Módulo 1, Parte 2

Introducción al modelado del sistema climático

Increases in computing speed and memory have led to the development of more sophisticated models that describe physical, chemical and biological processes in greater detail

Spectrum of models (from the simplest to the most complex models):

Energy balance models: use one box to represent the Earth system and solve the global energy balance to deduce globally averaged surface air temperature

Full complexity three-dimensional climate models: include the explicit solution of energy, momentum and mass conservation equations at millions of points on the Earth in the atmosphere, land, ocean and cryosphere

Earth System Models (ESMs): the full complexity models + explicit simulation of the biosphere, the carbon cycle and atmospheric chemistry

Earth System Models of Intermediate Complexity: include the same processes as ESMs, but at reduced resolution, and thus can be simulated for longer periods

¿Podemos confiar en los resultados de los GCMs?

. Los GCMs están basados en principios físicos.

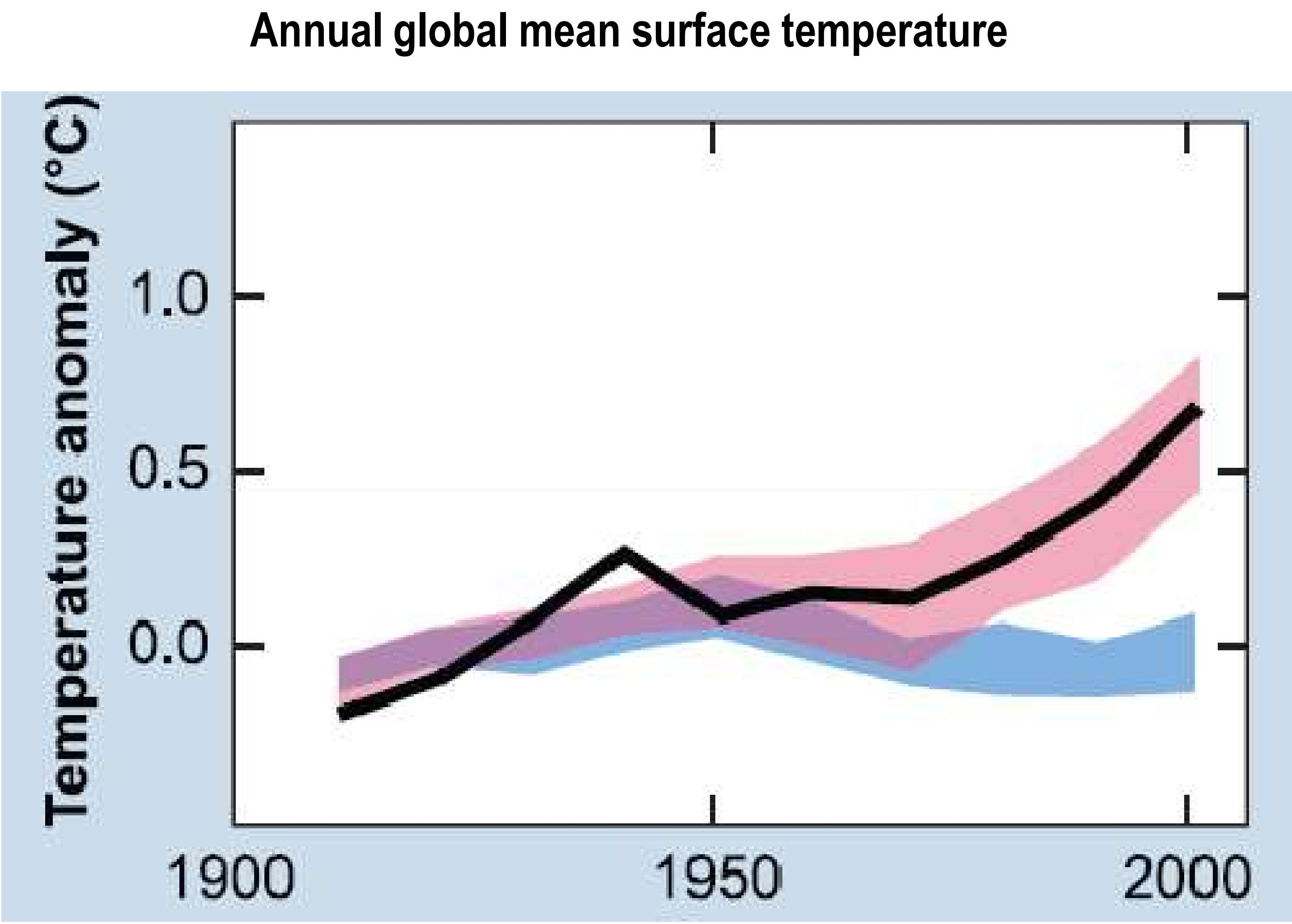
. Están ampliamente probados por una gran comunidad de modeladores y analistas climáticos.

. Simulaciones precisas en gran escala del clima actual y pasado.

. Simulación retrospectiva (hindcast #) precisa del cambio climático del siglo 20 incluyendo el contenido de calor del océano.

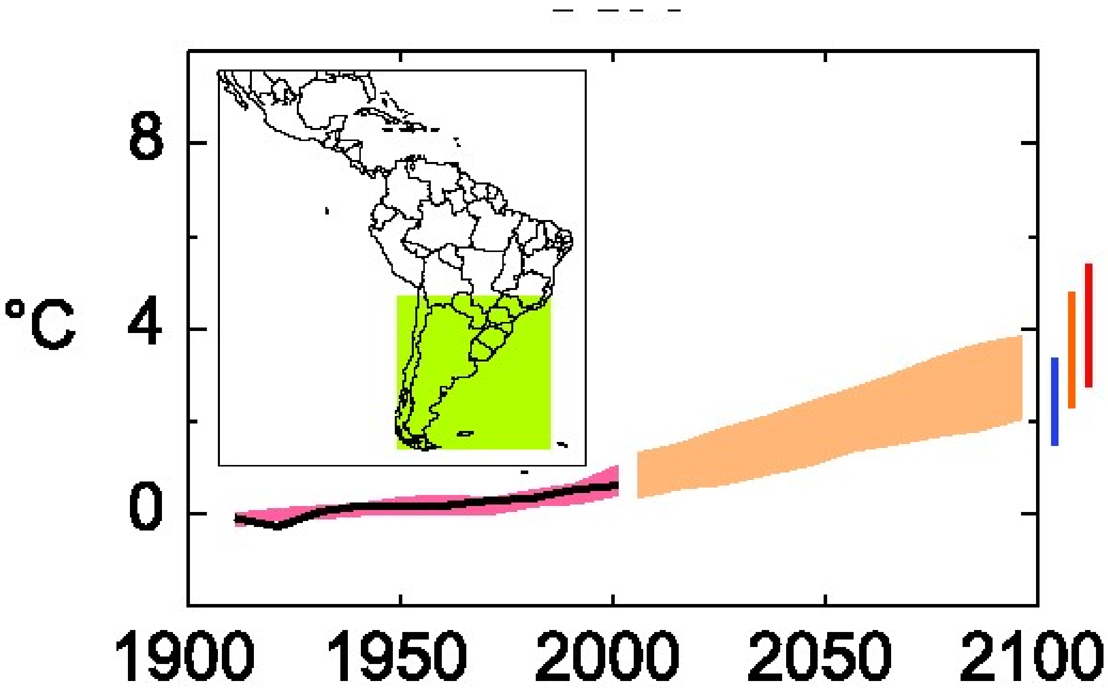
Hindcasting usually refers to a numerical model integration of a historical period where no observations have been assimilated. This distinguishes a hindcast run from a reanalysis.

Are the models reliable?



IPCC AR4

Regional climate projections: present ability



Large-area "average" indications of ranges of plausible climate changes for all continents

Sources of uncertainty

- very large natural variability (e.g. nonlinear interactions between ENSO and SAM);
- skill of global models at simulating tropical-extratropical teleconnections and their changes under anthropogenic forcing;
- some processes are poorly represented or not presently included in the models: e.g. carbon cycle, interactive vegetation, aerosols, sea ice, interactive ozone and methane,…;
- global model's resolution is still not adequate;
- large model-to-model disagreement (rather large inter-model spread for present-day and future simulations);
- uncertainties related to the future transient evolution of climate forcings

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- **Various factors, including climate variability and processes that are poorly understood or not represented, act to limit the information that can be obtained**

Characterizing Uncertainty

‘Uncertainty’ is a complex and multifaceted property, sometimes originating in a lack of information, and at other times from quite fundamental disagreements about what is known or even knowable (Moss and Schneider, 2000).

Furthermore, scientists often disagree about the best or most appropriate way to characterize these uncertainties: some can be quantified easily while others cannot.

Moreover, appropriate characterization is dependent on the intended use of the information and the particular needs of that user community. Scientific uncertainty can be partitioned in various ways, in which the details of the partitioning usually depend on the context (e.g. observations, models).

Observations. Uncertainty in measured quantities can arise from a range of sources, such as statistical variation, variability, inherent randomness, inhomogeneity, approximation, subjective judgement, and linguistic imprecision, or from calibration methodologies, instrumental bias or instrumental limitations.

Modelling studies. It is common to partition uncertainty into four main categories:

scenario uncertainty, due to uncertainty of future emissions of GHGs and other forcing agents;

model uncertainty associated with climate models;

internal variability and initial condition uncertainty; and

forcing and boundary condition uncertainty for the assessment of historical and paleoclimate simulations

Clim Dyn (2011) 37:407–418
DOI 10.1007/s00382-010-0810-6

The potential to narrow uncertainty in projections of regional precipitation change

Ed Hawkins · Rowan Sutton

For many regions even the sign of the change in mean precipitation is uncertain…

This large **uncertainty comes from three sources**:

1) model uncertainty : arises from each GCM projecting somewhat different future changes in climate in response to the same radiative forcings,
2) scenario uncertainty: results from the unknown future changes in anthropogenic forcings
3) the random, internal variability of climate.

Signal-to-noise ratio : how large is the expected change compared to the uncertainty in the prediction.

The dominant sources of **uncertainty depend on the climate variable and region**:

e.g. internal variability is a significantly more important factor for predictions of precipitation change than for predictions of temperature change

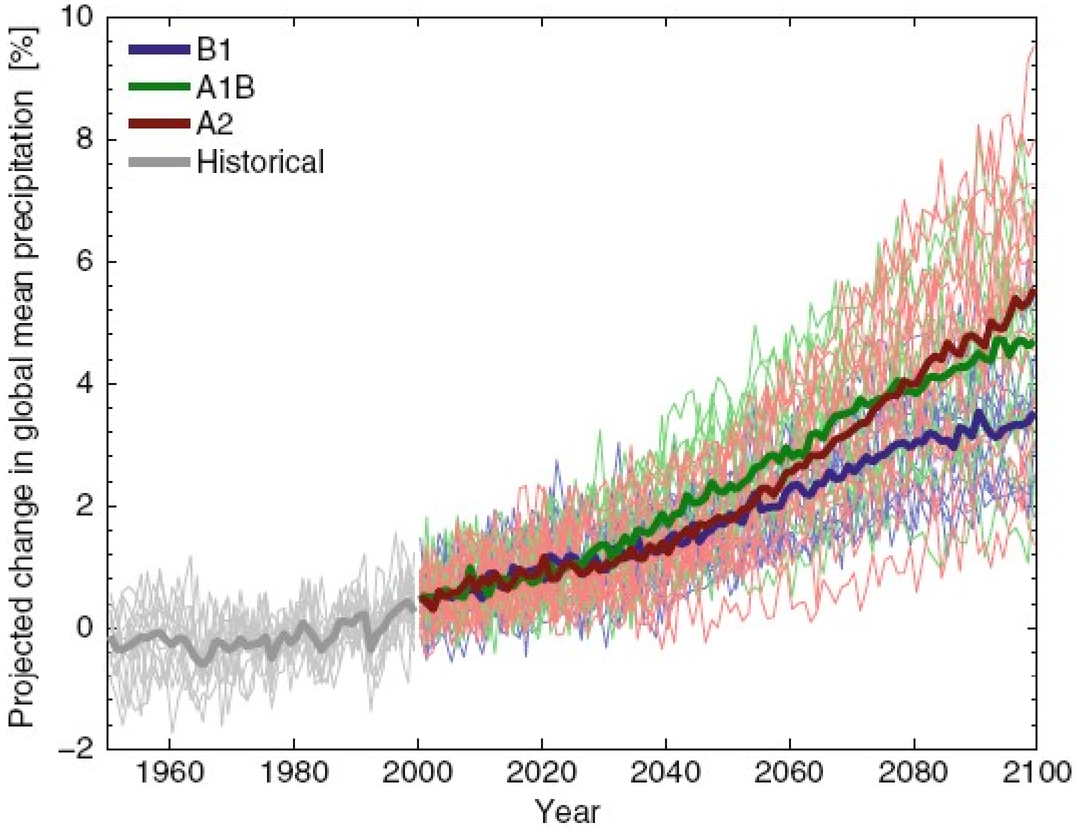


Fig. 1 CMIP3 projections of changes in global mean precipitation, relative to the mean of 1971–2000, for historical forcings and different future emission scenarios. The *different lines* each represent a different global climate model for SRES B1 (*blue*), A1B (*green*) and A2 (*red*) scenarios, with historical projections shown in *grey*. The *thick lines* represent the multi-model means for each scenario

Model uncertainty: for the same radiative forcings, different models produce different projections (shown by the spread between similarly coloured lines).

Scenario uncertainty: spread in the thick coloured lines.

Internal variability: 'wiggles' superimposed on the long term trends in each projection

On regional scales the intermodel spread can be far larger

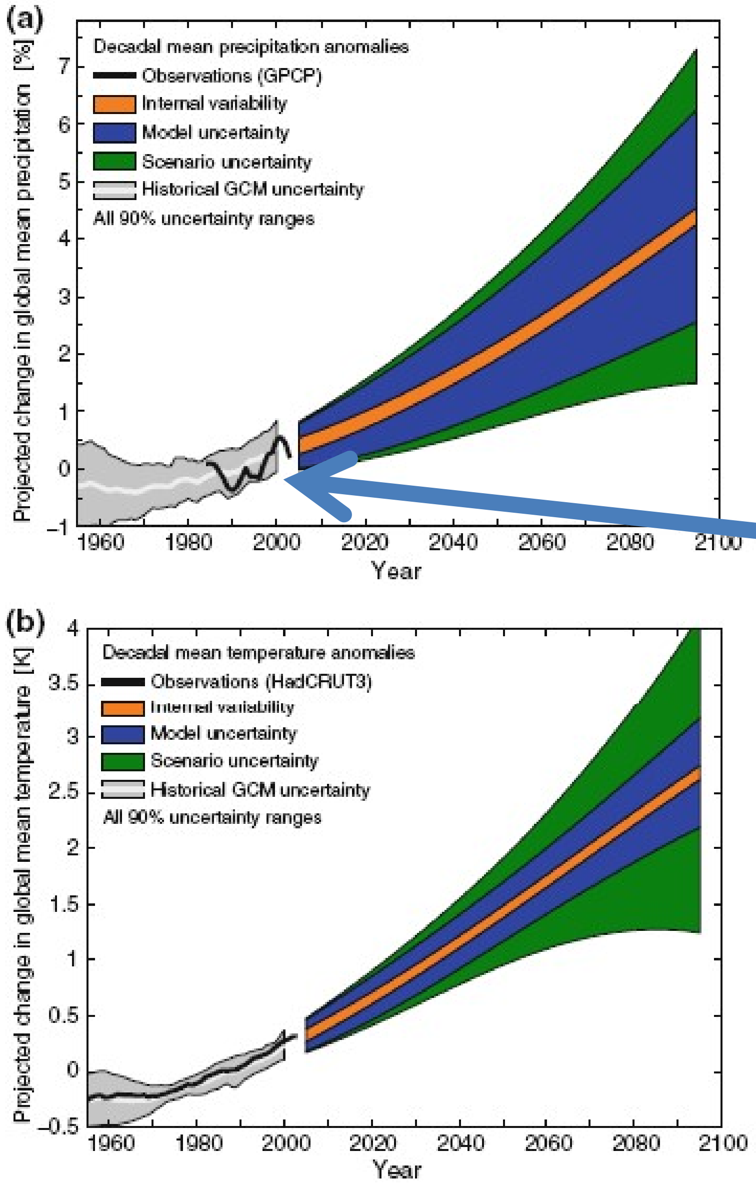


Fig. 2 The total uncertainty in CMIP3 global mean, decadal mean projections for the twenty-first century, separated into its three components: internal variability (*orange*), model uncertainty (*blue*) and scenario uncertainty (*green*). The *grey regions* show the uncertainty in the twentieth century integrations of the same GCMs, with the mean in *white*. The *black lines* show an estimate of the observed historical changes. **a** Precipitation, with observations from GPCP v2.1 (Adler et al. 2003). **b** Temperature, with observations

Precipitation: Throughout the century, model uncertainty (blue) is the dominant contributor, but at the start of the century, internal variability (orange) is important, and scenario uncertainty (green) becomes more important at the end of the century.

GCMs represent global decadal variability of precipitation, although the observed record is short and is itself subject to considerable uncertainty

Temperature: scenario uncertainty is more important than model uncertainty from mid-century onwards

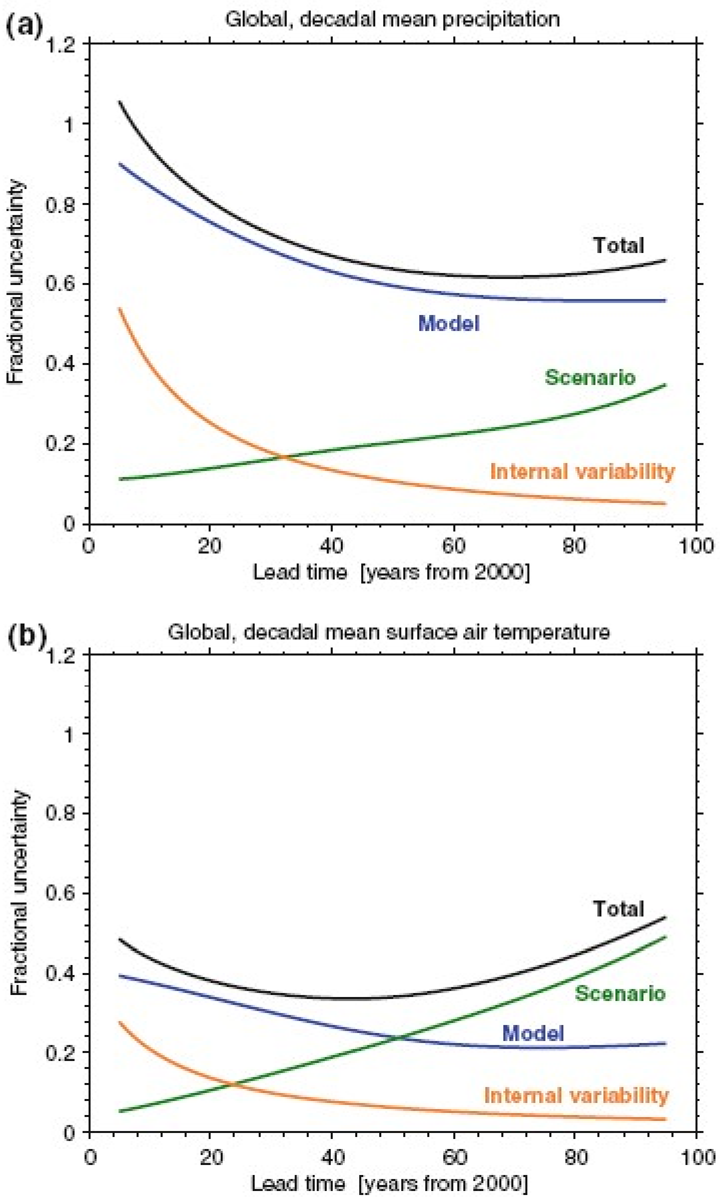


Fig. 3 The fractional uncertainty in decadal mean, global mean climate projections, defined as the uncertainty divided by the expected mean change for **a** precipitation, and **b** surface air temperature (after HS09)

Alternative representation of the uncertainty:

N / S

Fractional uncertainty (i.e. the uncertainty divided by the expected change)

The smallest fractional uncertainty for precipitation (or the largest signal-to noise ratio), occurs around 2070, far later than for temperature, which has the minimum around 2040

(a) Global Annual precip.:

model uncertainty (blue) is dominant for all lead times considered,
Internal variability (orange) is significant at short lead times, and
scenario uncertainty (green) only becomes important at the end of the century.

(b-d) For smaller regions and particular seasons, the contribution from internal variability is larger, but scenario uncertainty is generally still small.

European winter (DJF) rainfall (Fig. 4c) has a very large internal variability contribution, which is dominant until around 2050, likely related to the North Atlantic Oscillation (NAO).

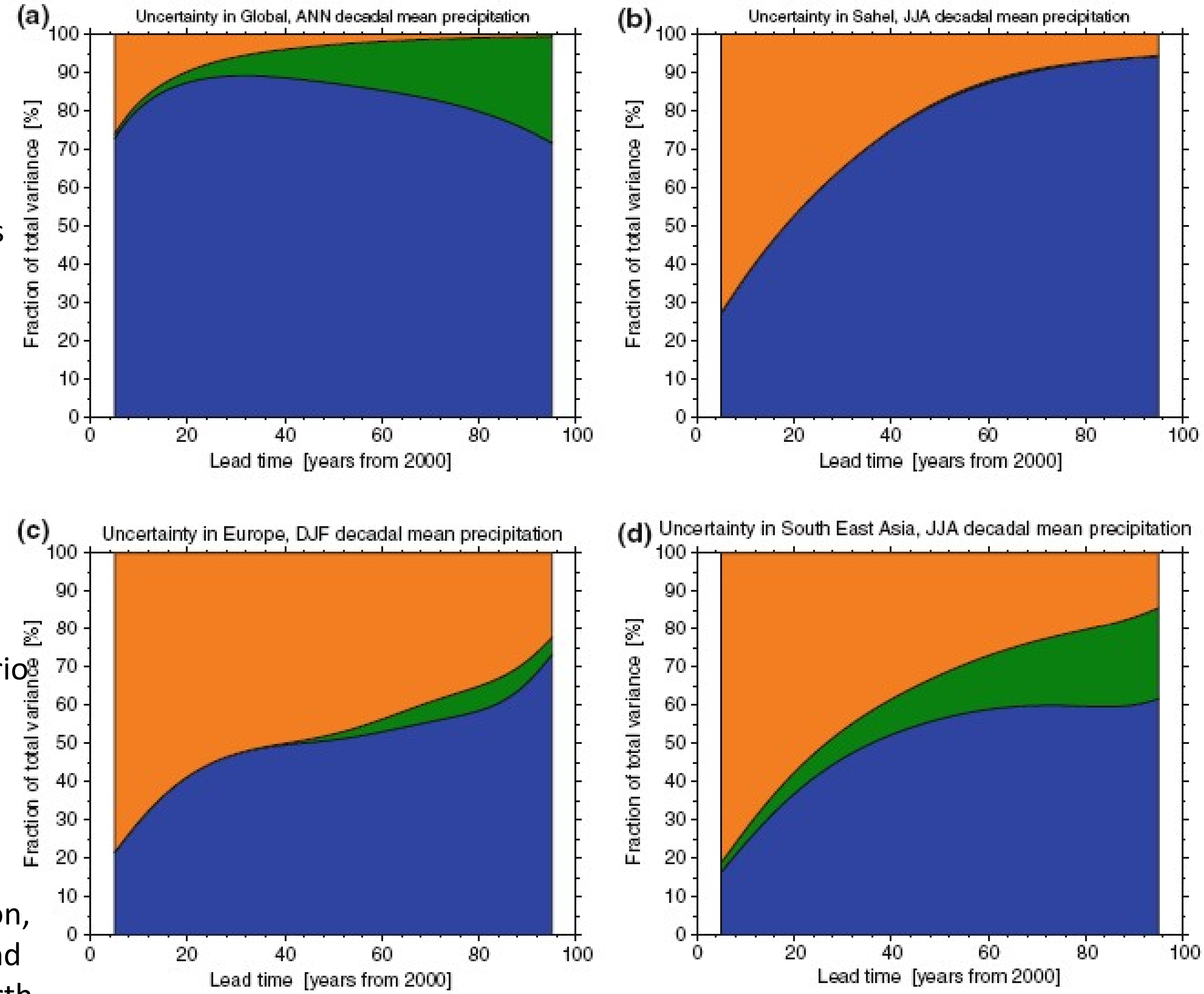
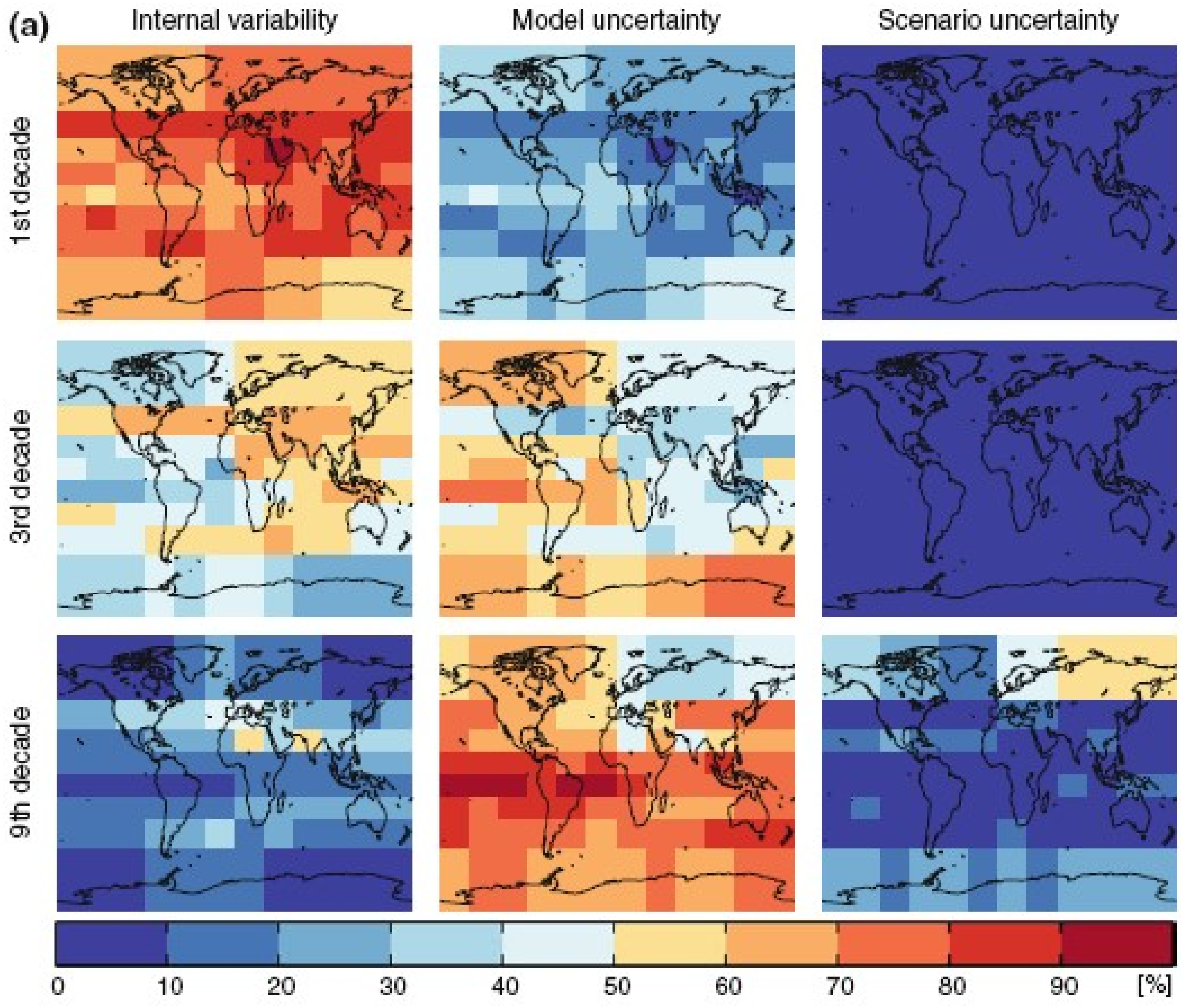


Fig. 4 Fraction of total variance in decadal mean precipitation projections explained by internal variability (*orange*), model uncertainty (*blue*) and scenario uncertainty (*green*), for a global, annual mean, **b** Sahel JJA mean, **c** European DJF mean, and **d** South East Asian JJA mean

Fig. 5 Fraction of variance explained by the three sources of uncertainty in projections of decadal mean seasonal precipitation changes, for **a** boreal winter (DJF), and **b** boreal summer (JJA). Each *grid cell* has the same area, roughly $5 \times 10^6 km^2$



Fuentes de incertidumbre - DJF

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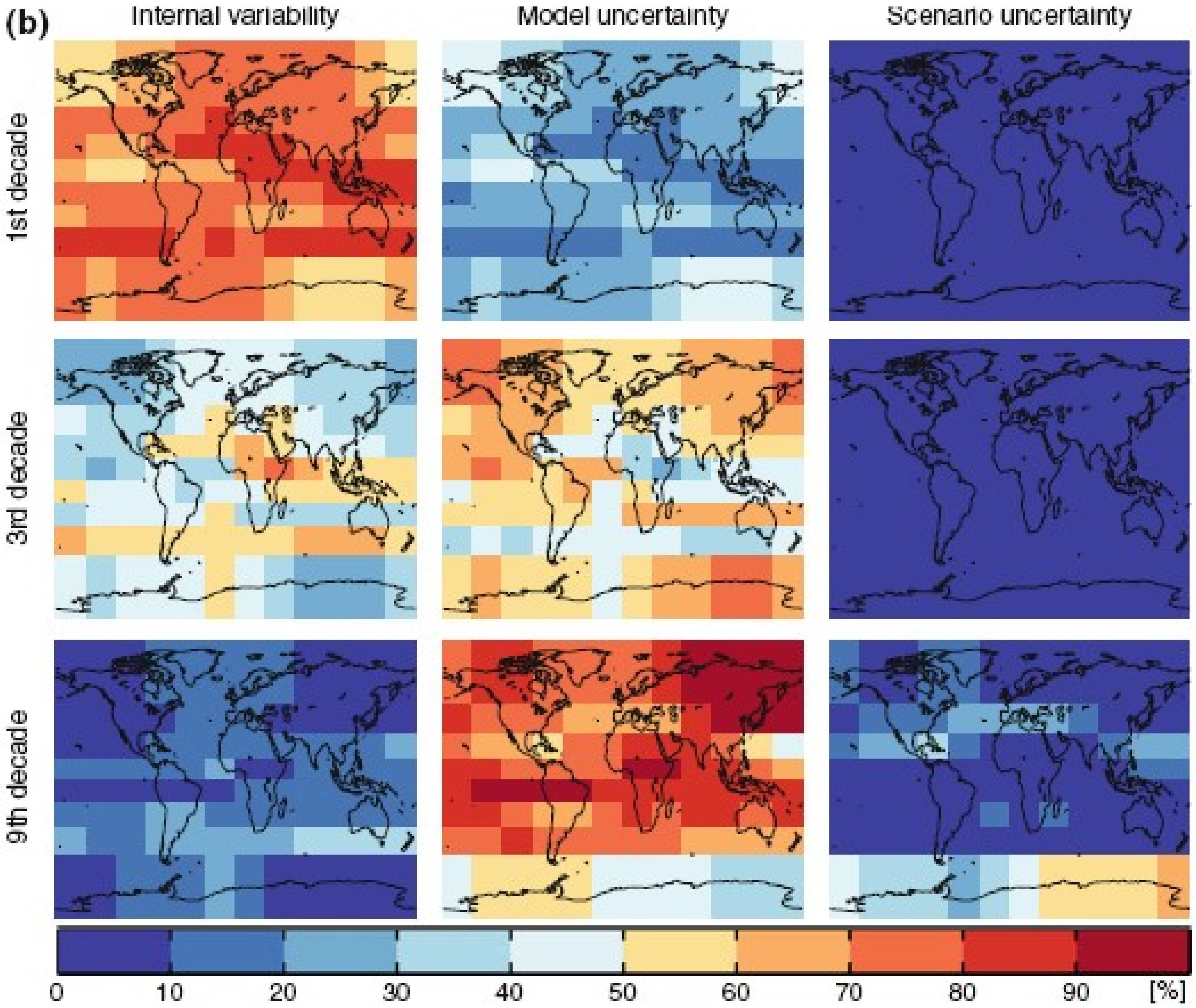


Fuentes de incertidumbre - JJA

The signal-to-noise ratio (S/N)

The signal-to-noise ratio (S/N) is often used to measure the robustness of a prediction. We now consider the S/N of these precipitation projections on regional scales,

$$\mathrm{S/N} = \frac{\Delta_{\mathrm{precip}}}{\sigma_{\mathrm{precip}}}, \tag{1}$$

where Δ_{precip} is the change in decadal means of seasonal precipitation, relative to 1971–2000, and σ_{precip} is the total standard deviation of the projections. To assess the significance of the S/N, we consider the null hypothesis that

Some additional considerations

In a subject as complex and diverse as climate variability and change, the information available as well as the way it is expressed, and often the interpretation of that material, varies considerably with the scientific context.

In some cases, two studies examining similar material may take different approaches even to the quantification of uncertainty.

The interpretation of similar numerical ranges for similar variables can differ from study to study.

It is necessary to pay close attention to the caveats and conditions that surround the results presented in peer-reviewed studies.

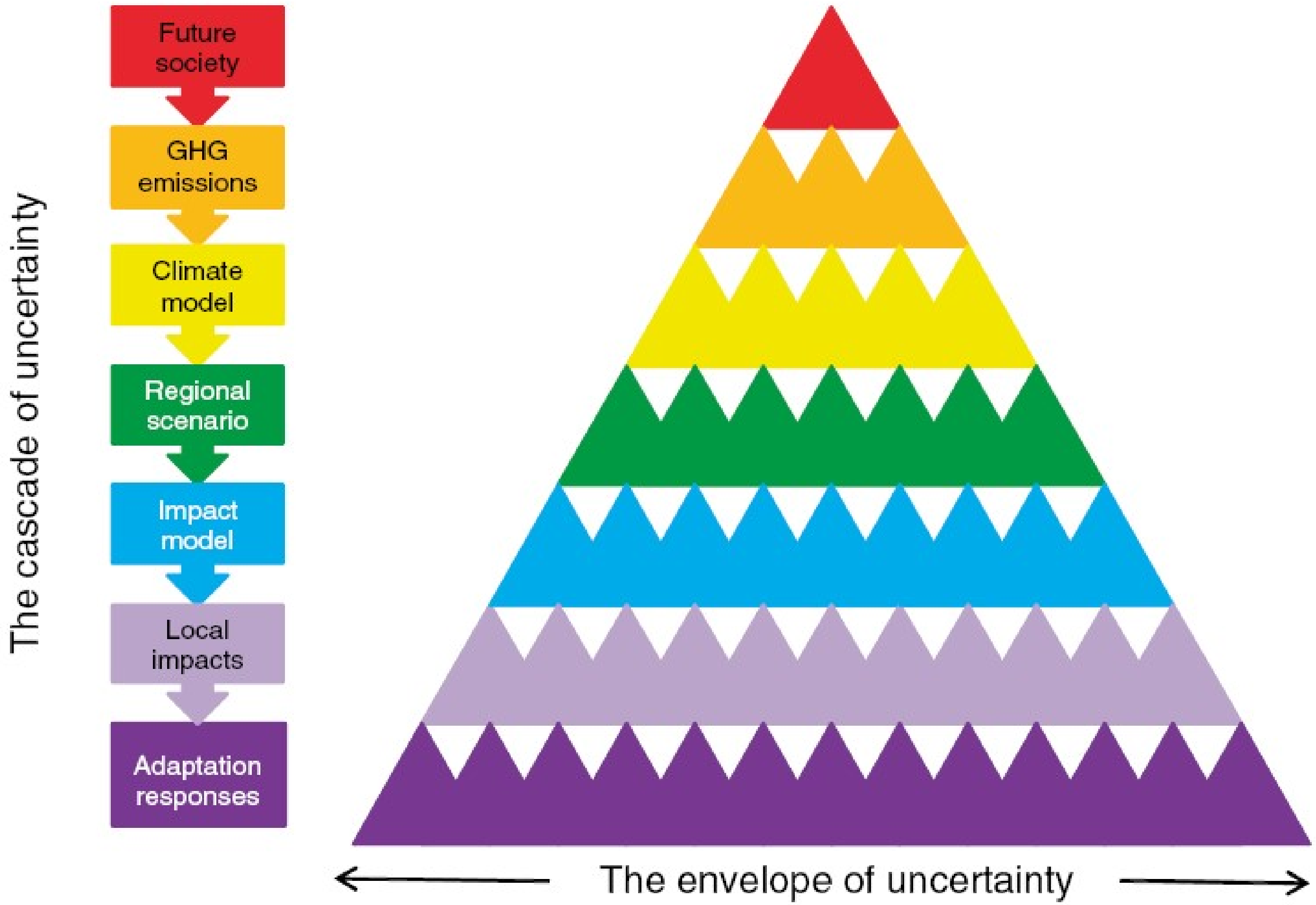


Figure 1. A cascade of uncertainty proceeds from different socio-economic and demographic pathways, their translation into concentrations of atmospheric greenhouse gas (GHG) concentrations, expressed climate outcomes in global and regional models, translation into local impacts on human and natural systems, and implied adaptation responses. The increasing number of triangles at each level symbolize the growing number of permutations and hence expanding envelope of uncertainty. For example, even relatively reliable hydrological models can yield very different results depending on the methods (and observed data) used for calibration.

Wilby and Dessai 2010

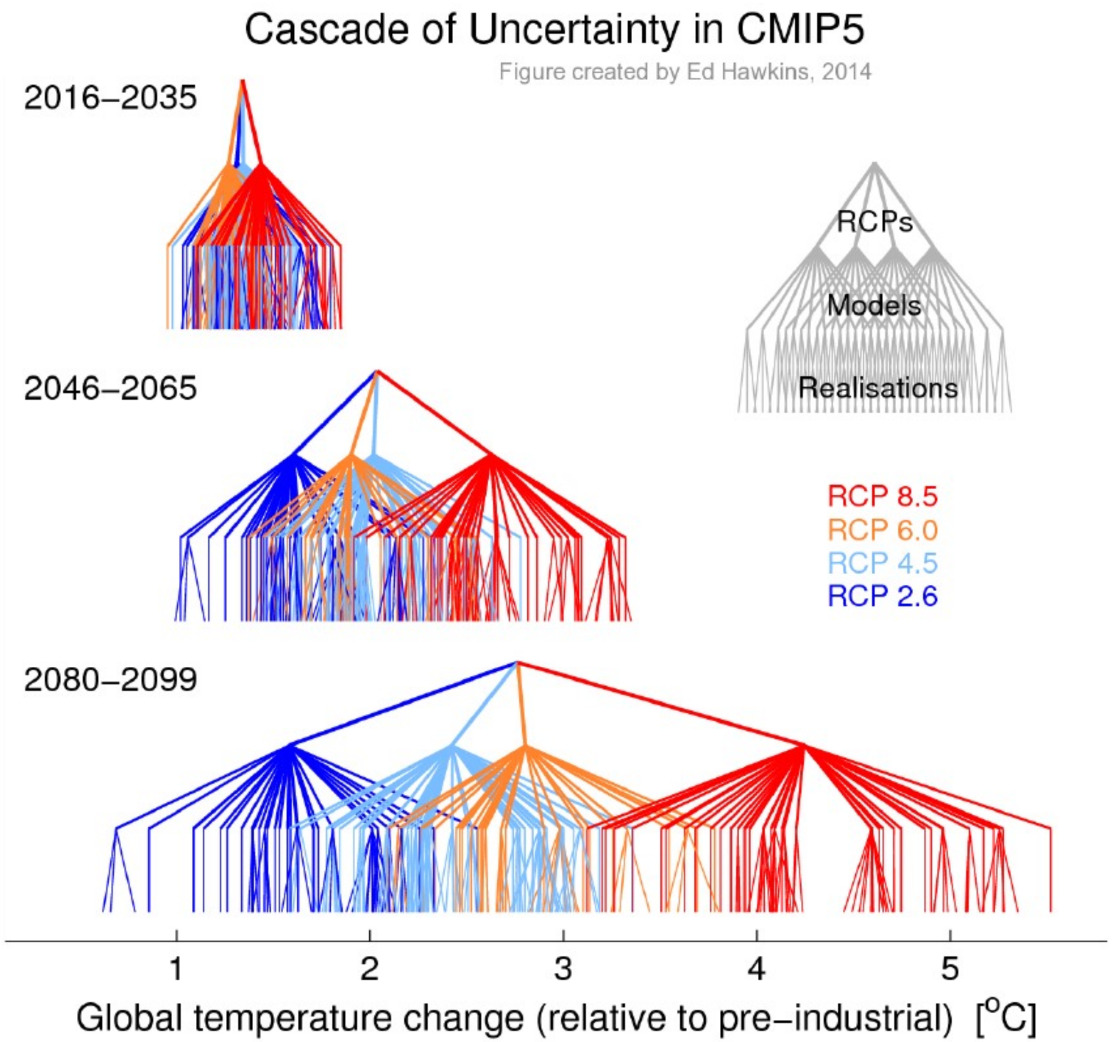


Figure 2: *The 'cascade of uncertainty' in global mean surface temperature from the CMIP5 simulations for different time periods as labelled. The three levels of the pyramid highlight the uncertainty due to the choice of RCP, GCMs and realisation of climate variability. Unfortunately not all the simulations have multiple realisations, resulting in a vertical line in the lowest layer. The intersection on the top row for each time period is the multi-scenario, multi-model, multi-realisation mean.*

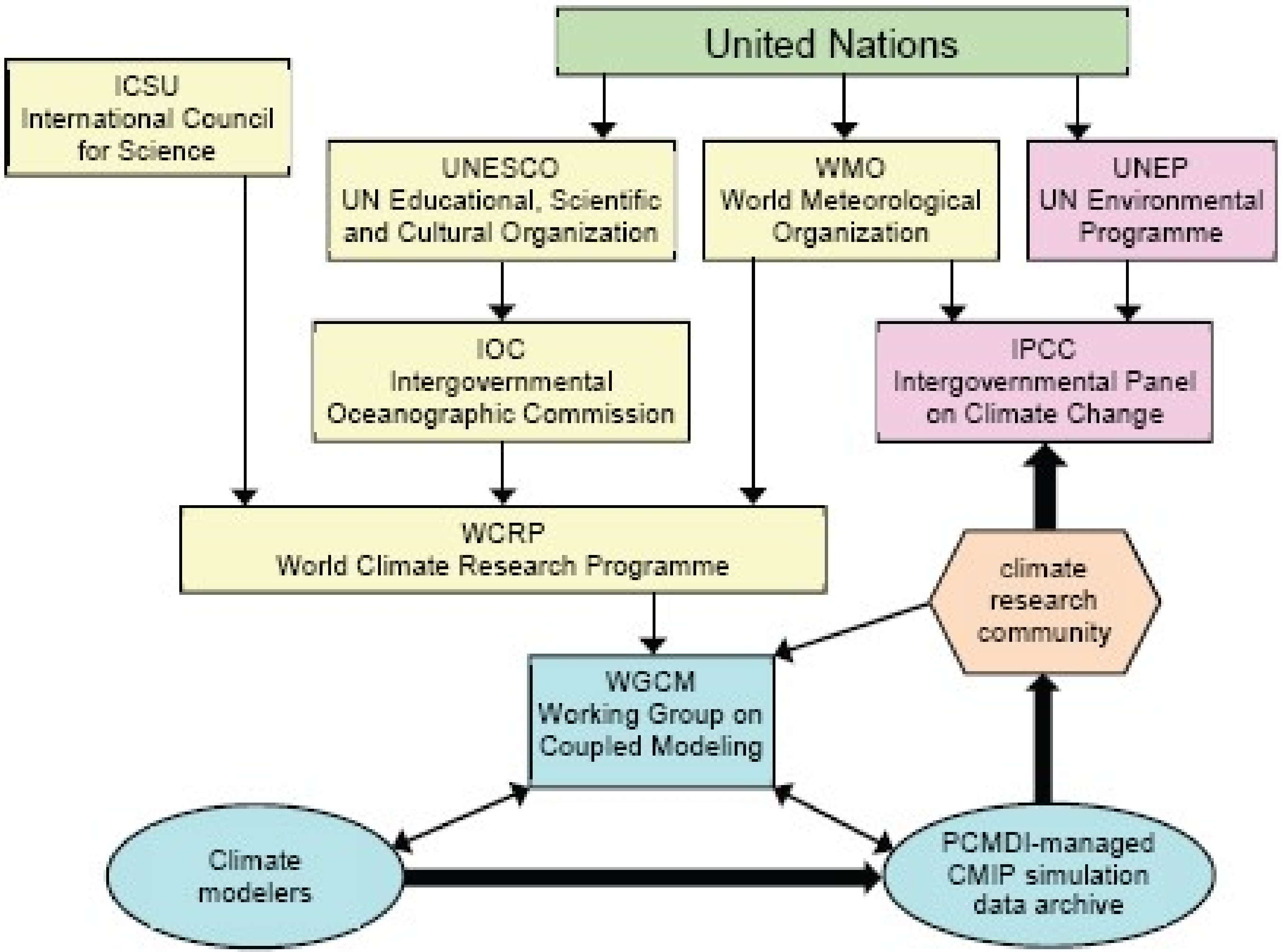


Fig. 1. The relationship of CMIP5 to organizations established to coordinate climate research activities internationally and to the IPCC, the modeling centers, and the climate research community.

Taylor et al 2012 (CMIP5)

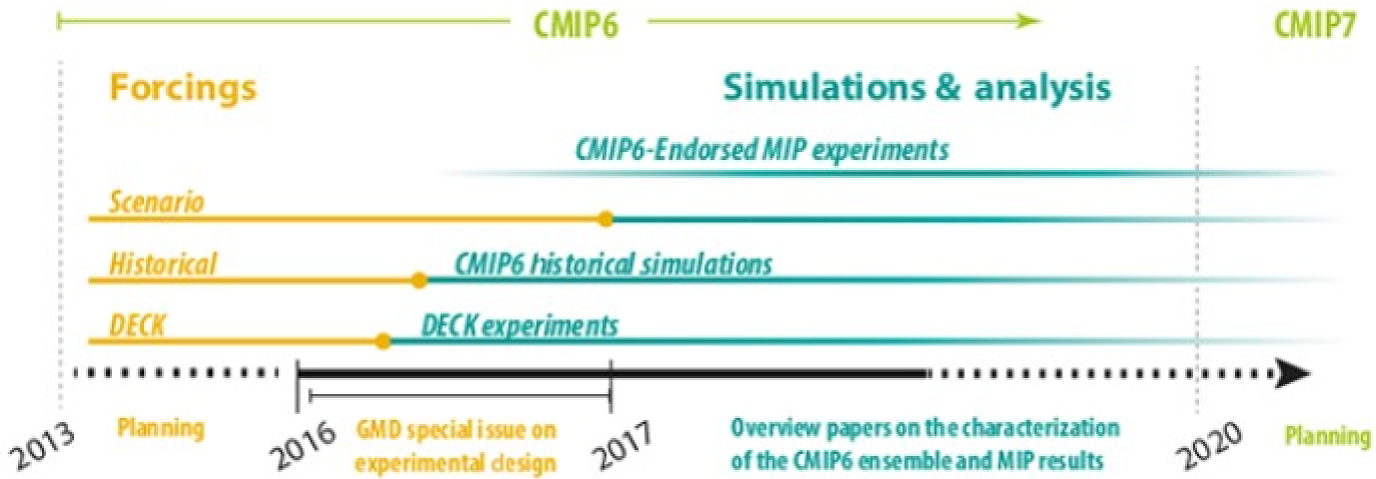


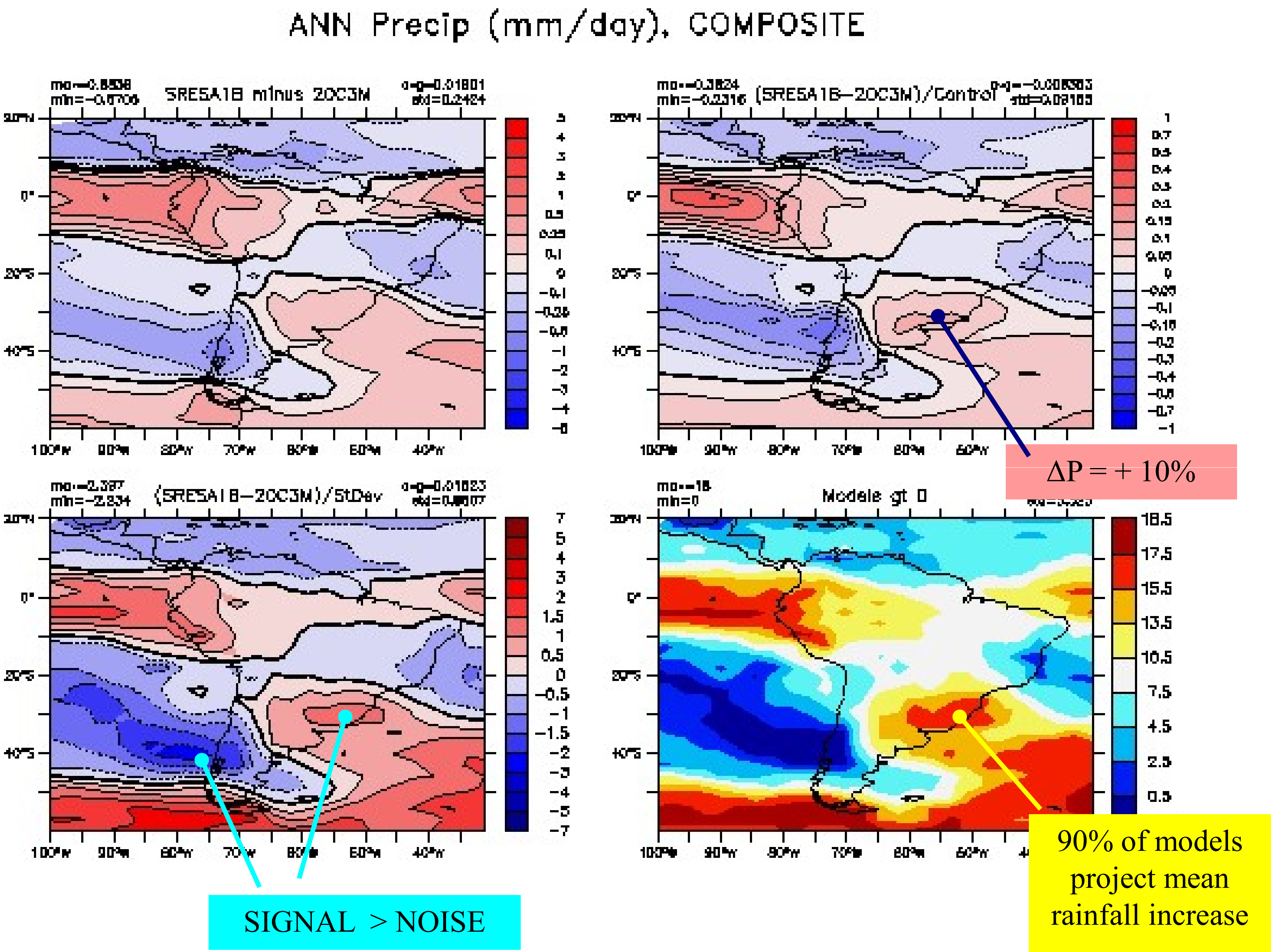
Figure 4. CMIP6 timeline for the preparation of forcings, the realization of experiments and their analysis.

Eyring et al 2016 (CMIP6)

Bonus

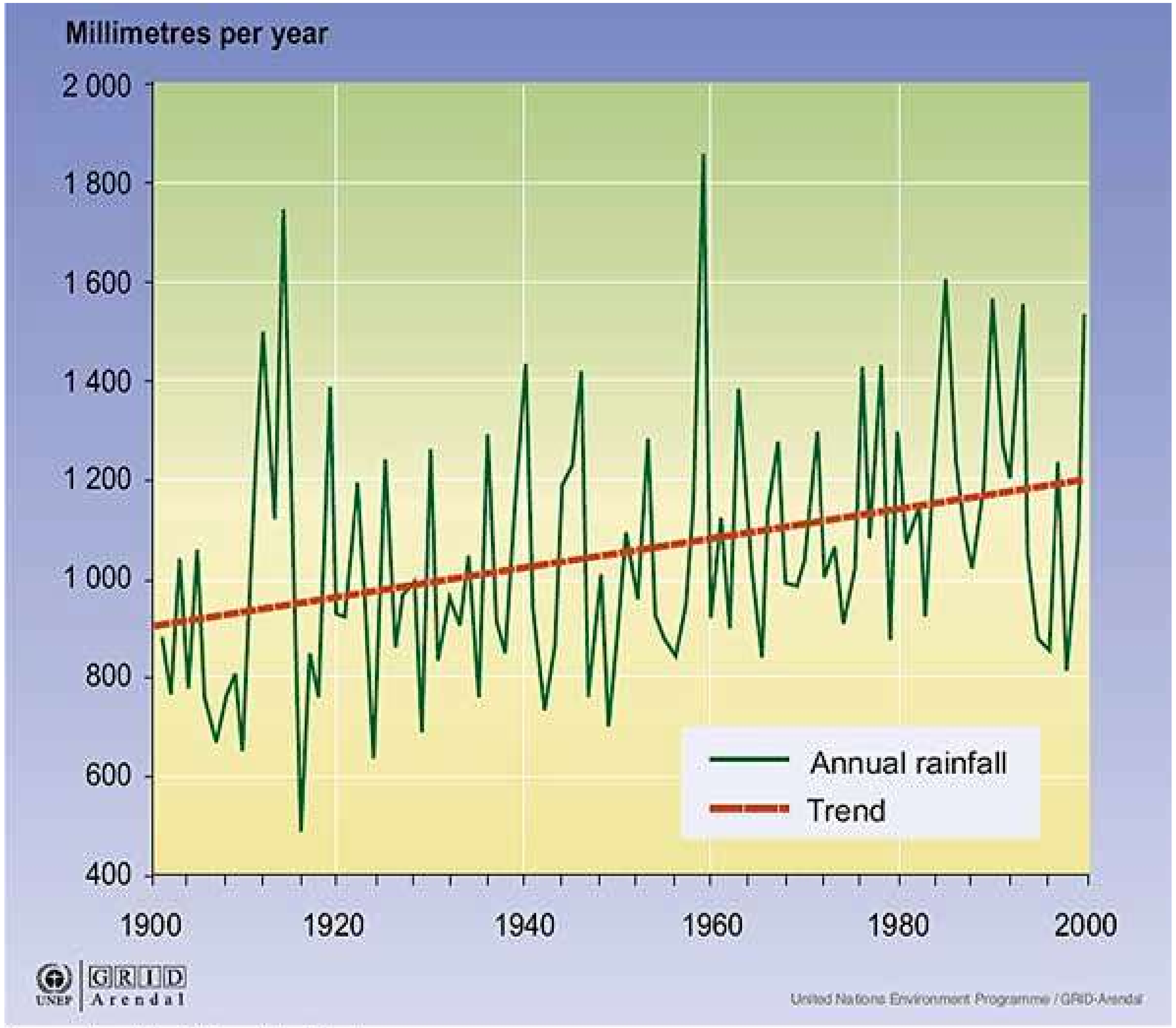
Caracterizando señal e incertidumbre en ensembles de AOGCMs en Sudamérica

ANNUAL MEAN COMPOSITE

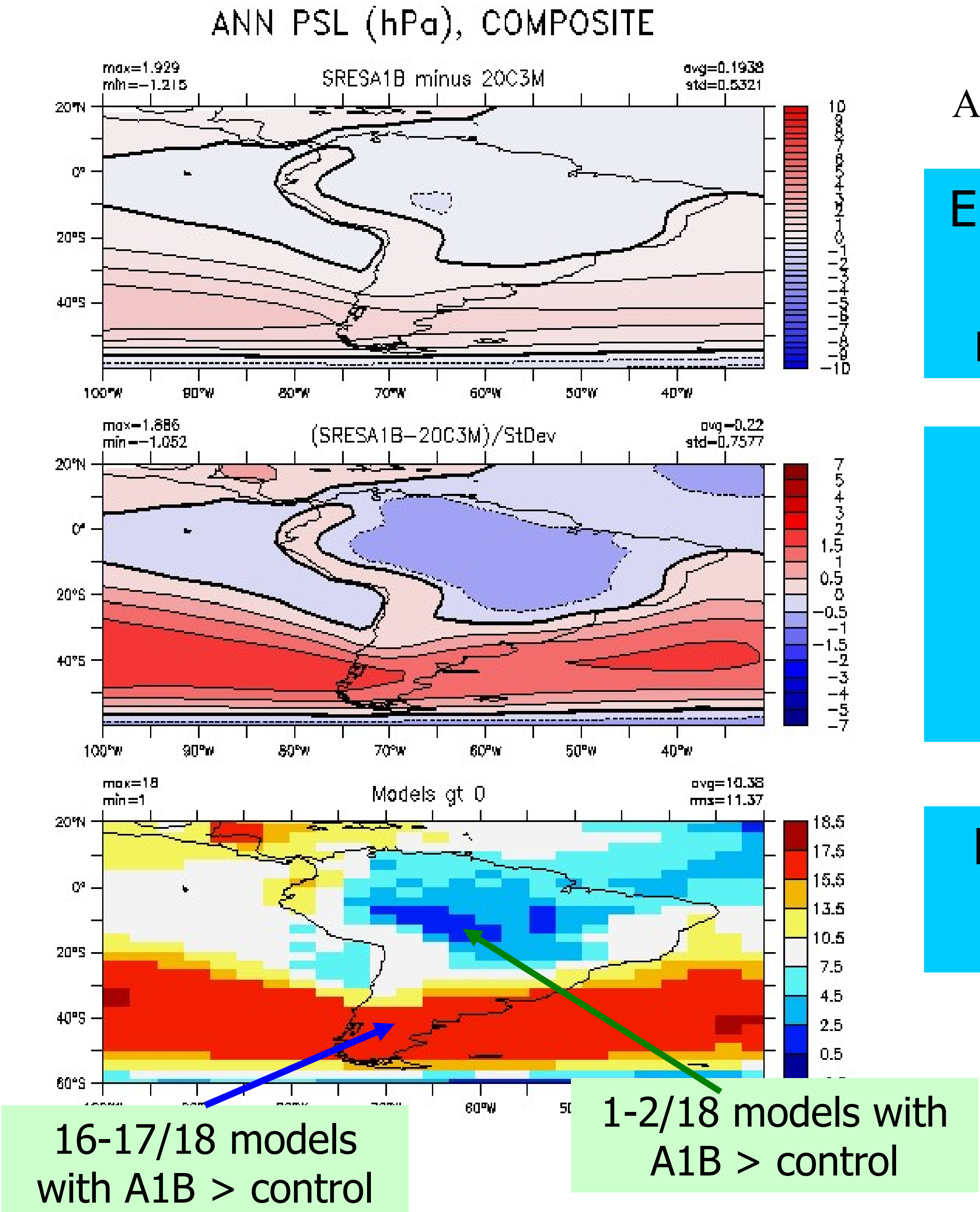


(Material inédito)

Observations: rainfall over Buenos Aires (in agreement with models results)



Source: Argentinian Meteorological Service



SEA LEVEL PRESSURE
ANNUAL MEAN COMPOSITE

Ensemble mean response = [A1B] – [control]

Brackets: mean over models

Signal / Noise =

([A1B] – [control])/

Std.dev.of A1B-cntrl among models

Number of models with

[A1B] – [control] > 0.

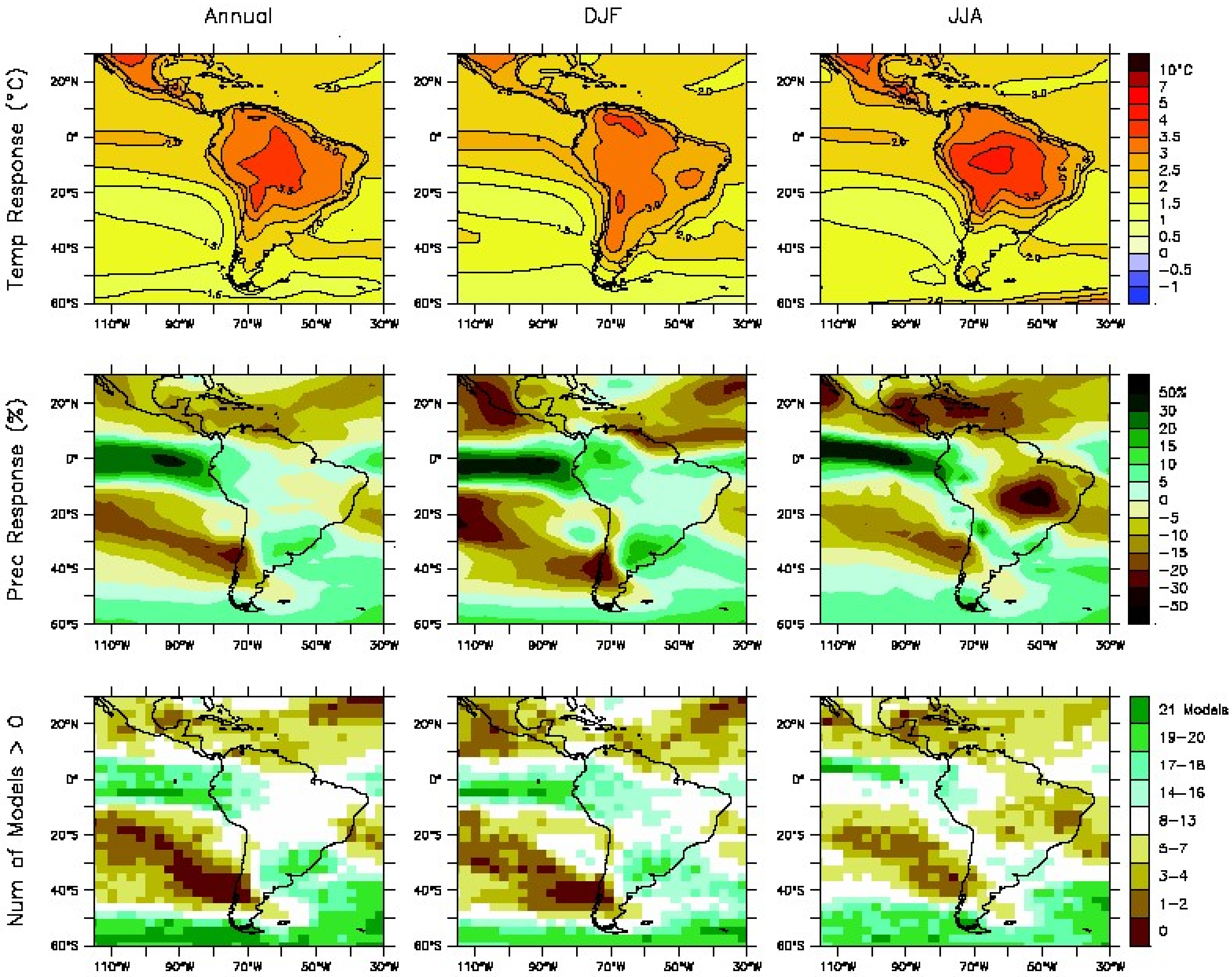


Figure 11.15. *Temperature and precipitation changes over Central and South America from the MMD-A1B simulations. Top row: Annual mean, DJF and JJA temperature change between 1980 to 1999 and 2080 to 2099, averaged over 21 models. Middle row: same as top, but for fractional change in precipitation. Bottom row: number of models out of 21 that project increases in precipitation.*