Sources of Uncertainty in Future Changes in Local Precipitation

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Climate Dynamics, in press

1. Research Questions

- What drives the uncertainties in projected local precipitation change? Is it mostly modelling uncertainty or natural variability?
- Do their relative roles vary spatially?
- Can we begin to understand these variations?
- What else does this teach us about the mechanisms of anticipated changes in the hydrological cycle?

2. Data

Main Ensemble:

- 'AS-PPE-A' – Atmosphere-Slab Model (HadSM3), Perturbed Physics Ensemble, with perturbed Atmos. parameters

  280 model versions

  Experiments – Cntl & $2xCO_2$, both run to equilibrium + 20 years

Other Ensembles:

- 'AO-PPE-A' – Atmosphere-Ocean Model PPE (HadCM3), with perturbed Atmospheric parameters

  17 model versions

  Experiments – Cntl (150 years) & A1B (1860-2099)
- 'AOC-PPE-C' – Atmosphere-Ocean-Carbon Model (HadCM3C) PPE, with perturbed terrestrial carbon cycle parameters

  17 model versions

  Experiments – Cntl (240 years) & A1B (1860-2099)
- 'AO-MME' – Atmosphere-Ocean Multi-Model Ensemble (CMIP3)

  16 models

  Experiments – Cntl (240+ years) & 1% CO_2 rise + 79 years stabilisation

3. Method

- Compute the total uncertainty in the change in 20-year mean precipitation (ΔP), at each grid point, for each season, and each ensemble:

$$\sigma^2_{\mathrm{Total}} = \frac{1}{n-1}\sum_{\mathrm{model}=1}^{n}\left(\Delta P_i - \overline{\Delta P}\right)^2$$

- Compute the natural variability (*eg.* by scaling the interannual variability; see paper for further detail), and then compute modelling uncertainty as a residual:

$$\sigma^2_{\mathrm{Model}} = \sigma^2_{\mathrm{Total}} - \sigma^2_{\mathrm{Natural}}$$

- Compute the fraction (%) of the total uncertainty that's due to modelling uncertainty:

$$R = \sigma^2_{\mathrm{Model}} \Big/ \sigma^2_{\mathrm{Total}}$$

  This is the metric plotted in Figs.1,2,3.
- Note that the magnitude of *R* is affected by the spatio-temporal scale of analysis. For example, use of longer time-means and/or larger space scales would increase *R*.

4. Patterns of the Sources of Uncertainty

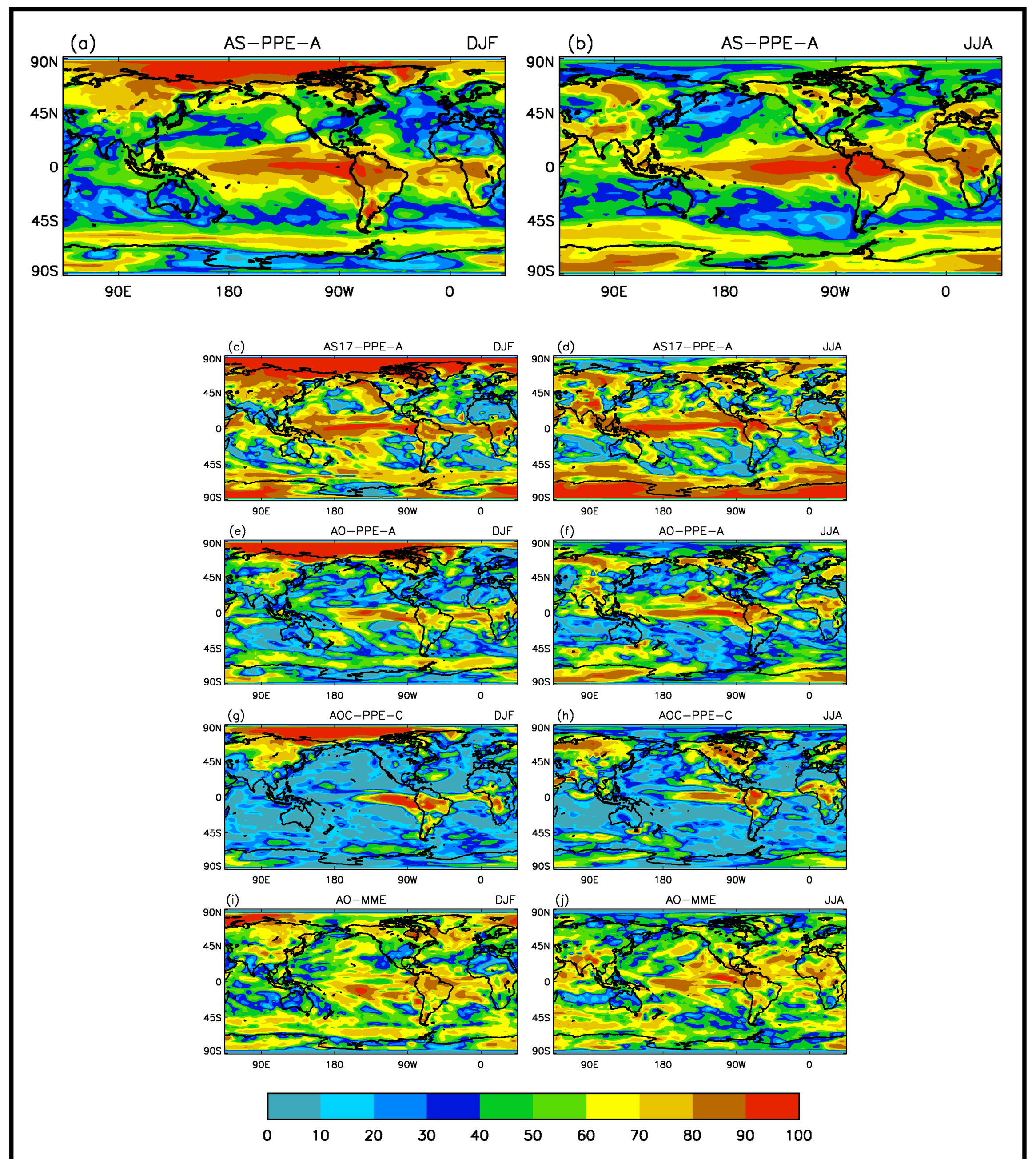

Fig.1 Maps of *R*, the percentage of total uncertainty in local precipitation change due to modelling uncertainty. (Note, AS17-PPE-A is a sub-ensemble of 17 models from AS-PPE-A, to illustrate the impact of using smaller samples.)

Figure 1 shows:

- A rich spatial structure in the pattern of the relative roles of modelling uncertainty and natural variability.
- Modelling uncertainty is dominant over the equatorial east and central Pacific, the equatorial Atlantic, the wet seasons of Africa and South America, parts of Asia, the mid-latitude summer continents, and the polar winters.
- Natural variability is dominant over the sub-tropical and lower mid-latitude oceans, Australia, and the Sahara in DJF.
- Uncertainties in modelling the terrestrial carbon cycle are often important over tropical land, the northern mid-latitude summer continents, and the winter Arctic.
- The large-scale pattern of *R* is broadly similar between all ensembles (except AOC-PPE-C)
- However, the smaller ensembles are more noisy and less useful for this type of study.

5. First-Order Explanations

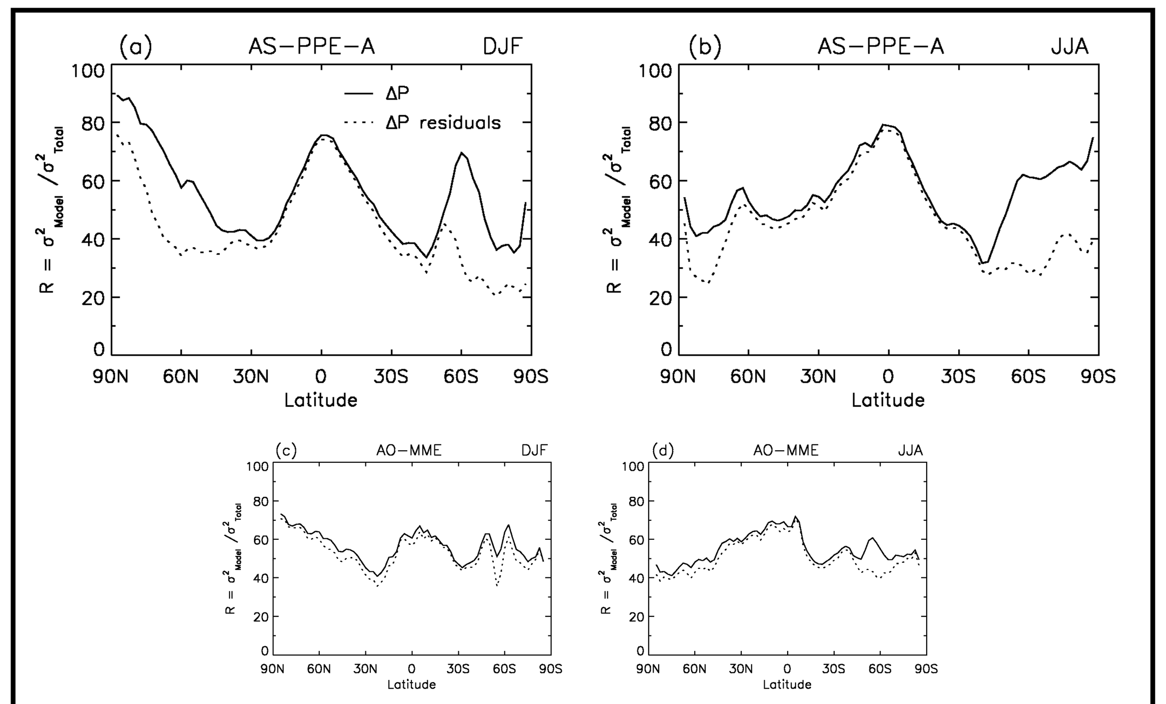

Fig.2 Zonal means of *R*, the percentage of the total uncertainty in local precipitation change due to modelling uncertainty. Solid line shows the standard analysis. Dashed line shows an analysis using the residual of local precipitation change after removing the component that is linearly related to $\Delta T_{\mathrm{Global}}$.

- Figure 2 shows that uncertainties in global climate sensitivity contribute little to uncertainties in modelling local precipitation change, except perhaps at high latitudes.
- Figure 3 shows that, for projected changes in local SSTs, modelling uncertainty is always the dominant driver of total uncertainty, and most strongly so in the tropics.
- Figure 4 shows how much of the SST variability is transferred to bidecadal variations in precipitation (during the 20th century).

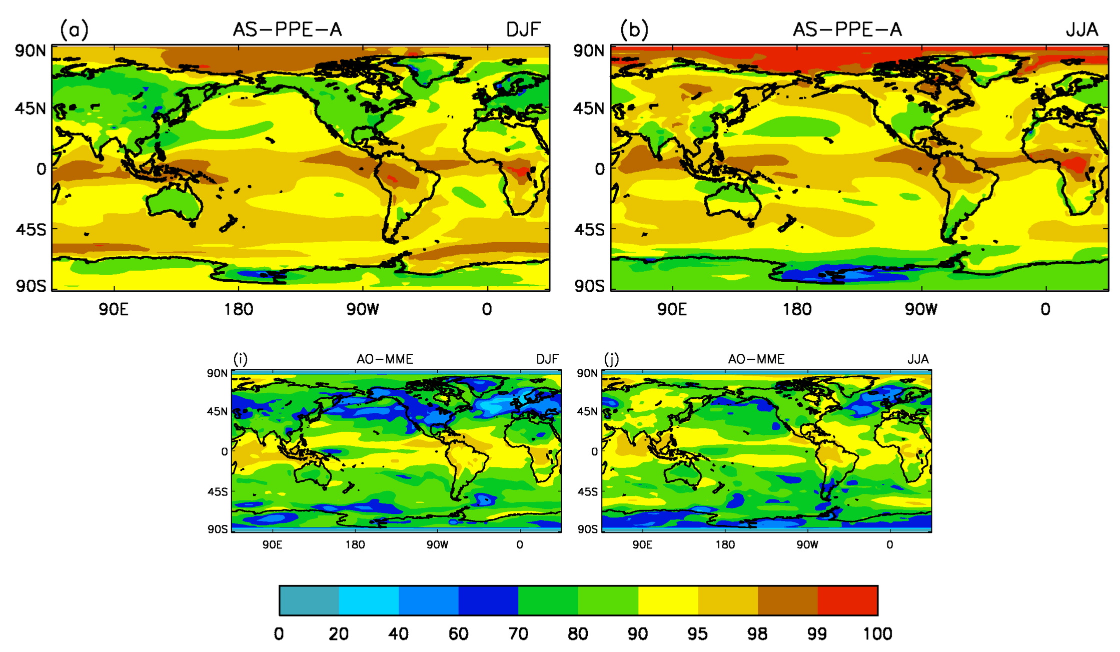

Fig.3 Maps of *R*, the percentage of the total uncertainty due to modelling uncertainty, for 1.5m air temperature. (Note the different scale to Fig.1.)

So:

- Over the equatorial oceans, the large uncertainty in modelling SST changes is transmitted to large uncertainty in modelling rainfall changes.
- Over much of the mid-latitude and arid sub-tropical oceans, chaotic atmospheric variations are likely to continue to dominate bidecadal anomalies in the 21st century. (But see exceptions listed in the paper.)
- Over the tropical continents, uncertain modelling of rainfall changes is not adequately accounted for by the transmission of uncertain SST changes, suggesting that uncertain modelling of the local response to GHGs (and of land-surface feedbacks) is also important.
- Over mid-latitude continents, uncertain modelling of SSTs, local radiative responses to GHGs, and chaotic variability, all play important and varying roles.
- In the polar winters, uncertain modelling of the remaining sea-ice fraction is critical.

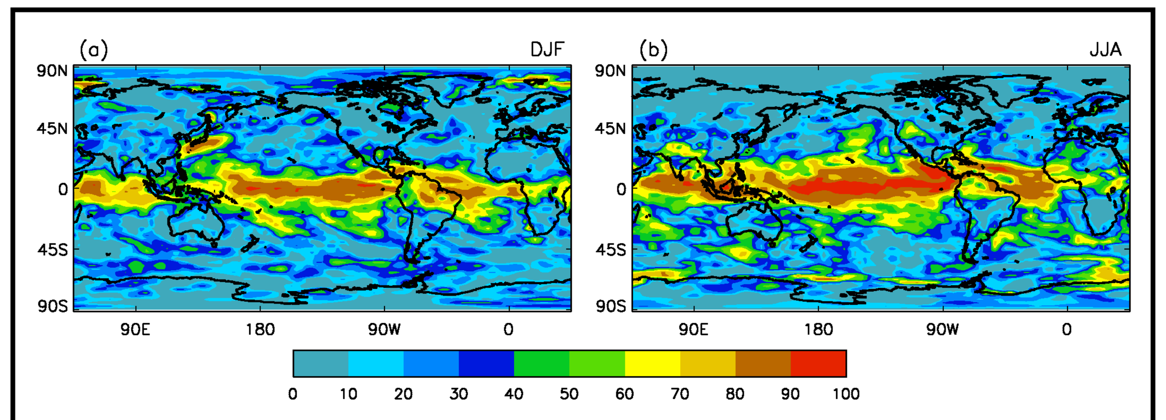

Fig.4 Maps of the percentage of variance of bidecadal seasonal mean precipitation that has been due to oceanic forcing in the 20th century. This is computed from an ensemble of 4 SST-forced 1870-2002 HadAM3 simulations.

6. Conclusions

- The balance between modelling uncertainty and natural variability varies widely for future changes in local precipitation.
- Modelling uncertainty dominates in the deep tropics, summer mid-latitude continents, and polar winters.
- Natural variability dominates in the sub-tropical and lower mid-latitude oceans, Australia, and the Sahara in DJF.
- The relative roles of modelling uncertainty and natural variability are broadly similar between the perturbed physics ensembles and CMIP3 data. But at local scales *R* is unreliable for small ensembles, such as CMIP3.
- In the moist maritime tropics, highly uncertain modelling of SST changes is transmitted to large uncertain modelling of local rainfall changes.
- Over tropical land, uncertain modelling of atmospheric processes, land surface processes and the terrestrial carbon cycle also appear to play a substantial role.
- In polar regions, inter-model variability of sea-ice anomalies drives an uncertain winter precipitation response.

Aside: Using *R* as an Alternative Approach for Quantifying Uncertainties in Projected Precipitation Change

Uncertainty in projected changes in precipitation is often quantified by counting the models with the same sign of anomaly (eg. IPCC AR4). But this:

- Does not quantify uncertainties in the amplitude of change, which is important for climate change impacts.
- Does not indicate whether the ensemble mean changes close to zero are robust or uncertain.

However, a variance-based measure of uncertainty that is useful for precipitation, can be derived by scaling the total uncertainty (or modelling uncertainty) by natural variability.

This metric is monotonically related to *R* (see paper for details), so it's pattern is identical to that of Figure 1. This provides a different, but complementary, view of the uncertainties in projected precipitation change.

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