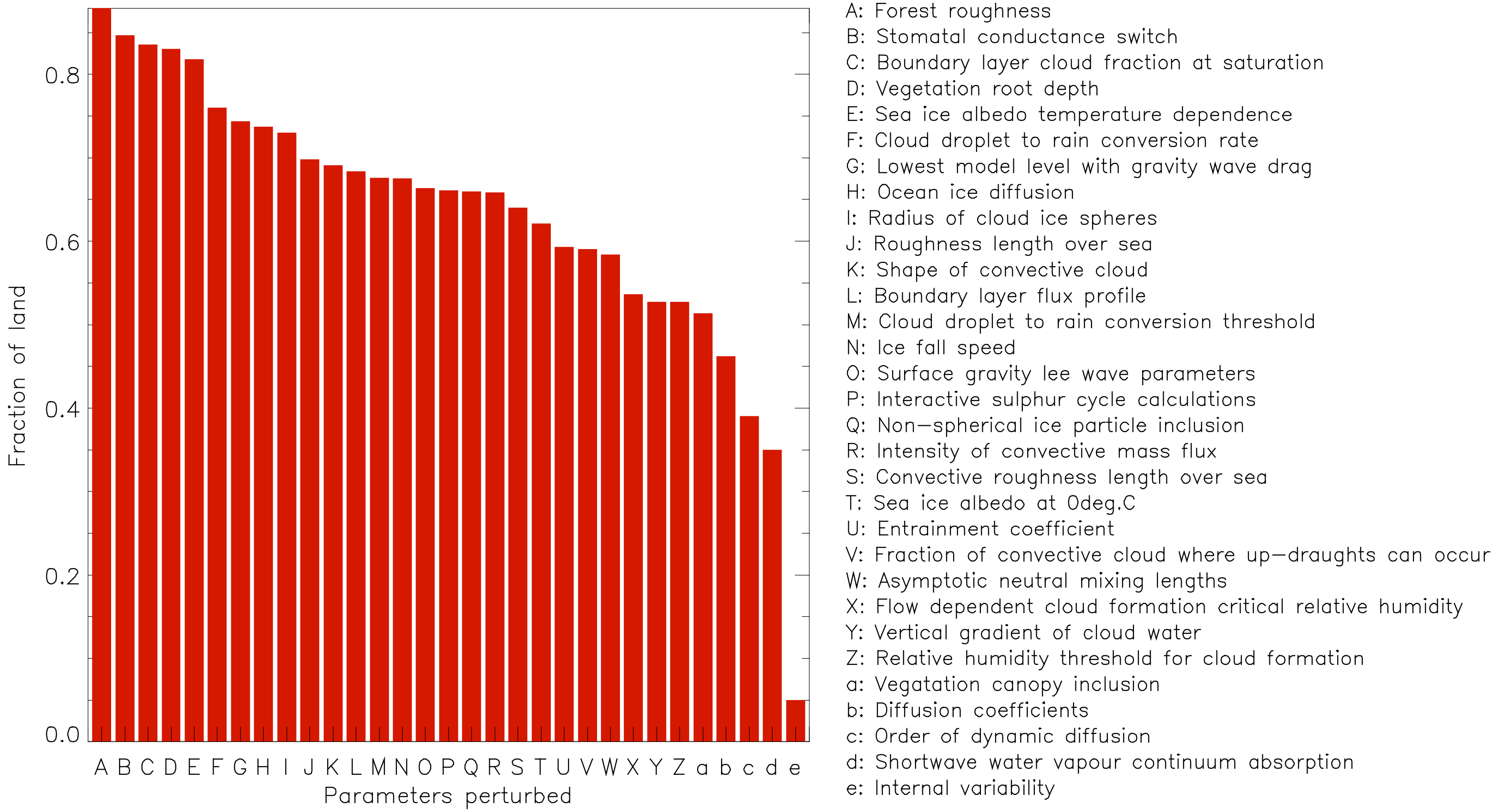
Understanding processes driving changes and their uncertainties



Global climate sensitivity (Rougier et al., 2009)

From QUMP and cpdn ensembles of HadSM3

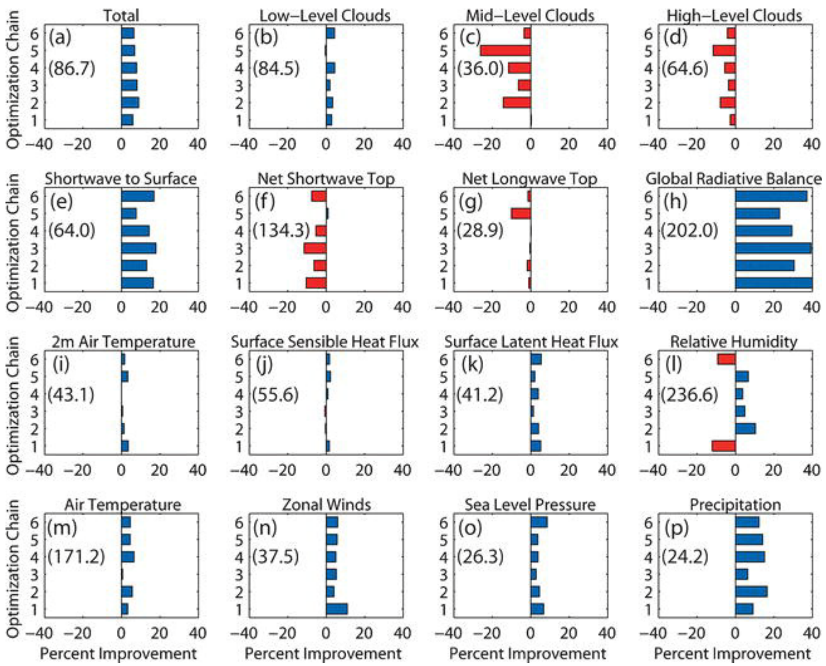
Understanding processes driving changes and their uncertainties



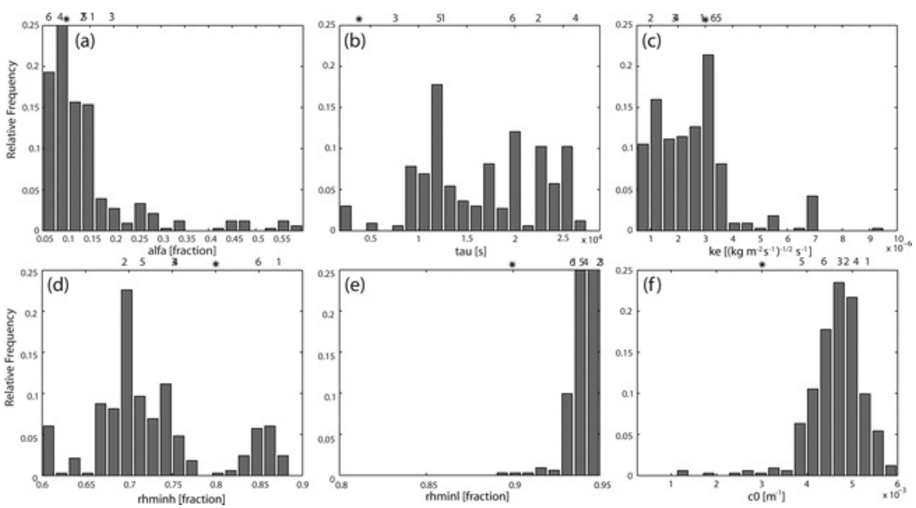
From QUMP ensemble of HadSM3

Regional changes in hot days (Clark et al., 2010)

Using a PPE to optimise skill in model development



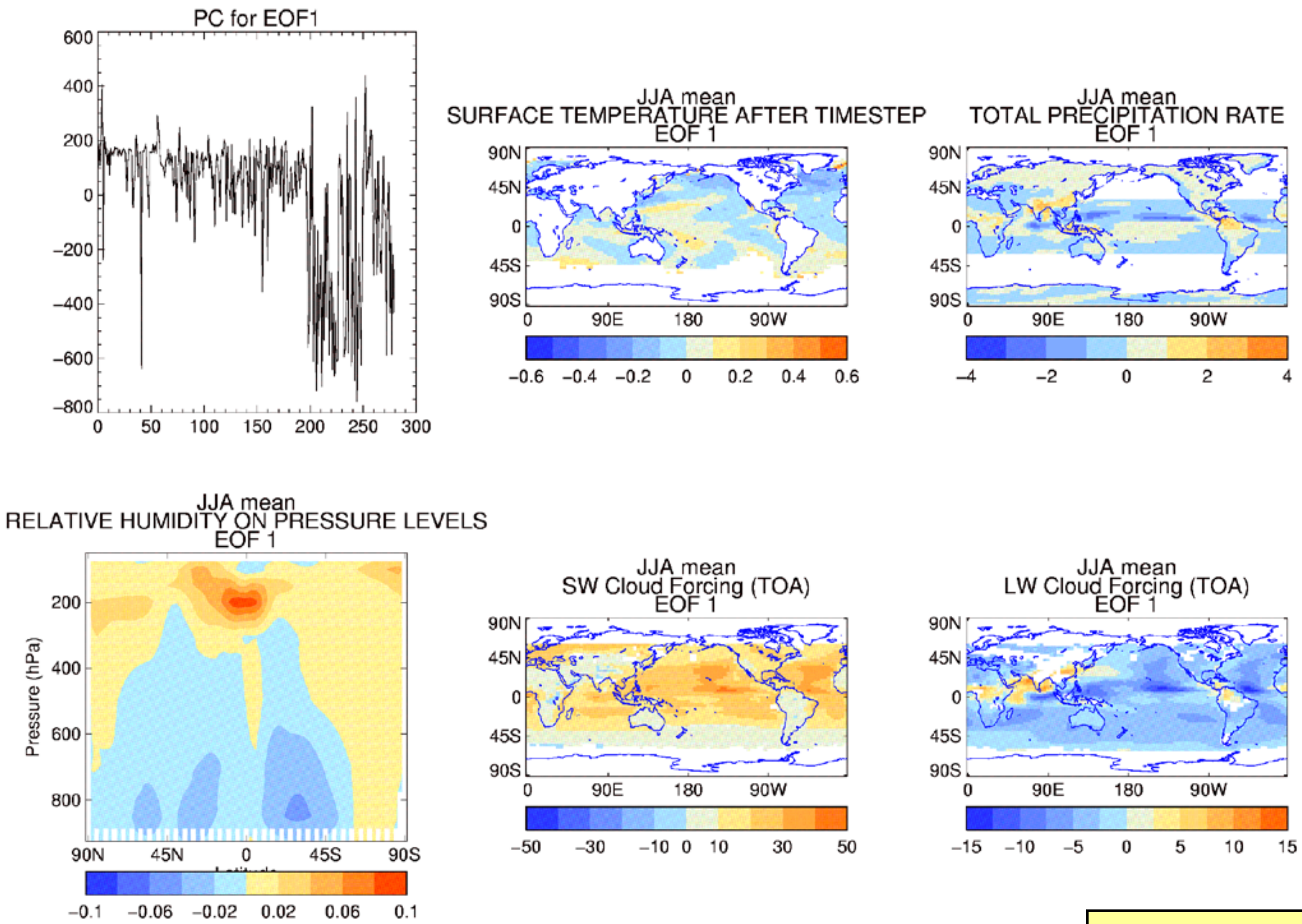
- **Can improve performance against a set of observables by identifying good parts of parameter space using a simulated annealing algorithm …**



- **… but the end point depends on where you start from, and the posterior distributions of parameter values are still quite broad**

Jackson et al (2008), CAM3.1

Using metrics of model performance to rule out unrealistic parts of parameter space

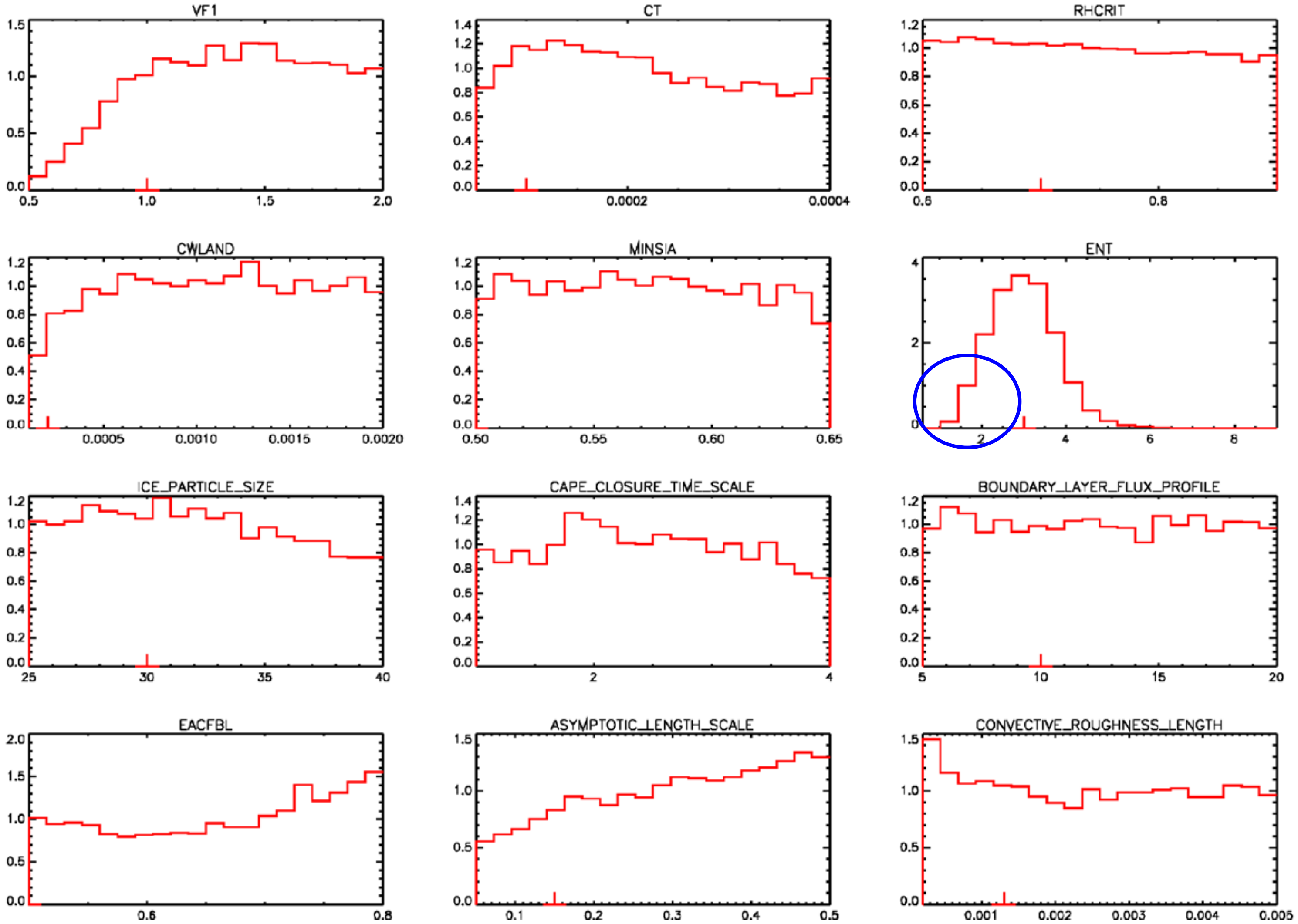


To date, effort mostly focused on multiannual means of key observables

e.g., Met Office QUMP project uses eigenvectors of seasonal mean fields of 12 variables

Sexton et al. (2011), submitted

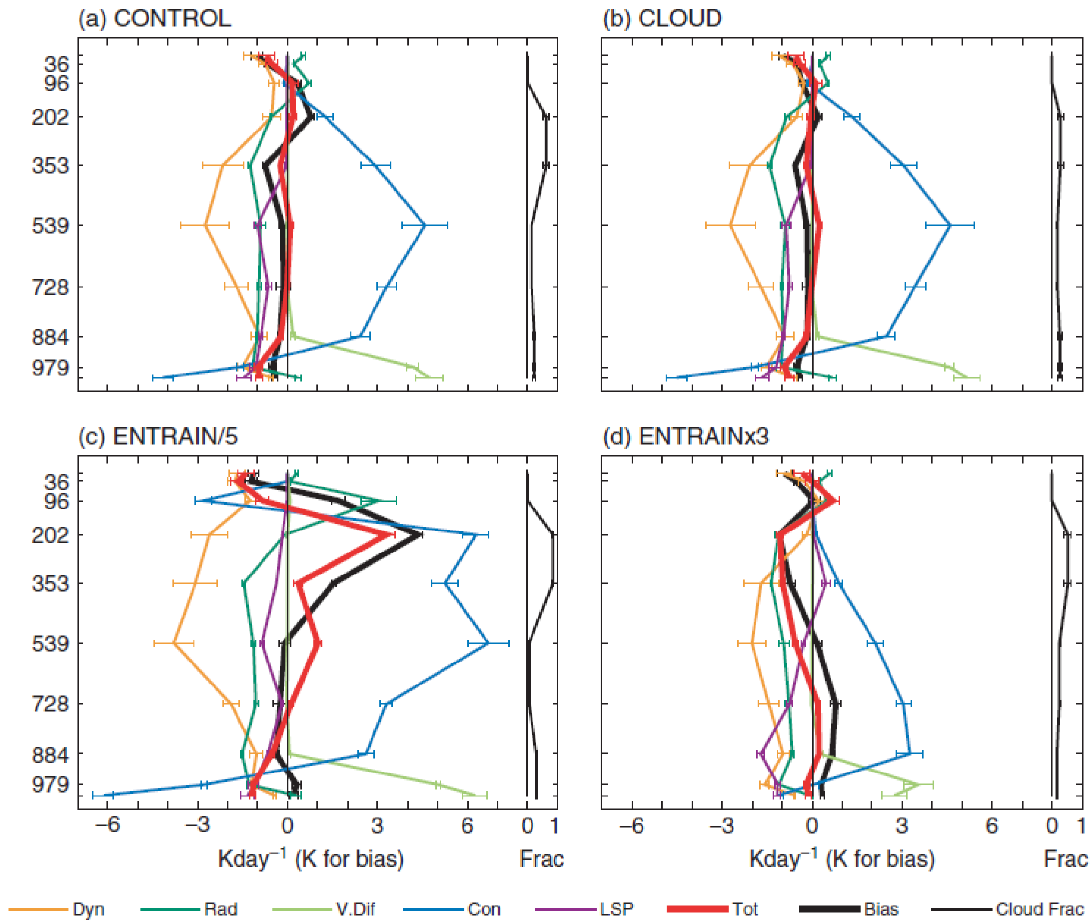
Constraining parameters using mean climate observables



- **Low values of the entrainment parameter (which gives high climate sensitivity in HadCM3) are ruled out quite effectively, but the degree of constraint found on other parameters varies**

Sexton et al. (2011), submitted

Additional possibilities for observational constraints

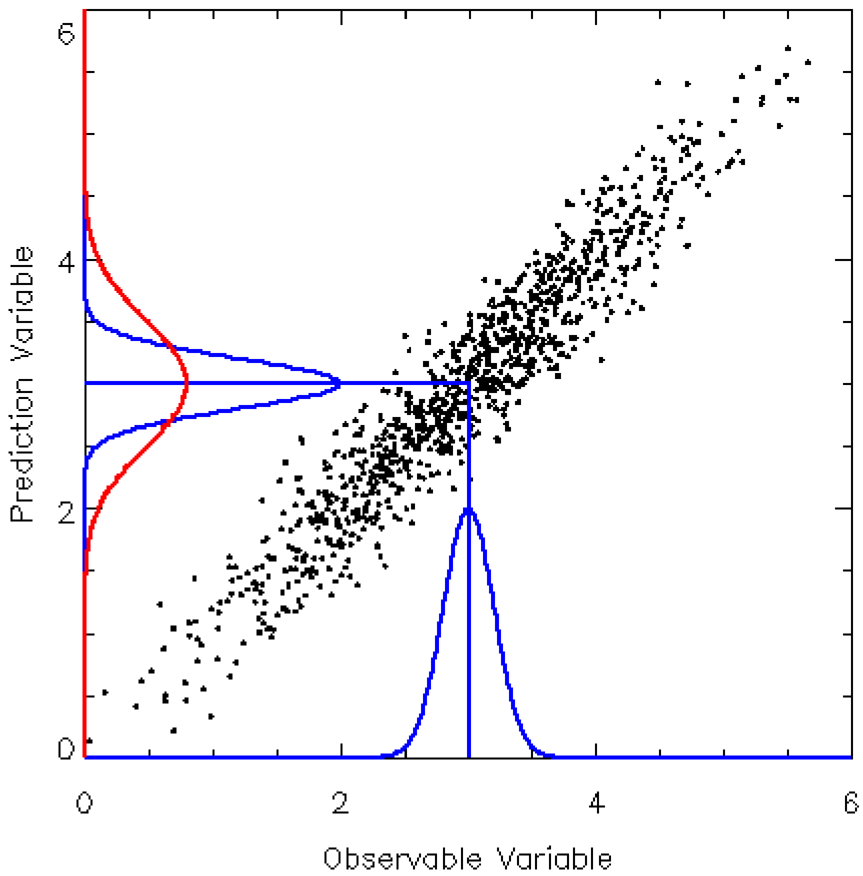


e.g., initial NWP error tendencies can also be used to downweight low settings for entrainment (Rodwell and Palmer, 2007)

- **Potential to use the response of the fast physics in NWP to cheaply identify good parts of parameter space**
- **Potential to achieve a stronger overall constraint by combining evidence from NWP and climate evaluations in "seamless model assessment"**

Making observationally-constrained projections from climate model ensembles: One approach

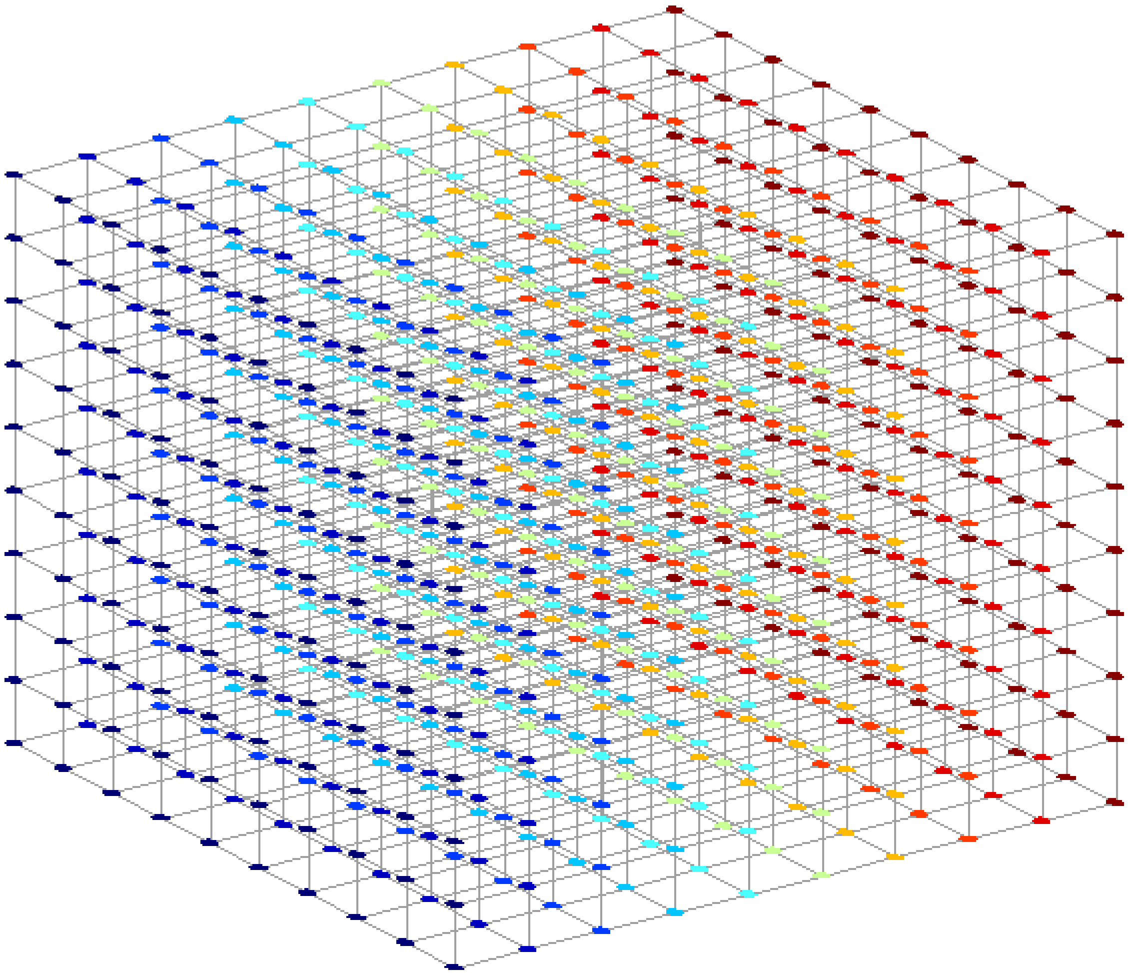
- Find relationship
- Find observed value
- Read off prediction
- Find observational uncertainty
- Use to diagnose prediction uncertainty
- Add uncertainty diagnosed from scatter
- Caveats: Relationship may be specific to the ensemble used; Relies on ability to specify observational uncertainties accurately



e.g. Allen et al (2000), Stott and Kettleborough (2002), Piani et al (2005), Knutti and Meehl (2006), Stott et al (2006), Sanderson et al (2008)

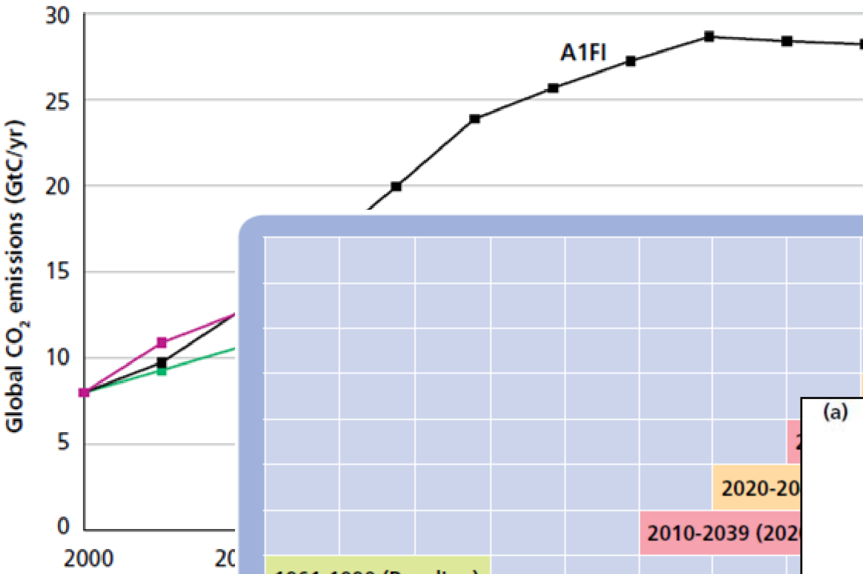
Another approach: Bayesian climate prediction based on PPEs

- **Expert prior distributions for model parameters**
- **GCM simulations sampling the parameter space of one climate model**
- **Train an emulator to predict GCM output anywhere in parameter space**
- **Compare each emulated model variant with past observations and assign a relative likelihood**
- **Form a weighted posterior distribution of predictions**
- **Done by constructing a joint probability distribution of all uncertain objects in the problem**
- **Good for handling multivariate prediction problems**

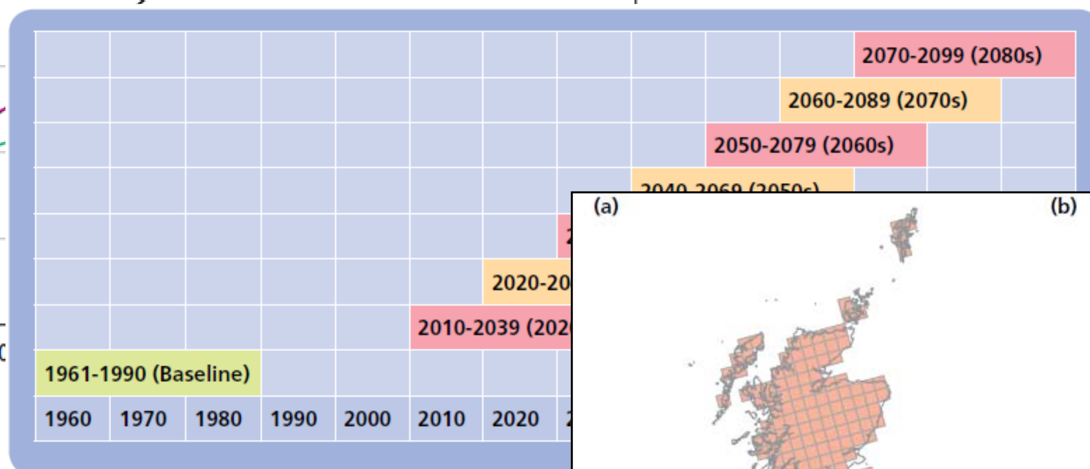


e.g., Goldstein and Rougier (2004)

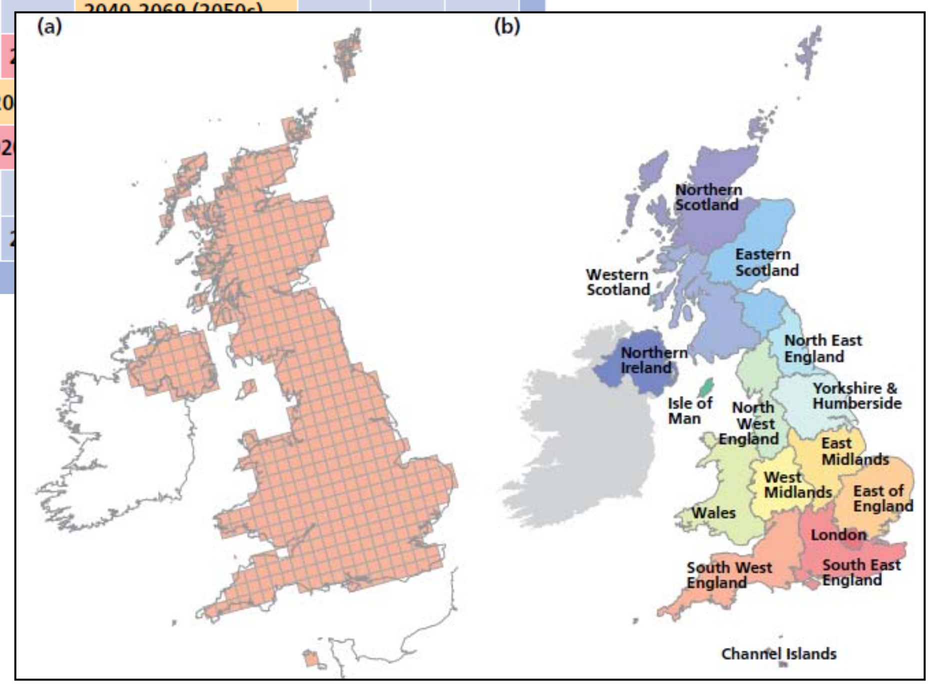
UKCP09: Probabilistic national scenarios derived from climate model ensembles



Three different emission scenarios

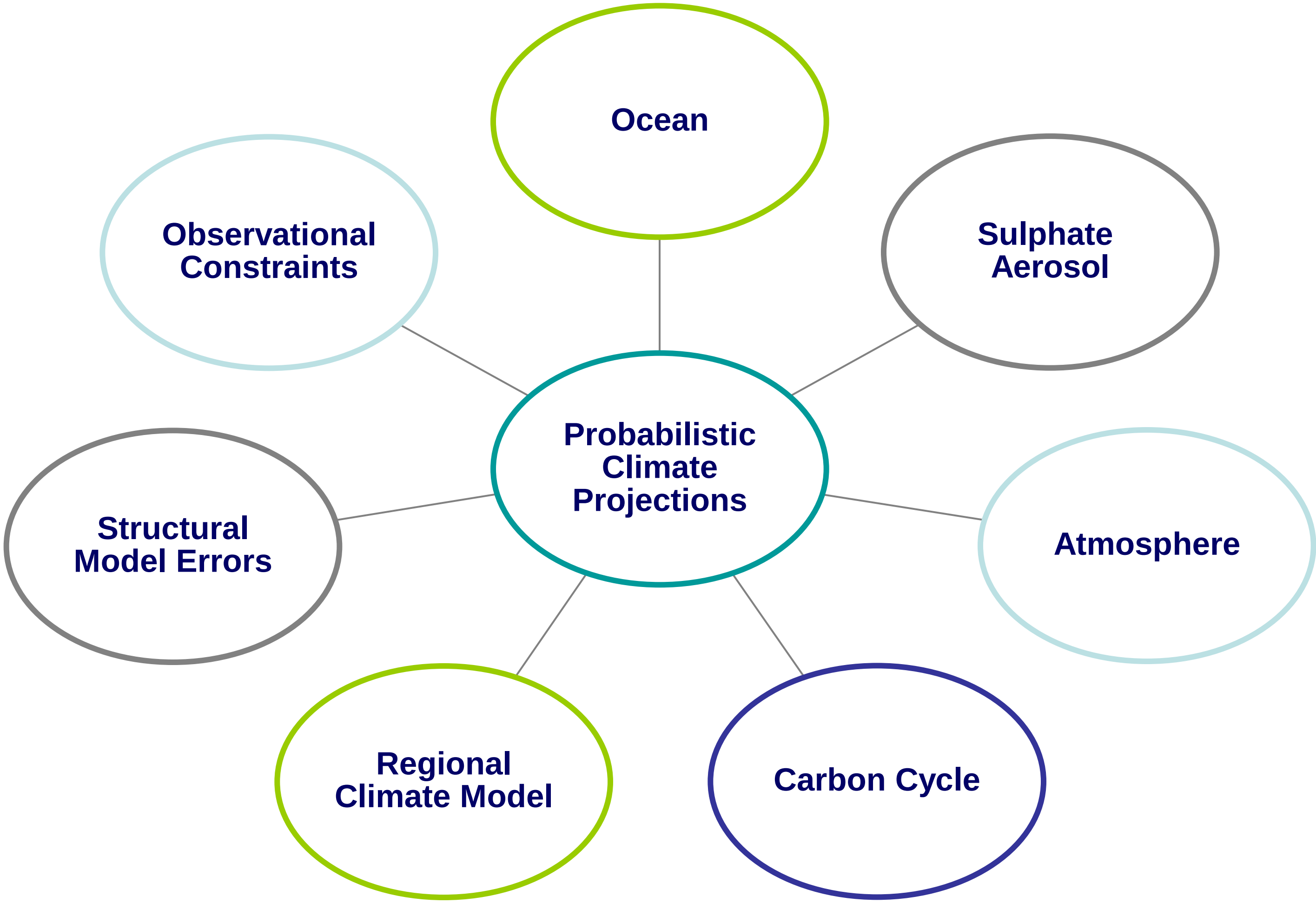


Seven different timeframes



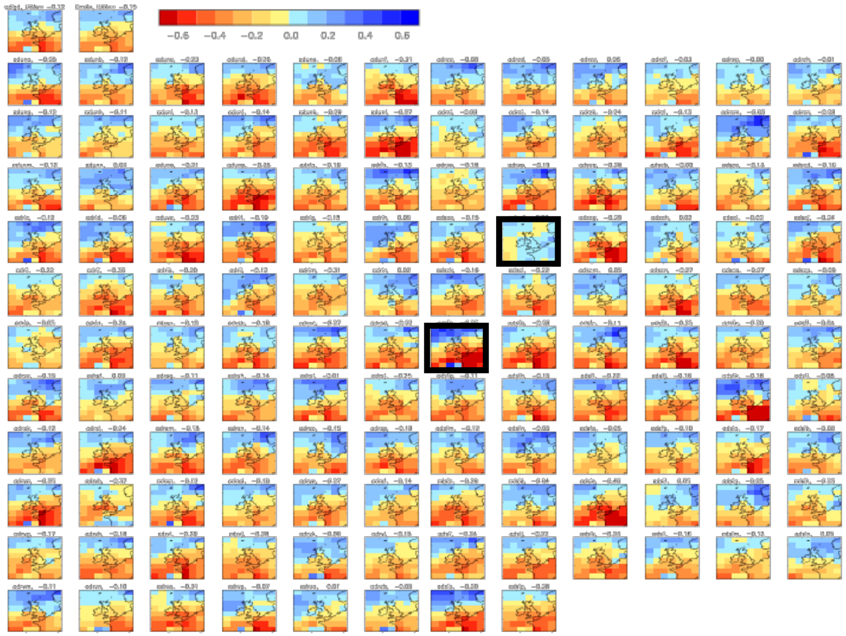
25km grid, 16 admin regions, 23 river-basins and 9 marine regions

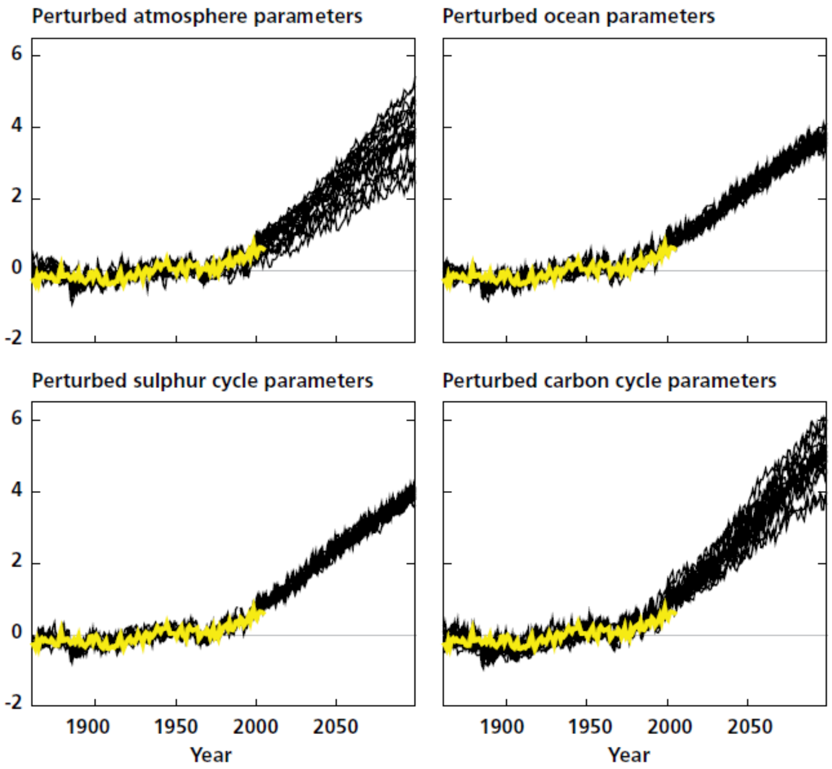
Inputs to probabilistic projections for UKCP09



Sampling uncertainties realistically

- UKCP09 was based on 400 different variants of the Met Office Hadley Centre climate model HadCM3, systematically sampling uncertainties in key processes, and augmented by results from other international climate models





Estimating effects of structural model error: “Discrepancy”

- **Discrepancy represents model errors (arising from missing or structurally deficient representations of processes) which cannot be resolved by varying uncertain parameters in the model used for the perturbed parameter ensemble (HadSM3)**

- **For UKCP09, we estimated this by using an international ensemble of 12 alternative climate models (AR4, CFMIP) as set of proxies for the real system.**

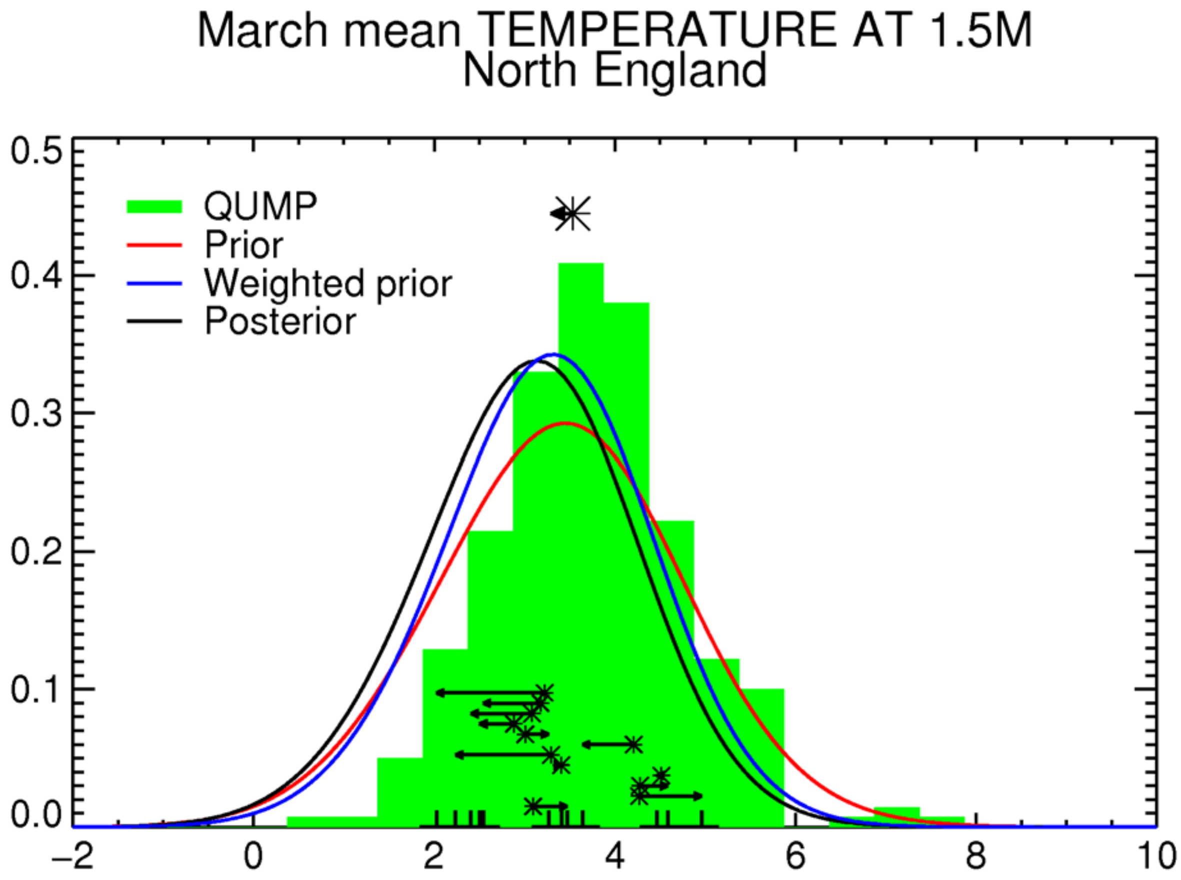
- **For each multimodel ensemble member, find a few points in the HadSM3 parameter space which give the closest historical and climate change simulations that we can find.**

- **The outstanding mismatches are then estimates of the effects of missing or structurally deficient representations of processes in HadSM3**

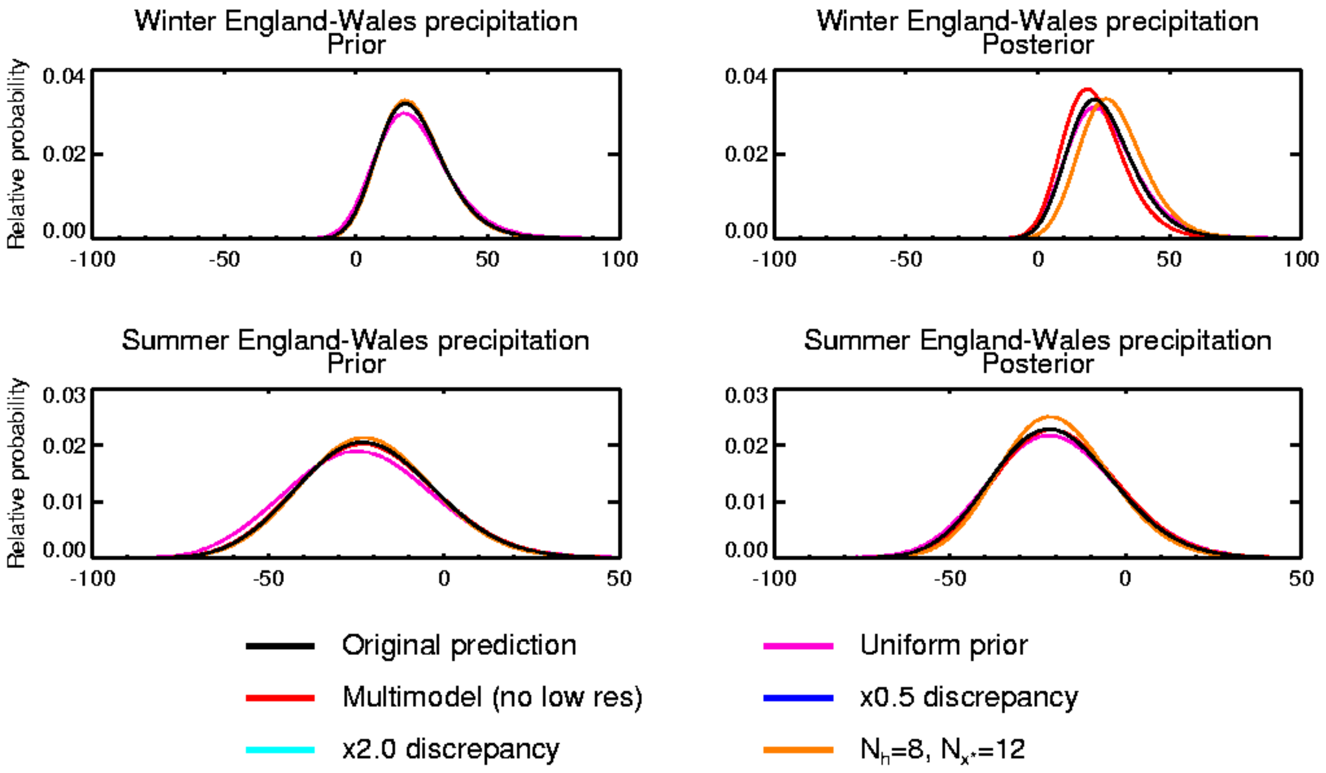
- **Pool these distances over all 12 multimodel ensemble members to give an estimated distribution for discrepancy**

- **Main caveat: Does not account for systematic errors common to all the models**

Combining perturbed parameter ensembles, multi-model ensembles and observational constraints

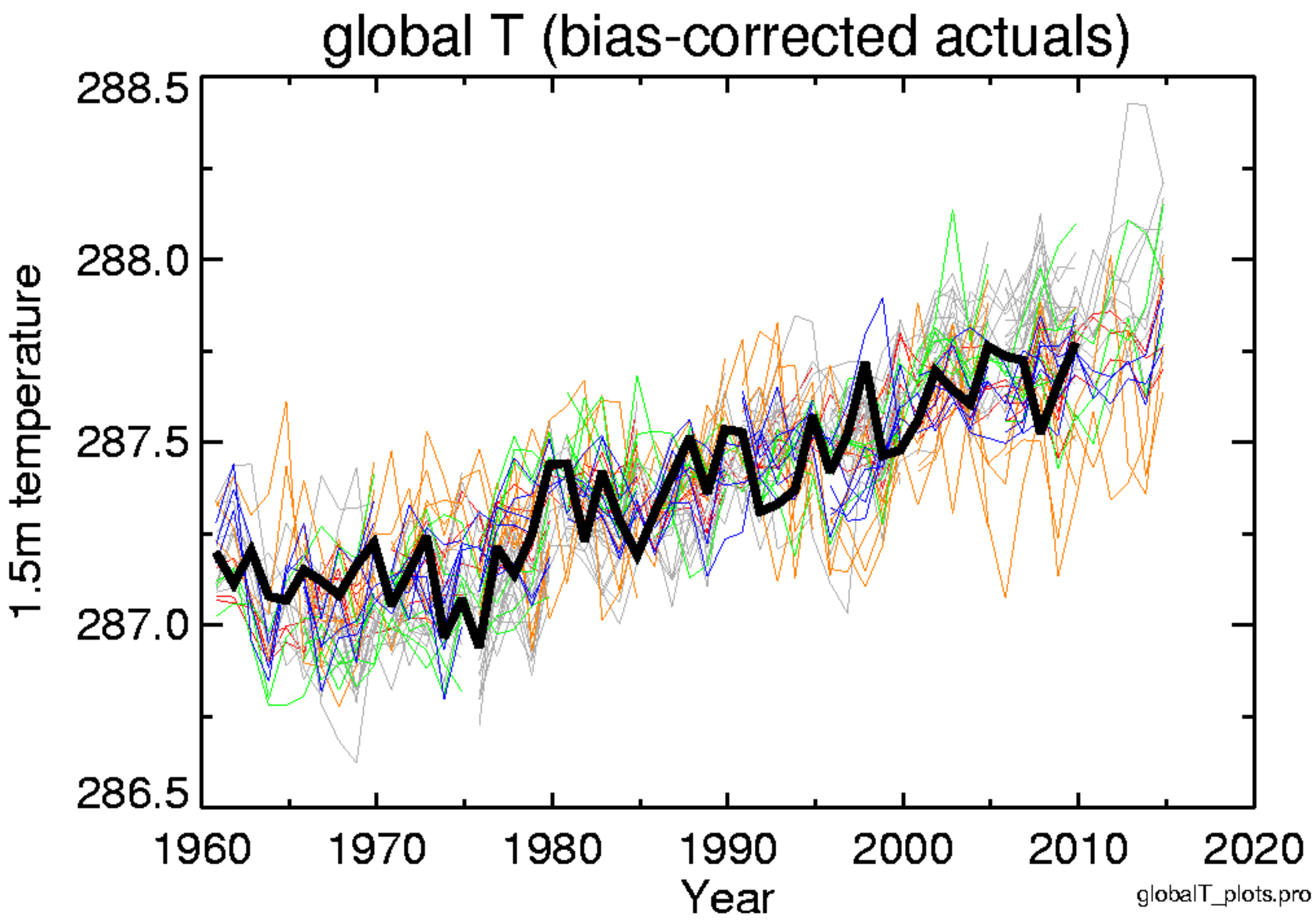


Testing the robustness of the results



- Projections inevitably depend on expert assumptions and choices
- However, sensitivities to some key choices can be tested

The future: Application to seamless prediction systems ?



Lines represent:

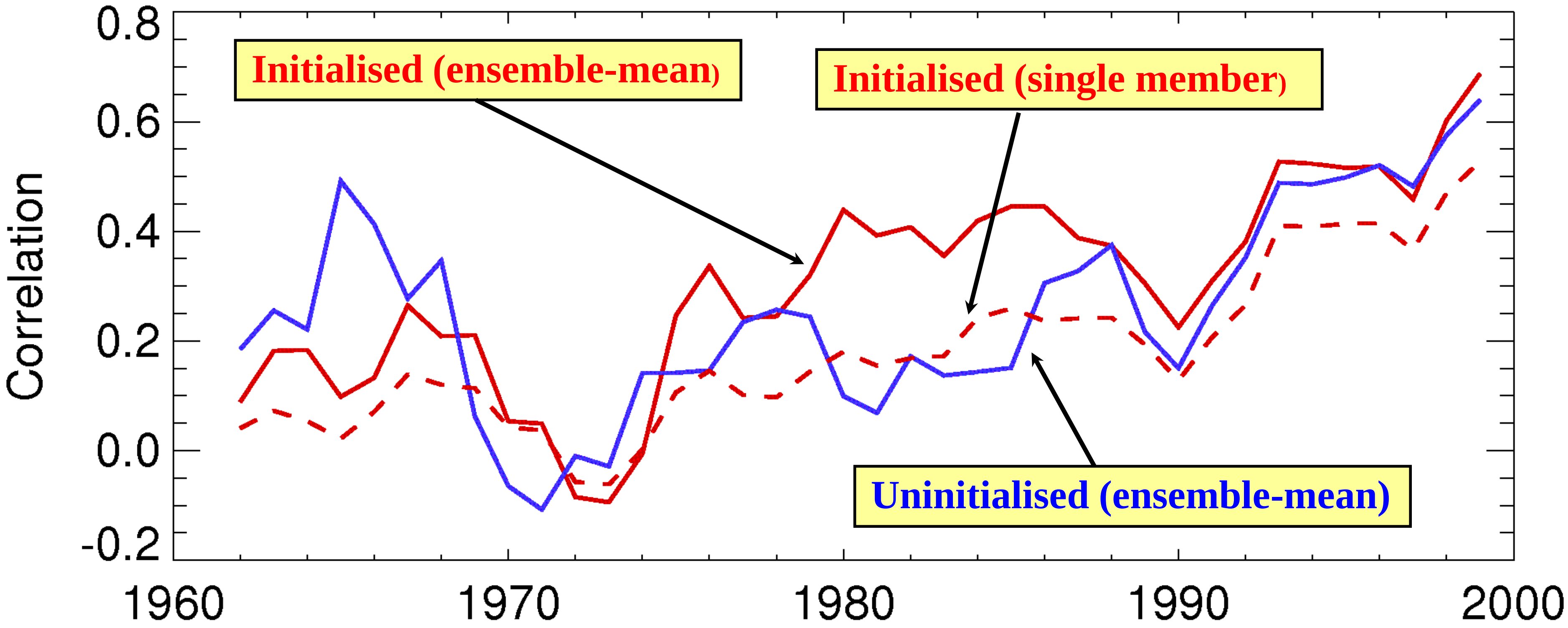
ERA40/Interim

Nine variants of HadCM3

Other models

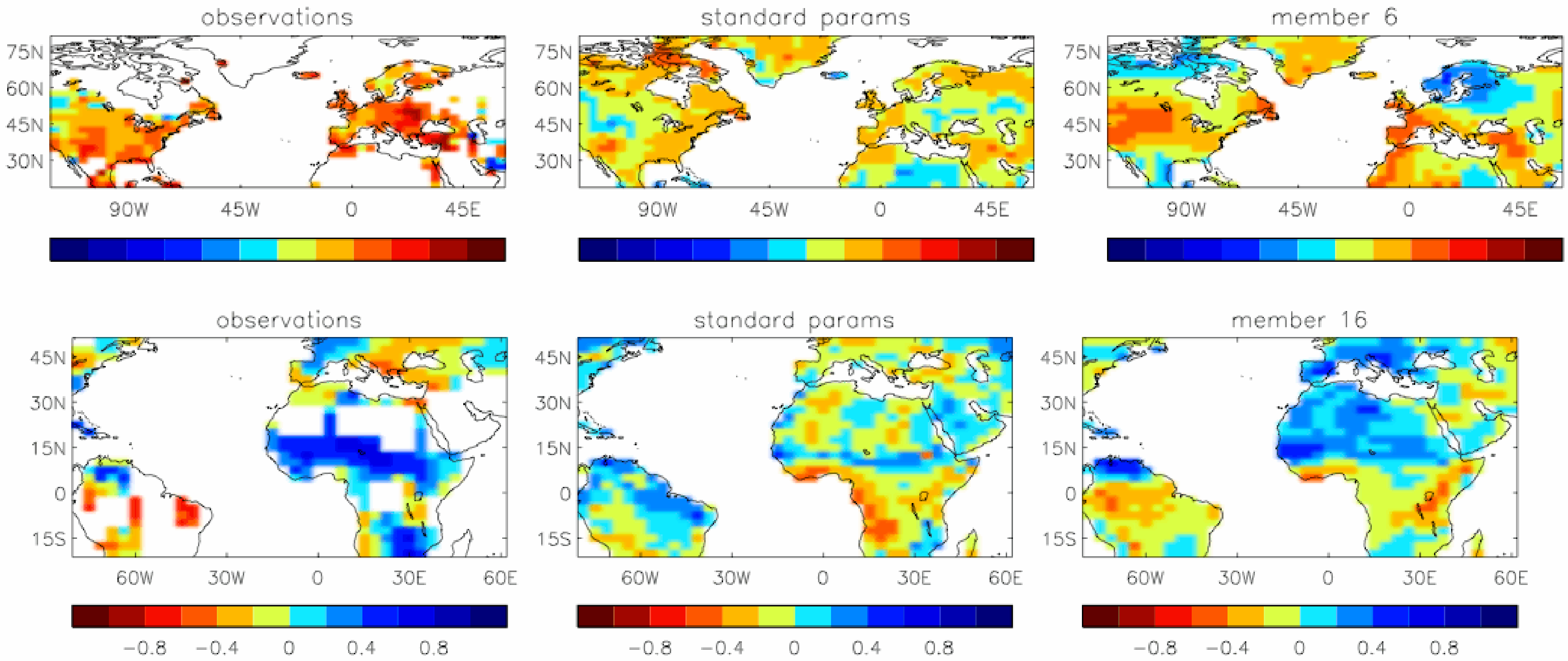
• FP6 ENSEMBLES project included a first go at assessing multi-model, stochastic physics and perturbed parameter ensembles in initialised seasonal-to-decadal hindcasts

Effects of initialisation and sampling uncertain model parameters



Time series of pattern correlation with observations: 9 year mean surface temperature over land

Can PPEs be designed to sample key drivers of predictability on seasonal-to-decadal time scales ?



Correlation between the AMO index and detrended 5-year averaged June-July-August surface temperature anomalies (top row) and precipitation anomalies (bottom row). Observations (left panels), and different members of a HadCM3 perturbed physics ensemble (middle and right panels).

Summary

- Study of perturbed parameter ensembles in climate simulation and prediction has grown
- A systematic approach to sampling model uncertainties, useful alongside the community multi-model ensemble approach
- Properties depend on the chosen base model, and the experimental design
- Applications in understanding drivers of uncertainty, model optimisation, finding relationships between observables and future predictions, and identifying structural model limitations
- Can be used to make climate projections providing a basis for adaptation decisions, when combined with multi-model information and observational constraints

Outlook

- Should be seen as complementary to multi-model and stochastic physics approaches

- Effectiveness in initialised near-term forecasting should be assessed.. as well as in centennial projections

- Application of observational constraints is particularly important in PPEs. Scope to develop this in seamless prediction context