What does uncertainty really mean when applied to information derived from climate models?

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To quote a leading scholar of uncertainty:

"There are known knowns.

These are things we know that we know.

There are known unknowns.

That is to say, there are things that we know we don't know.

But there are also unknown unknowns.

There are things we don't know we don't know."

Donald Rumsfeld

- Forcing (or Scenario Uncertainty)
- Response (or Model Uncertainty)
- Internal (or Natural Variability)

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- Response (or Model Uncertainty)
    - Climate Sensitivity
    - Parametric Uncertainty
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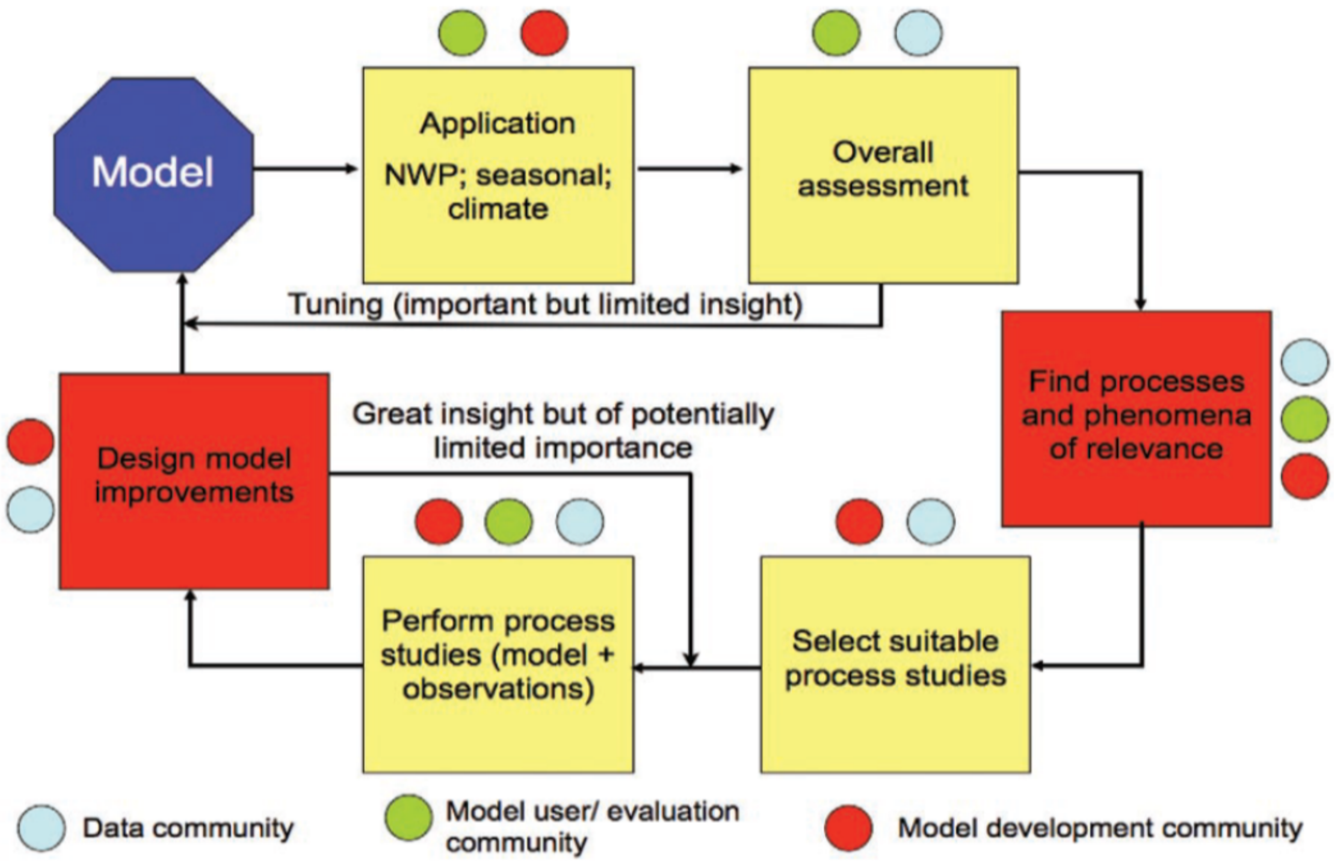
- Resolution
- Uncertainty to Initial Conditions



Assessing Climate Models

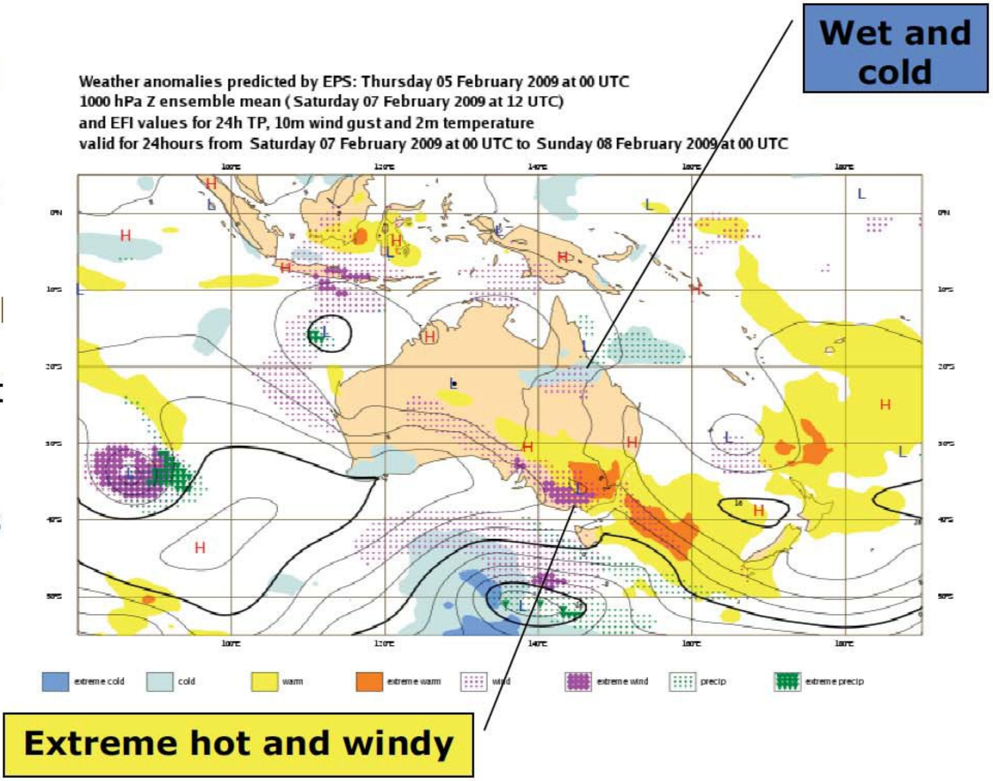
Figure above shows climate model development and testing which involved multiple stages and contributions of the model development community, the model user/evaluation community, and the data community. (Jakob, BAMS, 2010). Current climate models are calibrated during development to match observations within reasonable uncertainty ranges. Sources of uncertainty include the forcing on the climate system, the system response to forcing, natural internal variability of the climate system, incomplete representation of small scale processes, and poorly understood processes.

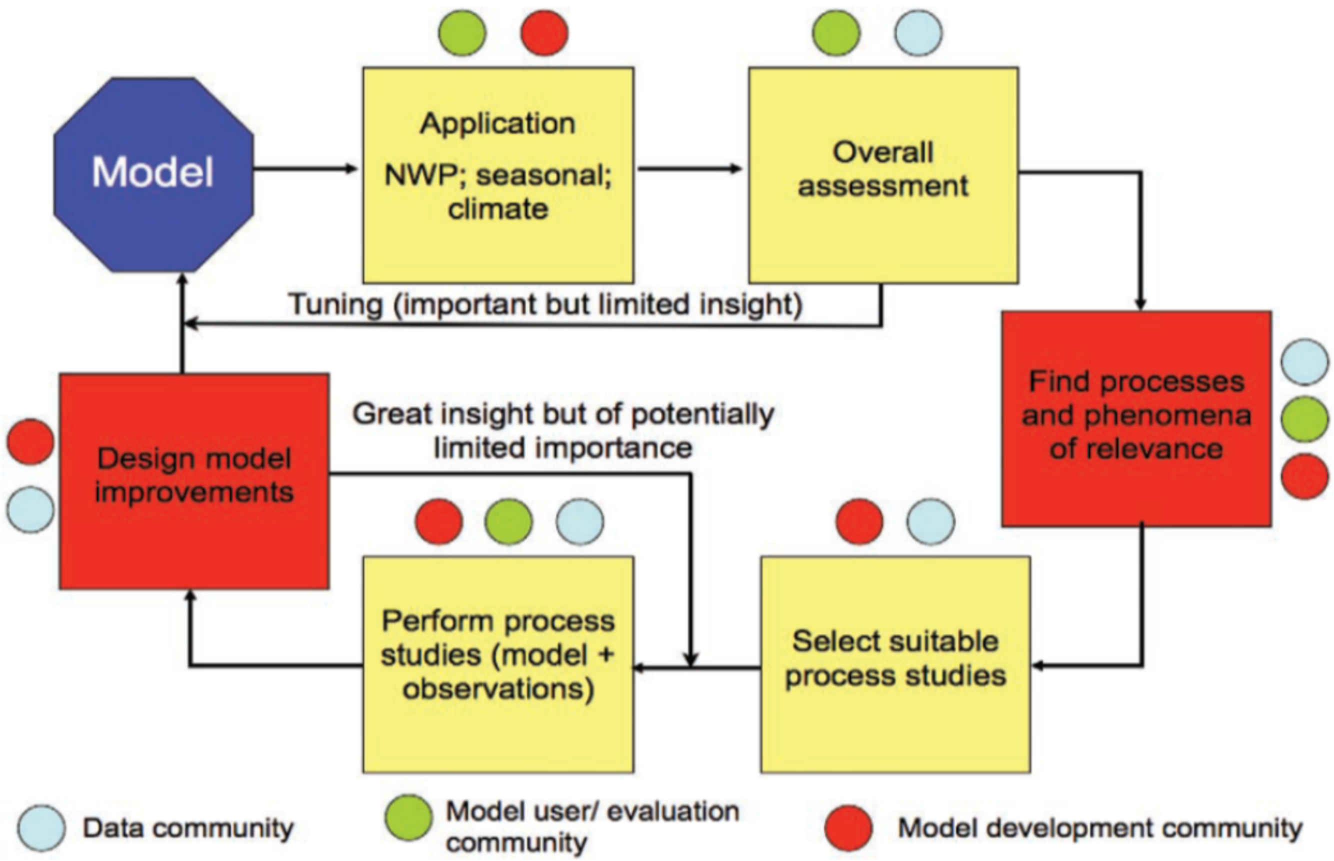
Reforecast advantage: facilitates quantitatively assessing how unusual an event is

EPS I-EFI 05@00+48/72h vt 07@00-08@00

The forthcoming Interactive EFI (I-EFI) can be used to identifies areas where the ensemble forecast distribution is significantly different from the climatological distribution, and visualize the grid point distributions.

This plot shows the I-EFI +48/72h forecasts issued on 5@00UTC and valid between 7@00UTC and 8@00UTC.





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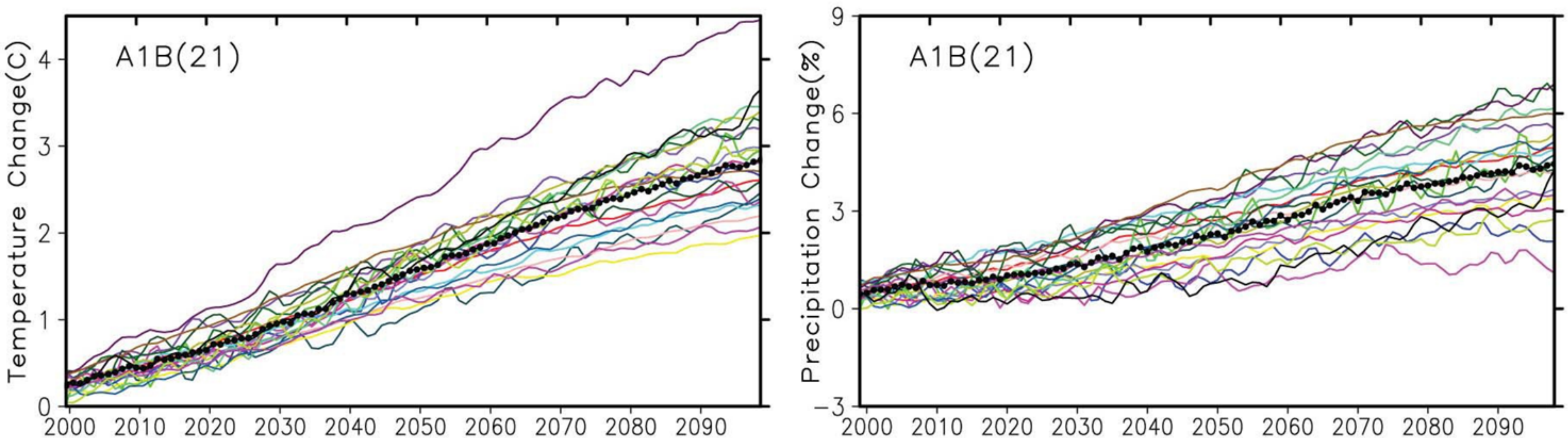
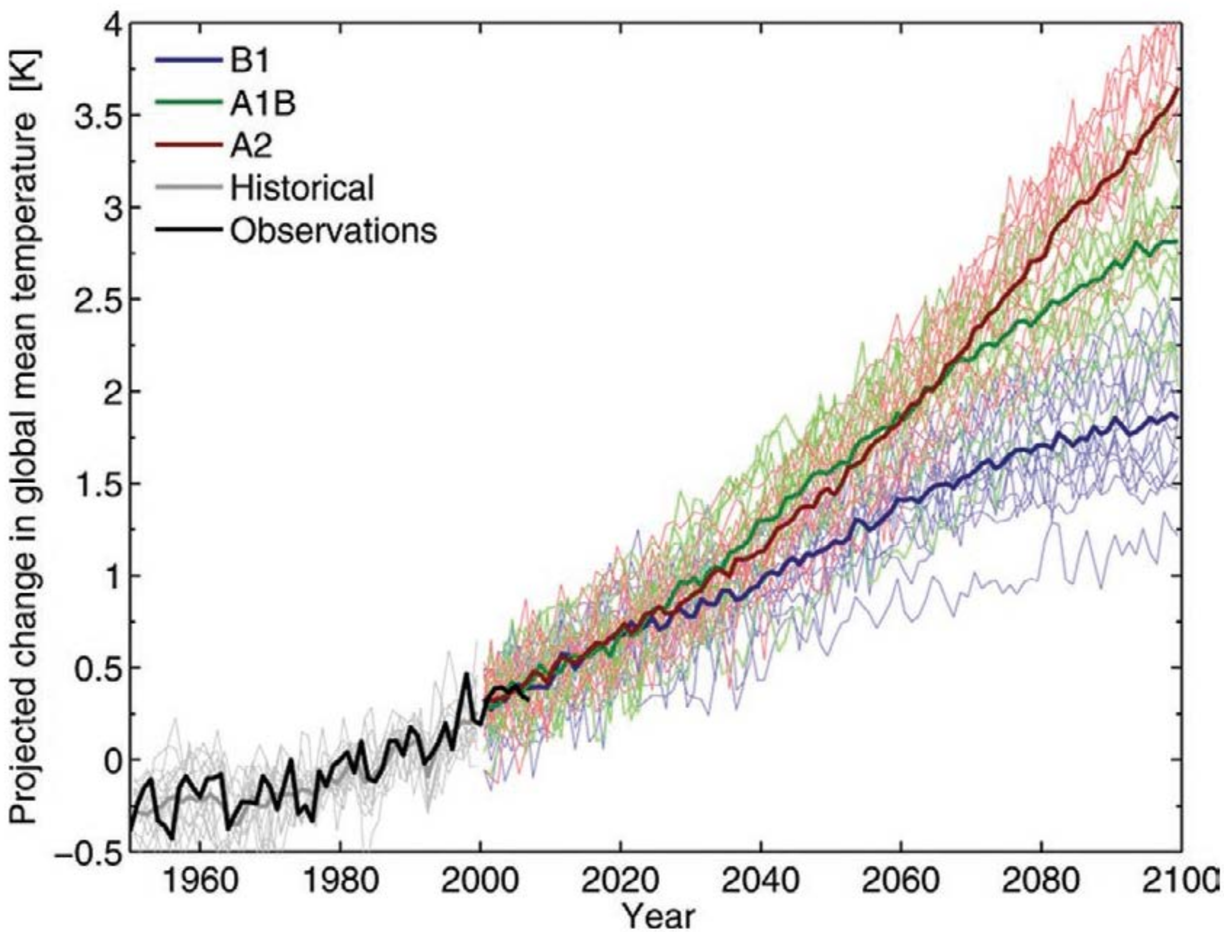
Model "Uncertainties": Ensemble Spread ≠ Uncertainty

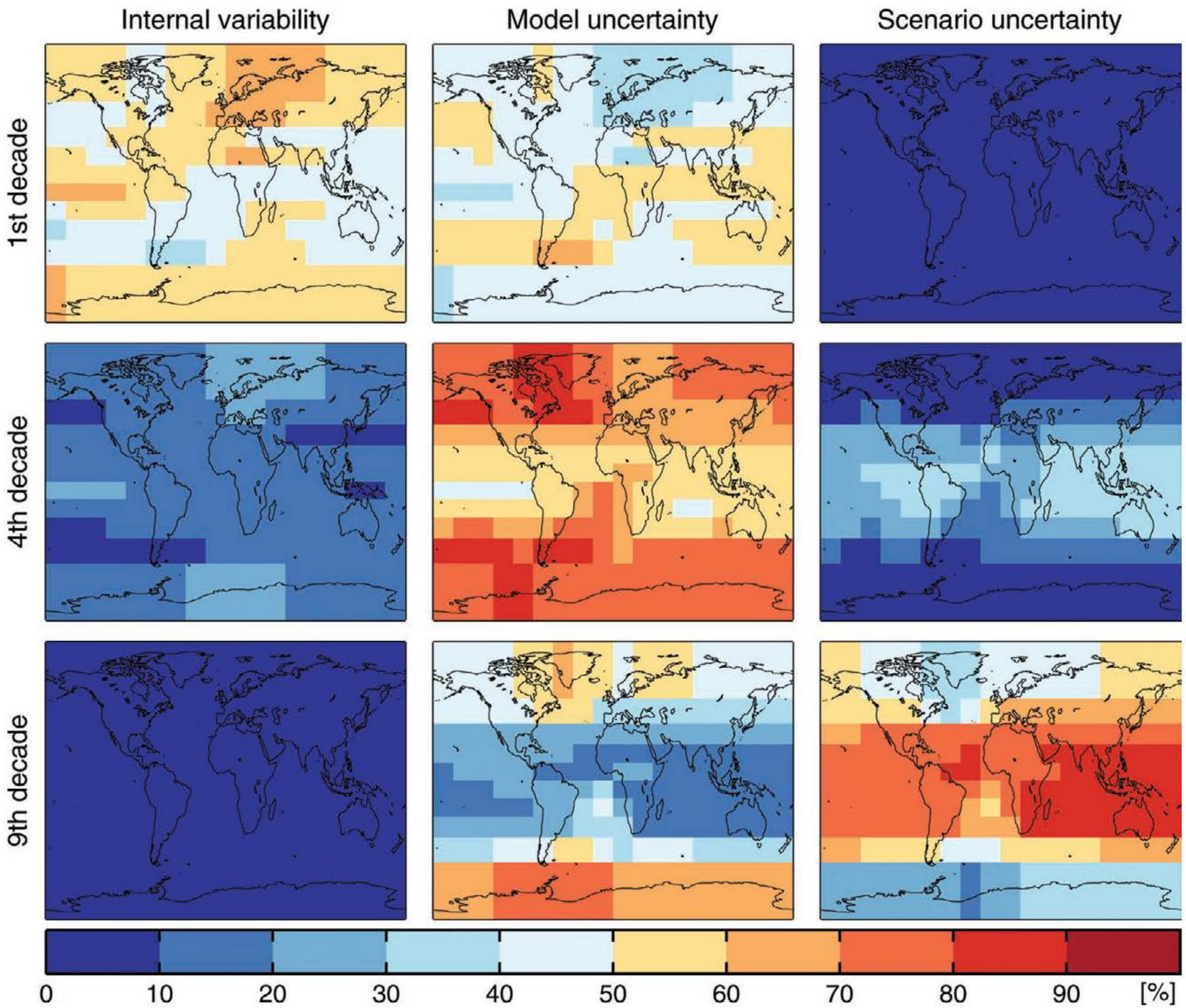
Most commonly characterized by the spread in a multi-model ensemble of climate projections run at different international centers, and collected in a common archive.



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

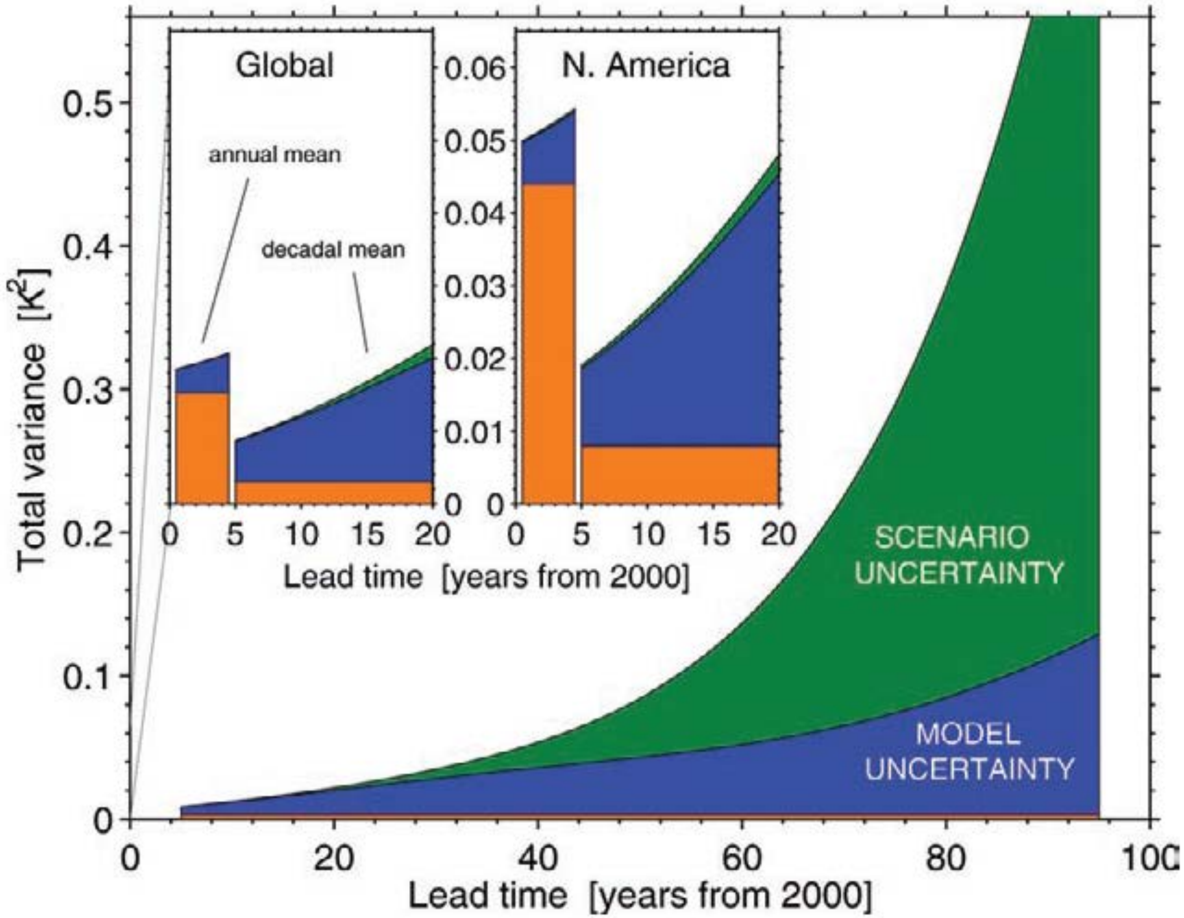
Global mean, annual mean, surface air temperature predictions from 15 different emission scenarios from 2000-2100 (thin lines): SREAS A2(red), A1B(green), and B1(blue), designated as high-, medium-, and low-emissions paths, respectively. The same models forced with historical forcings are shown as the thin gray lines, and the observed global mean temperature from 1950-2007 (Brohan et al, 2006) are shown as a thick black line. The multimodel mean for each emissions scenario is shown with thick colored lines demonstrating how uncertainty in future emissions gives rise to uncertainty in climate predictions. The different scenarios give nearly identical predictions until 2025, demonstrating the delayed effect of future emissions. (Hawkins and Sutton, 2009)





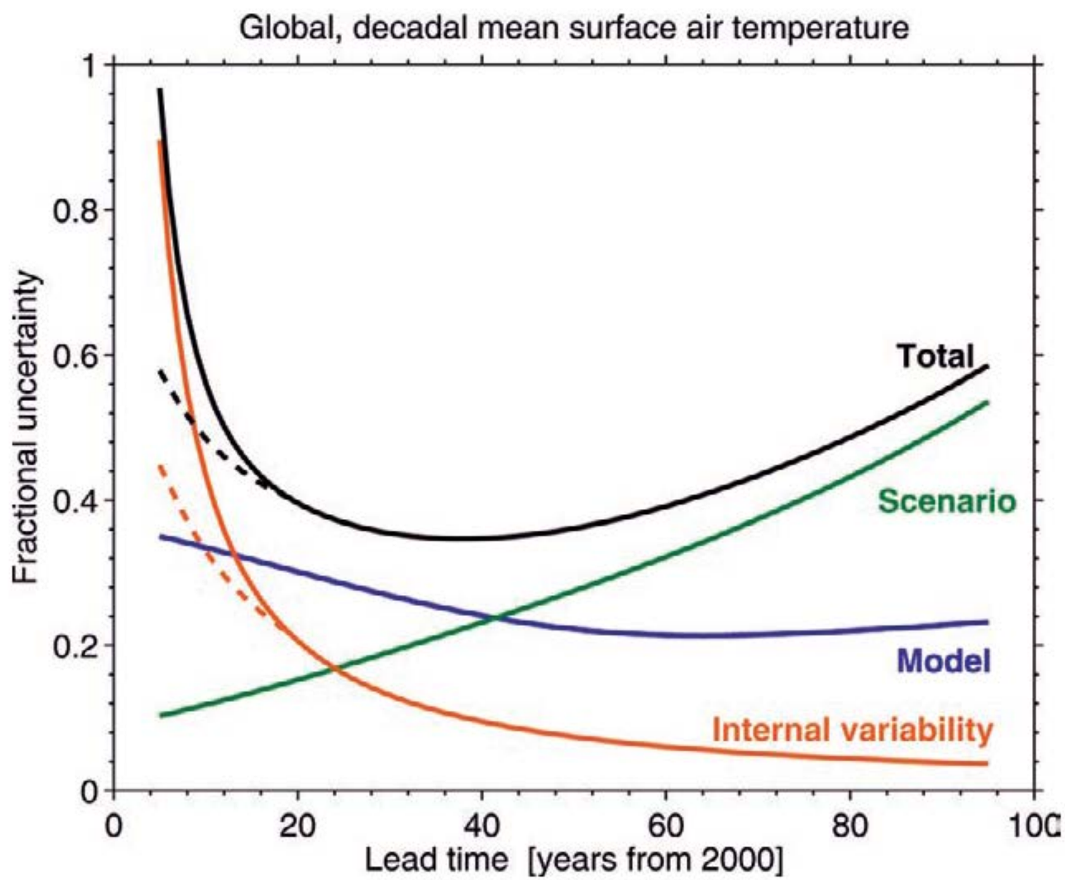
(Hawkins and Sutton, *BAMS* 2009)

Maps of the sources of uncertainty for decadal mean surface temperature for various lead times give information on where any reduction in uncertainty will have the most benefit. The columns show variance explained by (left) internal variability, (mid) model uncertainty and (right) scenario uncertainty for the first (top), fourth (mid) and ninth (bot) decade. Even on regional scales, the uncertainty due to internal variability is only a significant component for lead times up to a decade or two. The largest differences between models occur at high latitudes where climate feedbacks are important and even by the end of the century, the emissions scenario is less important than model uncertainty for the high latitudes, but dominates the tropics.

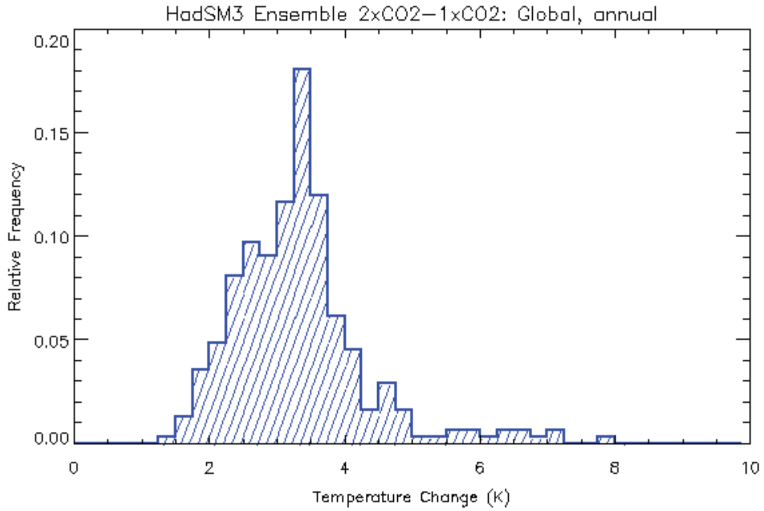


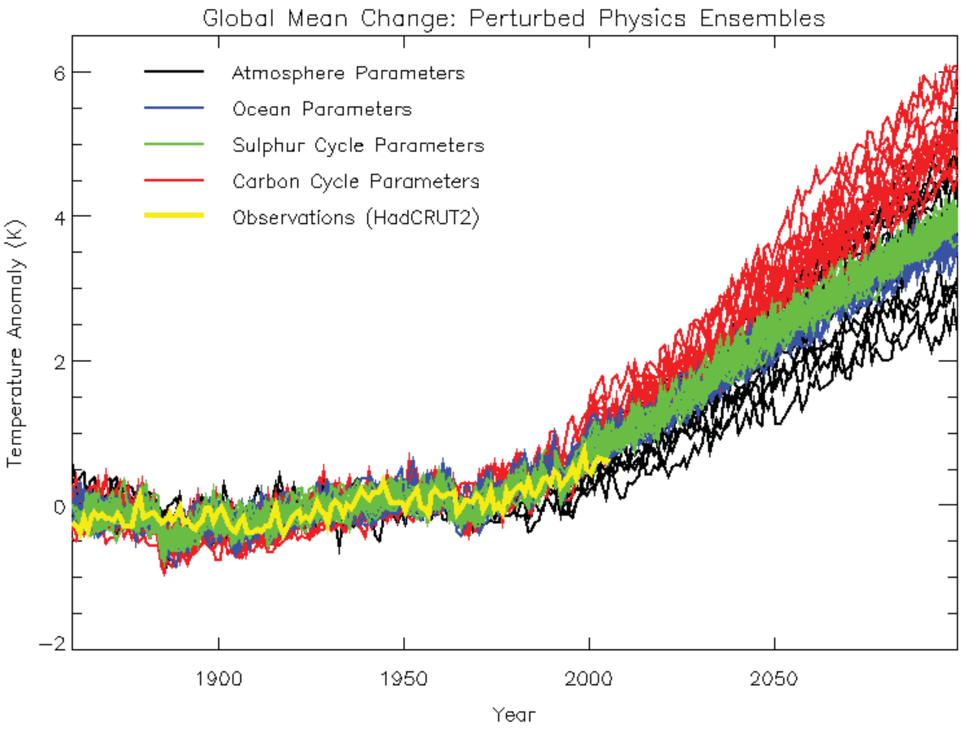
The relative importance of the three sources of uncertainty changes significantly with region, forecast lead time, and the amount of any temporal meaning applied. Main panel: Total variance for the global mean, decadal mean surface air temperature predictions, split into the three sources of uncertainty. Insets: As in the main panel, but only for lead times less than 20 yr for (left) the global mean and (right) a North American mean. The orange regions represent the internal variability component. The uncertainty in the regional prediction is larger than for a global mean. (Hawkins and Sutton, 2009)

Relative importance of each source of uncertainty in decadal mean surface air temperature predictions is shown by the fractional uncertainty (the 90% confidence level divided by the mean prediction), for the global mean, relative to the warming since the year 2000 (ie a lead of zero years). The dashed lines indicate reductions in internal variability, and hence total uncertainty, that may be possible through proper initialization of the predictions through assimilation of ocean observations. (Smith, et al, 2007)



A primary integrated metric of uncertainty in response to GHG forcing is climate sensitivity



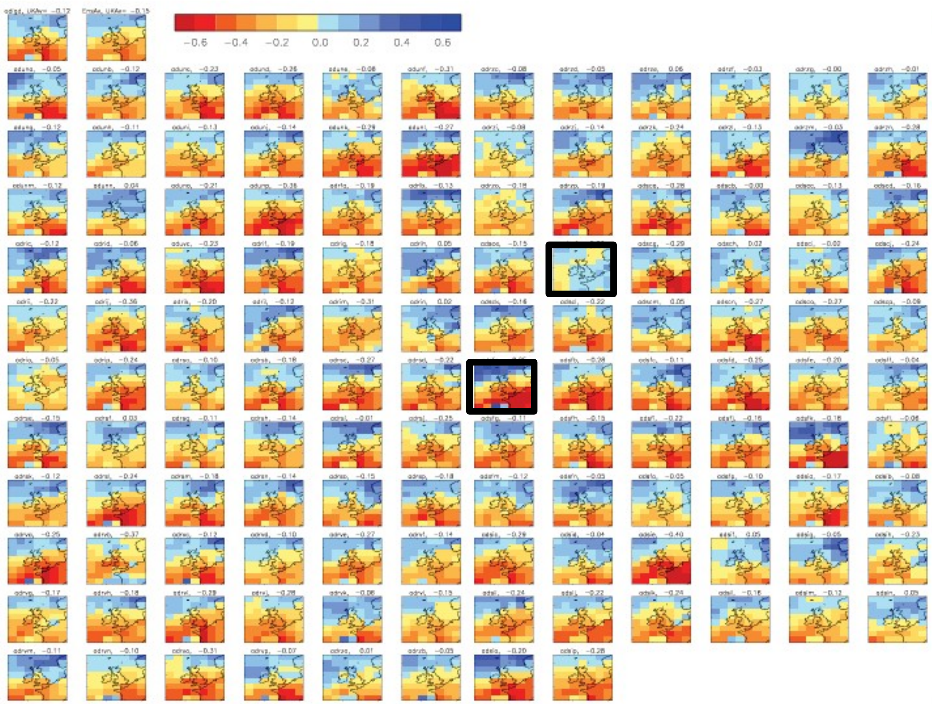


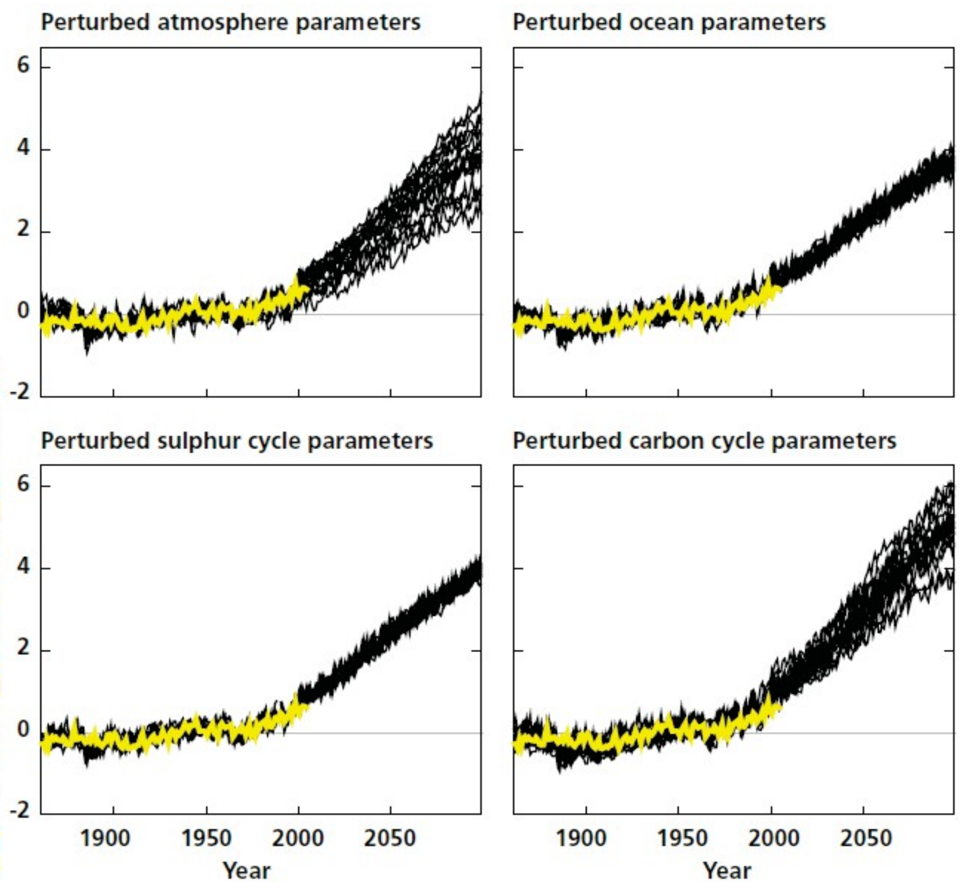
- Much work focused on atmosphere parameters (understanding drivers of uncertainty in climate sensitivity and regional climate change)
- But also simulations looking at ocean, sulphur cycle, carbon cycle: Important if a more comprehensive sampling of uncertainties is needed to provide robust information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

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

Sampling Climate Model Uncertainties

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





James Murphy, UK Met Office, 2012

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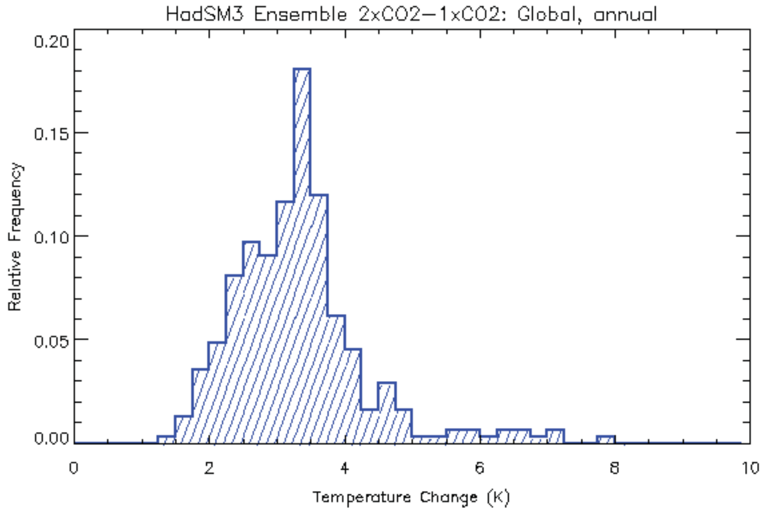

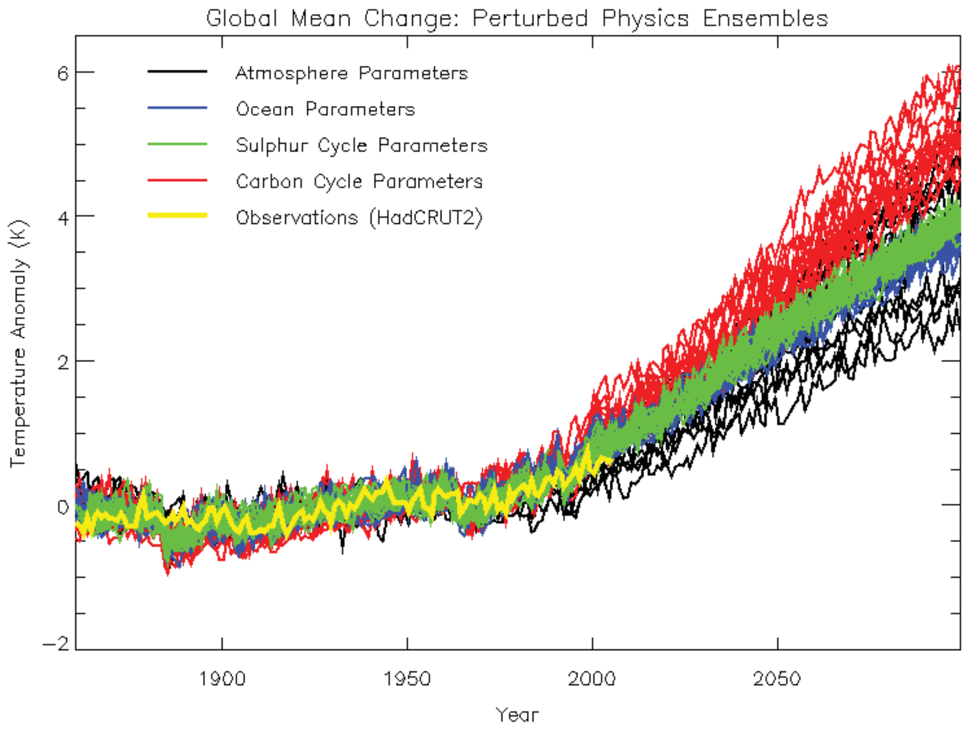

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Uncertainty also results because certain processes or features are not included in most climate models or are modeled poorly or incompletely

These include:

- Ice sheets
- Interactions of sea ice and ocean circulation
- Aerosols and aerosol-cloud interactions
- Complexities in the carbon cycle (e.g., methane clathrates)
- Stratosphere-troposphere interactions
- Cumulus convection

Since ensembles composed of current climate models do not represent many of these features, these ensembles do not take into account these: ***structural uncertainties.***

Therefore, ensembles do not represent all the known uncertainties

Multi-model ensemble concept

- **Two main sources of error:**
  - **initial conditions: -> ensemble concept**
  - **model formulation: -> multi-model concept**

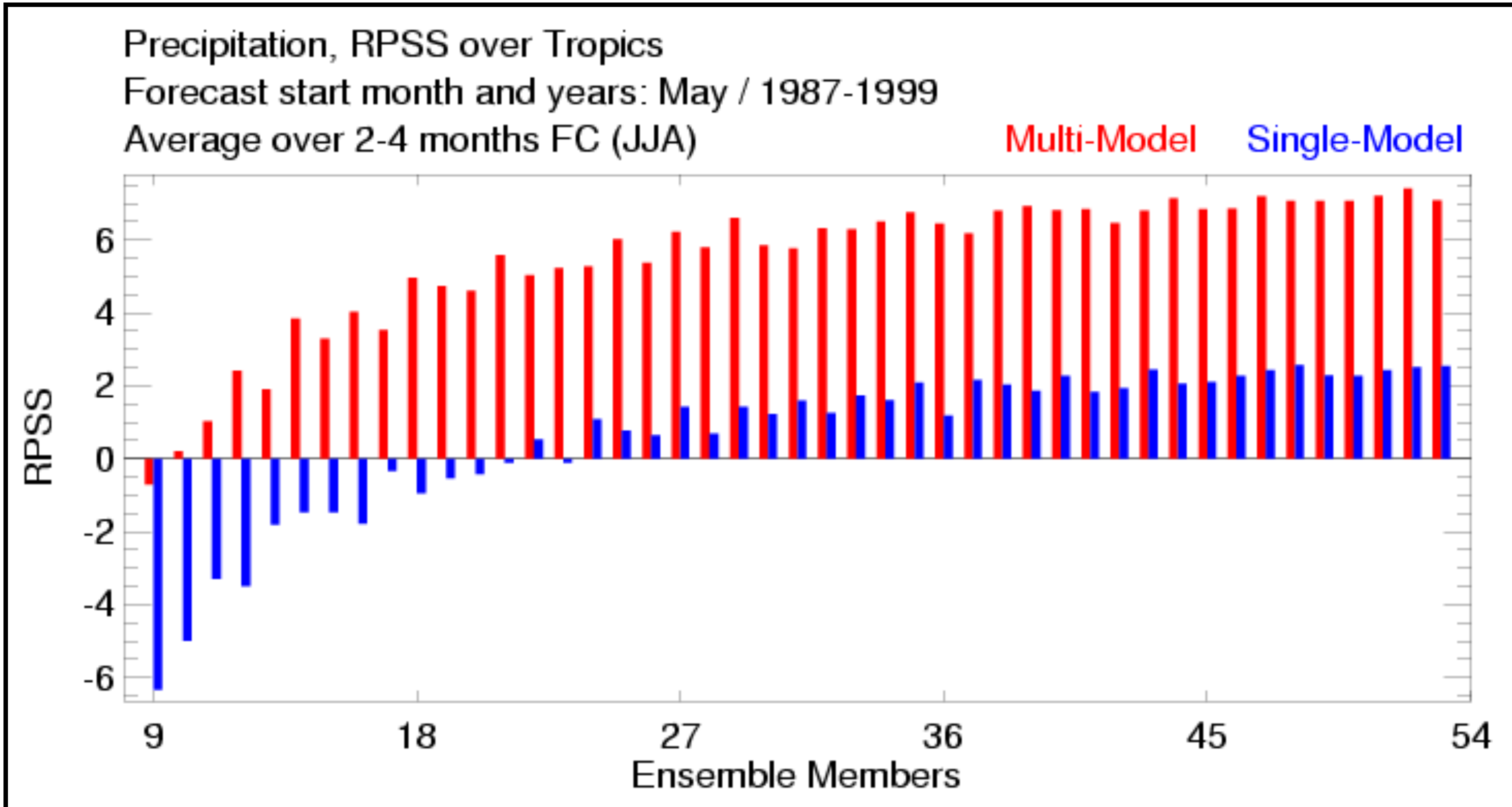
- **The multi-model approach provides a "consensus" forecast**

- **Two general approaches to combine models:**
  - **merging models with equal weights**
  - **estimating optimal weights for each model, based on past performance**

- **Main difficulty: finding robust weights**

Source: R. Hagedorn, ECMWF

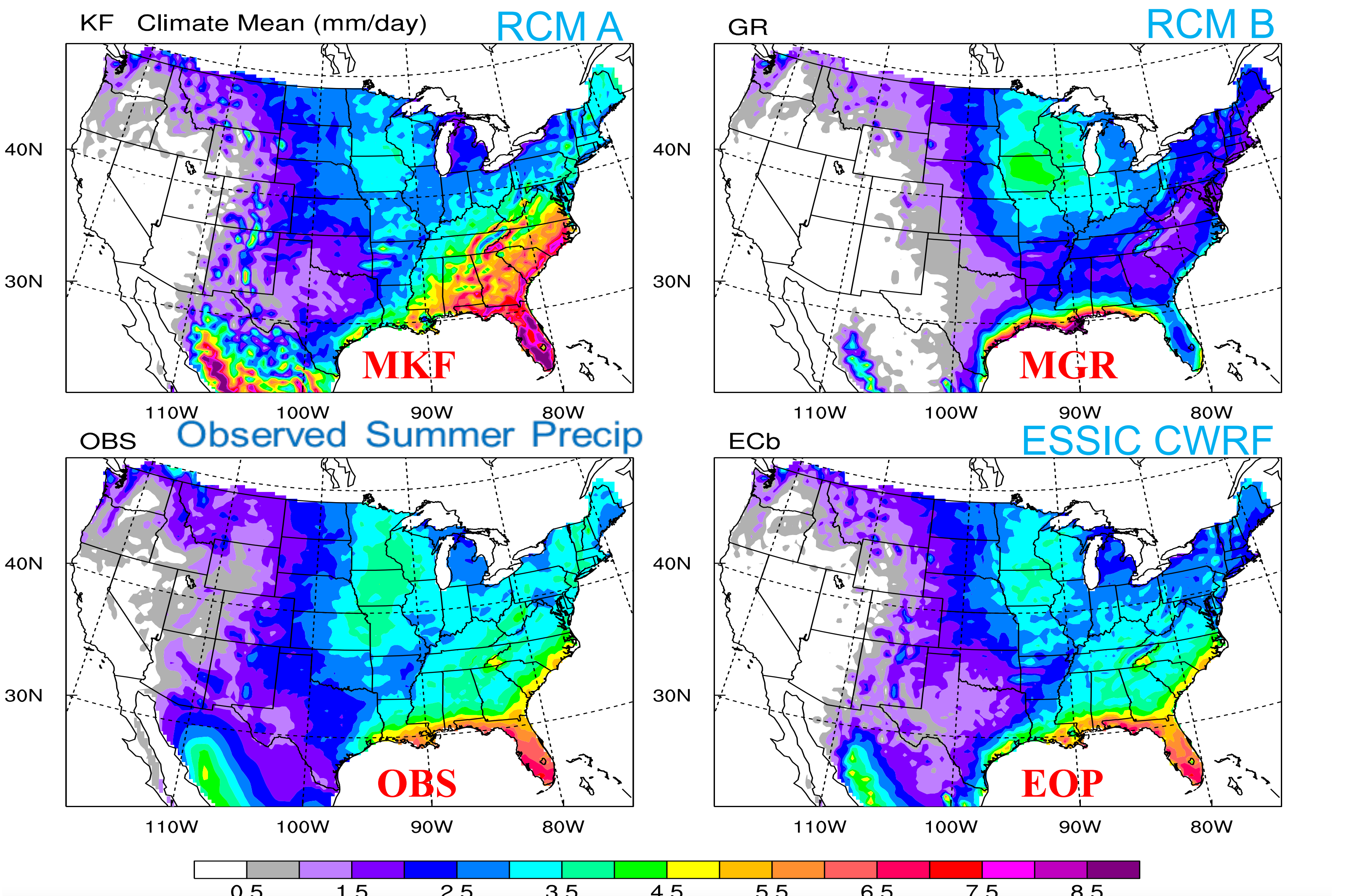
Effect of Increasing Ensemble Size



From DEMETER (ECMWF)

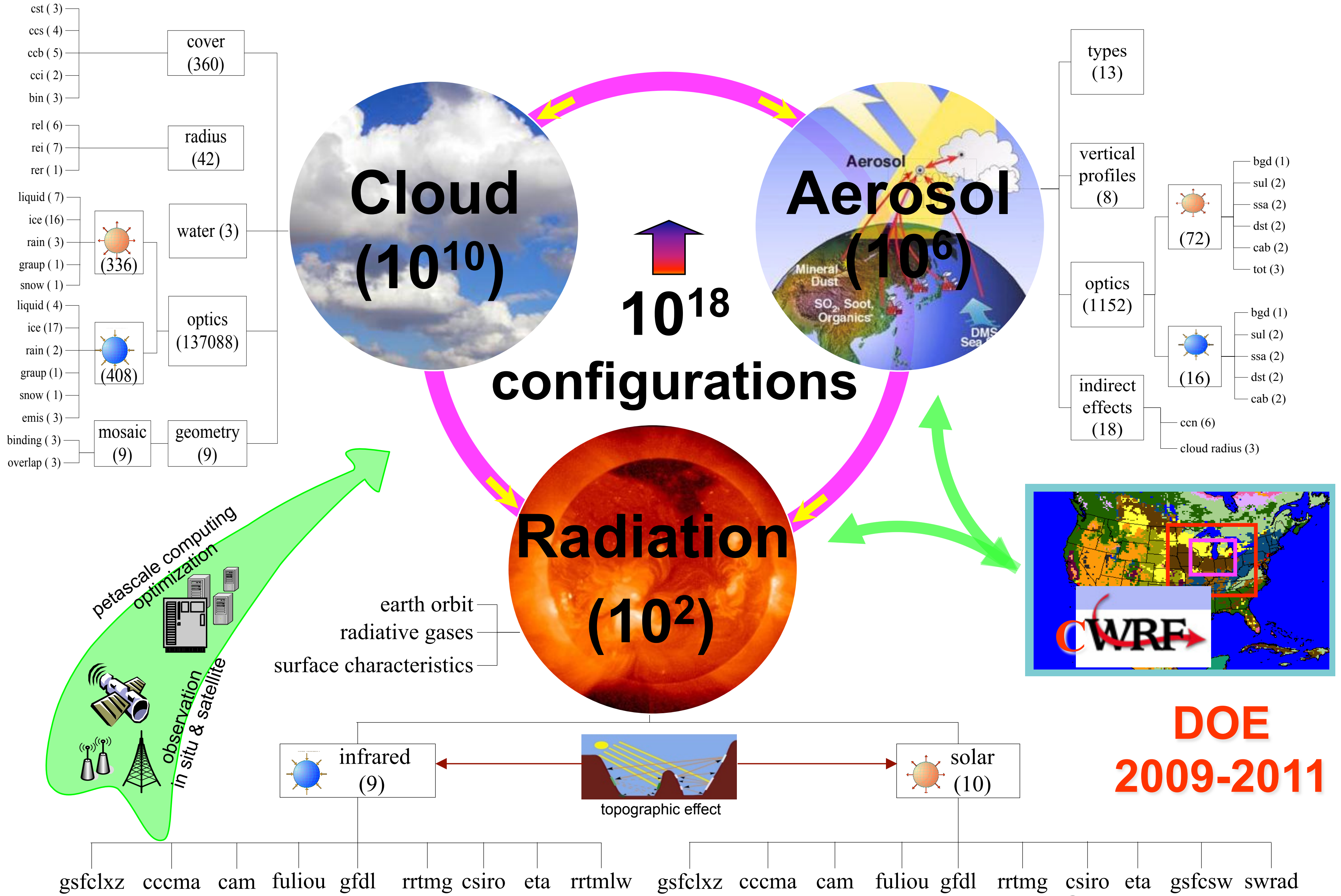
Climate Information: Responding to User Needs
BRINGING DATA, MODELING AND PREDICTION INTO GOVERNMENT AND BUSINESS DECISION-MAKING

Optimized Physics-Ensemble Prediction



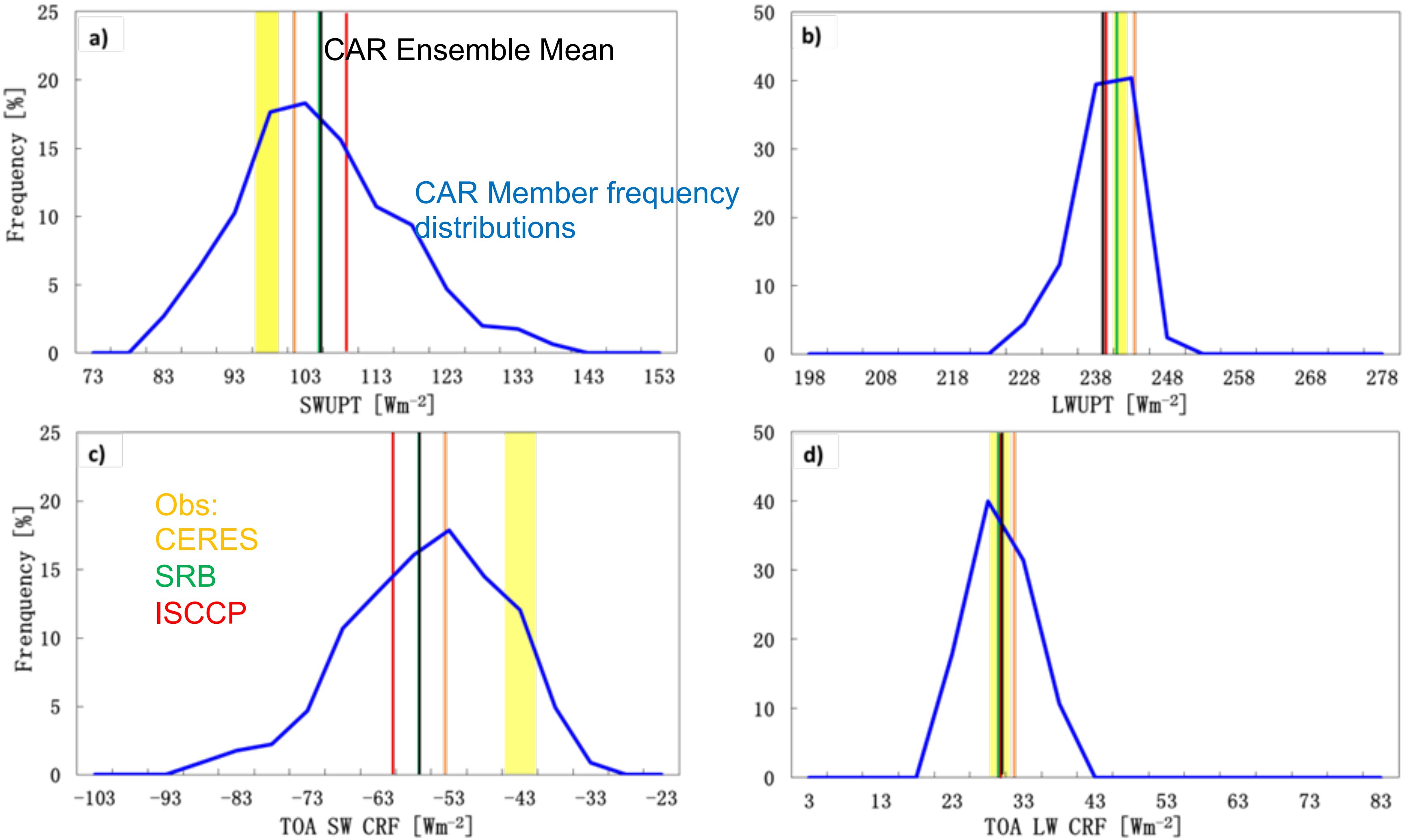
Courtesy X-Z Liang

Cloud-Aerosol-Radiation Ensemble Model



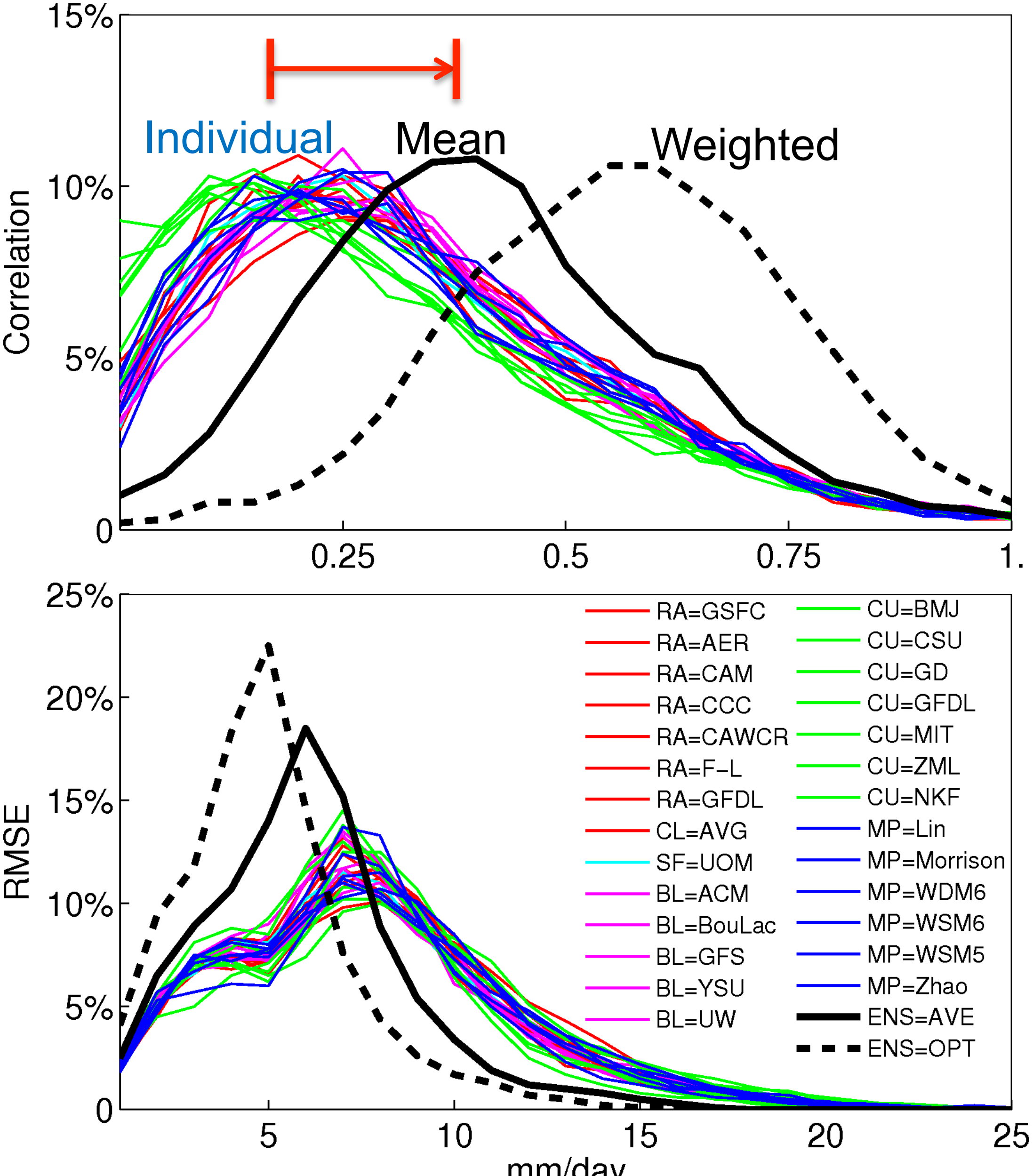
DOE 2009-2011

Courtesy X-Z Liang



Frequency distribution of TOA upward radiative flux and Cloud Radiative Forcing averaged over [60ºS, 60ºN] in January 2004 from the CAR ensemble of 960 members

CWRF Optimized Physics Ensemble Prediction of Precipitation In summer 1993



The physics ensemble mean substantially increases the skill score over individual configurations, and there exists a large room to further enhance that skill through intelligent optimization.

Spatial frequency distributions of correlations (*top*) and rms errors (*bottom*) between CWRF and observed daily mean rainfall variations in summer 1993. Each line depicts a specific configuration in group of the five key physical processes (*color*). The ensemble result (ENS) is the average of all runs with equal (Ave) or optimal (OPT) weights, shown as *black solid* or *dashed* line.

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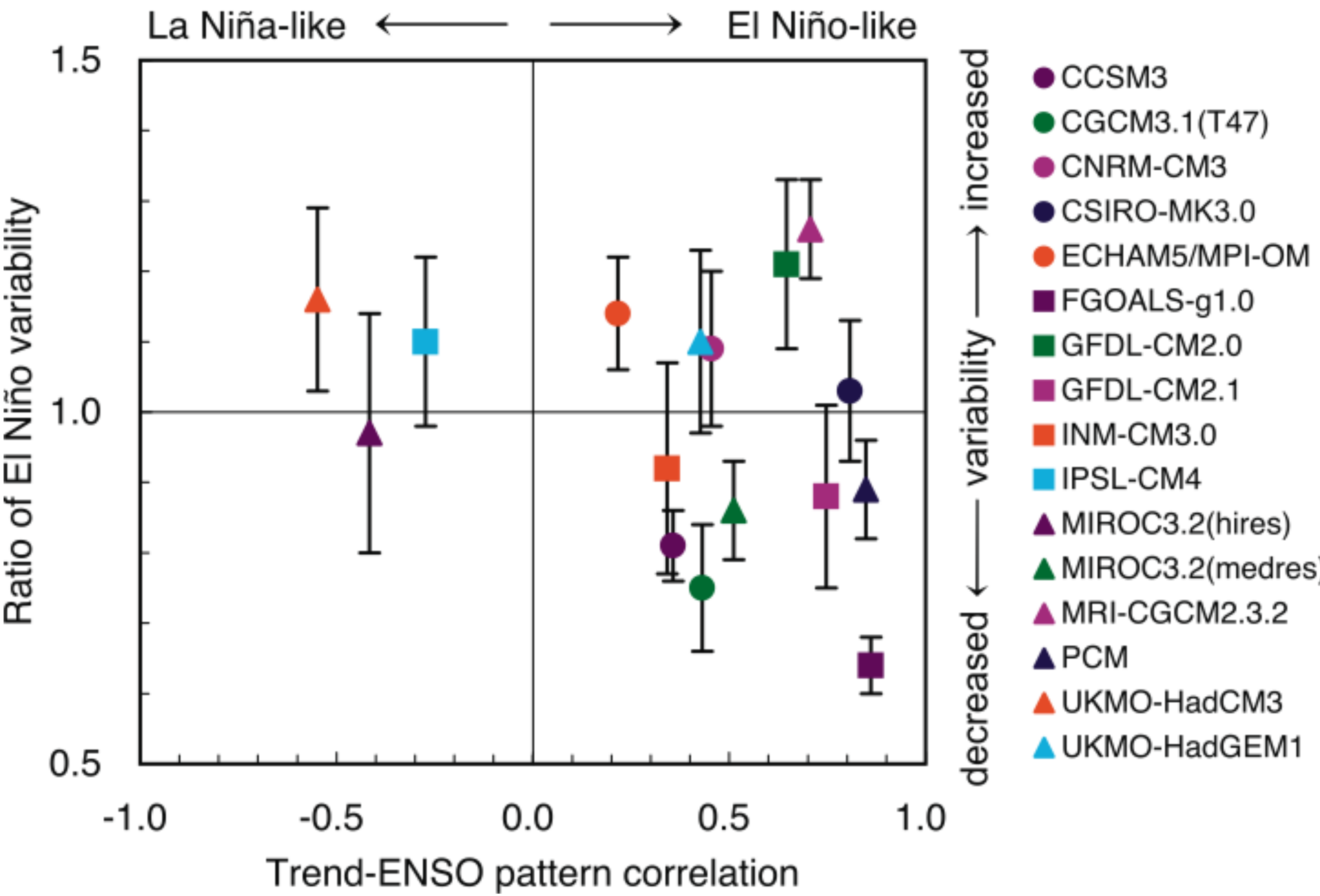
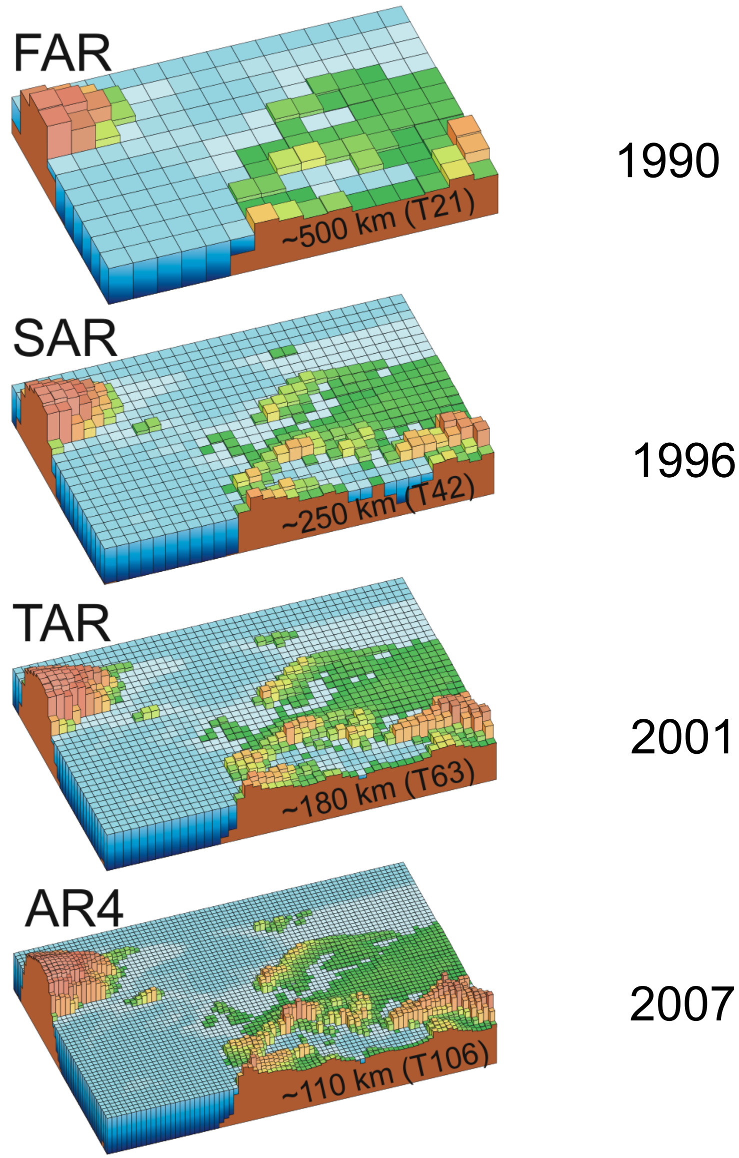

La Niña-like
El Niño-like
1.5
1.0
0.5
-1.0
-0.5
0.0
0.5
1.0
Ratio of El Niño variability
Trend-ENSO pattern correlation
decreased ← variability → increased
CCSM3
CGCM3.1(T47)
CNRM-CM3
CSIRO-MK3.0
ECHAM5/MPI-OM
FGOALS-g1.0
GFDL-CM2.0
GFDL-CM2.1
INM-CM3.0
IPSL-CM4
MIROC3.2(hires)
MIROC3.2(medres)
MRI-CGCM2.3.2
PCM
UKMO-HadCM3
UKMO-HadGEM1

Geographic resolution characteristic of the generations of global climate models used in the IPCC Assessment Reports



Summary

- An important distinction between uncertainty characterization for climate change versus seasonal to interannual prediction is the role that hindcasts play
- Optimal selection and weighting of models/parameterizations can be an important part of an overall strategy not only for quantification, but also reduction of uncertainty leading to improved predictive skill
- Structural uncertainties due to incomplete or poor representation of processes in climate models, do not readily lend themselves to quantification
- Uncertainty Quantification is in its infancy, clearly dependent on space and time scales
- An important research challenge for UQ is how to combine quantifiable uncertainties (e.g., from ensembles) with unquantifiable or qualitative uncertainties (e.g., structural, from incomplete representation of processes)