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International Centre for Theoretical Physics**



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**WCRP and ICTP Interpreting Climate Change Simulations: Capacity
Building for Developing Nations Seminar**

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Uncertainties in global climate models.

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Uncertainties in global climate models

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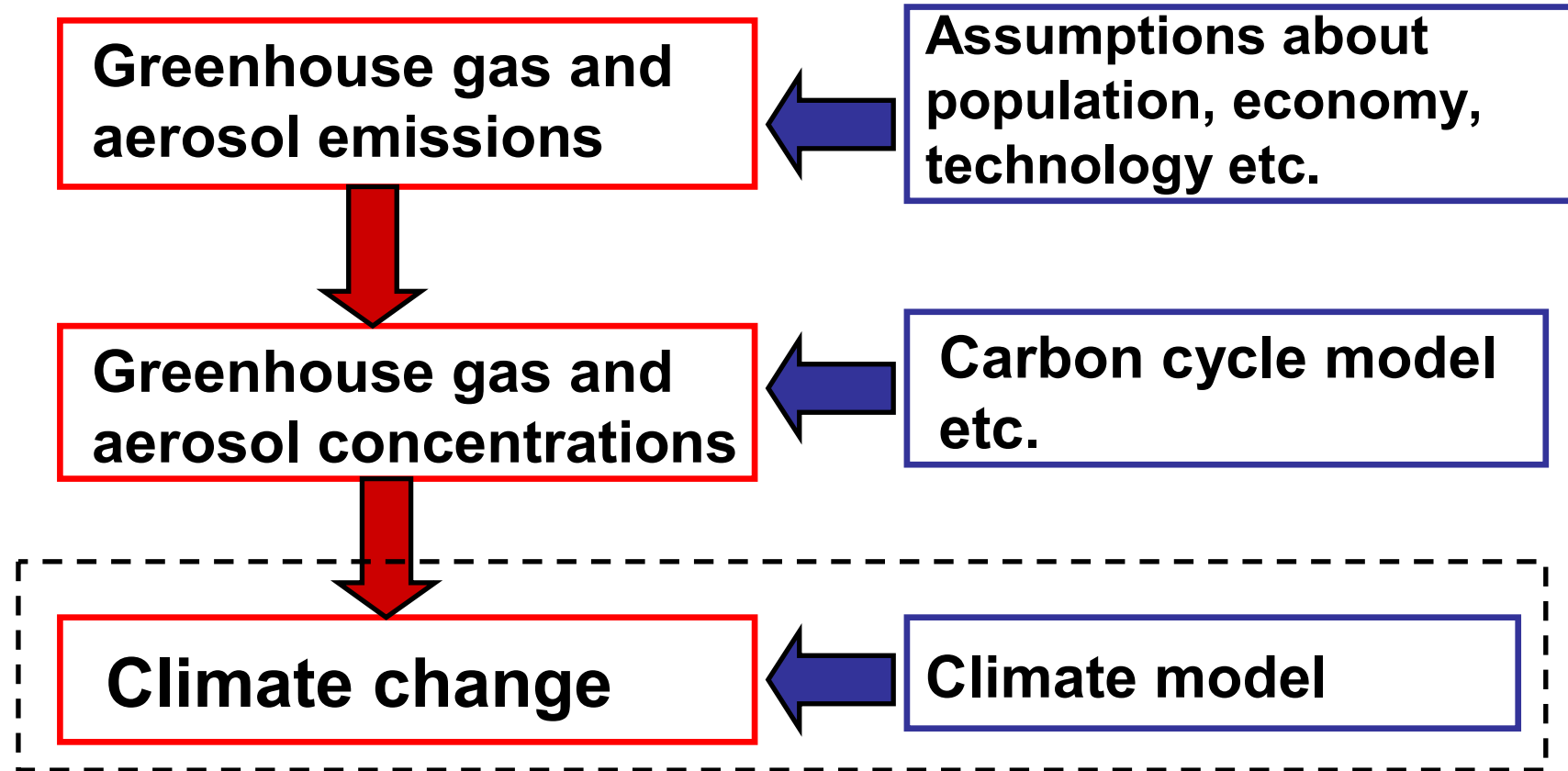
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Outline

- Sources of uncertainty
- How can we estimate the reliability of global climate models in simulating future climate change?
- Conclusions

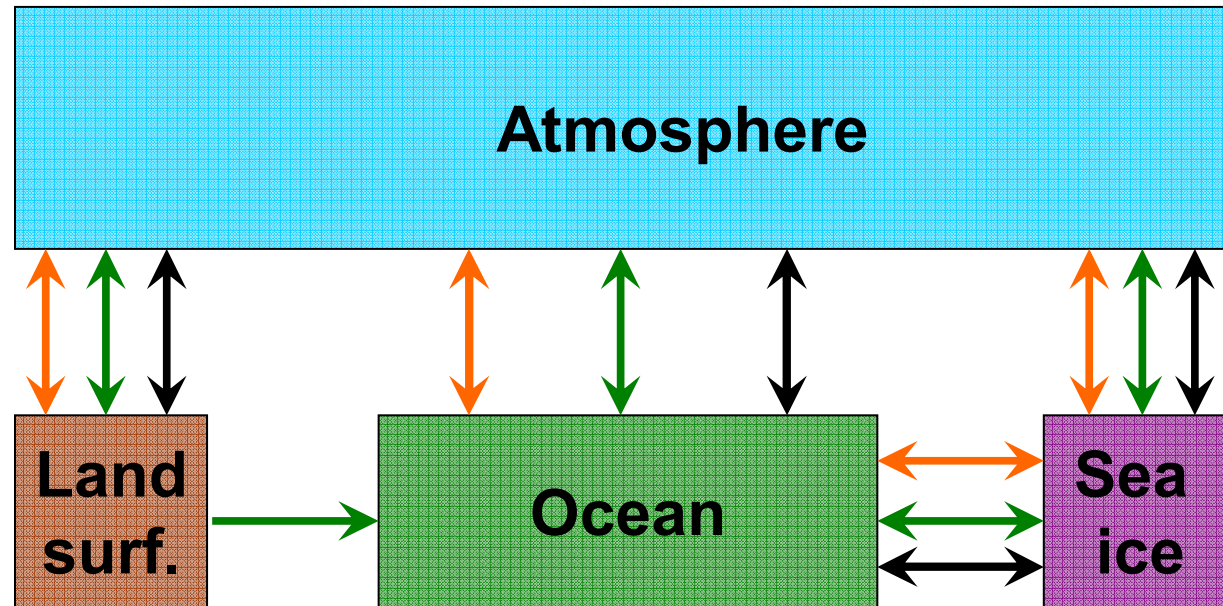
Sources of uncertainty

Construction of climate projections



Each step of the calculation has its own sources of error. This talk focuses on the last step: **how reliable are simulations of climate change in the optimal case that forcing is known?**

Global climate model (CMIP3 set-up)



Exchange of heat (\longleftrightarrow), water (\longleftrightarrow) and momentum (\longleftrightarrow) between the model components

Other components (carbon cycle, interactive vegetation, atmospheric chemistry...) **not included in CMIP3**

Structure of an AGCM

- **Global 3-dimensional grid**

($\Delta\lambda \sim \Delta\phi \sim 2.5^\circ \sim 250 \text{ km}$; $\sim 20\text{-}30$ levels)

- **Primitive equations**

$$\frac{\partial u}{\partial t} = -u \frac{\partial u}{\partial x} - v \frac{\partial u}{\partial y} - \omega \frac{\partial u}{\partial p} - \frac{\partial \Phi}{\partial x} + fv + F_x$$

$$\frac{\partial v}{\partial t} = -u \frac{\partial v}{\partial x} - v \frac{\partial v}{\partial y} - \omega \frac{\partial v}{\partial p} - \frac{\partial \Phi}{\partial y} - fu + F_y$$

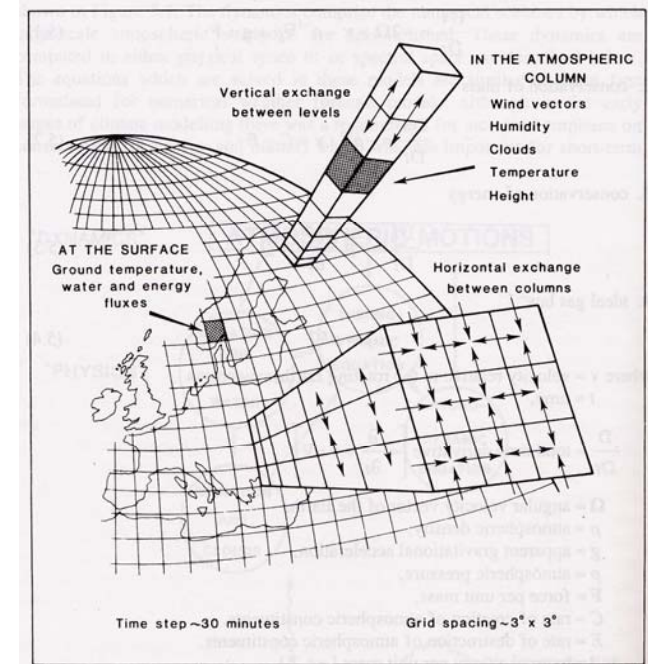
$$\frac{\partial T}{\partial t} = -u \frac{\partial T}{\partial x} - v \frac{\partial T}{\partial y} - \omega \frac{\partial T}{\partial p} + \omega \frac{RT}{c_p p} + \frac{Q}{c_p}$$

$$\frac{\partial \Phi}{\partial p} = -\frac{RT}{p}$$

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial \omega}{\partial p} = 0$$

$$\frac{\partial q}{\partial t} = -u \frac{\partial q}{\partial x} - v \frac{\partial q}{\partial y} - \omega \frac{\partial q}{\partial p} + S_q$$

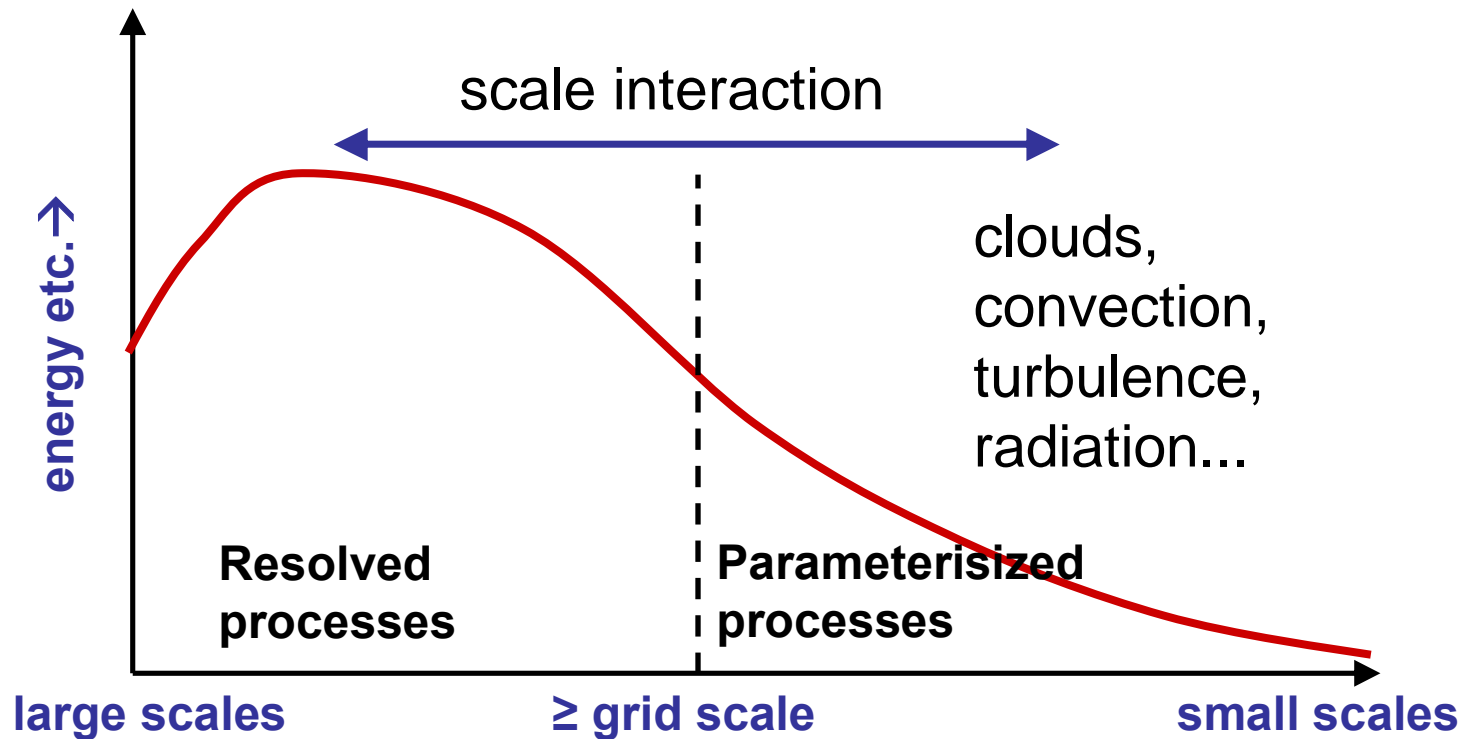
$$\frac{\partial X}{\partial t} = -u \frac{\partial X}{\partial x} - v \frac{\partial X}{\partial y} - \omega \frac{\partial X}{\partial p} + S_X$$



Equations are near to **exact** but need to be solved with **limited resolution**.

The effect of unresolved processes on the resolved scales needs to be presented in a semi-empirical fashion, i.e., by **parameterization**.

Parameterization problem

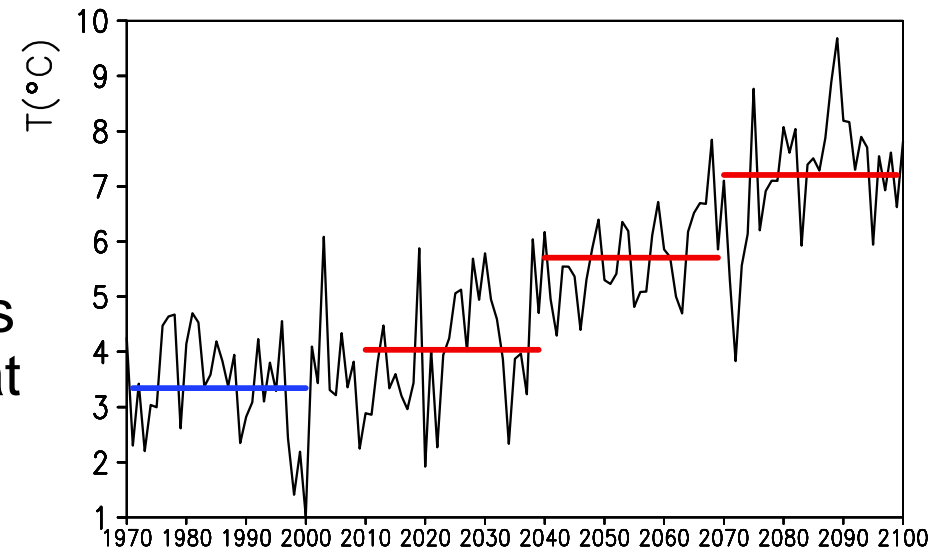


Energy and water cycles are strongly affected by parameterised processes → important uncertainty in climate change simulations

The problem will be reduced by improving model resolution, but it will never be eliminated.

Internal climate variability

- Climate varies even without external cause – both in model simulations and in nature
- This internal variability defines a lower limit of uncertainty that can not be reduced by any model
- In century-scale projections, genuine modelling uncertainty (due to parameterizations, etc.) generally dominates over internal variability - but not necessarily in the near future.



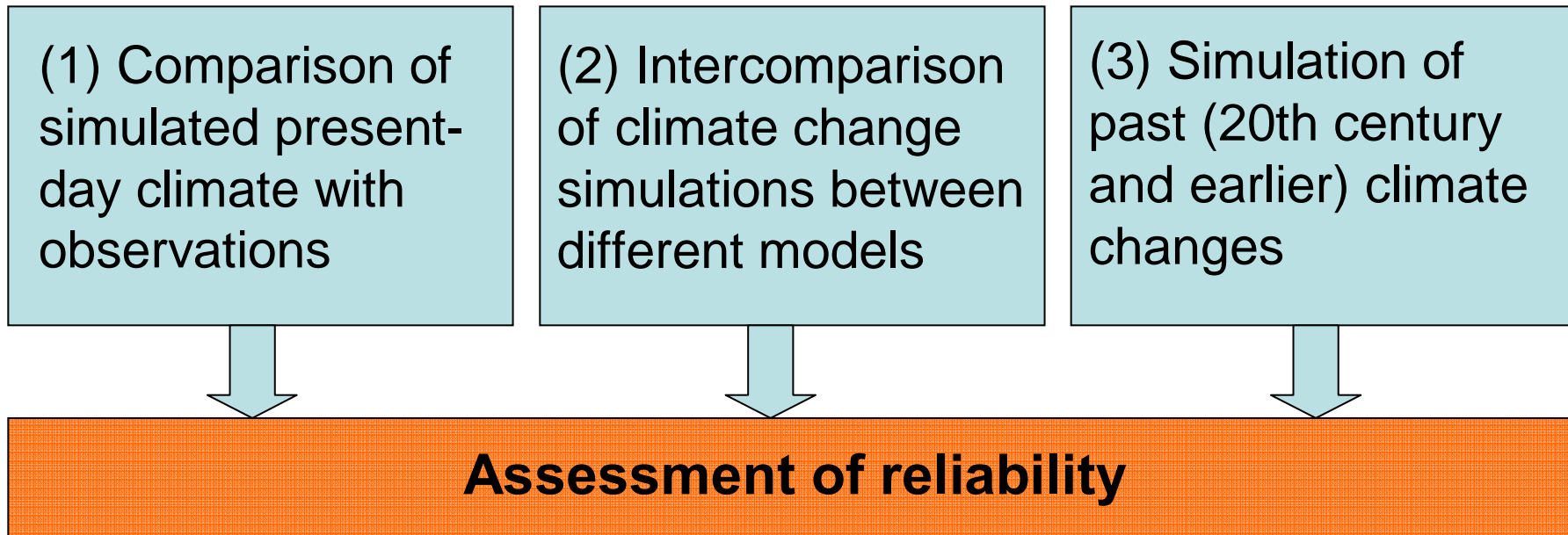
Example:

Annual mean temperature
in southern Finland
in a climate model simulation

How reliable are simulations of future climate change?

In terms of verification, climate modellers are less well-off than weather forecasters. However, there are indirect methods.

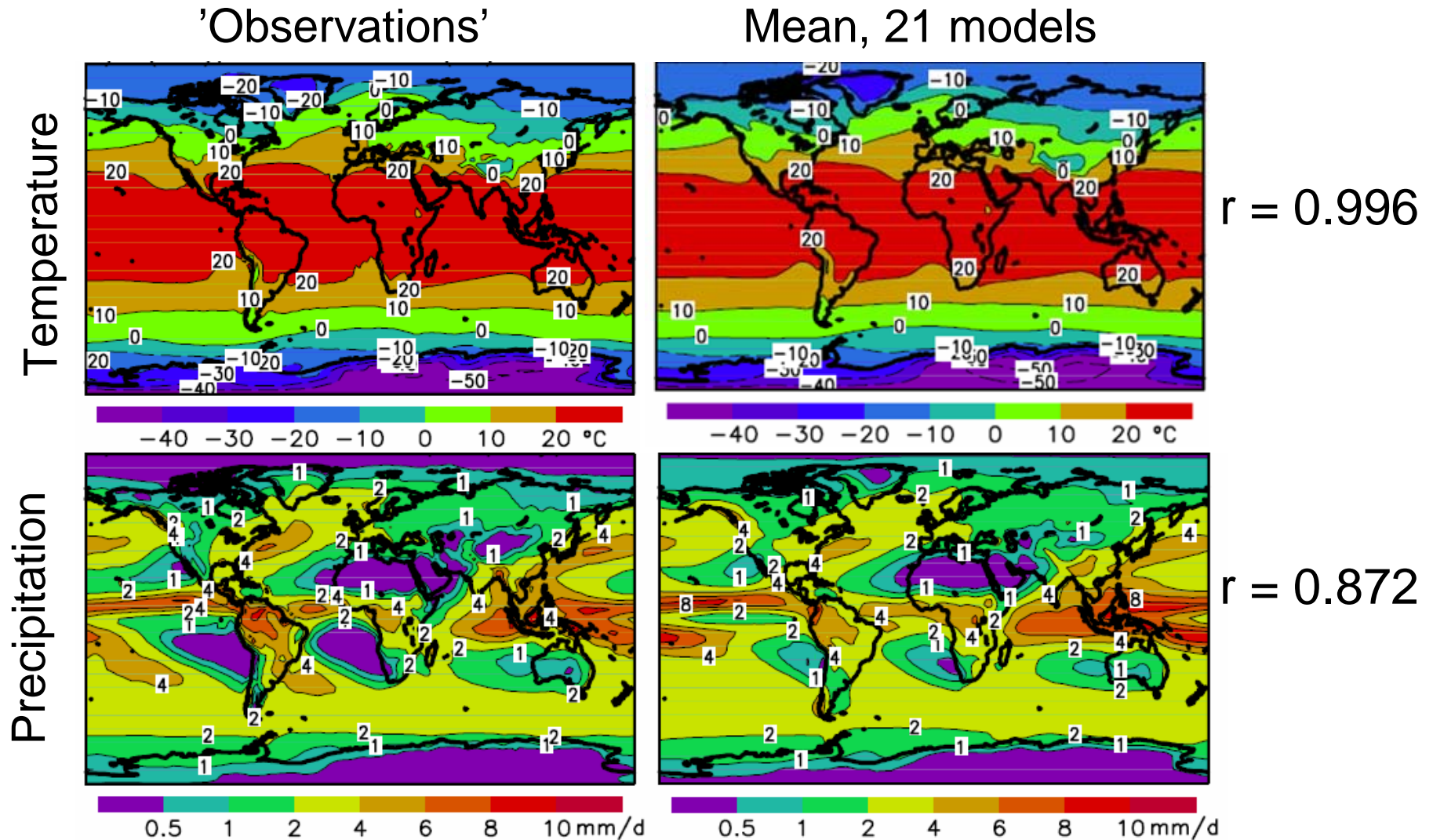
How to estimate the reliability of simulations of future climate change?



- **All these methods have limitations**
 - None of them alone tells everything
 - Even the three methods together do not tell everything
 - Three methods together tell more than any of them alone

How well do global climate models
simulate present-day climate?

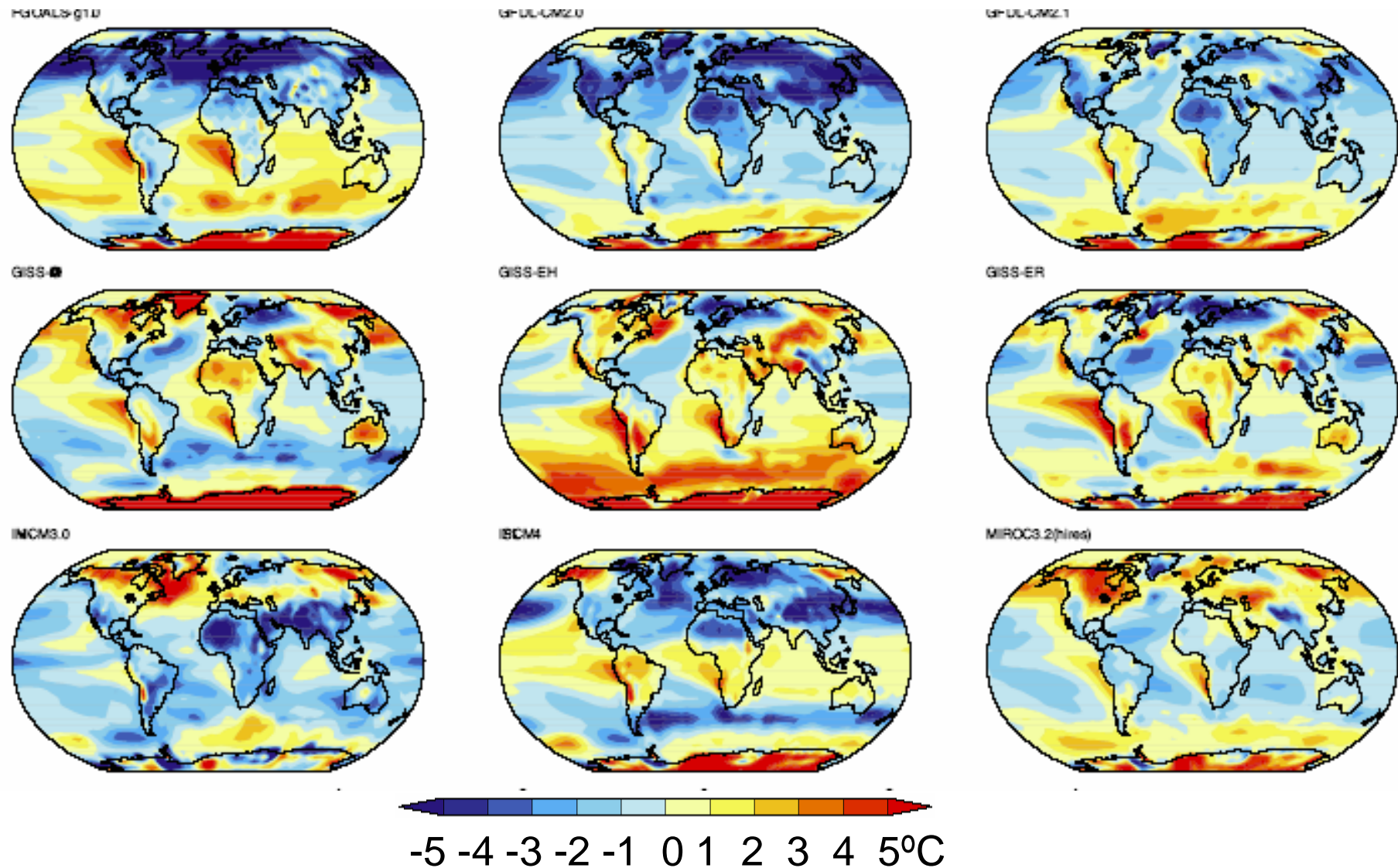
'Observed' vs simulated (multi-model mean) annual mean present-day climate



→ A high degree of similarity (particularly for temperature) but differences in details (larger for individual models than multi-model mean!).

Biases in present-day annual mean surface air temperature in some individual models

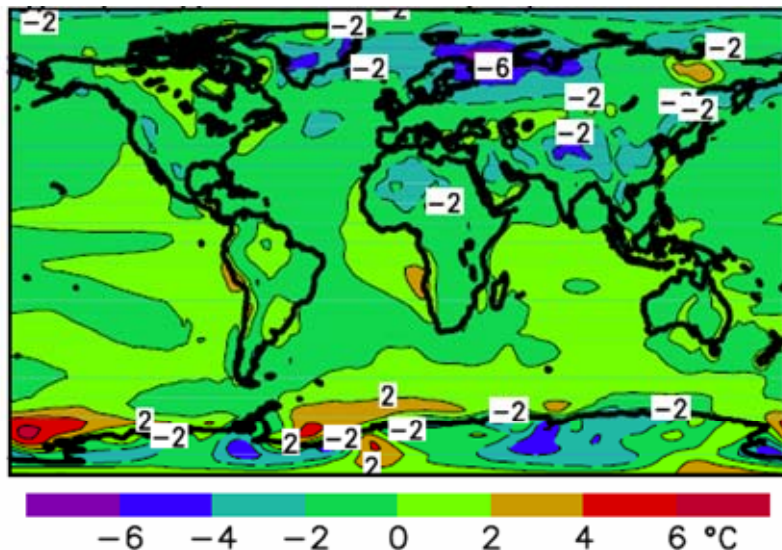
(WG1 AR4, Fig. S8.1b)



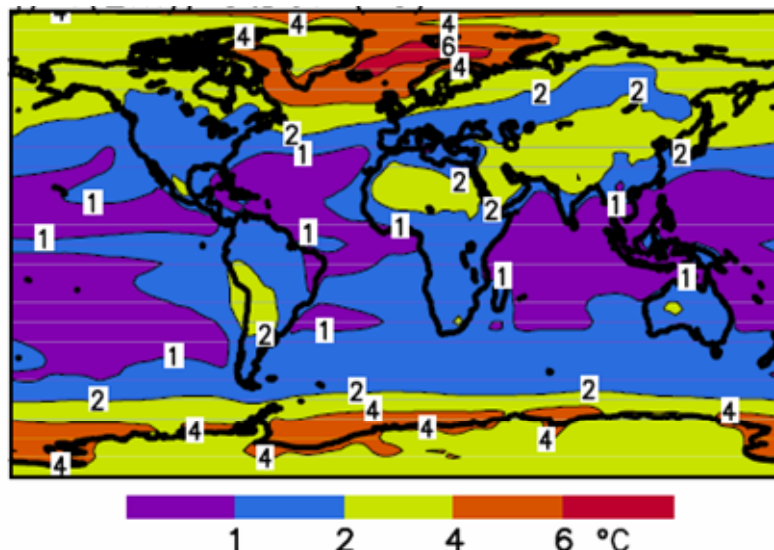
Temperature biases in 21 CMIP3 models

(Räisänen, 2007, Tellus 59A, 2-29)

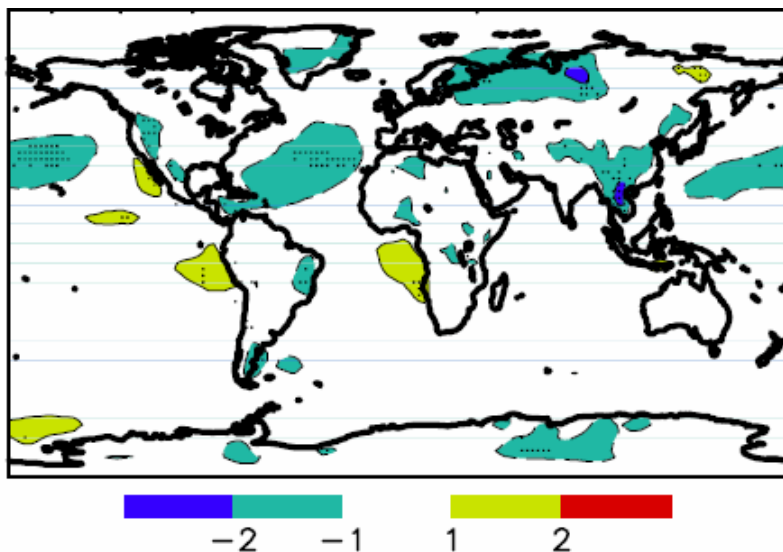
multi-model mean bias



inter-model StDev



Mean / StDev

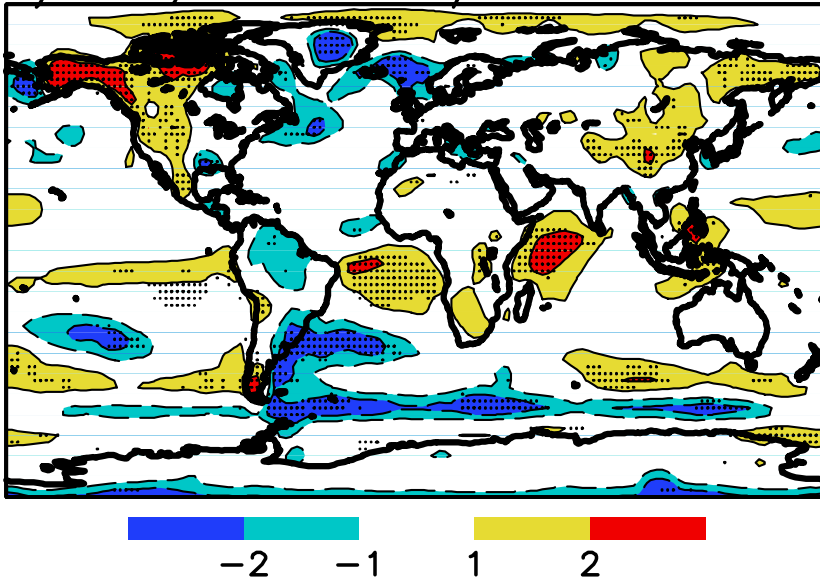


In most areas, $|\text{Mean}| < \text{StDev}$:
biases more random than
systematic.

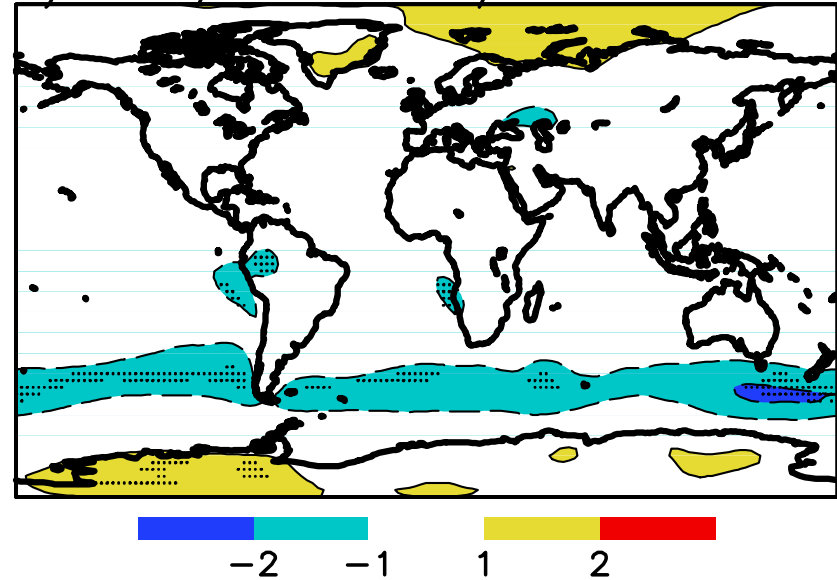
Very few areas (2%) with the
same sign of bias in all models
(stippling)

Precipitation and sea level pressure biases in 21 CMIP3 models: ratio between multi-model mean bias and StDev

n) Prec, mean bias / StDev



o) MSLP, mean bias / StDev



Biases in precipitation tend to be slightly more systematic than those in temperature and sea level pressure – but is this because precipitation is more difficult for models or because observations of precipitation are more unreliable?

Verification statistics for annual mean present-day climate: analysis of 21 CMIP3 models

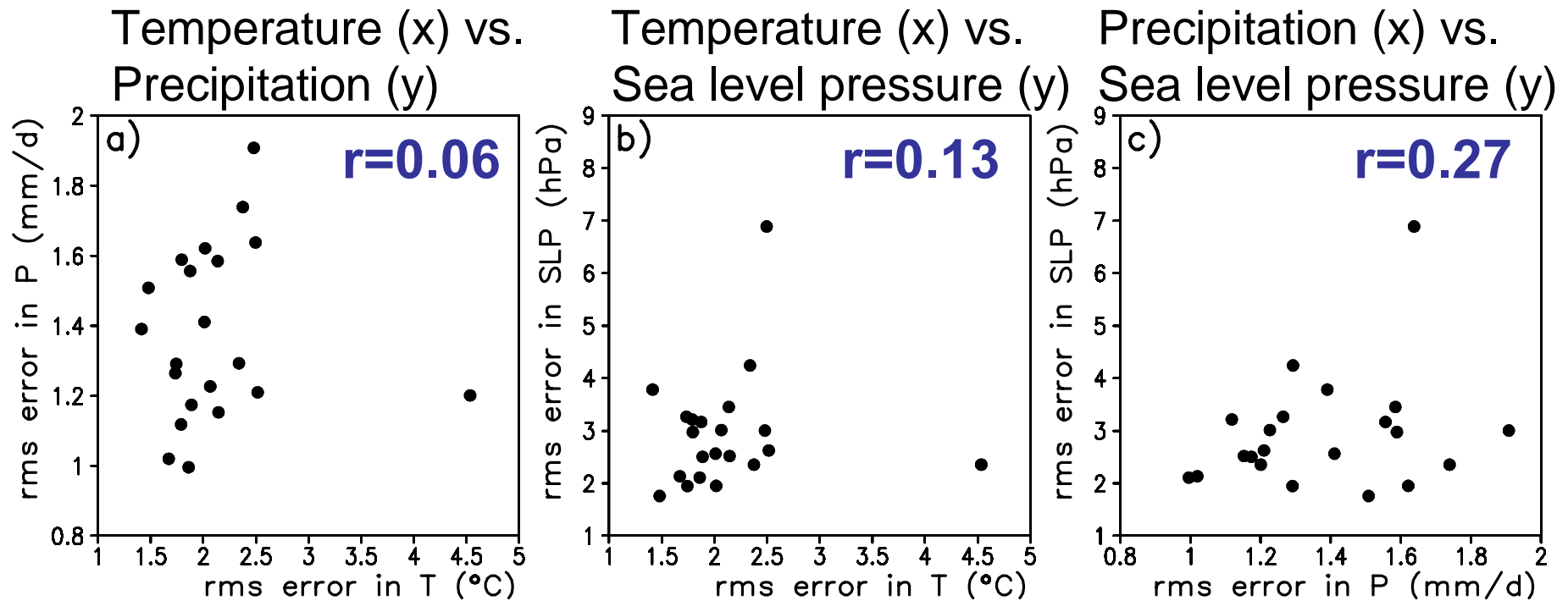
	rms error				Spatial correlation			
	Mean	Min	Max	21M	Mean	Min	Max	21M
T(2m) (°C)	2.32	1.58	4.56	1.43	0.989	0.968	0.994	0.996
Prec (mm d ⁻¹)	1.35	0.97	1.86	0.95	0.775	0.597	0.867	0.872
MSLP (hPa)	3.96	2.06	8.33	2.65	0.880	0.497	0.984	0.945

Mean, Min, Max: statistics for individual models

21M: statistics for 21-model mean climate

- 1) In comparison with the overall spatial variability, temperature is simulated best, followed by sea level pressure and precipitation
- 2) Biases in individual models tend to cancel out: performance of the **21-model mean** similar to the **best individual models**

Performance of individual models for different variables: rms errors in annual mean T, P and SLP



→ 'Universal' ranking of models extremely difficult!

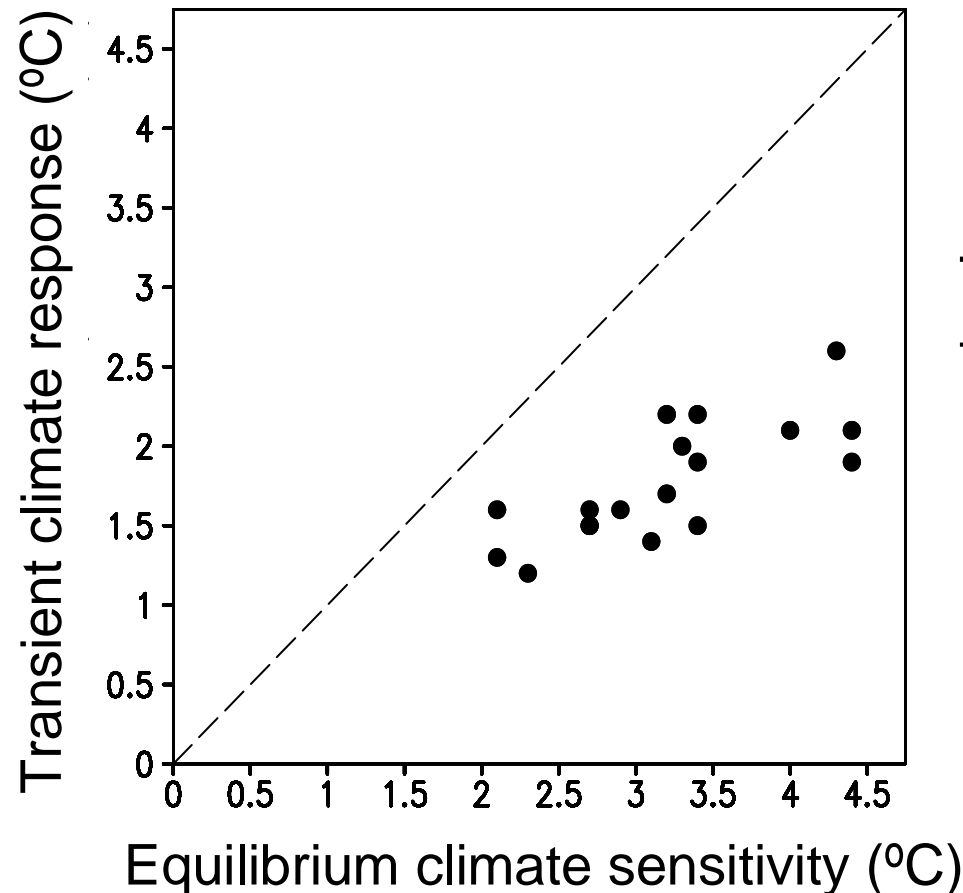
An important, but unresolved issue

- **Biases in present-day time mean climate tend to vary in sign between different models** (for most variables and areas)
- **This is – in principle – good news:**
 - if the same is also true for simulated climate changes, then the variation of climate changes between different models might be a good measure of the actual uncertainty
- **However, modellers know the present-day climate**
 - if the unsystematic nature of the biases results from a 'pull towards a common attractor' (= tuning), then the previous suggestion may not hold

Uncertainty in climate change simulations, as inferred from variation between models

1. Global mean temperature change

Equilibrium climate sensitivity (ECS)* and Transient climate response (TCR)** in CMIP3 models



ECS: 2.1-4.4°C (mean: 3.3°C)

TCR: 1.2-2.6°C (mean: 1.8°C)

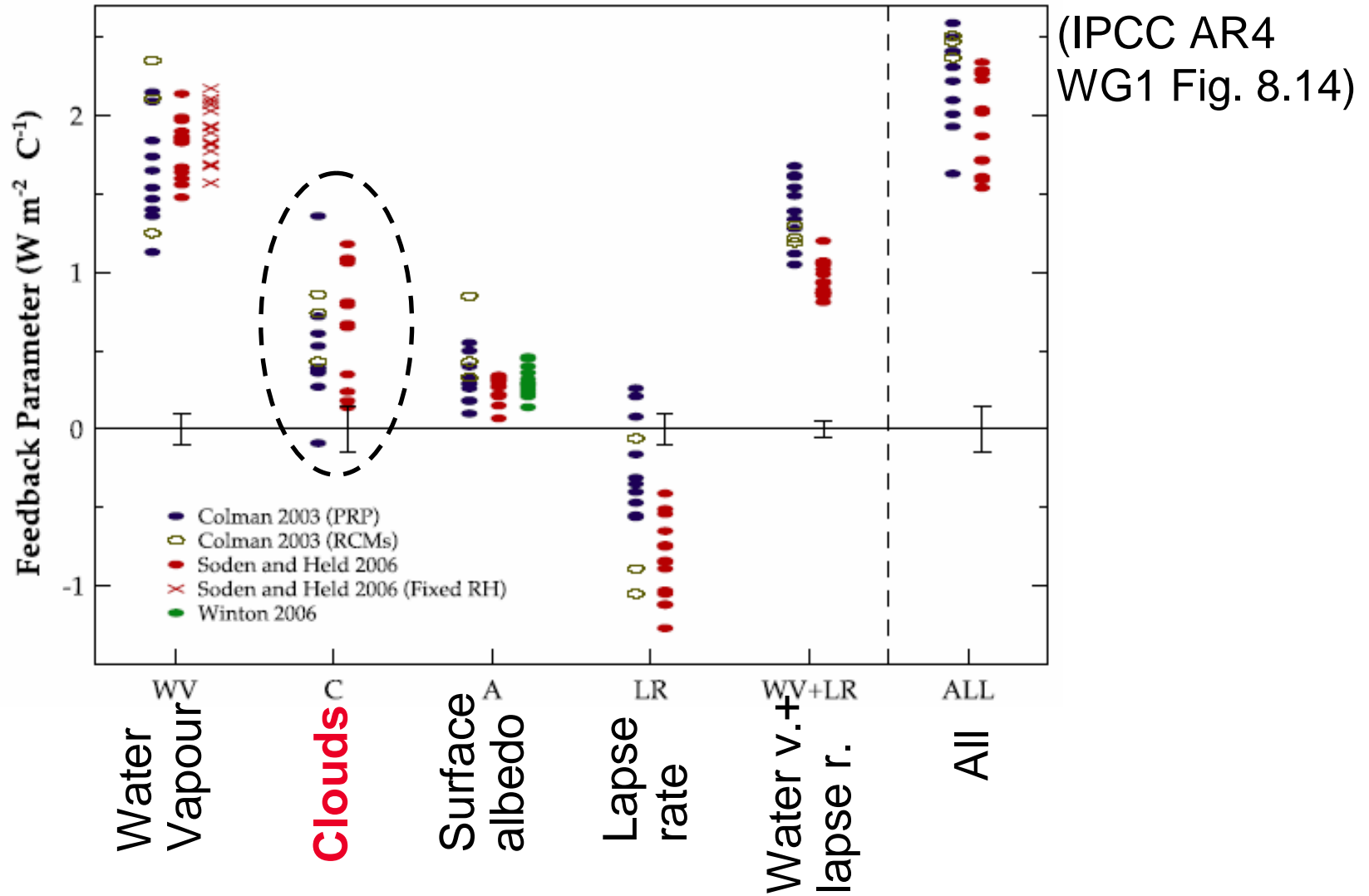
The difference mainly reflects the effect of ocean heat uptake

All uncertainty not necessarily captured by the CMIP3 ensemble

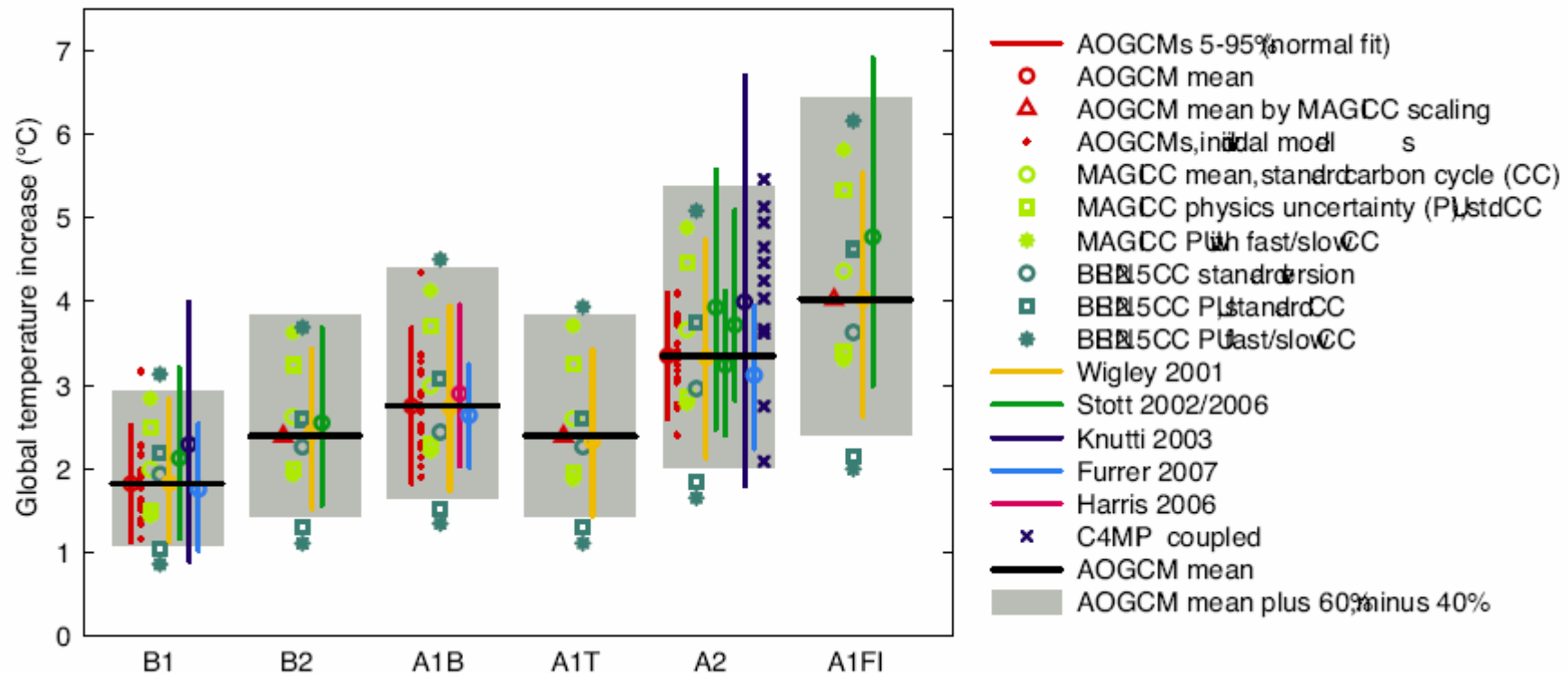
* Equilibrium global mean warming due to doubling of CO₂

** Warming at CO₂ doubling (70 years) when CO₂ increases 1% per year

Uncertainties in feedbacks to equilibrium global warming: changes is clouds dominate



Global mean warming from 1980-99 to 2090-99, under six SRES marker scenarios (IPCC AR4, WG1 Fig. 10.29)



'Likely' uncertainty ranges, including uncertainty in carbon cycle:
B1: 1.1-2.9°C; **A1B:** 1.7-4.4°C; **A2:** 2.0-5.4°C; **A1FI:** 2.4-6.4°C

Range of CMIP3 simulations (varying set of models)

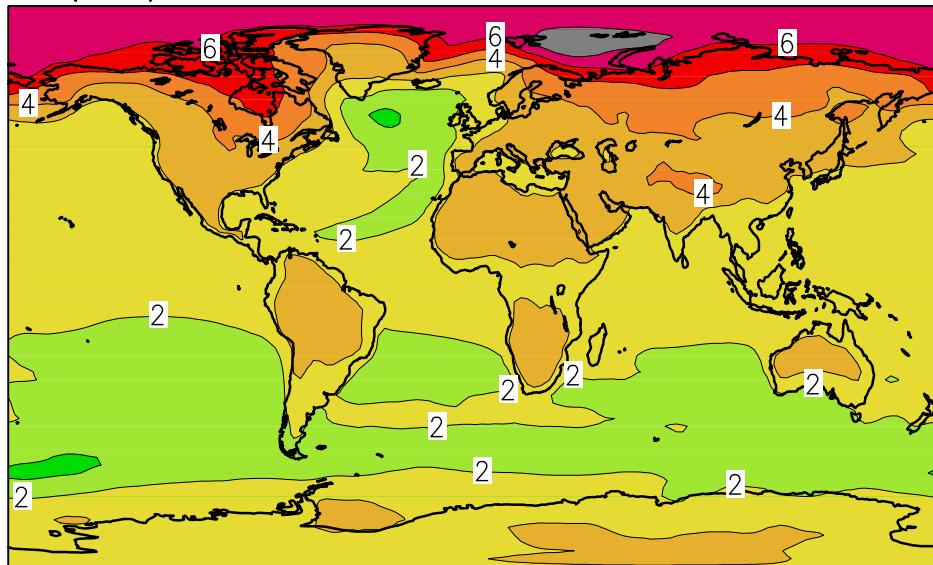
B1: 1.2-3.1°C; **A1B:** 1.9-4.3°C; **A2:** 2.4-4.1°C

Uncertainty in local / regional climate changes

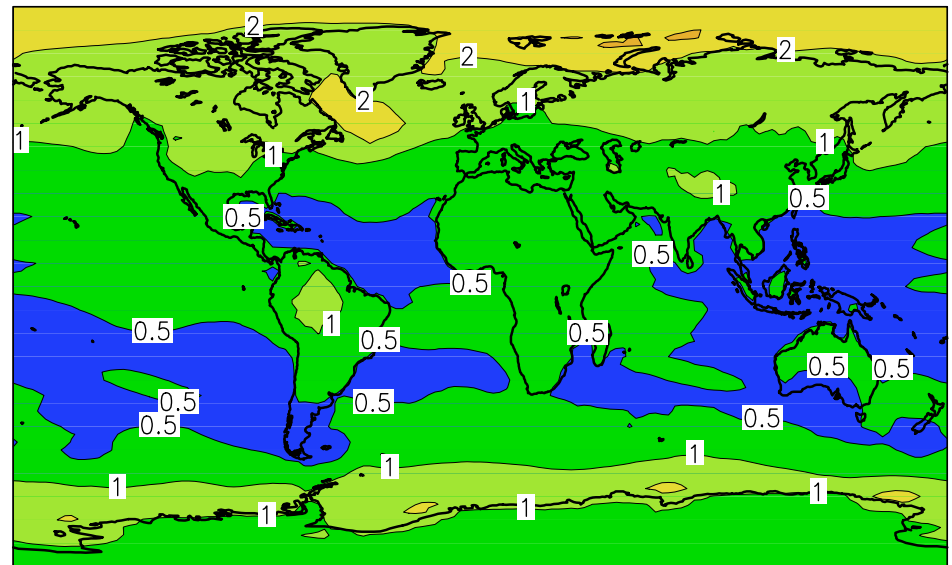
- **Intercomparison of CMIP3 simulations for the A1B scenario**
 - 22 models
 - only one ensemble member for each
- **Differences in simulated climate change result from**
 - differences between models
 - internal variability
 - to small extent, differences in forcing?
- **Uncertainty in emission scenarios is not included in this comparison**

Annual mean temperature change: 1970-1999 to 2070-2099, SRES A1B

22-model mean (°C)



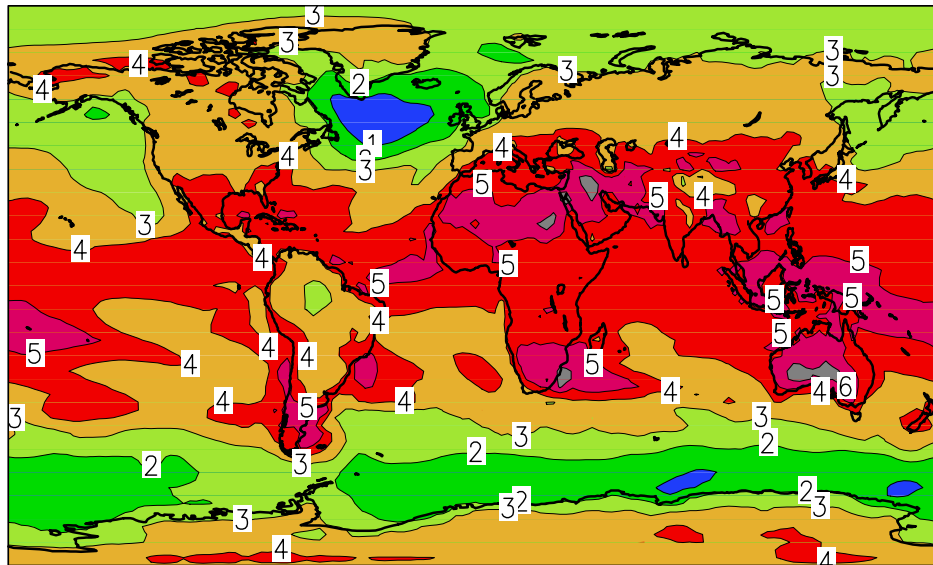
Standard deviation (°C)



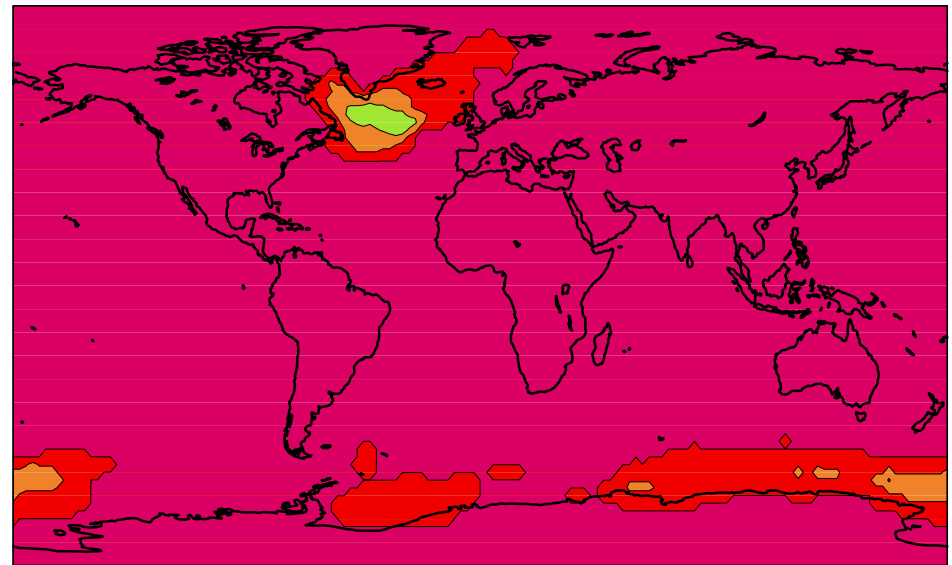
Both the average warming and the inter-model differences are largest in high northern latitudes

Annual mean temperature change: agreement between models

mean / standard deviation



fraction of models with $\Delta T > 0$

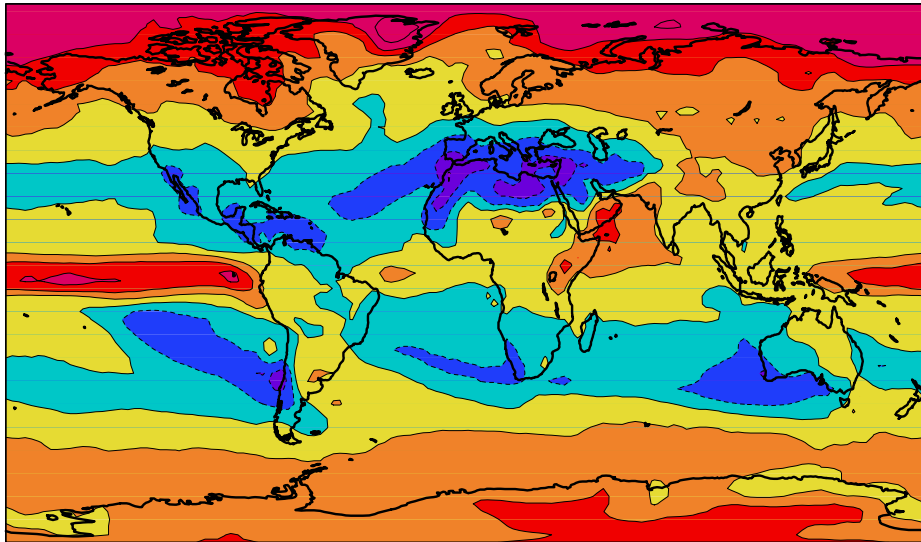


1 2 3 4 5 6 0 10 25 50 75 90 100 %

- 1) All models simulate some warming over practically all land areas
- 2) Best 'relative agreement' in the tropics: standard deviation increases more sharply towards high latitudes than the average warming

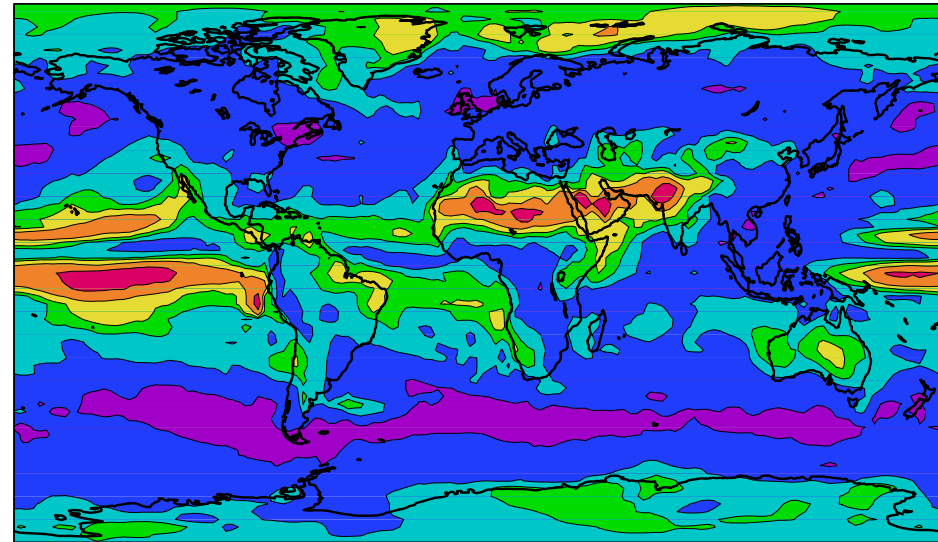
Annual mean precipitation change: 1970-1999 to 2070-2099, SRES A1B

22-model mean (%)



-30 -20 -10 0 10 20 30 %

Standard deviation (%)

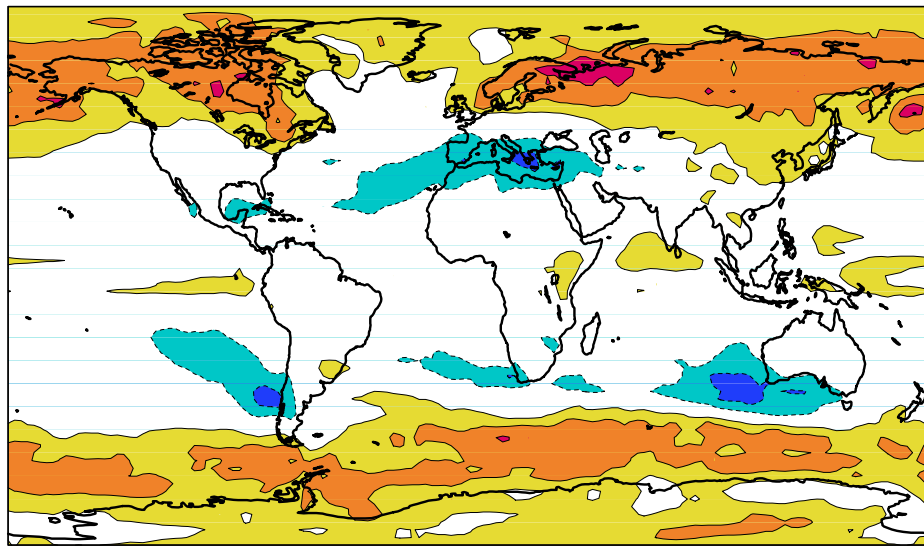


5 10 15 20 30 50 %

Largest intermodel variation (in per cent units) in the subtropics and in the the Actic

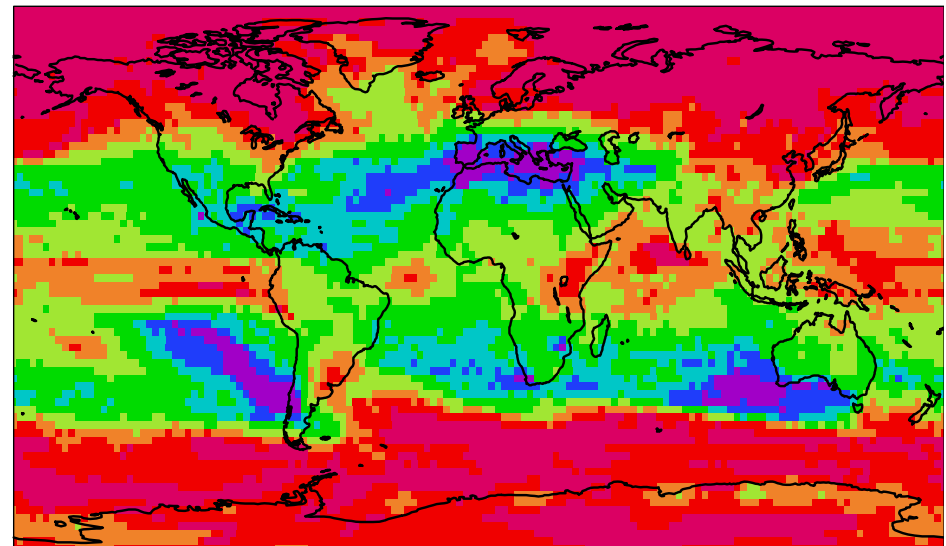
Annual mean precipitation change: agreement between models

mean / standard deviation



-3 -2 -1 1 2 3

fraction of models with $\Delta P > 0$

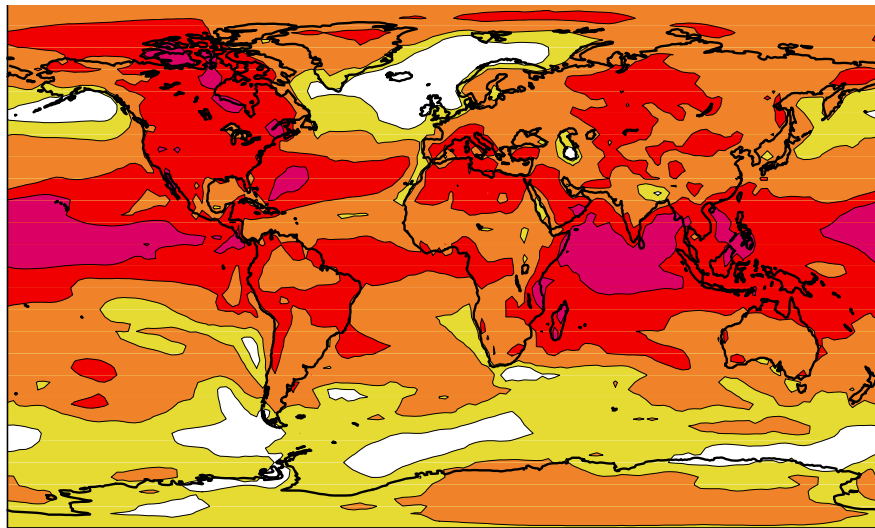


0 10 25 50 75 90 100 %

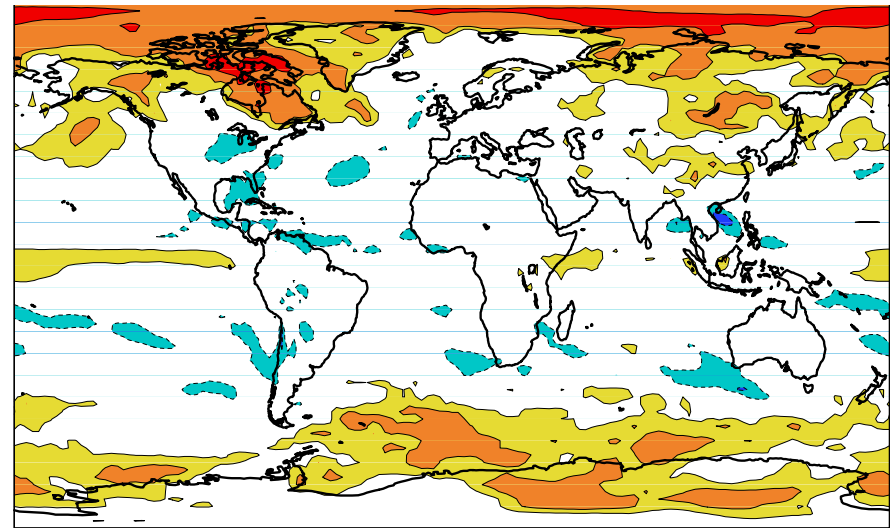
- 1) Models agree less well on changes in precipitation than temperature
- 2) Best 'relative agreement' in high latitudes (increase) and in parts of the subtropics / lower midlatitudes (decrease)

Are differences in local climate change connected to differences in global warming?

$\text{corr}(\Delta T, \Delta T_{\text{glob}})$



$\text{corr}(\Delta P, \Delta T_{\text{glob}})$



-0.9 -0.8 -0.6 -0.4 0.4 0.6 0.8 0.9

-0.9 -0.8 -0.6 -0.4 0.4 0.6 0.8 0.9

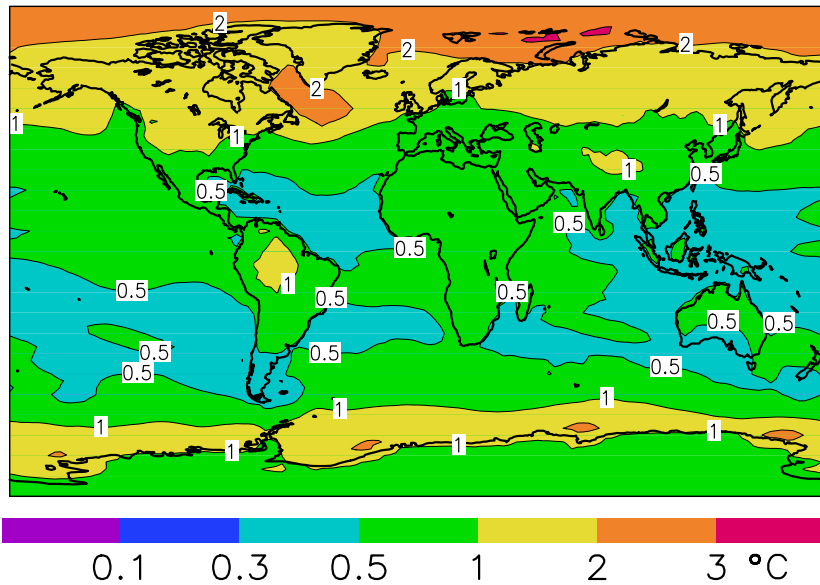
- **Temperature:** high correlation in most land areas and low-latitude oceans
- **Precipitation:** low correlation, excluding some high-latitude regions

Role of internal climate variability (1)

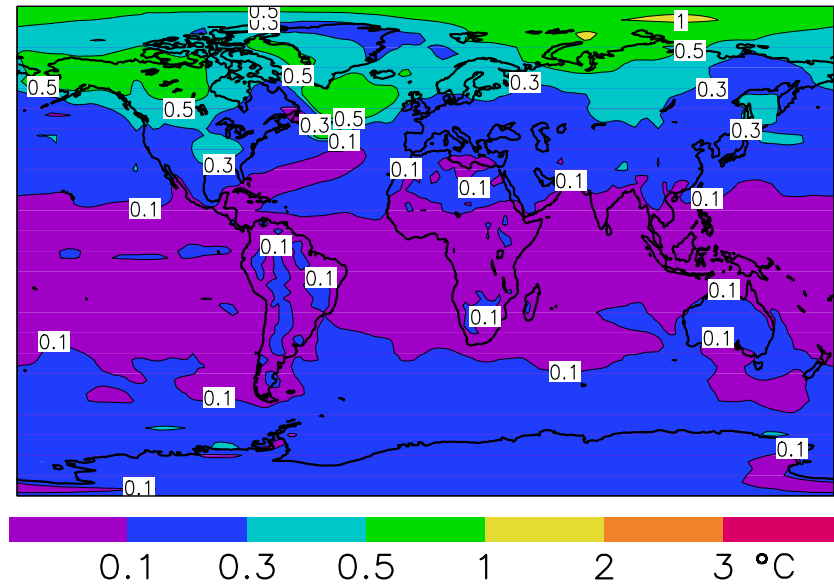
- In the late 21st century, inter-model differences in climate change are generally much larger than the differences expected from internal variability alone. This is particularly true for temperature.

Annual mean T change, A1B, 1970-1999 → 2070-2099

StDev between 22 models



StDev in a single-model ensemble (CCSM3, 7 runs)



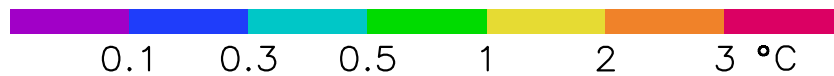
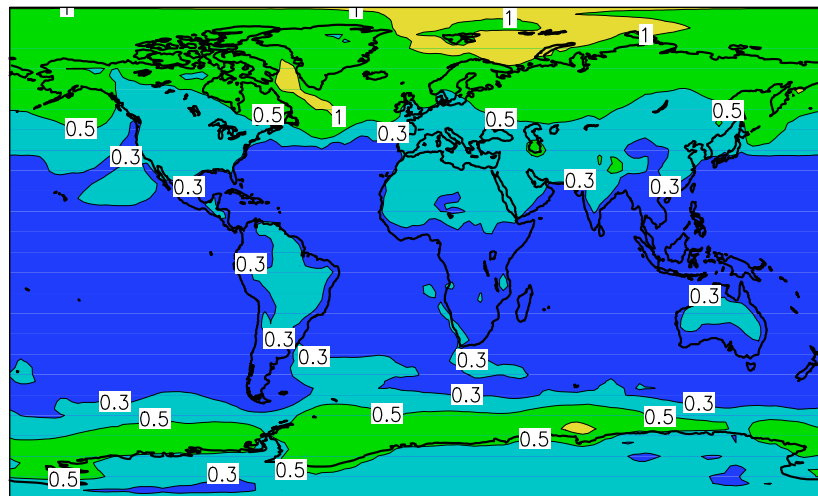
→ **Single-model initial-condition ensembles give a far too optimistic idea of the actual uncertainty**

Role of internal climate variability (2)

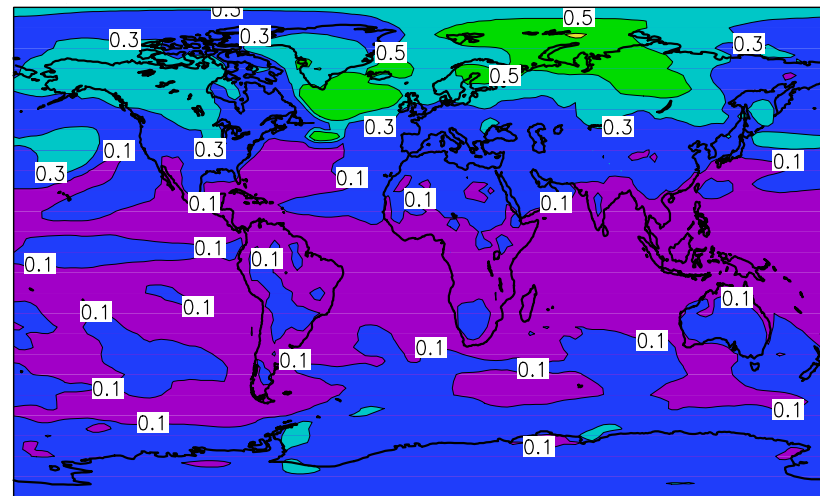
- In closer-term projections, internal variability covers a somewhat larger part of the uncertainty – simply because the inter-model differences play a smaller role when climate changes are smaller.

Annual mean T change, A1B, 1970-1999 → 2008-2037

StDev between 22 models



StDev in a single-model ensemble (CCSM3, 7 runs)

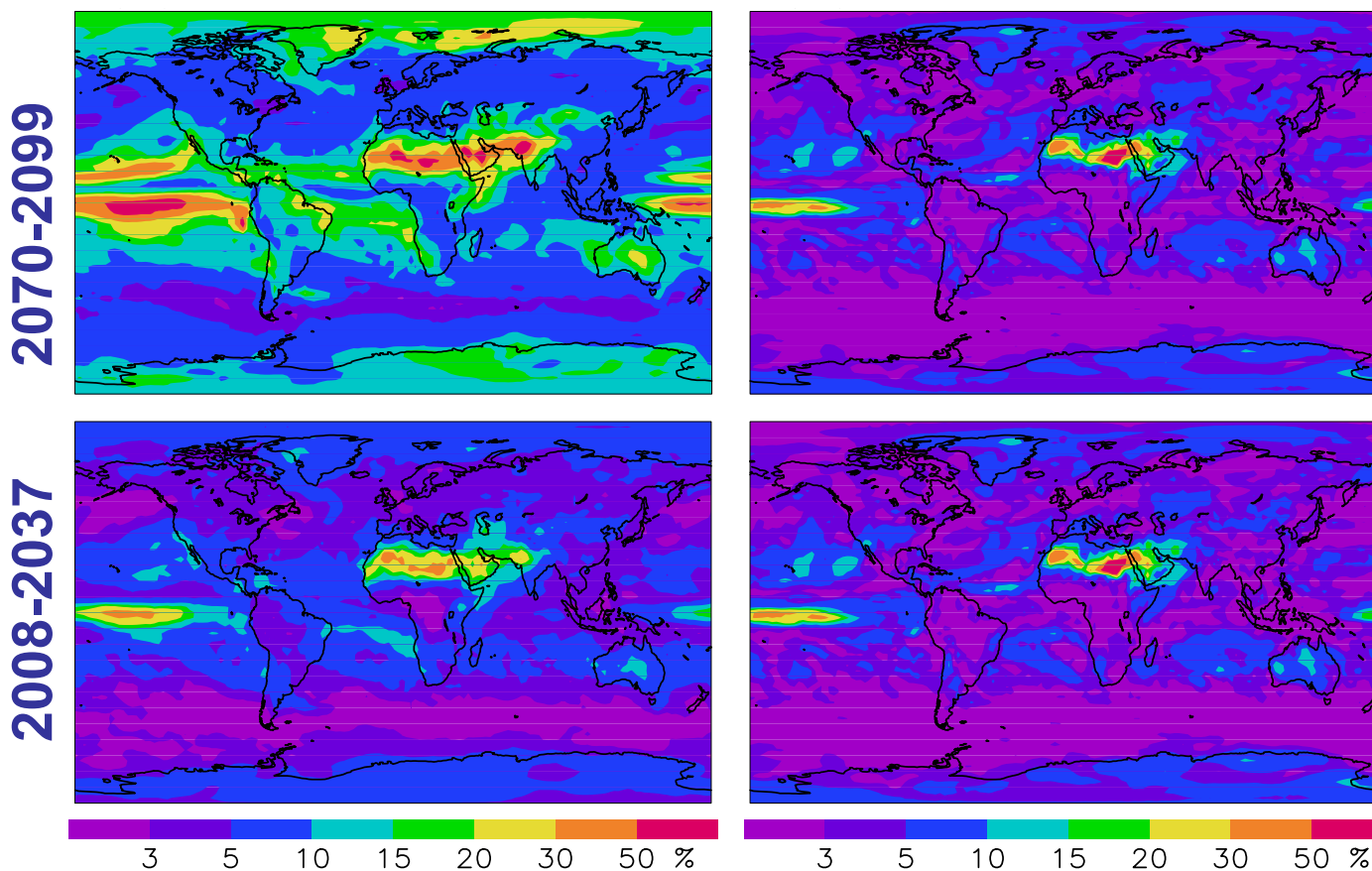


Role of internal climate variability (3)

- For precipitation, internal variability is a relatively more important uncertainty than for temperature – but still second to model differences in the late 21st century

Annual mean P change, A1B, 1970-1999 → 20XX-20YY

StDev between 22 models StDev in a single-model ensemble (CCSM3, 7 runs)

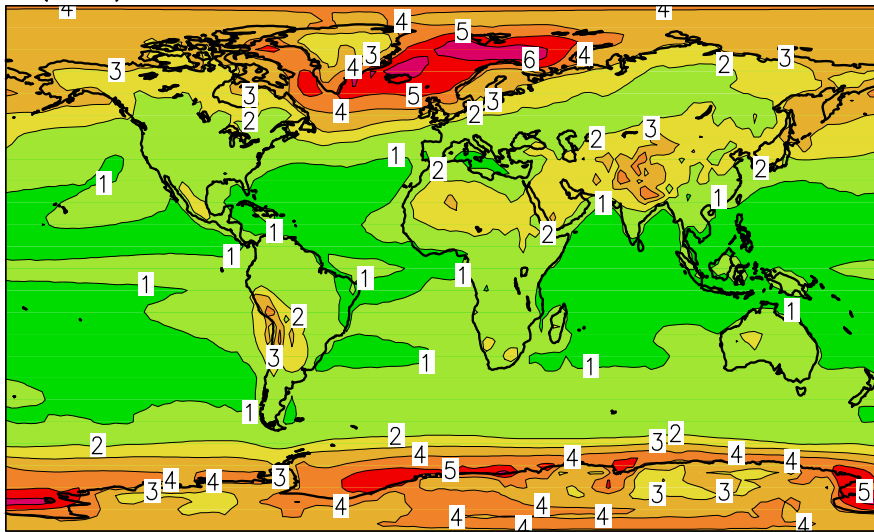


What do biases in control climate tell about model reliability in simulating climate changes?

- **”Biases in control climate indicate that there must be something wrong in the model”**
 - but what does this mean in quantitative terms?
- **Biases in control climate might adversely affect** some of the **feedback processes** that regulate the simulated climate changes
- **This important issue is still poorly understood!**

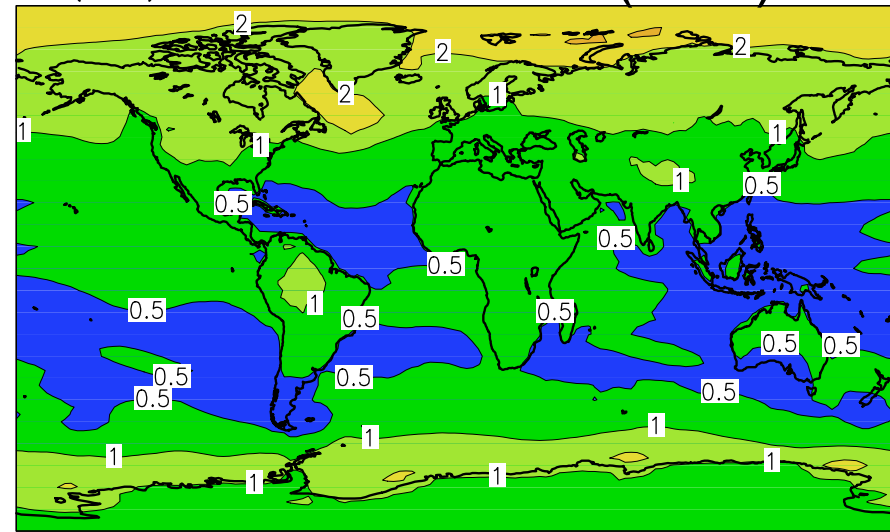
Inter-model variation of present-day biases vs. inter-model variation in climate changes

StDev in T_{Ann} , 1970-99



0.5 1 2 3 4 5 6 °C

StDev in ΔT_{Ann} ,
1970-99 to 2070-99 (A1B)

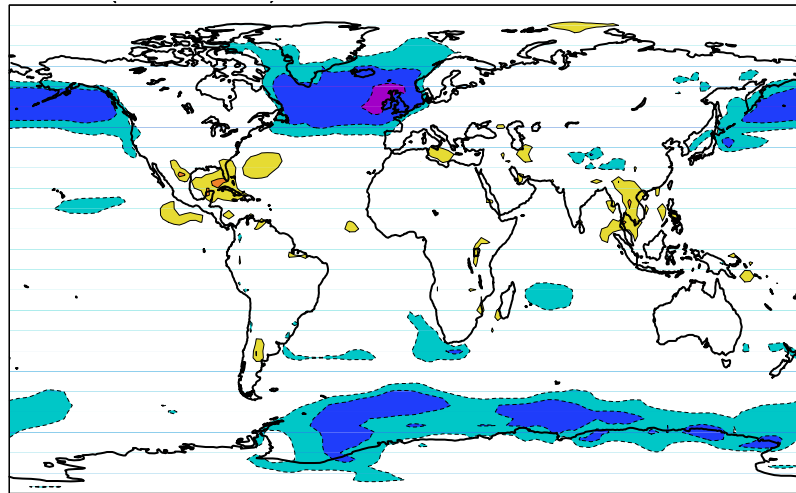


0.5 1 2 3 4 5 6 °C

Magnitude of present-day biases is not a direct measure of uncertainty: errors in the simulation of present-day and future climates tend to cancel out – at least to the extent that this can be judged from intercomparison of model simulations

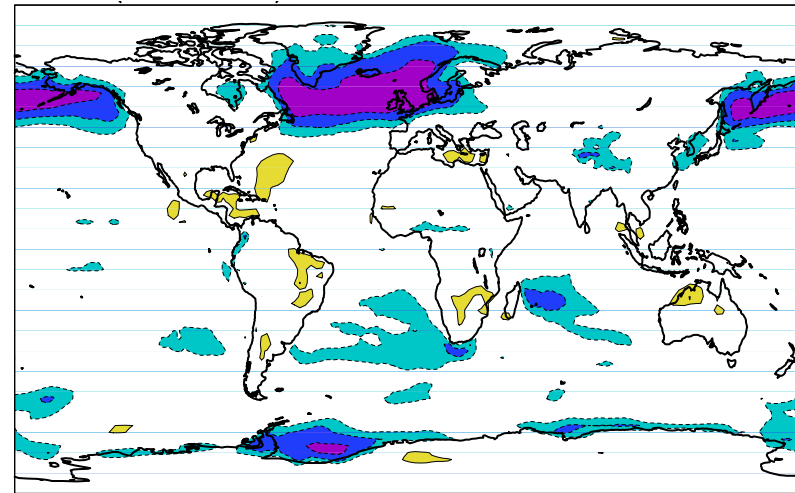
Inter-model correlation between present-day temperature and 21st century warming

Annual mean



-0.8 -0.6 -0.4 0.4 0.6 0.8

Winter (DJF)



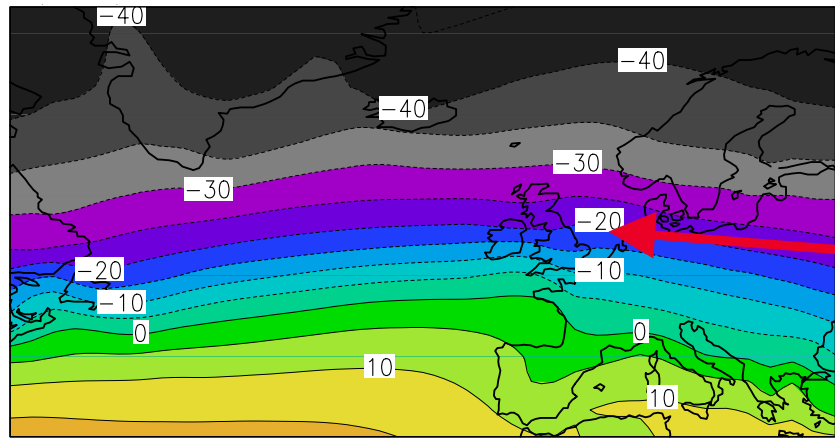
-0.8 -0.6 -0.4 0.4 0.6 0.8

In most areas, the correlation is low: simulated present-day climate is a poor predictor of simulated climate changes (this also turns out to be true for other variables).

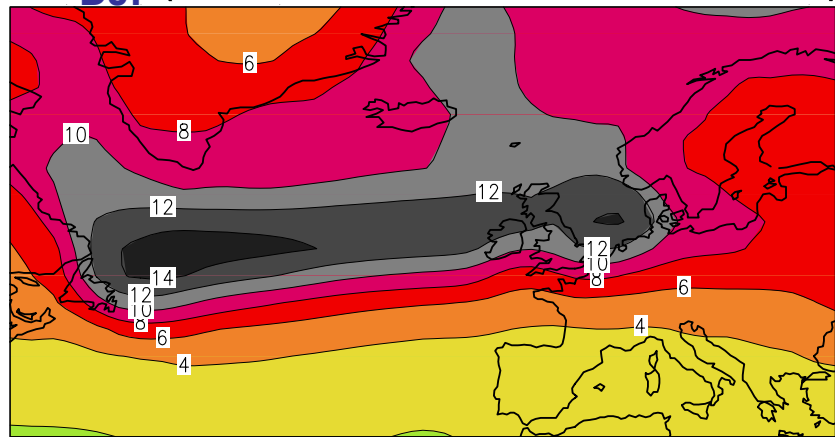
Areas near the ice edge are an important exception →

DJF temperatures in the North Atlantic in the **** model

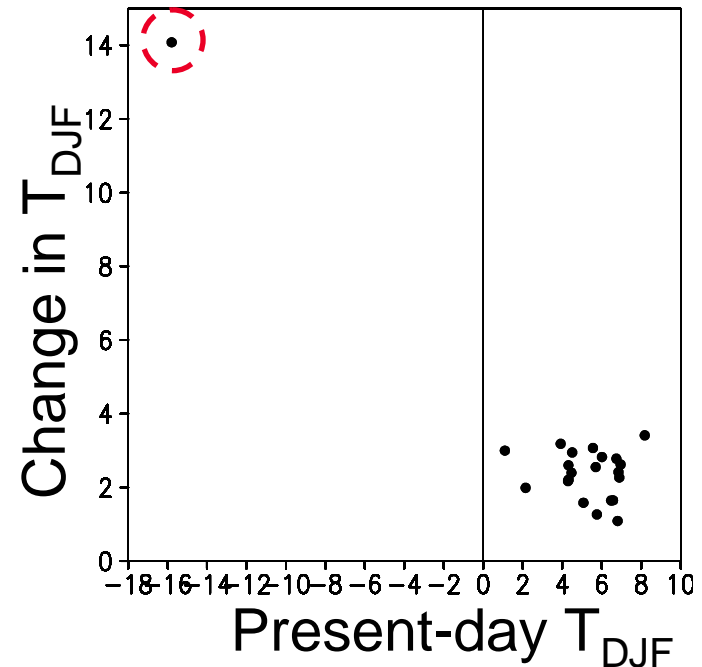
T_{DJF} (1970-1999)



ΔT_{DJF} (1970-1999 \rightarrow 2070-2099)



Scatter plot of CMIP3 simulations for the North Sea (55°N, 5°E)



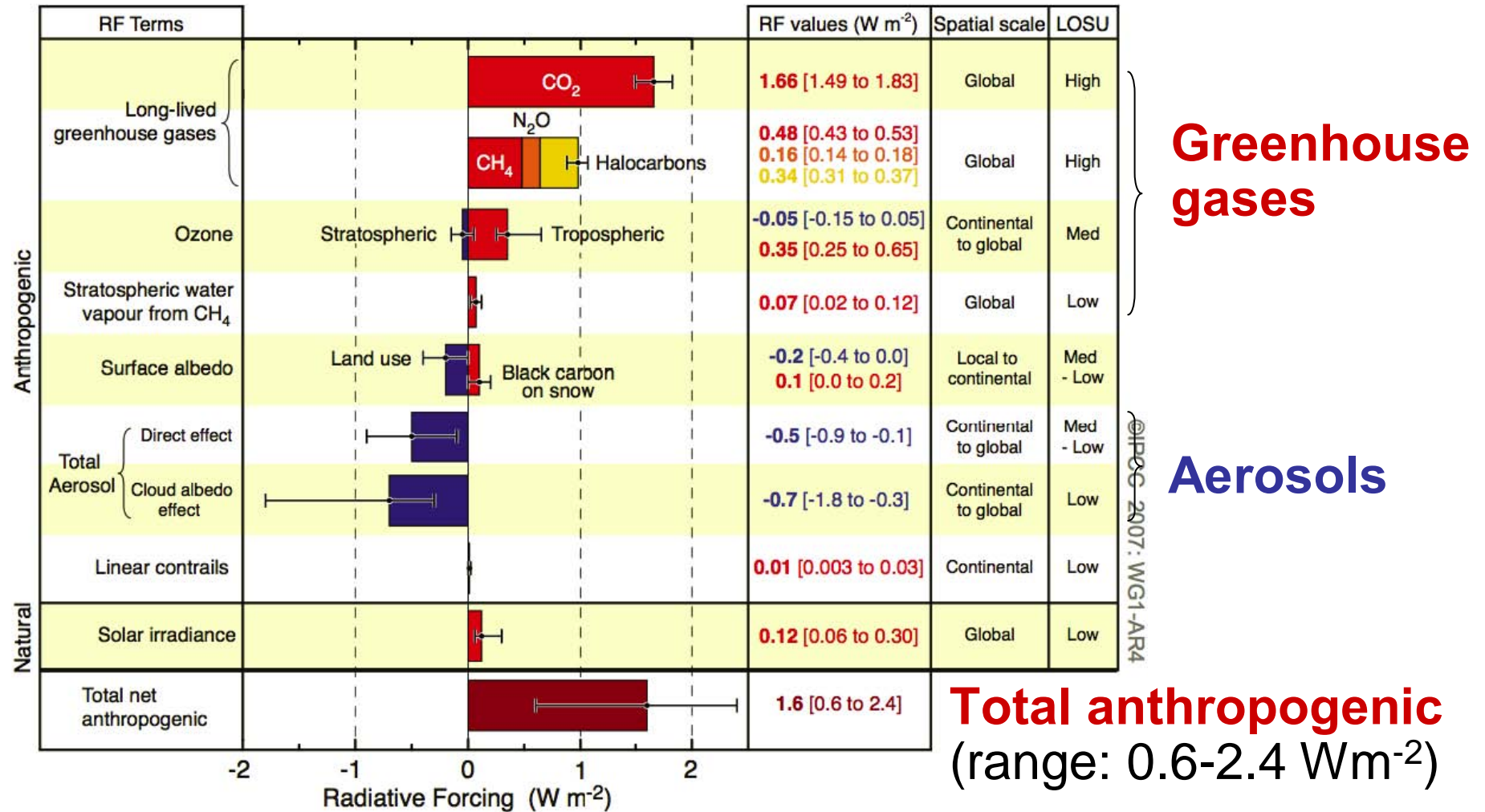
Implications

- **In most cases**
 - no simple relationship between present-day climate and simulated climate changes – at least not for those variables that are most commonly and most easily verified
- **Thus**
 - good performance in simulating local present-day time mean climate may not be a very strong predictor of model reliability
- **However**
 - be aware of outliers. Don't be shy to throw away bad models, if you have strong reasons to suspect that their biases have a serious impact on their climate change response
- **Analysis of variability and individual processes**
 - potentially more useful than verification of time mean climate, but also more challenging to conduct

How well can models simulate past climate changes?

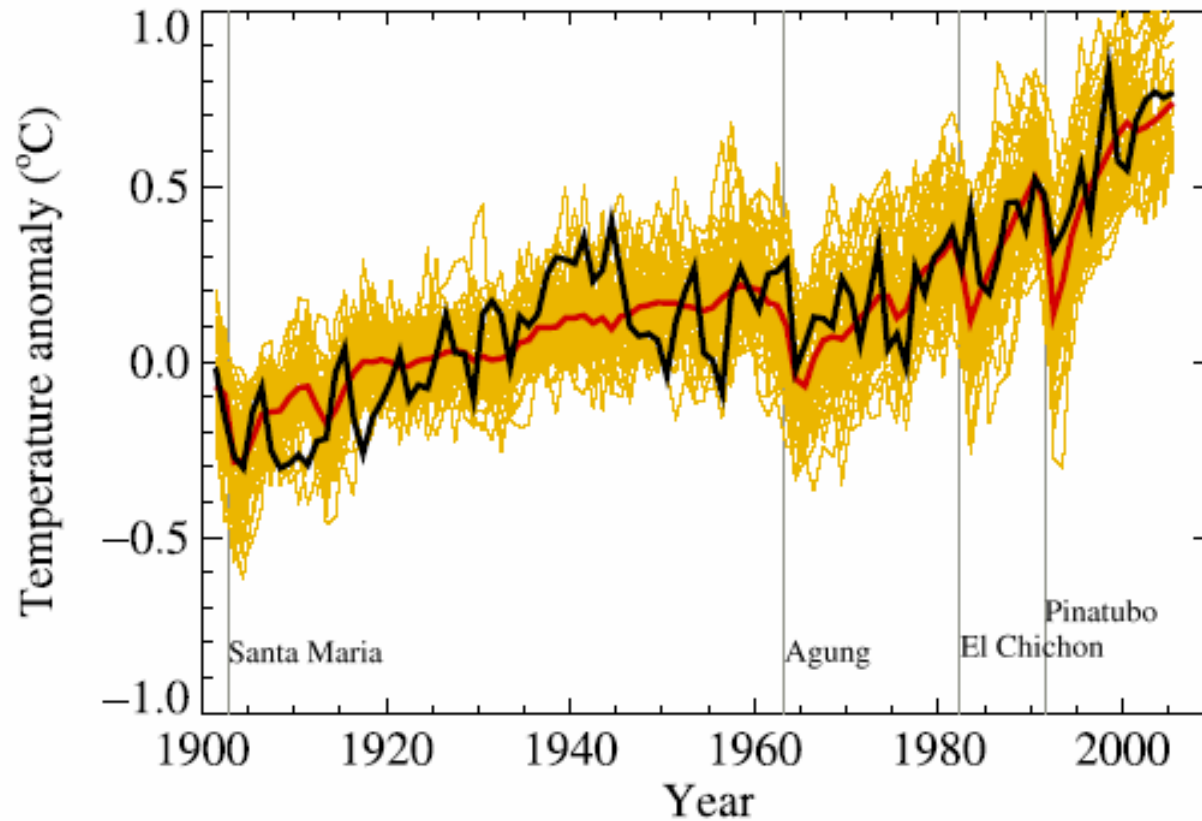
- **In principle**
 - for the simulation of future changes, the simulation of past changes provides the most objective test that is available
- **Complications**
 - Uncertainties in forcing
 - Internal climate variability (particularly on regional scales)
 - Lack / uncertainty in observations (for many variables)
- **Focus in this talk on the instrumental period**
 - palaeoclimates also provide opportunities for model evaluation, but with (at least) equally large complications in interpretation

Radiative forcing components (2005)



Both good and bad agreement between simulated and observed climate changes may partly result from errors in forcing.

Simulation of global mean temperature changes, 1900-2005 (IPCC AR4 WG1 FAQ 8.1, Fig. 8.1)

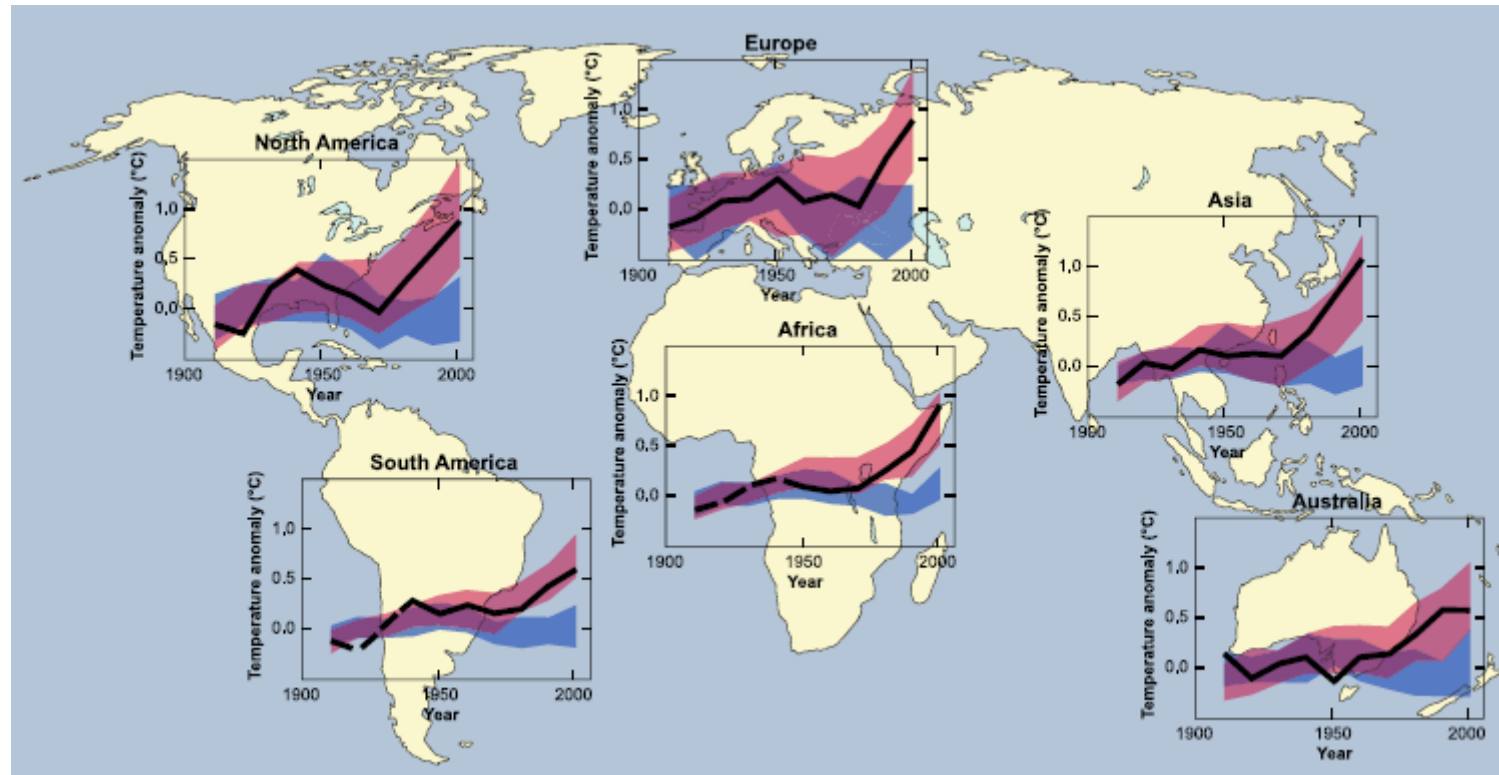


Black: observations

Red and yellow: mean and variability of 58 simulations by 14 CMIP3 models, including both natural and anthropogenic forcing.

- 1) **Good agreement!**
- 2) **Warm period around 1940 not well captured by models?**
(extreme event of internal climate variability??)

Simulation of continental-scale temperature changes (IPCC AR4 WG1 Fig. SPM.4)



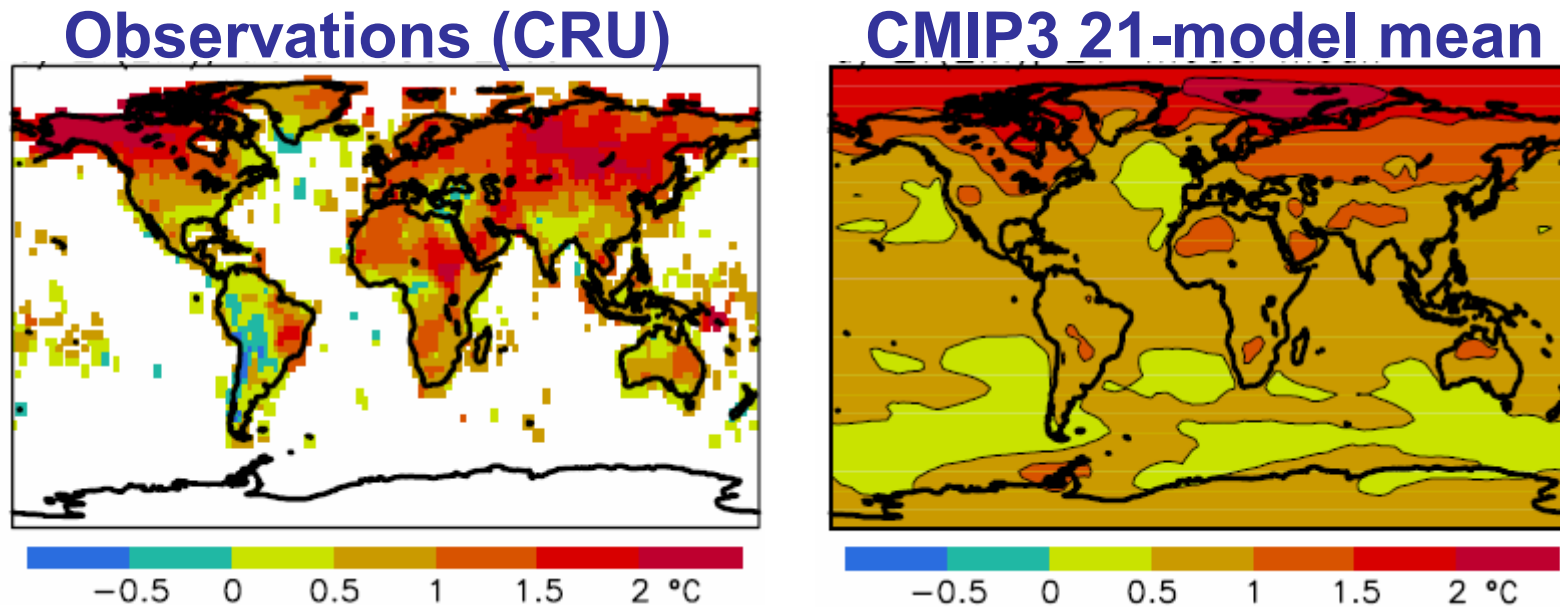
Simulations with anthropogenic + natural forcing



Simulations with only natural forcing

”It is likely that there has been significant anthropogenic warming over the past 50 years averaged over each continent except Antarctica”

Comparison between observed and simulated temperature trends, 1955-2005

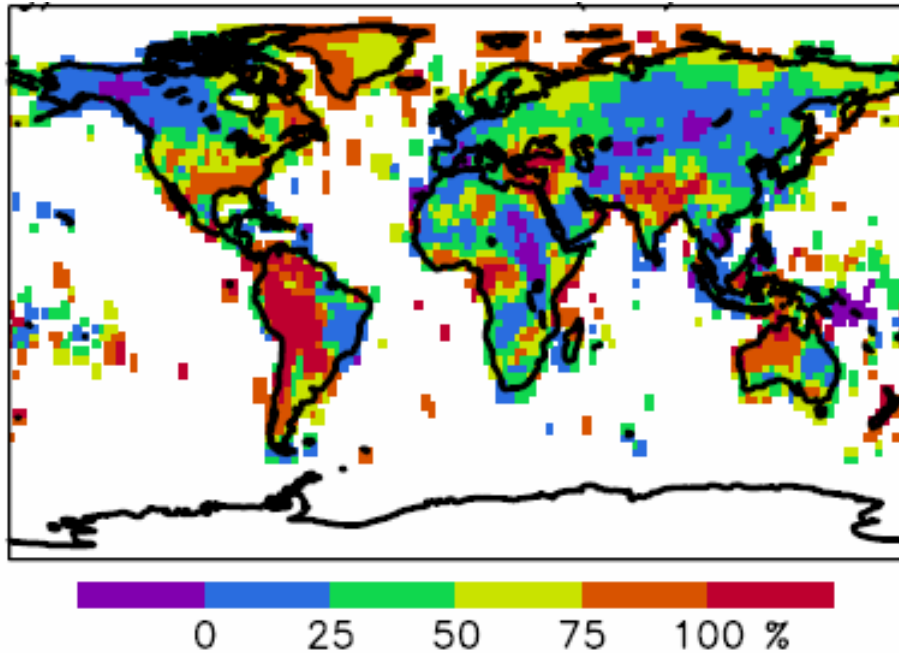


Similar global mean warming, but only broad similarity ($r = 0.48$) in geographical patterns

But: because of internal variability, no perfect agreement would be expected even if the models were perfect!

Comparison between observed and simulated temperature trends, 1955-2005 (2)

Fraction of models with $\Delta T_{sim} > \Delta T_{obs}$



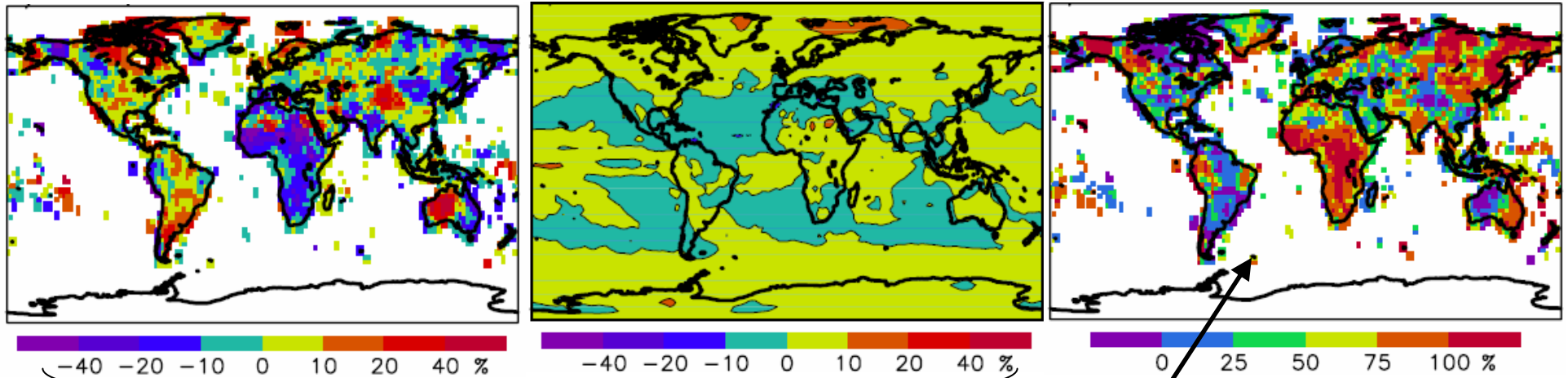
In most areas, observed temperature changes were within the range of the changes simulated by the 21 models

The reverse was true in only **12%** of the verification domain.

Comparison between observed and simulated precipitation trends, 1955-2005

Observations (CRU) 21-model mean

Fraction of models with $\Delta P_{sim} > \Delta P_{obs}$



Correlation = 0.23

Observed precipitation change out of the range of model simulations: **23%** of the verification domain

Comparison between observed and simulated climate trends: conclusions

- **Low signal-to-noise ratio on regional scales, particularly for precipitation but also for temperature**
 - therefore: compare observations against the range of simulations, not only the multi-model mean
- **Temperature trends well captured by the range of model simulations in most areas, precipitation trends less well**
 - errors in precipitation response to increasing GHGs?
 - problems with forcing (aerosols, land use changes etc)?
 - Inhomogeneity in observations?
 - Underestimation of natural variability in models?
- **Past performance is not a water-proof predictor of future performance**
 - With increasing greenhouse gas forcing, the relative importance of model errors will grow larger

General conclusions

- **Global climate models show substantial skill** in simulating both
 - the present-day climate, and
 - 20th century climate change, particularly the large-scale temperature evolution
- **Nevertheless, models are not** (and will never become) **perfect**
- **Variation of model results** gives a first useful estimate of uncertainty in future climate changes
- **The non-trivial question** is how the actual uncertainty relates to this inter-model variation!