

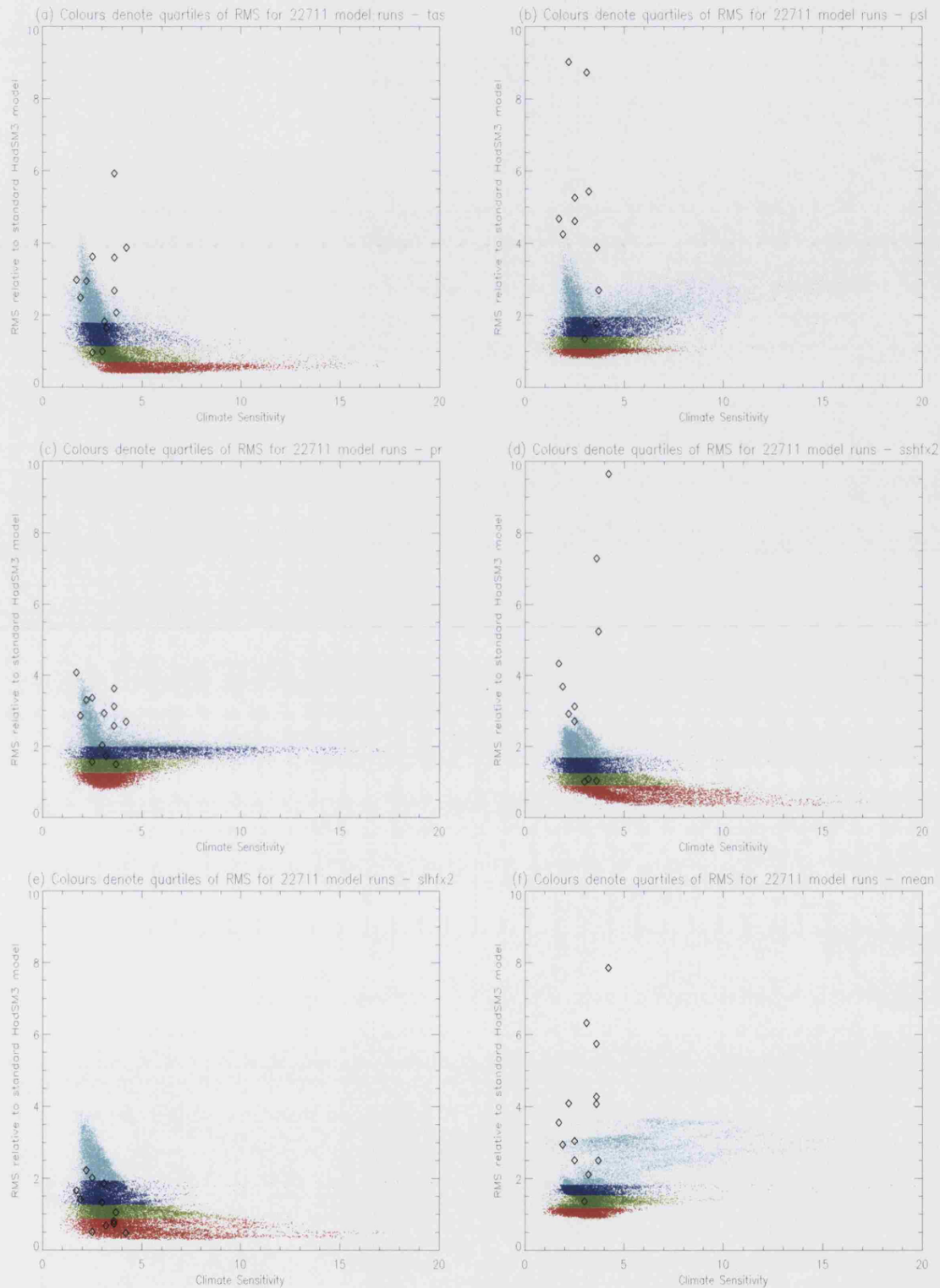


Figure 7.10: The RMSE, relative to the standard model, is plotted against CS for 22712 simulations in five different variables – (a) surface temperature, (b) sea surface pressure, (c) precipitation, (d) surface sensible heat flux from sea and (e) surface latent heat flux from sea. Panel (f) shows the average RMSE error over these five variables. The values for 13 GCMs taken from the CMIP II project are plotted as black diamonds.

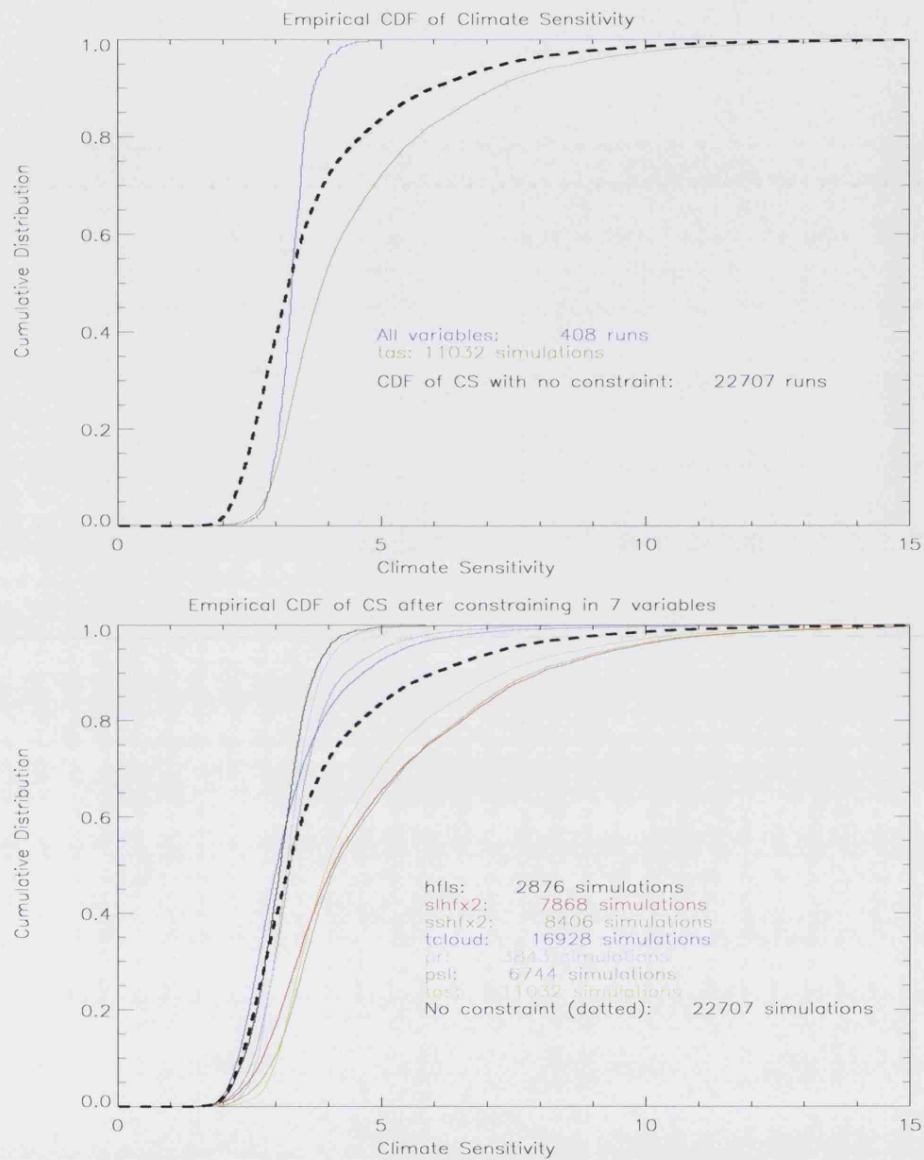


Figure 7.11: The Cumulative Distribution Function of CS for the grand ensemble, including only simulations with an RMS error no higher than the worst member of the 64 member standard ensemble. In the top Figure, temperature is used as the observational constraint (green). Also shown is the effect of constraining in 7 different observational variables simultaneously. The variables shown are heat flux latent surface, total precipitation rate, sea surface pressure, 1.5m temperature, surface sensible heat flux from sea, surface latent heat flux from sea, total cloud amount. The number of simulations left after applying constraining in each variable is shown adjacent to each variable's name.

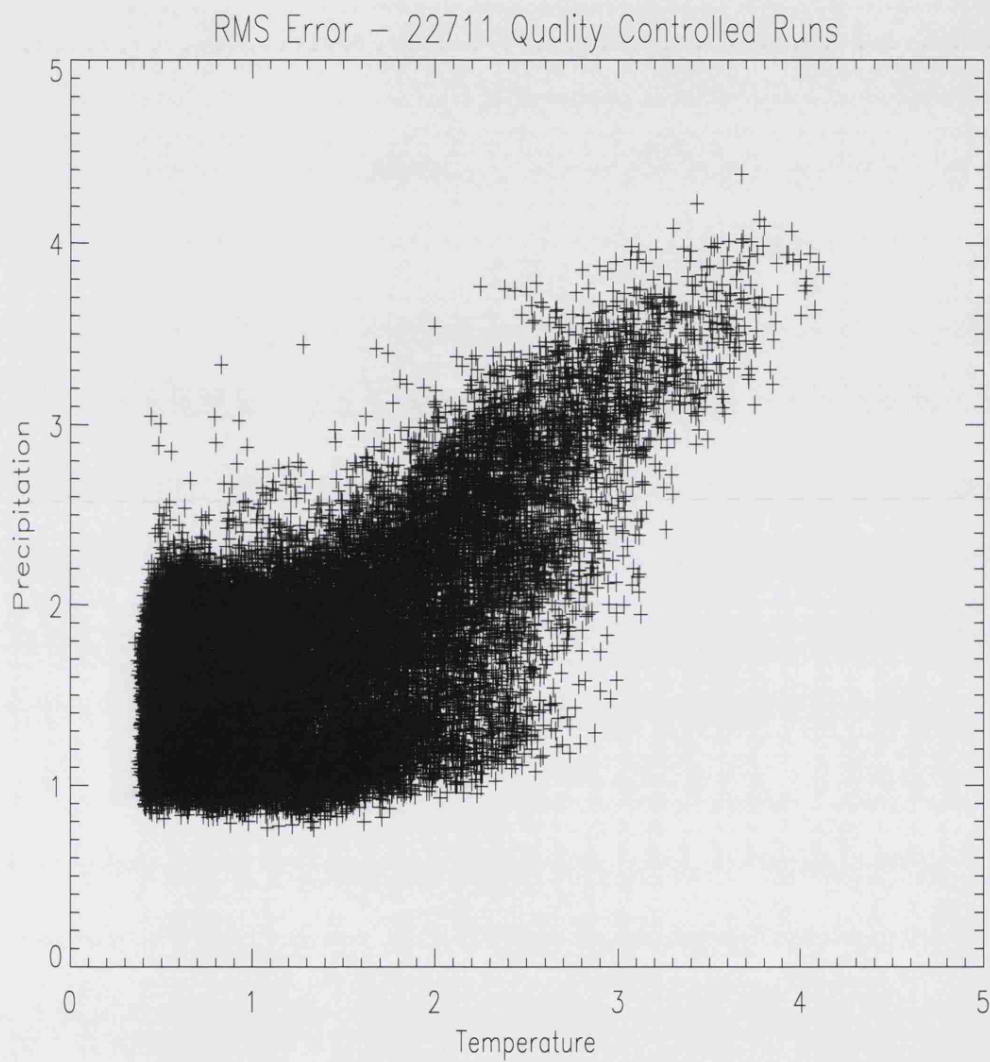


Figure 7.12: RMSE, relative to the standard model, for precipitation and temperature for 22711 quality controlled simulations. There is a pattern for simulations with a worse score in one variable to have a worse score in the other, although a number of exceptions exist.

## Chapter 8

# The relevance of global means for climate policy

### 8.1 Introduction

Climate simulations might provide information on strategies to mitigate or adapt to climate change. This Chapter looks at the utility of GMST (Global Mean Surface Temperature) as an index variable for policy and impact studies. The relevance of GMST as an index is then discussed from the point of view of mitigation and adaptation policies.

In recent years, there has been a significant rise in interest in potential impacts of climate change. Such impacts inevitably occur on sub-global length scales. Examples include the recent UK Climate Impacts Program (UKCIP), the recent IPCC Fourth Assessment Report Solomon *et al.* (2007a) and the Stern report on the Economics of Climate Change Stern (2006). It is often the case that climate simulations are taken as the basis for impact studies or adaptation strategies and important uncertainties are ignored. An inadequate treatment of inter-model differences and known uncertainties can result in over-confidence in the use of climate simulations, especially if uncertainties are lost either by assuming future climate is known (using a single, deterministic simulation) or by assuming a one-to-one relationship between



GMST and local impacts. This could lead to a lack of flexibility in planning or commitment to sub-optimal (or damaging) action due to over-confidence.

Plans for stabilisation of GHGs are often expressed in terms of GMST commission (2007); Parry *et al.* (2007); Solomon *et al.* (2007a); Toth *et al.* (2003); Yohe *et al.* (2004). GMST is used in impact studies for a number of reasons; it is supposed that models can produce realistic hindcast simulations of GMST Solomon *et al.* (2007a) and it is a fairly intuitive statistic to deal with. Many impact studies relate changes in GMST directly to impacts Stern (2006) (p.180), Parry *et al.* (2007). This approach poses a number of problems that will be discussed in this Chapter. In particular, information on the regional responses to climate change and the associated uncertainties is lost. It is shown here that relating GMST change directly to sub-global climatic impacts can be highly misleading. Climate can be forecast, at best as a distribution Smith (2002) with its inherent uncertainties; moreover these uncertainties are larger on smaller length scales.

As a consequence of the analysis presented in this Chapter, it is shown that constraining GMST (or CS), even to within a very narrow range, may not provide a strong constraint on regional changes. The consequences of this are discussed.

Using data from the CPDN experiment, the problem of how GMST change relates to regional change is looked at in this Chapter. For some variables and length scales, such as GMST, the models produce consistent results. In other cases, such as regional precipitation changes, the models produce inconsistent results and raise important questions about the degree of flexibility required in adaptation decisions. The extent to which GMST changes provide information on the length scales most obviously relevant for impact studies is investigated. The cause of climatic change is global but the impacts are always local. Whilst there are climatic changes that are local in extent, such as land-use change and volcanic activity, the simulations used here look at the possible effects of doubling atmospheric concentrations of  $CO_2$ , a GHG that mixes throughout the atmosphere and thus has a global impact. Nowhere

is affected by a global mean *per se*; rather each region and location experiences its own local climate. Whilst global mean statistics do have an important part to play in climate science, their relevance in terms of their direct use for climate impacts is limited.

Two specific questions are discussed in this Chapter;

1. What does a 2 degree rise in GMST mean for decision-makers? Different spatial patterns of change, and associated uncertainties, can be averaged out to give the same value of GMST. It is shown in this Chapter that many different local changes in climate can result in a 2 degree rise in GMST. The uncertainty in response to a doubling of  $CO_2$  is looked at on a variety of length scales for simulations with a fixed GMST response. This allows for an assessment of how much information GMST provides on climatic changes on various length scales.
2. How different is a rise in GMST of 2 degree Celsius compared to a rise of 3 degrees? This question has importance both for policy decisions and localised impact assessment. In the case of adaptation, it is important to know how quickly our adaptation plans may have to change – if 3 degrees is much worse than 2 degrees, we should prepare accordingly or least be flexible enough in our plans to adapt to the consequences of greater warming effectively. It may be that the local effects of a monotonic rise in GMST change result in non-linearities in regional climate response and adaptation methods planned accordingly. Another example of the limitation of annual mean global mean metrics, shown in this Chapter, is that there can be different effects in summer and winter e.g. a drier winter and a wetter summer should not be assumed to be equivalent to “annually no change” for impact assessment.

Planning mitigation strategies can be helped by understanding how policies targeting GMST may result in different regional responses. For example, if it is

thought that rising GMST might lead to an increased risk of flooding in London, policies could be adopted to mitigate this risk. It would then be useful to know how much more risk is attributable to a 3 degree rise compared to a 2 degree rise. This work is also relevant to the problem of constraining CS in previous work in Chapter 7 and in the literature in general Annan & Hargreaves (2006, 2007); Forest *et al.* (2007); Hegerl (2006); Knutti *et al.* (2006), where attempts are made to constrain uncertainties in the value of CS. The utility of such global constraints for decision-makers reliant on regional climate information is questioned in this Chapter. Regional uncertainties are examined here for a narrow range of GMST change (0.2 degrees Celsius). Approaches that constrain climate change using CS may not reduce regional uncertainties to manageable levels; indeed it is shown that for simulations with 2 degrees GMST rise the range of 8 year mean DJF warming simulated in the Central North American region is from 1 to 7 degrees Celsius. The structure of this Chapter is as follows. Section 8.1.1 describes the data sets used in this Chapter. Section 8.2 answers question 1) above by analysing the distribution of temperature and precipitation changes on various length scales for a set of simulations with 2 degree GMST rise. Section 8.3 answers question 2) above, the difference between simulations with 2 degrees GMST rise and 3 degrees GMST rise. Section 8.4 examines the assumption that regional responses are linear with respect to GMST rise. Section 8.5 discusses the results presented in this Chapter and the implications for mitigation and adaptation decisions. Section 8.6 gives conclusions.

### 8.1.1 Data Sets Used

Data from a grand ensemble of 45644 simulations is analysed in this Chapter. Model simulations within a narrow range of 0.2 degrees GMST change are analysed in terms of their regional distributions. Where simulations are said to have a GMST rise of  $X$  degrees, this refers to all simulations with a GMST change of between  $X$

$\pm 0.1$  degrees Celsius. Changes in 8 year mean temperature and precipitation (the regional time series are described in Chapter 4) are studied on the regional scale (regions are defined as in Giorgi & Mearns (2000)), and the grid-box level (in the HadSM3 model, grid-boxes are 3.75 degrees in longitude by 2.5 degrees in latitude – roughly 200 by 200 kilometres) for seasonal temperature and precipitation. The set of 402 quality controlled simulations with  $2 \pm 0.1$  degrees of GMST rise (defined by the difference between the last 8 years of the doubled  $CO_2$  phase and the last 8 years of the control phase for comparability with the available regional data) is referred to hereafter as the 2 degree set. Similarly, further sets of 2441 and 795 quality controlled simulations with 3 and  $4 \pm 0.1$  degrees of GMST rise are referred to as the 3 and 4 degree sets respectively.

## 8.2 What does a 2 degree rise in GMST mean?

This Section looks at the level of regional uncertainty associated with the 2 degree set of simulations, as described in Section 8.1.1. This analysis is motivated by two questions that are important for assessing the utility of GMST as a target, or basis, for decisions:

1. To what extent can mitigation strategies based on GMST change reduce significant regional risks?
2. To what degree of certainty can impact studies link GMST to particular impacts?

These questions can be informed by looking at the distribution of climate response on various length scales when considering simulations with a given GMST rise. Model diversity is now examined beginning on hemispheric length scales, then smaller regions. It is shown that model diversity increases significantly when analysing the distribution of temperature and precipitation response on regional length scales.

### 8.2.1 From global to super-continental length scales

This Section looks at seasonal changes for the 2 degree set in temperature and precipitation on global and super-continental length scales: namely, the Northern and Southern hemisphere, the tropics and the extra-tropics.

Figure 8.1 shows the change in global mean, tropical, Northern hemisphere extra-tropics and Southern hemisphere extra-tropics for temperature and precipitation. The changes shown are in terms of the 8 year seasonal mean under a doubling of  $CO_2$  concentrations. For each region, four plots are shown – DJF (December through February mean), JJA (July through August mean) for temperature and precipitation. The x-axes in Figure 8.1 are deliberately set at a wider range than the distributions of change might appear to justify so that similar distributions on smaller length scales can be compared on the same x-axes.

The range of temperature change is from 1.5 to 2.5 degrees Celsius in the global mean and 2 to 4 degrees in the Northern hemisphere in both seasons. Southern hemispheric change in temperature is lower – 1 to 2 degrees in DJF and about 2 degrees in JJA. The lower levels of warming simulated in the Southern hemisphere is partly due to there being more ocean in the Southern Hemisphere than the Northern hemisphere (and oceans typically warm by less than land masses). The range of precipitation change is greater on the hemispheric level than the global level; 0–20% in the Northern hemisphere and -10–+10% in the Southern hemisphere. In the summer months, the magnitude of warming is less than in the winter. The global mean range is very tight, showing a increase of about 0–5%. Inferring temperature changes on a hemispheric scale from the GMST change is robust across the 2 degree set. This suggests that is not unreasonable to infer global or hemispheric temperature response from GMST rise. In contrast, precipitation changes are always not robust – even the sign of the change is uncertain in the Southern hemisphere in the 2 degree set despite all simulations having a GMST change within a range of 0.2 degrees Celsius. This suggests that it is not possible to robustly infer

the direction of Southern hemispheric precipitation response based on GMST rise in the HadSM3 model. This difference can be seen from the variable magnitude of temperature change between the DJF and JJA seasons in the Northern and Southern hemispheres. These hemispheric differences will often cancel out on the global scale (in both DJF and JJA it will be summer in one hemisphere and winter in the other).

There are two reasons for the narrowness of these hemisphere-averaged ranges. First, averaging over many grid-boxes is expected to reduce the sampling variability considerably. Second, regional variations in the sign of precipitation change partially off-set each other e.g. an area with reduced simulated precipitation and an area with increased simulated precipitation can cancel out, when averaged, to show little or no change. Large changes of different sign in regional precipitation change can cancel out; information that is hidden when using global mean statistics. Figure 8.2 shows the same statistics as Figure 8.1 but for different areas: the tropics, Northern hemispheric extra-tropics and Southern hemisphere extra-tropics. These areas are smaller than the global and hemispheric areas shown in Figure 8.1. The range of temperatures for these areas is similar in magnitude to the hemispheric averages, although the Northern extra-tropics does show a wider range of temperature response (the range has a width of about 2 degree Celsius in both seasons). Furthermore, the magnitude of warming in the Northern hemisphere extra-tropics is higher than on global and hemispheric scales – about 3 degrees in JJA and 4 degrees in DJF. Notably, precipitation in the tropics is very tight in distribution. On super-continental length scales, the sign and magnitude of temperature change is robust across the model ensemble, with a range of up to 2 degrees Celsius in some areas and seasons. Precipitation change is generally robust, but in regions such as the Southern hemisphere the response is more uncertain (the change in precipitation response varies from  $\sim -15\%$  to  $\sim +10\%$ ). When taking averages over large areas, significant changes in precipitation are cancel out. For example, it is shown



in Figure 8.8 that the tropics show precipitation responses in different directions on a grid-box level, but the cancellation of these changes gives the tight distribution shown in the Tropics in Figure 8.2.

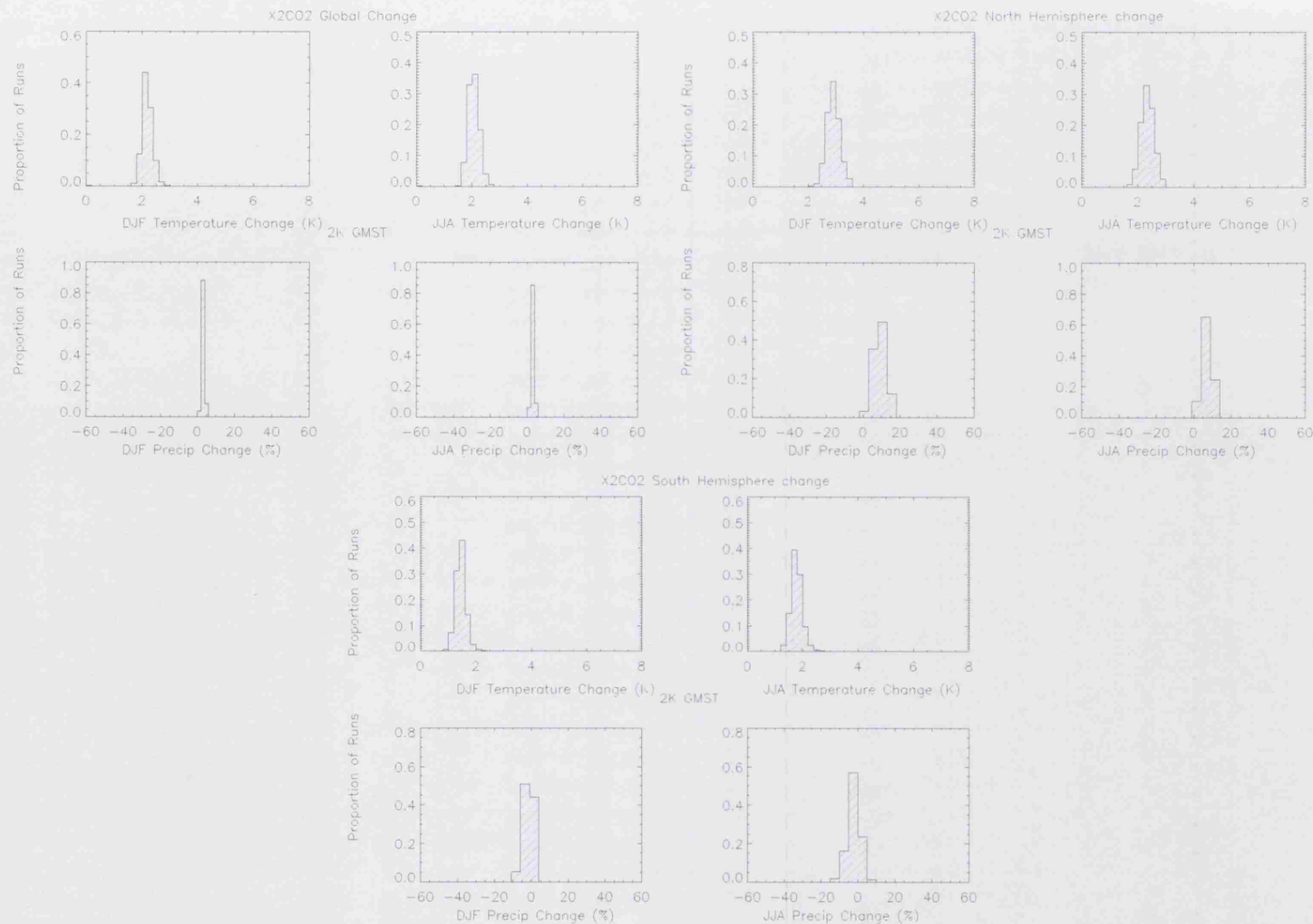


Figure 8.1: The distribution of 8 year DJF (JJA) temperature (precipitation) is shown for simulations for the 2 degree set. The  $x$ -axis range is maintained for following regional plots for ease of comparison. Note that there is little variance in precipitation where averages are taken over these large areas.

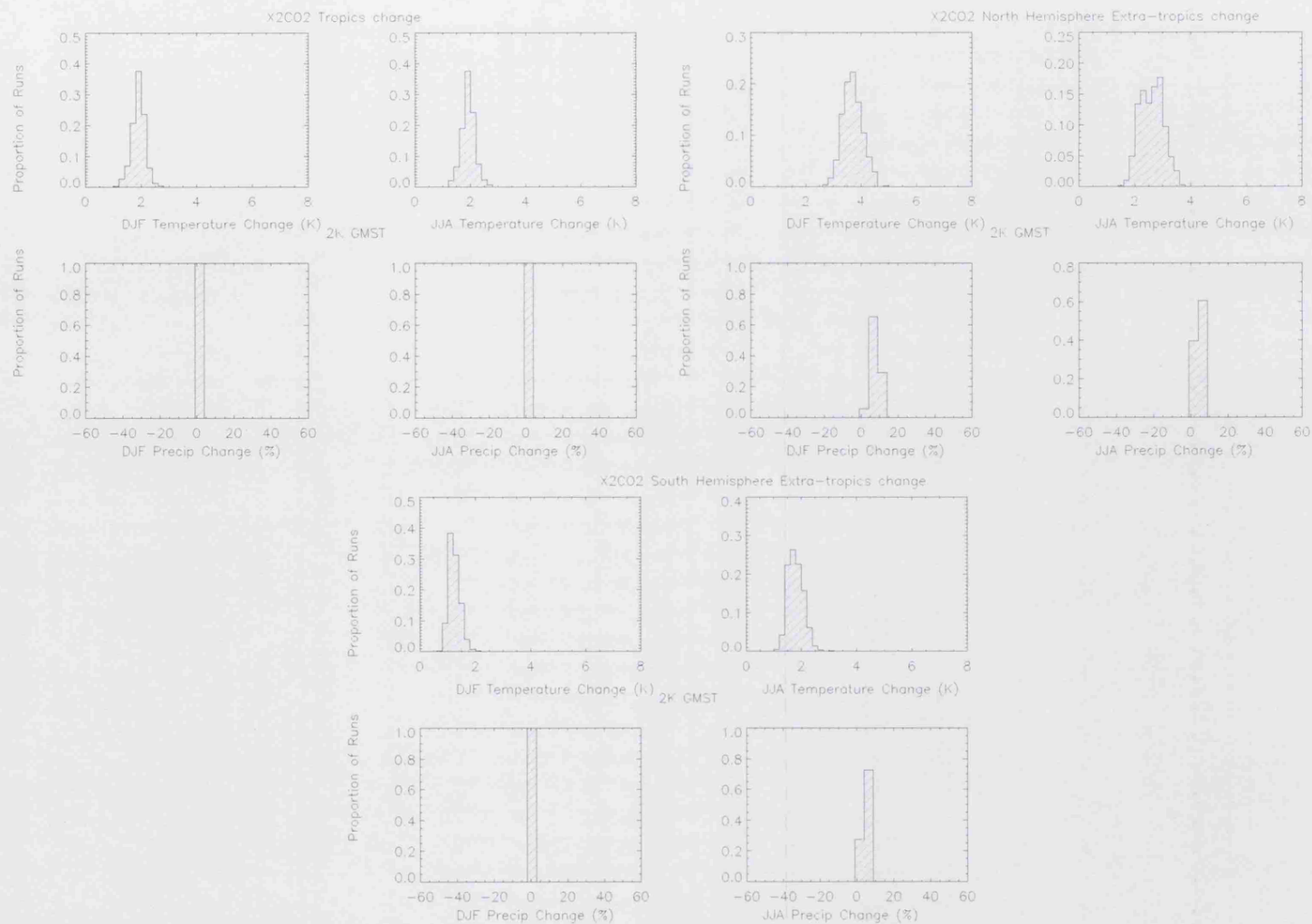


Figure 8.2: The distribution of 8 year DJF (JJA) temperature (precipitation) is shown for simulations for the 2 degree set. The  $x$ -axis range is maintained for following regional plots for ease of comparison.

### 8.2.2 Regional Impacts

Arguably, almost all climate impact decisions require information on regional or lower length scales. This subsection shows that model diversity increases significantly when looking at regional temperature and precipitation change compared with continental and super-continental areas. Regional precipitation change is shown in this Section to be particularly uncertain with a lack of robustness in simulating the sign or magnitude of change.

Figure 8.3 shows the seasonal change in regional temperature and precipitation. Three regions are selected for comparison – Australia, Central North America and Northern Europe. All the land regions' (plus the global, hemispheric, tropical and extra-tropical areas) minimum and maximum change in seasonal temperature and precipitation for the two degree set are shown in Tables 8.1, 8.2 and 8.3. In no cases is there a fall in temperature in either season. In almost every case, the sign of precipitation change is uncertain; the exceptions are Greenland, Antarctica and the Global mean. The regional changes in temperature and precipitation are dealt with in turn.

| Region                 | Variable | Season | Min     | Max  |
|------------------------|----------|--------|---------|------|
| Australia              | Temp     | DJF    | 0.957   | 3.00 |
| Australia              | Temp     | JJA    | 0.859   | 2.79 |
| Australia              | Precip   | DJF    | -28.3   | 59.8 |
| Australia              | Precip   | JJA    | -33.4   | 50.6 |
| Amazon Basin           | Temp     | DJF    | 1.23    | 5.42 |
| Amazon Basin           | Temp     | JJA    | 1.00    | 5.72 |
| Amazon Basin           | Precip   | DJF    | -25.9   | 13.2 |
| Amazon Basin           | Precip   | JJA    | -30.8   | 15.8 |
| Southern South America | Temp     | DJF    | 0.650   | 2.69 |
| Southern South America | Temp     | JJA    | 0.640   | 3.09 |
| Southern South America | Precip   | DJF    | -7.13   | 18.8 |
| Southern South America | Precip   | JJA    | -19.5   | 26.9 |
| Central America        | Temp     | DJF    | 1.24    | 3.77 |
| Central America        | Temp     | JJA    | 1.64    | 4.00 |
| Central America        | Precip   | DJF    | -42.0   | 105. |
| Central America        | Precip   | JJA    | -37.8   | 78.7 |
| Western North America  | Temp     | DJF    | 0.320   | 4.56 |
| Western North America  | Temp     | JJA    | 2.12    | 5.30 |
| Western North America  | Precip   | DJF    | -28.3   | 41.2 |
| Western North America  | Precip   | JJA    | -26.4   | 18.3 |
| Central North America  | Temp     | DJF    | 0.887   | 7.22 |
| Central North America  | Temp     | JJA    | 2.29    | 8.48 |
| Central North America  | Precip   | DJF    | -34.2   | 46.3 |
| Central North America  | Precip   | JJA    | -44.8   | 30.0 |
| Eastern North America  | Temp     | DJF    | 1.03    | 5.43 |
| Eastern North America  | Temp     | JJA    | 1.95    | 4.58 |
| Eastern North America  | Precip   | DJF    | -16.0   | 43.6 |
| Eastern North America  | Precip   | JJA    | -10.8   | 30.8 |
| Alaska                 | Temp     | DJF    | 0.00134 | 9.57 |
| Alaska                 | Temp     | JJA    | 0.130   | 3.11 |
| Alaska                 | Precip   | DJF    | -8.41   | 68.9 |
| Alaska                 | Precip   | JJA    | -9.72   | 27.8 |
| Greenland              | Temp     | DJF    | 1.98    | 6.78 |
| Greenland              | Temp     | JJA    | 0.963   | 2.86 |
| Greenland              | Precip   | DJF    | 5.15    | 28.4 |
| Greenland              | Precip   | JJA    | 1.98    | 24.4 |
| Mediterranean Basin    | Temp     | DJF    | 1.40    | 4.11 |
| Mediterranean Basin    | Temp     | JJA    | 1.81    | 5.80 |
| Mediterranean Basin    | Precip   | DJF    | -25.5   | 26.3 |
| Mediterranean Basin    | Precip   | JJA    | -58.2   | 2.93 |

Table 8.1: The minimum and maximum change for DJF and JJA seasons for temperature and precipitation for the 2 degree set.

| Region              | Variable | Season | Min   | Max  |
|---------------------|----------|--------|-------|------|
| Northern Europe     | Temp     | DJF    | 1.32  | 6.31 |
| Northern Europe     | Temp     | JJA    | 0.987 | 4.11 |
| Northern Europe     | Precip   | DJF    | -2.97 | 40.0 |
| Northern Europe     | Precip   | JJA    | -23.8 | 27.0 |
| West Africa         | Temp     | DJF    | 0.992 | 3.28 |
| West Africa         | Temp     | JJA    | 0.708 | 3.30 |
| West Africa         | Precip   | DJF    | -62.4 | 108  |
| West Africa         | Precip   | JJA    | -38.6 | 56.0 |
| East Africa         | Temp     | DJF    | 0.827 | 4.28 |
| East Africa         | Temp     | JJA    | 1.34  | 4.16 |
| East Africa         | Precip   | DJF    | -11.8 | 40.7 |
| East Africa         | Precip   | JJA    | -25.4 | 58.8 |
| Southern Africa     | Temp     | DJF    | 0.929 | 2.60 |
| Southern Africa     | Temp     | JJA    | 0.975 | 2.65 |
| Southern Africa     | Precip   | DJF    | -14.8 | 29.4 |
| Southern Africa     | Precip   | JJA    | -36.6 | 4.35 |
| Sahara Region       | Temp     | DJF    | 1.09  | 4.42 |
| Sahara Region       | Temp     | JJA    | 2.14  | 4.32 |
| Sahara Region       | Precip   | DJF    | -77.9 | 146  |
| Sahara Region       | Precip   | JJA    | -40.2 | 121  |
| South East Asia     | Temp     | DJF    | 1.24  | 2.46 |
| South East Asia     | Temp     | JJA    | 0.978 | 2.78 |
| South East Asia     | Precip   | DJF    | -14.4 | 44.6 |
| South East Asia     | Precip   | JJA    | -30.8 | 33.7 |
| East Asia region    | Temp     | DJF    | 1.83  | 4.99 |
| East Asia region    | Temp     | JJA    | 1.83  | 4.55 |
| East Asia region    | Precip   | DJF    | -20.3 | 53.5 |
| East Asia region    | Precip   | JJA    | -16.1 | 38.5 |
| South Asia region   | Temp     | DJF    | 1.56  | 4.01 |
| South Asia region   | Temp     | JJA    | 0.715 | 3.23 |
| South Asia region   | Precip   | DJF    | -46.8 | 206  |
| South Asia region   | Precip   | JJA    | -12.0 | 50.6 |
| Central Asia region | Temp     | DJF    | 0.848 | 5.31 |
| Central Asia region | Temp     | JJA    | 2.01  | 5.81 |
| Central Asia region | Precip   | DJF    | -33.9 | 55.3 |
| Central Asia region | Precip   | JJA    | -36.1 | 64.6 |

Table 8.2: The minimum and maximum change for DJF and JJA seasons for temperature and precipitation for the 2 degree set.

## Temperature

Three regions are selected for more detailed examination in this Section – Australia (with relatively low warming of  $\sim 3$  degrees or less in DJF and JJA for the two degree set), Northern Europe (medium levels of warming of 4.1 degrees in JJA and 6.3 degrees in DJF) and Central North America (high levels of warming of 8.5 degrees in JJA and 7.2 degrees in DJF). All three regions selected for comparison warm in both seasons, but with considerable differences in magnitude. Australia warms by about 2 degrees in both seasons (plus or minus about 1 degree) and Central North America typically warms by over 4 degrees, with a wide range of change from 2 degrees up to 8 degrees. Warming is generally greater during the winter months (DJF season for Central North America). Northern Europe similarly warms more during the winter, but typically by around 4 degrees in winter and 3 degrees in summer. The range of temperature change seen in regions such as Central North America raises difficulties in evaluating whether 2 degrees of global warming is a relevant target for local adaptation strategies. Considerably different policies are required to adapt to 2 degrees of regional warming than for 8 degrees.

## Precipitation

Unlike temperature, even the sign of precipitation change is uncertain in all four regions. In the Australia region, the range of precipitation change in both seasons ranges between roughly -30% up to +50% with the peak of the distribution close to 0 (no change). The distribution of Central North American precipitation is centred about 0 in the summer months and at about +10% in the winter with a range of (-34%, 46%) in DJF and (-45%, 30%). Most simulations show an increase in Northern European precipitation in both summer and winter, but with a wide range of values for the magnitude of this change. In these regions, especially Australia and Central North America, it is difficult to say what a 2 degree Celsius in GMST would mean for precipitation. It seems the change could be up to 50% in many regions,

| Region                         | Variable | Season | Min      | Max  |
|--------------------------------|----------|--------|----------|------|
| Tibet                          | Temp     | DJF    | 2.67     | 5.79 |
| Tibet                          | Temp     | JJA    | 1.94     | 5.58 |
| Tibet                          | Precip   | DJF    | -26.8    | 65.8 |
| Tibet                          | Precip   | JJA    | -14.0    | 16.5 |
| North Asia region              | Temp     | DJF    | 1.54     | 7.55 |
| North Asia region              | Temp     | JJA    | 1.06     | 4.74 |
| North Asia region              | Precip   | DJF    | 6.71     | 46.0 |
| North Asia region              | Precip   | JJA    | -2.99    | 17.2 |
| Antarctica                     | Temp     | DJF    | 0.246    | 2.28 |
| Antarctica                     | Temp     | JJA    | 1.07     | 5.28 |
| Antarctica                     | Precip   | DJF    | 0.162    | 19.9 |
| Antarctica                     | Precip   | JJA    | 6.24     | 27.9 |
| North Hemisphere               | Temp     | DJF    | 2.10     | 3.58 |
| North Hemisphere               | Temp     | JJA    | 1.63     | 2.97 |
| North Hemisphere               | Precip   | DJF    | -1.19    | 21.2 |
| North Hemisphere               | Precip   | JJA    | -0.690   | 17.0 |
| South Hemisphere               | Temp     | DJF    | 0.814    | 2.22 |
| South Hemisphere               | Temp     | JJA    | 1.22     | 2.72 |
| South Hemisphere               | Precip   | DJF    | -10.1    | 6.34 |
| South Hemisphere               | Precip   | JJA    | -14.6    | 9.10 |
| Tropics                        | Temp     | DJF    | 1.16     | 2.66 |
| Tropics                        | Temp     | JJA    | 1.21     | 2.78 |
| Tropics                        | Precip   | DJF    | -0.855   | 4.73 |
| Tropics                        | Precip   | JJA    | -0.938   | 4.82 |
| North Hemisphere Extra-tropics | Temp     | DJF    | 2.66     | 4.84 |
| North Hemisphere Extra-tropics | Temp     | JJA    | 1.58     | 3.75 |
| North Hemisphere Extra-tropics | Precip   | DJF    | -0.164   | 15.7 |
| North Hemisphere Extra-tropics | Precip   | JJA    | -0.00845 | 8.37 |
| South Hemisphere Extra-tropics | Temp     | DJF    | 0.751    | 2.01 |
| South Hemisphere Extra-tropics | Temp     | JJA    | 1.12     | 3.00 |
| South Hemisphere Extra-tropics | Precip   | DJF    | -1.28    | 6.77 |
| South Hemisphere Extra-tropics | Precip   | JJA    | -0.223   | 8.30 |
| Global                         | Temp     | DJF    | 1.64     | 2.80 |
| Global                         | Temp     | JJA    | 1.59     | 2.73 |
| Global                         | Precip   | DJF    | 1.31     | 5.48 |
| Global                         | Precip   | JJA    | 0.656    | 5.62 |

Table 8.3: The minimum and maximum change for DJF and JJA seasons for temperature and precipitation for the 2 degree set.



although it is not clear whether it will get wetter or drier.

The regional distributions, in general, show a wider range of behaviour in temperature and greater uncertainty in the sign of precipitation response than the histograms for larger areas. These results imply that that decision makers should not assume a robust relationship between the extent of global warming and regional precipitation response.

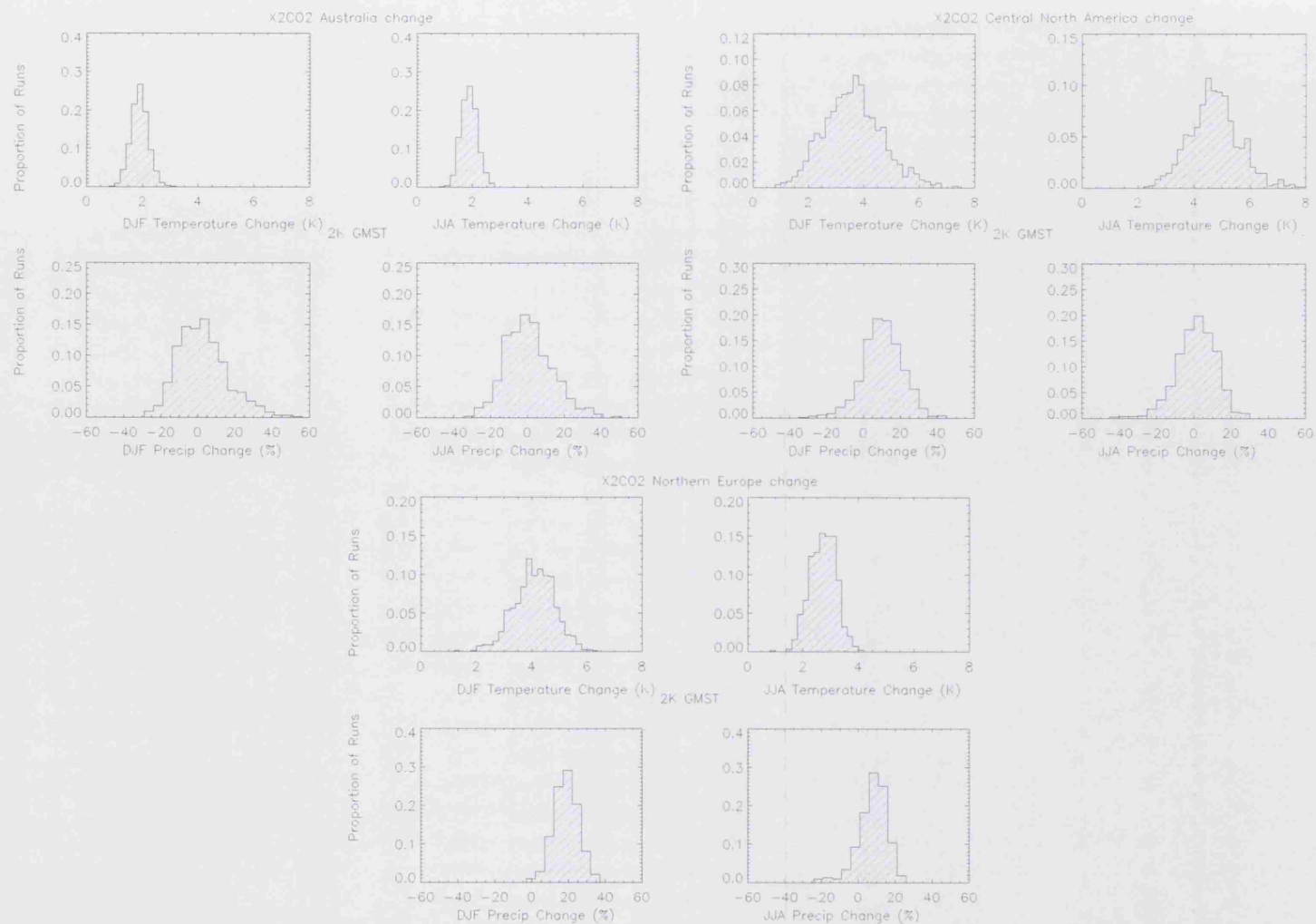


Figure 8.3: The distribution of 8 year DJF (JJA) temperature (precipitation) is shown for the 2 degree set. Whilst all simulations show an increase in surface temperature, the ensembles disagree on the sign of precipitation change in all regions and seasons shown.

### 8.2.3 Grid-scale Impacts

The impact of a 2 degree rise in temperature is important on scales as fine (and finer) as the HadSM3 grid resolution, as well as on regional scales. A land grid-box is typically of the order of  $10,000\text{km}^2$  in area for the HadSM3 model. Although this resolution is insufficient for many detailed impact studies, grid-box information is used in downscaling or impact assessment model, potentially introducing further uncertainties. Such downscaling procedures are only useful for guiding decision-makers when climate changes are simulated robustly on the grid-box level.

Figure 8.4 shows the median and size of the 10% – 90% central interval (this central range was chosen to give a conservative estimate of the diversity regional change and exclude any potential outliers that might have unphysical regional responses) for the 2 degree set for 8 year mean seasonal temperature change. The median change fields (DJF in panel (a) and JJA in panel (b)) show three features obscured when using GMST as the basis for decision-making:

1. Warming over land ( $\sim 3\text{--}5$  degrees) is greater than over the oceans ( $\sim 1\text{--}3$  degrees).
2. The magnitude of regional change varies considerably and, for the two degree set, simulations show up to 8 degrees of warming in Northern high latitudes' DJF season.
3. There is considerable variability with season. The most marked change is in the Northern high latitudes, showing  $\sim 8+$  degrees warming in the DJF season and almost no warming in the JJA season.

The width of the central 80% interval is shown in panels (c) and (d) of Figure 8.4. The width of this interval is typically 1–2 degrees over the oceans and 1–4 degrees over land. Northern high latitudes, where the greatest warming occurs, show a range of up to 6 degrees in the DJF season. The model diversity of up to 4 degrees in simulated land temperatures, based on the 2 degree set, is considerable.

The magnitude of grid-box level variability is further examined in Figure 8.7 in Section 8.3.2.

There is a large difference between the percentiles shown in panels (c) and (d) Figure 8.4 in terms of impacts; differences that are invisible when using a global mean. The range of variability present within each grid-box is much larger than for regional means – indeed, statistically, this must be case. It should also be remembered that the fields shown in Figure 8.4 represent contributions from many different simulations and thus the patterns of change may not be consistent with any individual model simulation.

There is more variability at the grid-box level than at the regional level. Information on fine spatial levels is often highly uncertain, especially for precipitation. This suggests that decision-makers should consider the possibility that large regional changes are consistent with apparently low levels of global mean change e.g. panel (b) of Figure 8.4 shows a median Summer temperature response over the USA of 4–6 degrees Celsius for the 2 degree set. If these model results are taken to be indicative of the real world, adaptation strategies would be necessary even under modest levels of global warming.

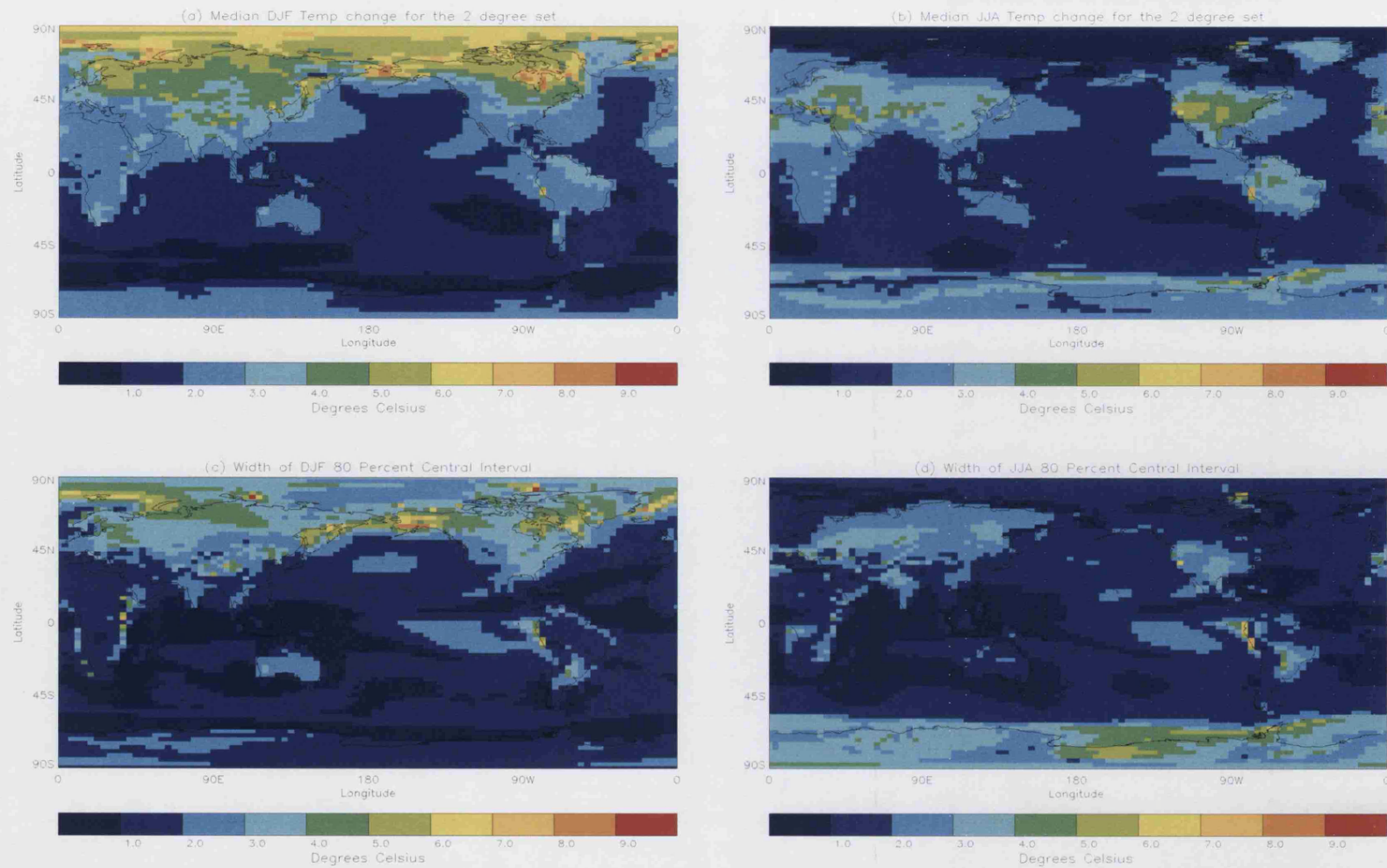


Figure 8.4: Median temperature change for the 2 degree set for the DJF (panel (a)) and JJA (panel (b)) seasons. Also shown in panels (c) and (d) are the widths of the central 80 percent (10th–90th percentiles) of temperature change, respectively for the DJF and JJA seasons.

## 8.3 What is the difference between 2 and 3 degrees GMST?

### 8.3.1 Regional differences

Model diversity in the 2 degree set has been looked at from global to grid-box length scales. In this Section, a comparison is made between the 2 degree set and the 3 degree set. Our ability to distinguish between simulations with different GMST rise is often implicitly assumed in impact studies Lynas (2007); Solomon *et al.* (2007a); Stern (2006). There is an important question to what level we can distinguish between such scenarios of GMST rise. Here, the question is asked “What is the difference between the 2 degree set and the 3 degree set on a regional level?”

It is shown in this Section for the first time that there are regional changes in temperature and precipitation consistent with both the 2 and 3 degrees sets.

For each of the two different sets of simulations considered (the 2 degree set and the 3 degrees set) there is a distribution of temperature and precipitation changes at each region, as shown in Section 8.2. Where these distributions overlap, there is a chance that a randomly selected simulation from the 2 degree set will be warmer (or wetter) than a simulation randomly selected from the 3 degree set. The size of this overlap places a limit on the value of GMST as a target for mitigation. Where this overlap is significantly greater than 0 GMST rise is a less effective tool for policy-makers.

The probability of an overlap between sets of simulations with GMST rise of 2 and 3 degrees Celsius in region  $r$  is calculated using a bootstrap Efron & Tibshirani (1994) method as follows. One simulation is selected at random from the 2 degree set and one at random from the 3 degree set and it is recorded whether the simulations from the 2 degree set is warmer than the simulation from the 3 degree set. This process is repeated 100000 times to estimate the probability of the overlap between the 2 degree set and the 3 degree set. Repeating this process 100 times in no case

gave a difference of greater than 1% in the estimates presented. This procedure was carried out for DJF and JJA temperature and precipitation (in the precipitation case the probability of a simulation from the 2 degree set being wetter than the 3 degree set was estimated).

The probability that a randomly selected simulation from the 2 degree set will be warmer(wetter) than a randomly selected simulations from the 3 degree set for each region and season is shown in Tables 8.4 and 8.5. A value of 0 (or 100) indicates that there is no overlap between these distributions. A value close to 50 indicates that there is no evidence to suggest that a simulation from the 3 degree set is likely to be warmer (wetter) than a simulation from the 2 degree set. Table 8.4 shows that the overlap between distribution varies by region e.g. in Greenland there is a 5% or less chance of a simulation randomly chosen from the 2 degree set being warmer than a simulation randomly chosen from the 3 degree set, whereas in South Asia there is roughly a 25% chance. Table 8.5 shows the probability of a randomly selected simulation from the 2 degree set being wetter than a randomly selected simulation from the 3 degree set is close to 50%. For some regions, such as Central Asia there is more chance that a 2 degree simulation will be wetter than a 3 degree in the DJF season but drier in the JJA season. For precipitation there is typically a significant probability of overlap – it is difficult to tell whether regional precipitation will be wetter for simulations from the 2 degree set than the 3 degree set. The presence of overlaps in these distributions puts limitations on our ability to assess the potential impact of climate change in terms of GMST rise.

It might be argued that the magnitude of overlap seen in Tables 8.4 and 8.5 can be reduced if only simulations that re-produce the current climate “accurately” are included and the range of behaviour might be reduced if a sub-set of simulations that perform well in-sample are analysed. In order to test this hypothesis, the probability of overlap was calculated for simulations with a low in-sample RMSE score in 7 different variables as calculated in Chapter 7, Section 7.5, calculated in

a similar way to Stainforth *et al.* (2005), by comparing model output in the 8 year mean field for a particular variable with observations. Such an ad hoc filter is not recommended as means to reduce model diversity as discussed in Chapter 7; results are shown here simply to demonstrate that this filter does not have a significant effect on results even if it were statistical meaningful.

For each variable, the probability of overlap was calculated for 10% of simulations within the lowest RMSE score. The probability of overlap was also found using the mean RMSE score over the 7 variables (calculated as the arithmetic mean of the RMSE in all variables). These probabilities are shown in Tables 8.6 and 8.7. There is no clear indication that constraining by in-sample RMSE will significantly alter the magnitude of overlap. Tables 8.6 and 8.7 show that the existence of an overlap is not sensitive to the accuracy of simulations in re-producing present day climate.



| Region                 | % 2° > 3° (DJF) | % 2° > 3° (JJA) |
|------------------------|-----------------|-----------------|
| Australia              | 5               | 6               |
| Amazon Basin           | 8               | 14              |
| Southern South America | 4               | 10              |
| Central America        | 14              | 12              |
| Western North America  | 9               | 6               |
| Central North America  | 20              | 23              |
| Eastern North America  | 16              | 11              |
| Alaska                 | 15              | 4               |
| Greenland              | 5               | 3               |
| Mediterranean Basin    | 6               | 10              |
| Northern Europe        | 11              | 5               |
| West Africa            | 4               | 9               |
| East Africa            | 9               | 10              |
| Southern Africa        | 5               | 4               |
| Sahara Region          | 5               | 2               |
| South East Asia        | 6               | 14              |
| East Asia region       | 16              | 16              |
| South Asia region      | 25              | 23              |
| Central Asia region    | 9               | 11              |
| Tibet                  | 13              | 11              |
| North Asia region      | 11              | 9               |
| Antarctica             | 13              | 9               |

Table 8.4: TEMPERATURE. The probability (in %) that a randomly selected simulation from the 2 degree set showing more warming, for regional DJF temperature, than a randomly selected simulation from the 3 degree set.

| <b>Region</b>          | <b>% 2° &gt; 3° (DJF)</b> | <b>% 2° &gt; 3° (JJA)</b> |
|------------------------|---------------------------|---------------------------|
| Australia              | 36                        | 63                        |
| Amazon Basin           | 39                        | 75                        |
| Southern South America | 37                        | 56                        |
| Central America        | 64                        | 67                        |
| Western N.America      | 37                        | 46                        |
| Central N.America      | 41                        | 73                        |
| Eastern N.America      | 45                        | 66                        |
| Alaska                 | 29                        | 23                        |
| Greenland              | 11                        | 33                        |
| Mediterranean Basin    | 46                        | 71                        |
| Northern Europe        | 28                        | 63                        |
| West Africa            | 65                        | 55                        |
| East Africa            | 61                        | 52                        |
| Southern Africa        | 59                        | 47                        |
| Sahara Region          | 59                        | 63                        |
| South East Asia        | 41                        | 59                        |
| East Asia region       | 67                        | 52                        |
| South Asia region      | 68                        | 40                        |
| Central Asia region    | 51                        | 38                        |
| Tibet                  | 56                        | 22                        |
| North Asia region      | 17                        | 21                        |
| Antarctica             | 12                        | 7                         |

Table 8.5: PRECIPITATION. The probability (in %) that a randomly selected simulation from the 2 degree set rise simulates a greater increase in regional DJF precipitation, than a randomly selected simulation from the 3 degree set.

| Region              | NONE | Temp | SSP | Precip | Cloud | SS HF | SL HF | HF LS | Mean |
|---------------------|------|------|-----|--------|-------|-------|-------|-------|------|
| Australia           | 5    | 5    | 3   | 3      | 6     | 6     | 5     | 6     | 5    |
| Amazon Basin        | 8    | 10   | 12  | 12     | 6     | 8     | 8     | 9     | 9    |
| Southern S.America  | 4    | 4    | 3   | 4      | 3     | 4     | 4     | 6     | 6    |
| Central America     | 14   | 18   | 16  | 16     | 15    | 14    | 14    | 19    | 16   |
| Western N.America   | 9    | 10   | 8   | 8      | 8     | 9     | 7     | 8     | 8    |
| Central N.America   | 20   | 31   | 19  | 26     | 19    | 27    | 24    | 23    | 29   |
| Eastern N.America   | 16   | 21   | 13  | 16     | 16    | 17    | 16    | 17    | 18   |
| Alaska              | 15   | 11   | 17  | 10     | 15    | 13    | 15    | 10    | 17   |
| Greenland           | 5    | 4    | 5   | 4      | 5     | 4     | 5     | 4     | 6    |
| Mediterranean Basin | 6    | 6    | 9   | 5      | 7     | 6     | 5     | 10    | 6    |
| Northern Europe     | 11   | 12   | 8   | 10     | 13    | 11    | 12    | 14    | 12   |
| West Africa         | 4    | 5    | 6   | 6      | 5     | 5     | 7     | 6     | 5    |
| East Africa         | 9    | 14   | 13  | 13     | 8     | 13    | 14    | 12    | 11   |
| Southern Africa     | 5    | 7    | 6   | 9      | 6     | 10    | 11    | 7     | 8    |
| Sahara Region       | 5    | 6    | 10  | 8      | 5     | 7     | 8     | 7     | 6    |
| South East Asia     | 6    | 11   | 12  | 10     | 8     | 12    | 11    | 10    | 8    |
| East Asia region    | 16   | 21   | 20  | 17     | 14    | 17    | 17    | 18    | 18   |
| South Asia region   | 25   | 35   | 33  | 38     | 27    | 37    | 35    | 34    | 30   |
| Central Asia region | 9    | 9    | 11  | 8      | 10    | 9     | 10    | 9     | 7    |
| Tibet               | 13   | 18   | 20  | 15     | 14    | 18    | 17    | 13    | 13   |
| North Asia region   | 11   | 10   | 9   | 11     | 14    | 9     | 10    | 13    | 10   |
| Antarctica 13       | 21   | 18   | 16  | 11     | 19    | 18    | 12    | 17    |      |

Table 8.6: Probability (%) of a hotter region for simulations from the 2 degree set than the 3 degree set. Values are shown where both sets are constrained by in-sample RMSE in each of 7 different variables, and an aggregate over these 7. The constraining variables shown are Temperature, Sea Surface Pressure, Total Precipitation Rate, Total Cloud Amount, Sea Sensible Heat Flux, Sea Latent Heat Flux, Heat flux latent surface and the Mean Score over these 7 variables. Results are shown for the DJF season.

| Region              | NONE | Temp | SSP | Precip | Cloud | SS HF | SL HF | HF LS | Mean |
|---------------------|------|------|-----|--------|-------|-------|-------|-------|------|
| Australia           | 36   | 42   | 38  | 39     | 39    | 40    | 37    | 42    | 38   |
| Amazon Basin        | 39   | 37   | 37  | 36     | 40    | 38    | 42    | 37    | 40   |
| Southern S.America  | 37   | 34   | 34  | 32     | 31    | 34    | 33    | 38    | 32   |
| Central America     | 64   | 60   | 67  | 57     | 60    | 63    | 64    | 60    | 65   |
| Western N.America   | 37   | 37   | 31  | 35     | 38    | 37    | 41    | 31    | 33   |
| Central N.America   | 41   | 43   | 41  | 42     | 34    | 42    | 44    | 42    | 41   |
| Eastern N.America   | 45   | 38   | 49  | 47     | 49    | 39    | 41    | 41    | 37   |
| Alaska              | 29   | 29   | 33  | 23     | 29    | 30    | 30    | 32    | 33   |
| Greenland           | 11   | 11   | 11  | 9      | 11    | 9     | 11    | 11    | 12   |
| Mediterranean Basin | 46   | 41   | 50  | 46     | 46    | 45    | 46    | 49    | 46   |
| Northern Europe     | 28   | 32   | 28  | 27     | 28    | 32    | 31    | 29    | 28   |
| West Africa         | 65   | 66   | 66  | 63     | 62    | 62    | 65    | 66    | 66   |
| East Africa         | 61   | 61   | 58  | 62     | 58    | 60    | 61    | 61    | 64   |
| Southern Africa     | 59   | 68   | 58  | 54     | 60    | 62    | 56    | 62    | 64   |
| Sahara Region       | 59   | 56   | 63  | 62     | 53    | 60    | 63    | 56    | 62   |
| South East Asia     | 41   | 36   | 41  | 38     | 39    | 36    | 37    | 42    | 41   |
| East Asia region    | 67   | 72   | 71  | 70     | 68    | 73    | 71    | 72    | 75   |
| South Asia region   | 68   | 72   | 70  | 76     | 67    | 77    | 74    | 72    | 70   |
| Central Asia region | 51   | 55   | 50  | 53     | 49    | 52    | 58    | 48    | 54   |
| Tibet               | 56   | 58   | 56  | 61     | 53    | 58    | 62    | 52    | 58   |
| North Asia region   | 17   | 19   | 20  | 18     | 18    | 15    | 15    | 18    | 14   |
| Antarctica          | 12   | 13   | 11  | 8 0    | 12    | 10    | 10    | 19    | 12   |

Table 8.7: Probability (%) of a wetter region for simulations from the 2 degree set than the 3 degree set. Values are shown where both sets are constrained by in-sample RMSE in each of 7 different variables, and an aggregate over these 7. The constraining variables shown are Temperature, Sea Surface Pressure, Total Precipitation Rate, Total Cloud Amount, Sea Sensible Heat Flux, Sea Latent Heat Flux, Heat flux latent surface and the Mean Score over these 7 variables. Results are shown for the DJF season.

It has been shown in this Section that there are regional changes in temperature and precipitation consistent with both the 2 degree and 3 degree sets. Next, distributions of regional temperature and precipitation response are looked at in more detail. The magnitude of regional change is now shown not to be robust in some regions in either temperature or precipitation.

In Figure 8.5 the distribution of simulations from the 2 and 3 degree sets are compared for the three regions used in Figure 8.3. The distribution of simulations from the 2 degree set is shown in blue and the 3 degree set in red. There is some overlap for all regions, seasons and variables shown. The distributions of temperature are more distinct (the overlap in JJA temperature for Australia, Central North America and Northern Europe are 6%, 23% and 5% respectively compared to 63%, 73% and 63% for precipitation), with higher regional warming seen in all regions in the 3 degree set. In Australia, the extra one degree of GMST rise leads to a shift in the distribution of about 1 degree to the right, whereas in Central North America and Northern Europe, the difference between the distributions is a shift of almost 2 degrees. Such shifts in distribution are best interpreted alongside the associated uncertainties and their overlaps. It is interesting to note that in the Northern European region, warming is more extreme in the DJF season than in the JJA season, whilst in Central North American warming appears more extreme in the JJA season. Such seasonal differences can be important to decision makers e.g. it is thought that warmer summers will increase mortality rates through heat deaths, whereas mild winters reduce mortality rates through a reduction in cold-related deaths Parry *et al.* (2007). Thus the winter warming seen in Northern Europe might be considered less worrying than the summer warming simulated in the Central North American region. These results further suggest that studies on the seasonal impact of climate change based on one region would not translate to other regions.

It is apparent from Figure 8.5 that regions such as Central North America or North-

ern Europe must be prepared to adapt to more extreme regional warming than is expected on the global scale. This is a key result for decision-makers since it suggests that significant adaptation planning might be still necessary in the presence of more modest levels of global warming.

The distributions for precipitation are less distinguishable than for temperature. For Australia (both seasons) and the DJF season in other regions, the two distributions in Figure 8.5 almost indistinguishable (36% and 63% overlap in the DJF and JJA seasons respectively). It would be difficult, based on evidence from the HadSM3 model, to tell what difference a 3 hotter world would look like compared to a 2 degree hotter world. For DJF precipitation in Northern Europe, all simulations in the 3 degree set show an increase in precipitation. Although this result might not be robust when compared to other models or larger ensembles, the CPDN PPE provides evidence to support the assumption of an increase in precipitation (anywhere up to a 50% increase) for this region and season. The assumption of an increase in precipitation would not appear to be justifiable for say, JJA precipitation over Australia since the ensemble is not consistent on the sign of the change. Thus, it may not be necessary to develop different adaptation decisions reliant on regional precipitation change depending on a forecast changing between 2 and 3 degrees of warming – in either case we can not say whether precipitation will increase or decrease, and the distributions of regional behaviour are similar based on the simulations examined here.

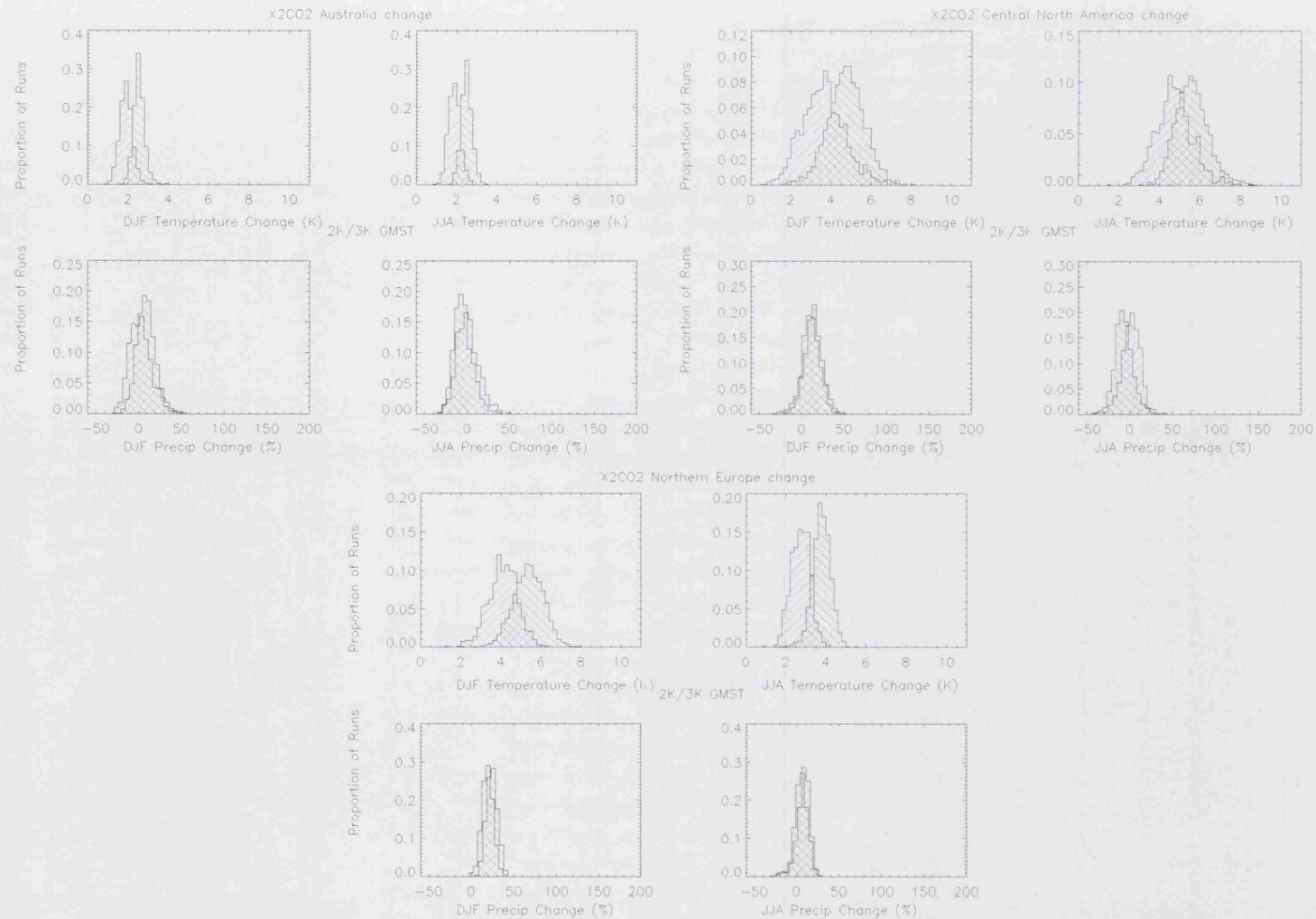


Figure 8.5: The distribution of 8 year DJF (JJA) temperature (precipitation) is shown for the 2 degrees set (blue) and the 3 degrees set (red). There is often a large overlap between the two ensembles, especially for precipitation. This shows that the 2 degree set and the 3 degree set are not always robustly distinguishable.

### 8.3.2 Grid-scale differences

Figure 8.7 shows histograms, similar to those shown on regional scales, for three selected grid-boxes; specifically those corresponding to the location of the cities of London (UK), Boulder (Colorado, USA) and Jakarta (Indonesia) (see Figure 8.6) although the grid-boxes are much larger than the cities themselves. The scale on the x-axis differs from Figure 8.5 in light of the increased range in precipitation seen at the grid-box level. Changes in temperature are again robustly positive for these three grid-boxes, with the 3 degree set typically showing greater warming than the 2 degree set, with a probability of overlap in DJF temperature of 12%, 22% and 6% for DJF temperature for the London, Boulder and Jakarta grid-boxes respectively. The upper end of warming in the boulder grid-box is over 8 degrees for the 3 degree set. Precipitation change is highly variable in the London and Boulder grid-boxes e.g. JJA precipitation change in Boulder ranges from a greater than 50% reduction to more than 100% increase for both sets of simulations. The Jakarta grid-box shows massively different responses in precipitation – from almost 100% decrease (almost no rainfall at all) to over 200% increase. Such variability is likely due to Jakarta lying in between rival patterns of change in the region, thus the extreme uncertainty does not suggest changes on a larger scale are unintelligible. The 3 degree set simulates precipitation to be wetter in summer and drier in winter, although there is much overlap in these distributions e.g. an overlap of 39%, 48% and 35% in DJF precipitation for the London, Boulder and Jakarta grid-boxes respectively. Note that Boulder shows a much wider range of values for temperature than Jakarta, but a much tighter distribution in precipitation. An area may show robust results in one variable and not another.

It is misleading to use such a wide range of model behaviour to drive downscaling models or impact assessment in areas such as Indonesia on the basis of these data. The most reasonable assessment of such information is that in many areas, on a grid-box level, the HadSM3 model versions used here do not allow us to make



statements about changing precipitation. In some areas and variables, models can rule nothing out.

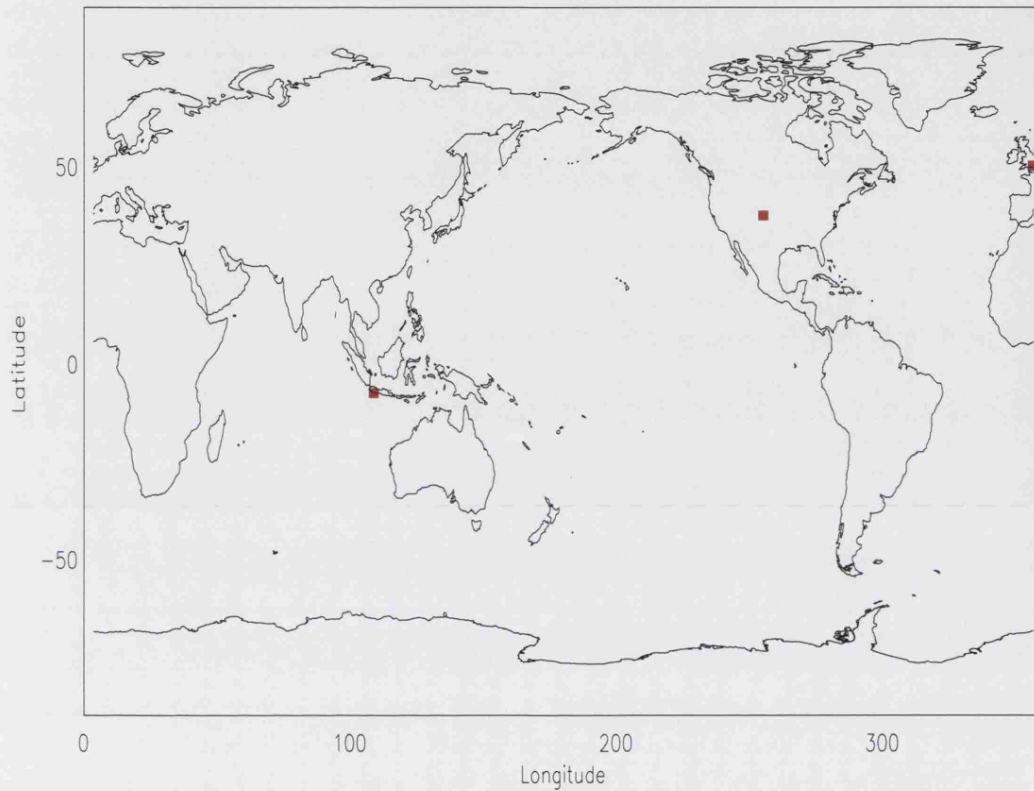


Figure 8.6: The three grid-boxes selected to look at local impacts are shown. These grid boxes are called London, Boulder and Jakarta since they contain those cities. It should be noted that the grid-boxes are much larger than the cities they contain.

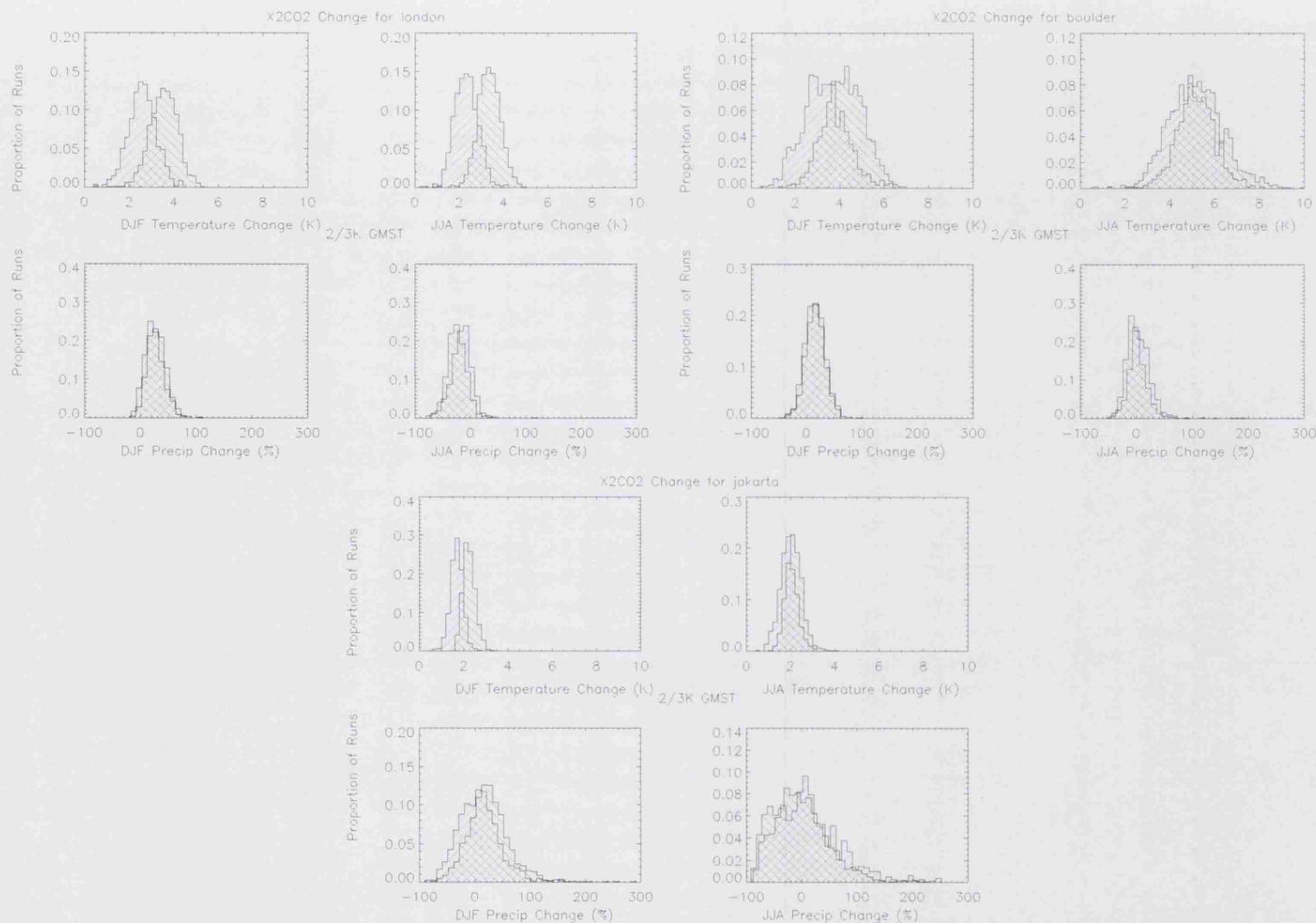


Figure 8.7: The distribution of 8 year DJF/JJA temperature/precipitation is shown for the 2 degree set (blue) and the 3 degree set (red). The grid-boxes that contain London, Boulder and Jakarta are shown. Note that the cities themselves are much smaller than the grid-boxes, which are typically  $50,000\text{km}^2$  in area.

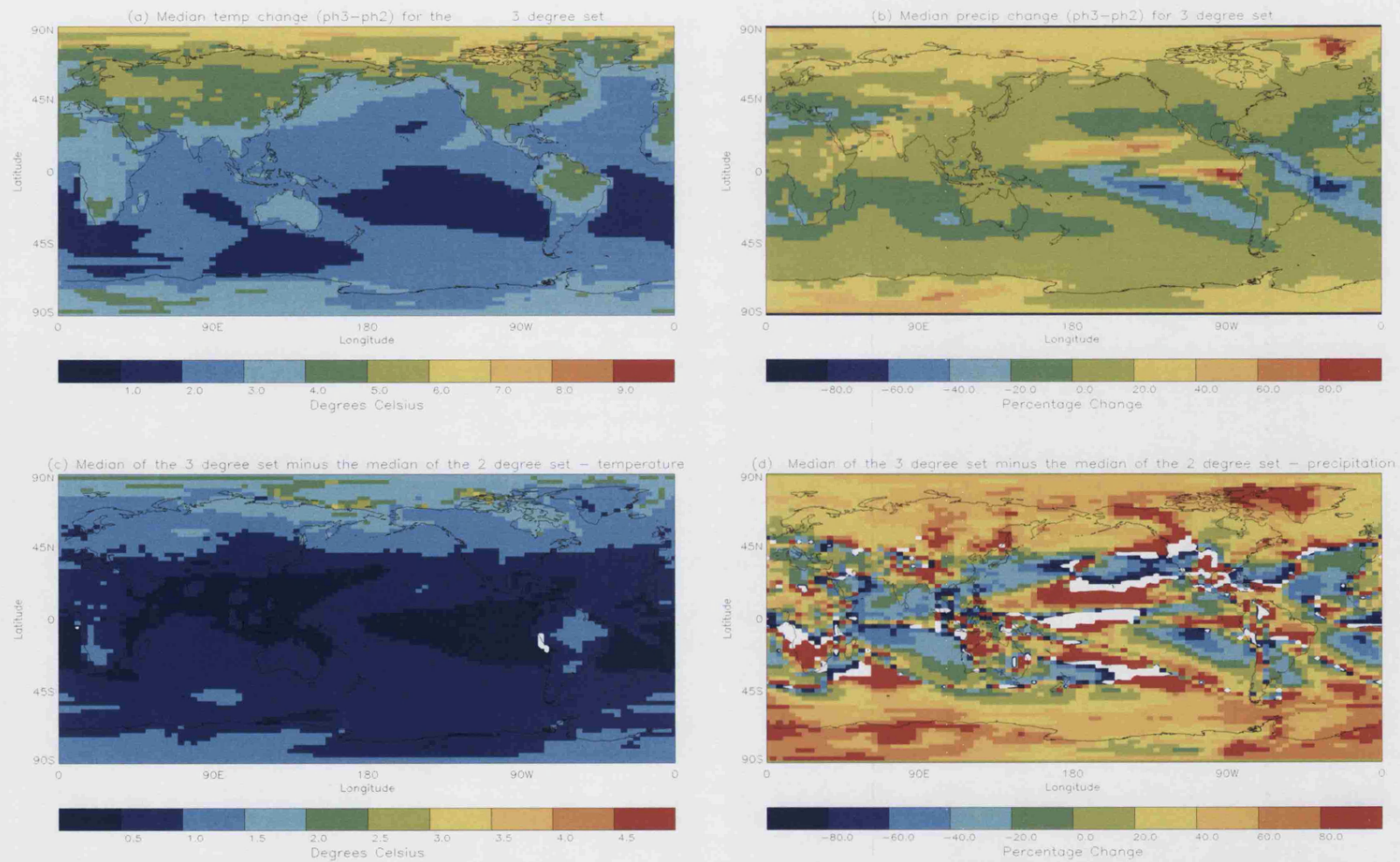


Figure 8.8: The median change in temperature (degrees Celsius) is shown in panel (a) and precipitation (mm per day) is shown in panel (b) over the 3 degree set. Also shown is the difference between this and the median temperature rise in temperature for the 2 degree set in panel (c) and precipitation in panel (d).

Having examined the variability within the 2 and 3 degree sets, Figure 8.8 shows the median change in GMST (panel (a)) and total precipitation rate (panel (b)) for the 2 degree set simulations and the difference between these simulations and the 2 degree set in panels (c) and (d). As expected from previous analyses, the regional distribution of warming shown in panel (a) is for oceans to warm the least (typically by 1–3 degrees), and the Arctic region the most (typically by 6–7 degrees Celsius). In general, inland regions warm by more than coastal regions. These patterns of regional temperature change for simulations with a fixed GMST change are consistent with the regional changes seen in the standard HadSM3 ensemble in Chapter 6 and across the CPDN grand ensemble in Chapter 7. Panel (c) shows the difference between the median warming for the 3 degree simulations minus the 2 degree simulations. There are few areas that show a negative value (negative values indicate the median in the 2 degree set is greater than the median in the 3 degree set) and considerable areas show a difference of less than 0.5 degrees, particularly in the ocean. The median of the 3 degree set is up to 3 degrees warmer than the 2 degree set in the Arctic where the most rapid warming occurs.

Panels (b) and (d) in Figure 8.8 show the same statistics, but for precipitation. It is notable that, unlike temperature, the median change in precipitation (panel (b)) under a doubling of  $CO_2$  concentrations is negative over large areas. This variability in local response is most noticeable around the tropics; the equatorial pacific and the Indian sub-continent show an increase of precipitation by more than 1 mm per day, whereas the East coast of Brazil shows a fall of more than 1 mm per day. The kind of regional variety shown here is lost in a global mean, with many of the features in this field cancelling each other out. This, together with basic counting statistics, explains how a tight distribution of global mean precipitation is consistent with large uncertainties in local changes. An important conclusion from this analysis is that global mean values destroy impact-relevant information on regional and local scales. One example of this is that at the global mean level

a misleadingly small change in precipitation (about 0–5% increase) hides changes of 50% or more at the regional level and over 200% at the grid-box scale. These changes are vital for adaptation planning and suggest that global mean metrics are of limited use to decision-makers.

## 8.4 Linearity of Regional Response

It has been proposed that regional climate response to forcings scales linearly with GMST change e.g. “the geographical pattern of the temperature, precipitation or other response is assumed to be independent of the forcing, the amplitude of this fixed pattern being proportional to the global mean change” Ruosteenoja *et al.* (2007), and “Seasonal temperature and precipitation have been shown to scale approximately linearly with the magnitude of global warming when analysing ensemble average change signals from multiple models” Diffenbaugh *et al.* (2007) and references therein. Other references to the linearity of regional climate change in proportion to global mean temperature change are made in Giorgi (2008); Solomon *et al.* (2007a). Whilst the CPDN experiment does not allow a consideration of the assumption of linearity to different magnitudes of forcing since the same doubled  $CO_2$  forcing scenario is used in all simulations, a similar question can be investigated – do regional responses scale linearly with GMST in the CPDN PPE? If this question can be answered in the positive it implies that it is possible to infer patterns of regional change based on GMST alone – this would save experimental resources (there is less need to store regional data or to explore the patterns of change within simulations with different values of GMST change) and would greatly increase the utility of global mean statistics as a basis for decision-makers. If there is evidence that this question should be answered in the negative it suggests that regional behaviour can be non-linear relative to global changes and that these regional responses can not be inferred directly from global means. Since the CPDN grand ensemble can be divided into sub-sets of simulations with similar levels of

GMST change, the robustness of regional response can be looked at across different model versions and values of GMST rise.

Regional response factors are defined in this Section, following Giorgi (2008), as the proportional change in regional climate response in seasonal temperature and precipitation with respect to GMST change. The regions used relate to the Giorgi regions Giorgi & Francisco (2000), as well as tropics, extra-tropics, Northern and Southern hemispheres. These regional response factors,  $R_i$ , for data set  $i$  and region  $R$  are calculated as follows: define the 8 year mean global mean temperature change from the doubled  $CO_2$  phase to the control phase as  $\Delta_G$  and the regional change (in temperature, or precipitation) as  $\Delta_R$ .  $R_i$  is estimated by the ensemble mean regional change proportional to the ensemble mean global mean temperature change. This regional factor is calculated here for four different sets of data with different values of GMST change – the standard HadSM3 model ICE and three sets of simulations with global mean temperature changes of  $2\pm0.1$ ,  $3\pm0.1$ ,  $4\pm0.1$  degree with 64, 402, 2441 and 795 available simulations respectively. The regional response for set  $i$  is defined as:

$$R_i = \frac{\Delta_{R,i}}{\Delta_{G,i}} \quad (8.1)$$

where  $\Delta_{R,i}$  denotes the ensemble mean change in region  $R$  for data set  $i$  for  $i = 1, 2, 3, 4$  and  $\Delta_{G,i}$  denotes ensemble mean GMST change. These regional response factors are calculated for 8 year mean DJF/JJA temperature (panels (a) and (b)) and DJF/JJA precipitation (panels (c) and (d)). Figure 8.9 shows these regional response factors for four sets of data, based on the 64 member standard HadSM3 model and sub-sets of simulations with 2, 3 and 4 degrees of GMST change, respectively.

Estimates from the standard HadSM3 ICE are shown in black, from simulations with 2 degrees GMST change in blue, 3 degrees GMST in green and 4 degrees in red. Vertical black bars are shown for each region and set of simulations, denoting

| Region Code | Region                         |
|-------------|--------------------------------|
| aust        | Australia                      |
| amsa        | Amazon Basin                   |
| ams         | Southern South America         |
| amc         | Central America                |
| amnw        | Western North America          |
| amnc        | Central North America          |
| amne        | Eastern North America          |
| amal        | Alaska                         |
| grnl        | Greenland                      |
| eum         | Mediterranean Basin            |
| eun         | Northern Europe                |
| afw         | West Africa                    |
| afe         | East Africa                    |
| afs         | Southern Africa                |
| afsh        | Sahara Region                  |
| asse        | South East Asia                |
| ase         | East Asia                      |
| asso        | South Asia                     |
| asc         | Central Asia                   |
| astb        | Tibet                          |
| asn         | North Asia                     |
| ant         | Antarctica                     |
| hmn         | North Hemisphere               |
| hms         | South Hemisphere               |
| trop        | Tropics                        |
| hmnt        | North Hemisphere Extra-tropics |
| hmst        | South Hemisphere Extra-tropics |

Table 8.8: Region codes and names for the 27 areas used to calculate regional response factors.

$\pm 2$  standard deviations in the estimate of the mean regional response. Regions are denoted using the table of region codes shown in Table 8.8.



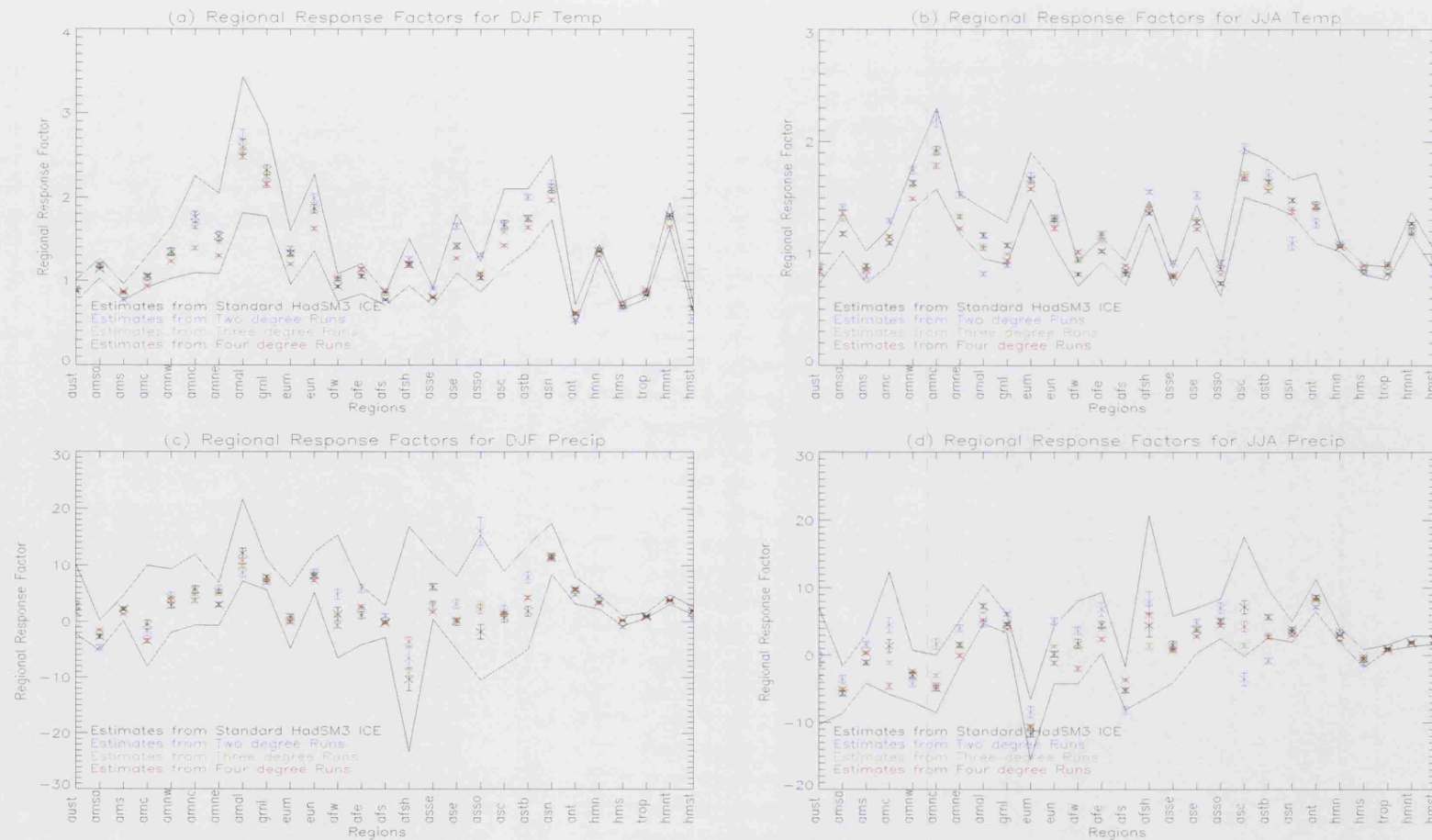


Figure 8.9: Regional response factors for 27 regions shown in Table 8.8 in four different variables. DJF temperature response factors are shown in panel (a), JJA temperature in panel (b), DJF precipitation in panel (c) and JJA precipitation in panel (d). Estimates from the 2 degree set of simulations are shown in blue, the 3 degree set in green and the four degree set in red. Estimates from the individual simulations from the standard HadSM3 ICE are shown in black. The two black lines show the minimum and maximum regional response in simulations from the standard HadSM3 ICE. Vertical bars show 2 standard deviations in estimates of the mean regional response from each set.



Statistically, simulations with different values of GMST rise produce different estimates of the mean regional response rates (in many regions the estimates differ by over 2 standard deviations). The statistical significance is largely due to the low standard deviation of estimates in the mean since large sample sizes are used to form these estimates. It should be noted that even apparently small differences in estimates of regional response factors will multiply when estimating regional response for higher GMST change e.g. a difference of 1 in regional response factor estimates between *amnc* (Central Northern America) temperature response (panel (a)) relates to a 5 degree Celsius differences in estimated regional temperature under 5 degrees of global warming. For the larger areas representing the tropics, extra-tropics and hemispheric means the response factors are more consistent than for smaller areas. In precipitation (panels (c) and (d) of Figure 8.9) the regional response factors estimated from individual simulations in the standard HadSM3 model do not show a consistent sign of response (the upper and lower black lines often cover the lines  $Y = 0$ ). Furthermore, estimates of regional response from the different sets do not always agree on the sign of regional response. Regional precipitation change can not be robustly estimated where different sets disagree on the sign of regional response factors.

The results in this Section show evidence that the assumption of linear regional response to global mean changes is not relevant for precipitation response and there are significant uncertainties in the estimation of regional temperature response in many regions. These results show that GMST can not be assumed to be related in a linear way to regional responses in temperature and precipitation, although non-linearities are larger in some regions than in others.

## 8.5 Discussion

Even when model GMST is known, significant regional “uncertainties” remain, particularly for precipitation. In all the regions (of area comparable to or larger than

many nations) presented it is not clear whether precipitation will increase or decrease for the 2 degree set.

The difference between the 2 and 3 degree sets is not clear for precipitation – in some regions and seasons the distribution shifts further from 0 (wetter or drier than the 2 degree ensemble), in others it shifts towards 0 (less significant change than for the 2 degree ensemble). This may suggest a non-linear “dose-response” to rising temperatures in the model. For example, in Figure 8.5, JJA precipitation in Northern Europe increases under the 2 degree set, then shifts back towards 0 for the 3 degree set. This result may be peculiar to this model, or a robust feature over state-of-the-art climate models in general. It is difficult to compare such distributions to other models since there are no other suitably large ensembles amenable to the approach used in this Chapter<sup>1</sup>. Nonetheless, it is clear that the distributions shown in this Chapter should not be over interpreted and may contain model-specific features or biases.

GMST is commonly used in policy discussion as the key index for climate change Parry *et al.* (2007); Stern (2006). The use of GMST change as an index for climate change impacts is, at best, highly restricted and can even provide misleading information<sup>2</sup>. New approaches to communicating the results of large ensemble experiments would help motivate more robust impact assessment and aid better policy formulation.

The results presented in this Chapter also pose questions relevant to those interested in constraining model output. Whilst constraining GMST changes might be useful for reducing certain uncertainties, significant regional uncertainties remain. Attempts to constrain GMST are thus more useful for mitigation strategies that operate typically on global length scales (such as targets for global carbon emissions) than regional or local adaptation decisions.

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<sup>1</sup>To form a distribution for a narrow range of GMST either requires a very large ensemble of simulations or a specially designed experiment.

<sup>2</sup>In some model regions, a 2 degree increase in GMST might lead to over 6 degree increases in temperature or more. Thus, limiting GMST to a certain level may not restrict regional warming to sustainable levels.

The data presented in this Chapter has been in terms of an 8 year seasonal mean. Finer temporal scales would provide more relevant for many impact studies in order to evaluate an increased risk of flooding, droughts, heat waves etc. Such data is unavailable for the CPDN data set but, were any future large ensemble experiments to record such information<sup>1</sup>, the methods presented in this Chapter would be useful for assessing how robust certain impact studies might be. It is only with large ensembles of climate models that the tails of distributions can be evaluated. Small ensembles do not allow robust statements regarding the tails of distributions. The implications of the results presented in this Chapter are now discussed in terms of mitigation and adaptation decisions.

### 8.5.1 Mitigation

There is much uncertainty in how GMST will respond to increasing concentrations of GHGs Murphy *et al.* (2004); Stainforth *et al.* (2005). GMST and CS are often used as an index of this change. According to the IPCC AR4 Solomon *et al.* (2007a), the likely GMST rise over the next 100 years will be between 1.5 and 4.5 degrees Celsius (range of best estimates from 6 different emissions scenarios), with a best guess of 3 degrees. Studies suggesting that increases in GMST will have serious social and economic costs Parry *et al.* (2007); Stern (2006) have prompted discussion as to what is an acceptable level of warming for a given cost of mitigation measures. The extent to which mitigation policy relating to global mean temperature will limit regional changes has been shown to be unclear in this Chapter. There are uncertainties in determining how policy will relate to emissions, how emissions will relate to GHG concentrations, how quickly GHG will warm the Earth and how GMST relates to climate impacts. It is this last link that is dealt with in this Chapter e.g. if GMST were to rise by 2 degrees Celsius, what would this mean

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<sup>1</sup>Studies, such as those contributing to the IPCC Fourth Assessment Report, do record such data but the ensembles typically consist of at most 9 members, too few to carry out the analysis presented in this Chapter.

for temperature and precipitation changes in different regions? Under the scenario of a 2 degree GMST rise, regional impacts and uncertainties therein have been analysed using data from the CPDN experiment. The results from this Chapter show that mitigation of regional risks is difficult given the rapidity of simulated warming in some regions (typically over twice as fast as GMST rise in Northern high latitudes) and the significant uncertainties in regional response. For a GMST rise of 2 degrees Celsius, there can remain significant risks of exceeding 6 degrees or more of regional temperature change. It should be noted that this Chapter has only considered GMST rises of up to 4 degrees Celsius, whilst the CPDN PPE does not rule out values of CS of over 10 degrees Celsius. Regional responses from high CS simulations are not studied here since high CS simulations have not reached an approximate equilibrium by the end of the experimental phase<sup>1</sup>.

## 8.5.2 Adaptation and Impact Assessment

It has been shown in this Chapter that knowing GMST change can not be robustly translated into regional changes in temperature and precipitation. In many regions, in key variables, there are large uncertainties for a given GMST change, hence it would be misleading to suggest that certain regional impacts will occur at a particular GMST rise. For example, Table 8.1 shows that for a 2 degree GMST rise, the range of Greenland temperature change is from 1.98 to 6.78 degrees Celsius in the winter season. Such differences in temperature could lead to very different futures for the Greenland ice sheet and highlights the need to consider the regional variability associated with GMST rise. Such events can occur at a variety of different GMST increases although risk of regional impacts can change with GMST. More generally, local decisions based on GMST would need to be robust to the diversity of behaviour seen here, even assuming the HadSM3 model used to generate these

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<sup>1</sup>100% of simulations in the 2 degree set have 8 year GMST rise of more than 90% of CS. This percentage drops to 70% and 15% for the 3 and 4 degree sets and 0% for simulations with over 5 degrees of GMST rise, as explained in Section 4.4.1 and shown in Figure 4.6

distributions is perfect.

It has been shown in this Chapter is that different regions can require very different adaptation strategies. HadSM3 suggests that some regions are likely to face far more extreme climate changes than others e.g. Figure 8.5 has shown that simulated warming of up to 10 degrees in Central Northern America is consistent with 5 degrees of global warming, whilst Australians would expect half this level of warming. It is vital, when planning adaptation strategies, to consider the regional and seasonal differences in climate change. An important result in this Chapter is that a wide range of regional responses can be consistent with the same variable, season and GMST change. This suggests that adaptation strategies should be flexible in order to account for a wide range of regional changes in climate even when GMST is assumed to be known.

Presenting a distribution of simulations, as in this Chapter, also provides decision makers with some (albeit rudimentary) idea of model diversity; it is important to consider not only expected changes but the the chance of extreme levels of regional warming (e.g. 6 degrees or greater).

It has been shown that GMST can not be used to robustly infer regional changes.

## 8.6 Conclusion

Data from the CPDN experiment has been used here to look at regional model diversity for a given level of global warming. The large range of regional behaviour present suggests that GMST has limited utility as an index for adaptation policy and impact assessment. Using an ensemble of simulations as a distribution, rather than simply taking a mean, and looking at changes on the length scales relevant to impact studies provides a more relevant framework for making robust statements of climate change.

New results presented in this Chapter are:

- Regional changes can differ significantly (over 6 degrees Celsius for some re-

gions in 8 year mean seasonal temperature) for simulations with the same global mean temperature change.

- The spatial scales of model diversity have been quantified using the CPDN PPE. The magnitude of regional uncertainties for a given GMST change has been shown to vary with length scale and variable. The distribution of regional change has been used to present uncertainties in sub-global response on a variety of length scales - global, hemispheric, tropical and extra-tropical, regional and local. Uncertainties in precipitation are large – the sign of change is uncertain on length scales as large as many nations in most regions looked at.
- The distributions of regional change have been contrasted between the 2 and 3 degree sets. The magnitude of overlap between these distribution is large; in some regions and variables this overlap is over 20% for temperature and close to 50% in precipitation, indicating that it is not possible to robustly ascribe regional responses based on GMST.
- Even if GMST is constrained to within 0.2 degrees Celsius, significant regional uncertainties would remain. It follows from this result that global mean constraints are of limited use and that methods based on the patterns of change might be preferable.

## 8.7 Additional

Data for this Chapter has been taken from the CPDN experiment, as described in Chapter 4, Section 4.4.3. Data was available on regional and grid-box scale as 8 year seasonal means for each experimental phase. Analysis is based on these 8 year mean temperature and precipitation fields and climate changes are calculated by taking the difference between the last 8 years of the doubled  $CO_2$  and control phases. This approach assumes that the model simulations are roughly in equilibrium during

these years.

Figure 8.10 shows the time series of annual GMST for all three phases for the 2 and 3 degree sets. The distribution of these sets is shown in the left panels. The quality controlled ensembles are stable during the calibration phase, showing a little more variability in the control phase, then a marked increase in GMST at the start of phase 3 at the point of  $CO_2$  doubling. Whilst all simulations may not have converged to equilibrium by year 38, it appears that most of the transient warming has already taken place by year 38 in the final phase. It is assumed in this Chapter that the last 8 year mean of phases 2 and 3 provide an indicative estimate of regional climate changes.

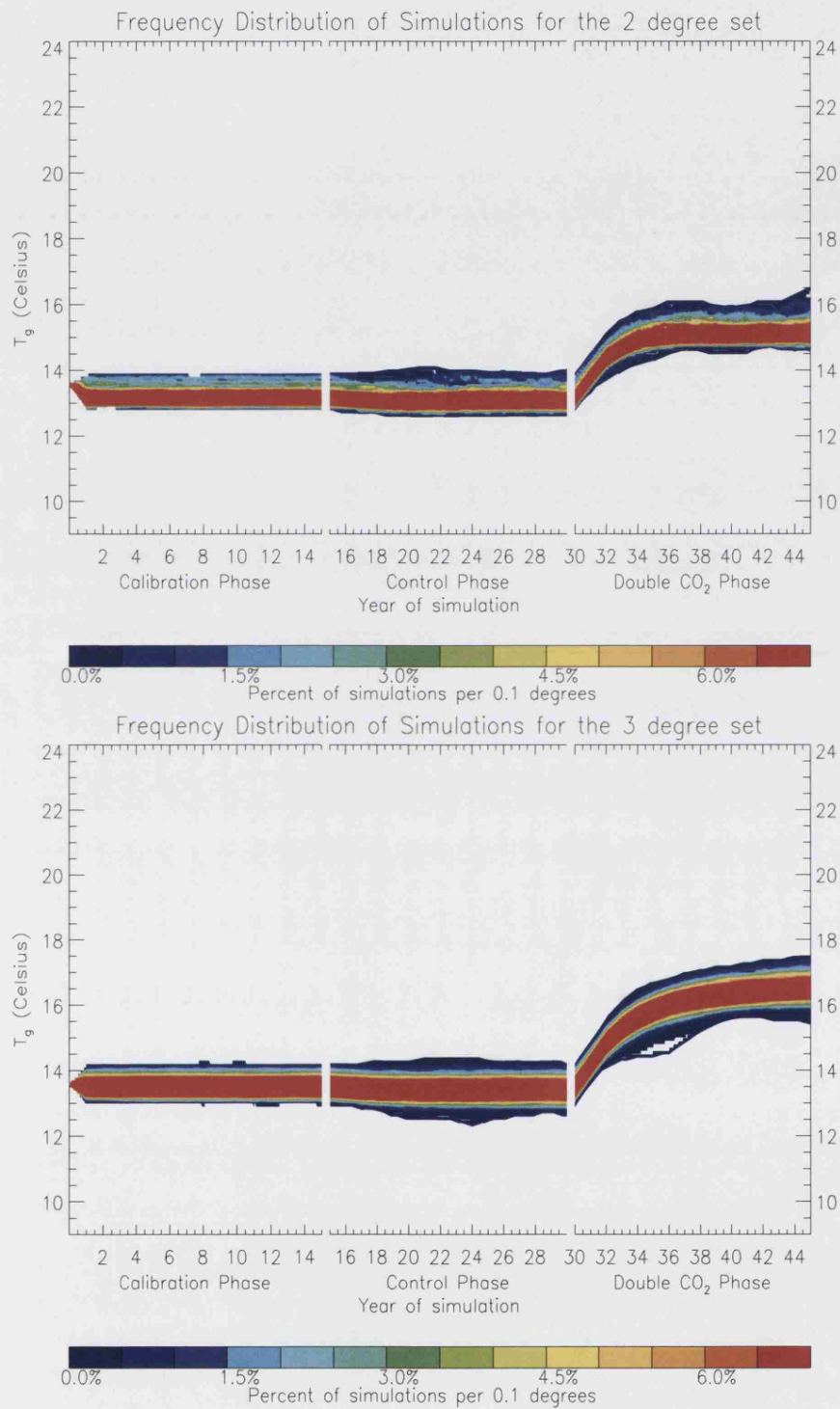


Figure 8.10: Time series for the 2 and 3 degree sets. Transient warming occurs at the point of  $CO_2$  doubling (year 30) and stabilises by the end of the final phase. Data on regional climate changes was available for the final 8 years of each phase.



# Chapter 9

## Conclusion

### 9.1 Overview

This Chapter summaries the results presented in this Thesis and interprets them as implications for climate science and decision makers. Possible ways for climate science to move towards providing more decision-relevant information are proposed and discussed.

Section 9.2 summarises results concerning the different types of uncertainty present in climate predictions. Important results from Chapters 6, 7 and 8 are explained in light of three different categories of uncertainty. The implications of the results presented in this Thesis are explained in Section 9.3. Section 9.4 gives suggestions for further work that leads directly on from this Thesis.

### 9.2 Uncertainties

The four main categories of uncertainty are presented in Chapter 2; forcing uncertainty, initial condition uncertainty, model uncertainty and model inadequacy. Forcing uncertainty is not dealt with in this Thesis. The three remaining uncertainties are listed below, together with the insights that arise from this Thesis:

### 9.2.1 Initial Condition Uncertainty

Initial Condition Uncertainty (ICU) (Chapter 6) has previously been little studied due to pressures on computational resources and the widespread assumption that the magnitude of ICU is small on climatic time and length scales. This assumption has been shown to be significant on some length and time scales in Chapter 6.

Whilst the question of the division of computational resources must depend critically on the goals of each particular experiment, it can not be assumed a priori that ICU is small. It has been shown that the magnitude of ICU can be large on regional length scales in key variables. Differences on a grid-box level of up to 10 degrees Celsius are shown in 8 year mean DJF temperature change due to doubling of  $CO_2$ , arising from perturbation of ICs alone in Section 6.3. Furthermore, it is argued that ICEs are important tools in the analysis of the distribution of climate, providing the ability to evaluate the internal variability of models and differentiate more robustly the differences between models and scenarios (Section 6.4).

### 9.2.2 Model Uncertainty

Model uncertainty is a result of the existence of a diversity of climate models. There are different ways to estimate model uncertainty; it is possible to use a multi-model ensemble or to perturb parameters in a single structural model to understand inter-model differences. Efforts to estimate model uncertainty are hampered by the availability of different structural models and their lack of independence. It is not possible to fully explore model uncertainty since there is no definable class of models that can be exhaustively sampled.

The parameter perturbation approach is used in Chapter 7 using data from the CPDN experiment. Using a set of parametrically “de-tuned” Bender (2008); Stocker (2004) models might give a more realistic view of predictive uncertainties than taking a model with a single set of parameters, tuned on past observations Allen *et al.* (2006). The choice of data set was further motivated by the availability of large

amounts of climate model data – 45644 simulations have been presented in this Thesis. Access to a large ensemble of climate models simulations allows for a more thorough analysis of model uncertainties than has previously been carried out. For comparison, the IPCC Fourth Assessment Report Solomon *et al.* (2007a), the largest attempt to synthesise research on climate change, brought together a total of only 58 simulations from 14 different modelling centres for an analysis of 20th Century climate; similar sized ensembles were also used to simulate future climate changes. The analysis of model uncertainties in the CPDN experiment yielded uncertainties of an unprecedented magnitude. In particular, the range of values for estimated Climate Sensitivity (CS) ranged from 0.9 to 16.4 degrees Celsius, as presented in Chapter 7. Chapter 7 also examines the problem of constraining model uncertainty in light of statistical good practice. It is shown that this problem is non-trivial and the results of constraining can depend on subjective choices such as which variable to use when evaluating simulations' in-sample performance. The results of Chapter 7 suggest that important aspects of model behaviour, such as CS, are not robust to changes in parameter values. The parametrically de-tuned HadSM3 model can provide very different estimates of CS and regional climate changes, suggesting that the value of CS in the standard HadSM3 model is misleadingly robust due to the tuning of parameter values.

### 9.2.3 Model Inadequacy

Model inadequacy is a result of the fact we do not have access to a perfect climate model, even if such a model might exist. All climate models are necessarily inadequate in some way due 1) a lack of accurate and complete representation of physical processes and 2) low resolution of model features and a lack of scientific understanding. The inadequacy of models is difficult to evaluate given the lack of out-of-sample climate data; other methods must be used to estimate the potential effect of model inadequacy on the utility of predictions. The quality of in-sample

fit and the diversity of model predictions provide lower bounds on out-of-sample model performance. A model not evaluated on out-of-sample data and then used to extrapolate can not be established as adequate, although a model can be shown to be inadequate by failing in-sample tests. Thus, climate predictions can only ever be conditional and provisional in nature.

#### **9.2.4 Constraining uncertainties and regional climate response**

The large range of behaviour in the CPDN ensemble is examined in Chapter 7. Chapter 7 discusses three methods that can be used to constrain this range of behaviour demonstrates some of the difficulties in constraining mode diversity in a way consistent with statistical good practice. The range and distribution of estimated CS is dependent on choices such as which method to use and which variables are looked at (Section 7.5).

Leading on from the results of Chapter 7, Chapter 8 looks at sets of simulations within a narrow range of GMST change. By choosing simulations with a specific value of GMST it is possible to examine the regional variations that are present when GMST change (or CS) is tightly constrained at a global level (in this case, to within 0.2 degrees Celsius). It is shown in Chapter 8 that there are still significant regional uncertainties present for simulations with similar GMST changes. This result holds deep implications for policy-making and model-based decision support (Section 8.5). Whilst the sign of temperature change is everywhere positive, the magnitude of regional temperature change can vary by over 4 degrees Celsius for simulations with very similar GMST change. In almost every region, the sign of seasonal precipitation change is uncertain. These results imply a limit to our ability to answer the question “What does a 2 degree world look like?”, and therefore the relevance of setting targets in terms of GMST. Furthermore, it is not clear how to apply pattern-scaling techniques in light of uncertainties in the direction of regional

response.

## 9.3 Implications

The results of this Thesis have implications for the future of climate modelling and for the manner in which climate models might be used to inform policy. In particular, it has been shown in Chapter 3 that the uncertainties involved in climate prediction are large and have not been fully explored or well communicated in the past.

The analysis of climate model data carried out in Chapters 3, 5, 6, 7 and 8 suggests that:

1. Climate scientists need to improve their communication of uncertainties. It is important for decision makers to be aware of the relative confidence they should place in different aspects of climate science. This can only take place with a transparent disclosure of uncertainties on the behalf of climate scientists.
2. The internal variability of climate models can be large, especially on small spatial scales. ICEs can be used to evaluate such uncertainties and provide an estimate of the robustness of model response. Large ICEs are increasingly necessary as climate modelling experiments move from equilibrium to transient simulations where a single, long, simulations can not be used to reliably estimate a model's internal variability.
3. Attempts to reduce uncertainties should be based on spatial patterns of change and not just global mean statistics, such as GMST or CS. It has been shown Allen (1999); Hegerl *et al.* (1997) that it is preferable for the purposes of the detection and attribution of climate change to look at the spatial patterns of change rather than global means. The analysis of spatial climate changes might be particularly useful in reducing the regional uncertainties that remain

when constraining climate change using global means. The large regional uncertainties presented in Chapter 8 suggest that spatial constraining of the pattern of climate change Forest *et al.* (2007) is an important avenue of future research.

4. Downscaling methods that interpret climate output with impacts models should take into account the diversity of model outputs. Downscaling and integrated modelling can only provide robust information once the range of climate simulations is taken into account. Since uncertainties will cascade as more layers of modelling are included, local impact assessment should at least include the range of behaviour simulated by climate models. Studies that treat changes in climate as known can not offer robust results since they do not reflect the inherent uncertainties in climate predictions. It is highly recommended that the sensitivity of impact studies to the assumptions about climate change is included.
5. Policy might better aim to be robust to uncertainties either in the type of decisions made or by remaining flexible. Decision making in the presence of uncertainty is a significant field of research in itself Jordaan (2005); Tversky & Kahneman (1974) and will not be dealt with in any detail here. Nonetheless, due to the inherently provisional nature of climate science it is necessary for decisions to remain flexible, taking into account the relative costs and benefits of action and in-action Stern (2006). In general, over-confident actions based on incomplete information are likely to be sub-optimal; it is important for climate science to provide all the information relevant to the problem, including a full treatment of uncertainty.
6. Monitoring climate is important, especially in ascertaining which data gives the best indication of future climate changes. The signal of climate change can be stronger in certain regions, variables and seasons. For example, the

HadSM3 model suggests that winter temperature change will be most significant over land in the high Northern latitudes. If this result is robust across structural models, this may suggest that the signal of climate change could be more robustly and quickly distinguished from noise that using a global mean.

Section 9.4 presents further work that leads on from this Thesis.

## 9.4 Further Work

This Section highlights some areas of further work that lead on from this Thesis. Three main directions of research are suggested here; **1)** Extension of results here to different structural models and to transient experiments, **2)** Design of climate modelling experiments to provide optimal use of resources and improve relevance to decision makers and **3)** In general, a more focused collaboration with decision-makers in order to investigate how climate models can be of most practical use. By working with the end-users of climate model output climate scientists can improve the relevance and communication of results and ensure their work has the most long-term impact on important decisions. Such a collaboration between the providers and users of climate science would be helped by the methods presented in this Thesis for evaluating uncertainties and an honest interpretation of the robustness of model output.

### 9.4.1 Transient Experiments

A key extension of this work is to check how robust key results are when looked at under different model structures and in the case of transient simulations. It is expected that some of the results presented in this Thesis are features of the HadSM3 model and that other models will behave differently. Since there are no other PPEs of similar size to the *climateprediction.net* experiment, many of the methods used in this Thesis are not currently possible for other structural models. For example, it

is not possible to look at the magnitude of ICU without large ICEs. Small ensemble size is problematic for a complete evaluation of model uncertainties.

An alternative CPDN experiment that uses transient forcings could be a more fruitful source of data. This new experiment, that uses the HadCM3 model with transient increases in GHGs to simulate climate from 1920–2080 using a perturbed physics grand ensemble. At the time of writing over 20,000 simulations had been completed in this transient experiment. The transient experiment allows further evaluation methods to be used since model time series can be compared to observations. In the CPDN equilibrium experiment, it was not possible to compare time series due to the experimental design. Comparing model output to observations will allow for improved understanding of the dynamics of the HadCM3 model. Of particular relevance is the concept of shadowing Daron & Stainforth (2008); Gilmour (1999); Judd (2008b); Sauer *et al.* (1997). Whilst different definitions exist, a model can be said to shadow noisy observations if it stays close to the noisy observations for a period amount of time. The ability of a model to shadow to within at least a useful degree of precision (this is known as  $\phi$ -shadowing Smith (2001)) is an important guide to its ability to match the dynamics of the underlying system. Other methods can be used, based on likelihood and probabilistic measures of model skill. Measures of model performance based on the similarity between model behaviour and the observed dynamics of the Earth's climate system hold potential to inform questions on the value of model predictions. A deeper understanding of systematic model errors can also help focus model development.

Another area of research that is likely to become very useful to decision makers is an evaluation of the short term (yearly to decadal) performance of state-of-the-art climate models. There are proposals to produce more forecasts on time scales of up to 10 years using current state-of-the-art climate models Keenlyside *et al.* (2008); Troccoli & Palmer (2007). Since predictions use information in the current state of climate and its internal variability, there is reason to believe they might



prove more accurate than simulations made without this information. The results will likely depend on how well observational analyses can be translated into model space. Yearly to decadal predictions have the advantage that they can be checked against observations in the not too distant future, unlike forecasts for 2080 and beyond or equilibrium experiments. Hindcast performance and the extent of model diversity can give an idea of the likely robustness of these forecasts.

### 9.4.2 Experimental design

Climate modelling experiments have focused on understanding the climate system from a scientific viewpoint. Attention is now turning to using climate models to inform decisions on climate impacts and mitigation policy. The relevance of climate science to such decisions might be improved in a number of ways by focusing models on pragmatic decision support rather than scientific understanding<sup>1</sup>. The precise form model improvement should take will not find a unique solution since decision-makers' needs vary. Potential paths towards providing more decision-relevant model output are listed below:

1. **Models** : Developing models with emphasis on the processes of interest to decision makers. This could include turning points in the climate system, such as ice-cap melting or shutdown of the Thermohaline Circulation, adding hurricanes or increasing resolution.

In some cases, climate models are not able to provide decision makers with any useful information. This is particularly true on small length scales. In such cases, statistical models could be useful e.g. providing an estimate of the local change in precipitation for the next 5 years based on a statistical fit to local data, although statistical models will likely fail when the system undergoes a dynamical change, especially due to turning points in the climate

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<sup>1</sup>Of course, scientific understanding must precede any attempt to use models to inform decisions. What is advocated here is rather that the use of models to inform decisions requires new ways of designing experiments and interpreting results

system.

2. **Design** : Experimental design could be influenced by the requirements of decision makers e.g. if a climate modelling experiment aims to inform impact assessment, perhaps running a large set of simulations, covering a range of structural models and parameter values, for the next 10–20 years would be of most direct use for decision support. In this case, different emission scenarios will likely have little effect Cox & Stephenson (2007), leaving experimental resources to be diverted to running larger ensembles or using a model with higher grid-box resolution.
3. **Ensembles** : Running ICEs of climate models allows for a quantification of the models' internal variability and an estimate of the scale of potential model error. The typical ensemble size of 1–9 members commonly used at present is often insufficient to evaluate a model's internal variability, which can be critical from a decision-makers' point of view.
4. **Data** : Due to constraints on computational resources it is often not practical to store all the output from a climate modelling experiment. Usually only a small subset of output is stored. Climate modelling experiments could be made more relevant to decision makers by storing specific variables of interest e.g. extreme values, local impact statistics, regional time series etc. It should be considered which variables are of most interest to scientists, for model development and for decision makers. The use of metadata is an important component of storing data. With limited storage capacity and time to analyse data, it is important to find “decision-sufficient” statistics that contain all (or as much as possible) the relevant information in the data set at large. Such statistics would be sufficient in the sense of decision-makers not benefitting from any further statistics of the data set.

## 9.5 Conclusion

The problem of climate prediction and a framework for evaluating climate models has been presented in this Thesis. A systematic categorisation of uncertainties has been introduced and explored using the largest set of climate simulations to date. Original work has been highlighted at the end of each Chapter. The main new results are that **1)** The presentation of model output in high-profile reports such as the IPCC AR4 obscures important information regarding uncertainties in climate model simulations, **2)** The effect of perturbing both initial conditions can be large on length scales relevant for decision-makers and that the internal variability can account for more model diversity than has been previously acknowledged, **3)** the effect of parameter perturbation on global and regional climate response can be huge. The de-tuned HadSM3 model versions generated by the CPDN experiment show that climate models can be highly sensitive to the values of uncertain parameter values, **4)** the range of model behaviour is not easily reducible in a physically and statistically consistent way and **5)** regional responses can not be robustly inferred from global mean changes. Global mean temperature is a much less decision-relevant statistic than was usually taken to be the case.

Whilst no result has been found that casts doubt on the link between rising GHGs cause and simulated warming (in fact, in a broad sense, the CPDN experiment adds evidence to support this relationship), it has been shown that the potential predictive skill of climate models is limited. It is important that uncertainties are understood as fully as possible and are communicated effectively to decision-makers. Not to do so will likely lead to sub-optimal policy, wasted resources and a loss of confidence in climate science.

# Appendix A

## Glossary

**Adaptation** Action taken to adapt to the impacts of climate change e.g. building flood defences.

**Albedo** The proportion of solar radiation reflected from the Earth's surface. After Baede (2007).

**Analysis** In a meteorological sense, an estimate of the state of the climate system.

**Anthropogenic** Man-made or caused by man. In this thesis, “anthropogenic” relates to the effect that the human race has on the Earth's climate.

**Attractor** The equilibrium set of states to which a dynamical system evolves to after a long time. Attractors are only well-defined in the equilibrium for certain types of mathematical system; they do not exist in real world systems Orrell (2007).

**Bootstrap** A non-parametric method of re-sampling used to estimate properties of an estimator, such as confidence intervals.

**Bounding Box** The range of values spanned by an ensemble in each dimension. The bounding box is defined by the minimum and maximum points of an ensemble in each dimension Judd *et al.* (2007); Weisheimer *et al.* (2004).

**Carbon Dioxide ( $CO_2$ )** A Greenhouse gas occurring naturally and as a result of burning fossil fuels such as oil, gas and coal. Carbon dioxide is often used as a reference against which other greenhouse gases are measured. After Baede (2007).

**Chaos** A mathematical term relating to deterministic systems that exhibit properties of sensitive dependence on initial conditions, recurrence and aperiodicity. Whilst neither the climate system or GCMs are chaotic in a strict sense, they are often both treated as such since they display chaotic-like properties.

**Climate** The distribution of weather over long time scales (30 years is used by the World Meteorological Organisation).

**Climatology** The long-run distribution of historical observations. Can also refer to the study of climate in general.

**Climate Change** An alteration of the climate distribution. Climate change can occur due to a number of sources both natural and anthropogenic. In the context of this thesis, the potential effect of increasing GHGs on the climate system is studied.

**Climate Model** A mathematical representation of the Earth's climate.

**climateprediction.net (CPDN)** A distributed computing experiment, launched to the public on 12th September 2003. A grand ensemble of parametrically perturbed versions of the HadSM3 model are run on home PCs in order to evaluate uncertainties in climate predictions.

**Climate Sensitivity (CS)** A number of definitions exist in the literature. In this thesis, climate sensitivity is defined via the following thought experiment: a model is run using pre-industrial concentrations of  $CO_2$  for a long-time, so that its mean global temperature can be calculated.  $CO_2$  concentrations are then doubled and the model run for a long time. The model then reaches a

new equilibrium global mean temperature. The difference between the doubled  $CO_2$  global mean temperature and the pre-industrial  $CO_2$  global mean temperature is the model's climate sensitivity.

**Democracy Plot** A plot showing the number (or percentage) of ensemble members that simulate an increase (or decrease) in a particular variable e.g. precipitation change. Democracy plots are useful for showing to what extent an ensemble agrees on the sign of the change.

**Dynamical System** A mathematical description of a deterministic process that develops over time. Here, dynamical systems refers to a set of differential equations that display sensitive dependence on initial conditions.

**Ensemble** A set of simulations run over the same time period. There are a number of different types of ensemble that are used for quantifying different quantities. See Initial Condition Ensembles, Perturbed Physics Ensembles and Grand Ensembles for details of these types of ensemble.

**Equilibrium Experiment** A climate modelling experiment in which models are used to estimate the equilibrium (long-run) response to forcing. In some cases equilibrium is not reached by the end of the experiment and must be estimated.

**Feedbacks** Interactive mechanisms that cause a non-linear response. An initial process causes another which in turn affect the original process, or the system itself. Feedbacks can be either positive (exagerrating the base effect) or negative (dampening the effect).

**Forcing** An agent that forces a system into a new set of dynamics. The IPCC uses the term “radiative forcing” to understand the effect of forcing agents: “The radiative forcing of the surface-troposphere system due to the perturbation in or the introduction of an agent (say, a change in greenhouse gas concentra-

tions) is the change in net (down minus up) irradiance (solar plus long-wave; in  $\text{Wm}^{-2}$ ) at the tropopause AFTER allowing for stratospheric temperatures to readjust to radiative equilibrium, but with surface and tropospheric temperatures and state held fixed at the unperturbed values.” Baede (2007).

**Flux adjustment** An artificial adjustment made of the model for some physical variable such as heat, water or salt. A flux adjustment is usually calculated such that the model produces more realistic dynamics and behaves in a similar way to the Earth’s climate.

**Heat Flux Adjustment (HFA)** A flux of heat into the ocean from the atmosphere so that a slab ocean displays Sea Surface Temperature and heat transport similar to that of a dynamic ocean. This is discussed in more detail in [chapterhflux].

**General Circulation Model (GCM)** Despite some variability in the literature, state of the art climate models are referred to here as General Circulation Models. Also called Global Climate Models.

**Global Mean (Climate Model)** An average taken over the entire model state space. GCMs operate in a 3 dimensional grid system on discrete time steps. The global mean can be calculated as the volume-weighted mean over the entire Earth [this is discussed in more detail in Chapter 4. Since observations are far more heterogeneous and sporadic, they are often adjusted and filtered through a model in order to produce an estimate of the global mean. This is also known as the analysis.

**Global Mean Surface Temperature (GMST)** The global mean value of surface temperature calculated over a certain period, usually annual or decadal, using observations.

**Grand Ensemble** A set of model simulations containing two layers of perturba-

tion. At the higher level, either different structural models or the same model with different parameter values is used. At the lower level, each of these models is run using a set of different initial conditions. A grand ensemble is a collection of initial condition ensembles run using models with different dynamics.

**Greenhouse Gas (GHG)** An atmospheric gas that absorb and emit radiation at specific wavelengths. This property cases the *greenhouse effect*. Greenhouse gases include methane, water vapour and carbon dioxide. In some modelling studies, the total effect of GHGs is simplified to the equivalent concentration of  $CO_2$ . The climateprediction.net experiment investigates the effect of doubling  $CO_2$  concentrations from 275 parts per million to 550 parts per million.

**Grid box** A set of 3 dimensional points that make up a climate model.

**Initial Condition** The starting state of a model simulation at time zero. In the case of a GCM, this will be of very high dimension.

**Initial Condition Ensemble (ICE)** An ensemble of model simulations in which each run's initial condition is changed slightly. In the case of the climateprediction.net experiment, the ocean temperature in one grid box is perturbed by a small amount.

**In-sample** Data that was used to build or estimate parameters in a model. This contrasts with *out-of-sample*.

**Local** In this thesis, referring to length scales roughly equal to a model grid box i.e.  $\sim 40,000 \text{ km}^2$ .

**Mitigation** Action taken to prevent or limit climate change e.g. reducing carbon emissions.

**Mixing time** The time taken for two *initial condition ensembles* to become statistically indistinguishable.



**Model version** A copy of a standard structural model with parameter perturbation. In the case of the *climateprediction.net* experiment, the HadSM3 model structure is used throughout sometimes with its standard (original) parameter values but mostly with various parameters perturbed. The HadSM3 model with a non-standard set of parameter values is called a HadSM3 model version.

**Multi-model Ensemble** An ensemble in which more than one model is used..

**Nonlinear** Not linear. In general, nonlinear systems do not have the property of additivity ( $f(x + y) = f(x) + f(y)$ ) or homogeneity ( $f(ax) = af(x)$ ).

**Numerical Weather Prediction (NWP)** Computational modelling of the Earth's weather system. In this thesis, NWP refers to weather prediction on time scales up to two weeks.

**Observation** Meteorological measurements of the Earth's surface. Raw data is post-processed, usually using models, to obtain a uniform grid of values across the Earth.

**Out-of-sample** Data that was not available at any stage in the building or development of a model.

**Parameter** Multiple definitions exist. In climate modelling, a parameter is any non-mathematical constant (such as  $\pi$  or  $e$ ) that defines the model and as such is not state-dependent. Parameter values define the model and its behaviour, unlike initial conditions that do not affect the model's behaviour or dynamics. Parameters do not change with time.

**Parameterisation** A representation of physical processes in a climate model not explicitly simulated in the model. Parameterisations are often statistical, arising as a result of finite model resolution.

**Perturbed Physics Ensemble (PPE)** An ensemble in which simulations are run using the same structural model but using more than one set of parameter values.

**Probability** The classical definition treats probability as the relative frequency of occurrence of total number of events. Bayesians treat probabilities in a subjective fashion. In this thesis, neither approach is adopted explicit, rather it is assumed that a probability is any quantity that meets the Kolmogorov axioms of probability and is intended to be used as such.

**Probabilistic** An expression of uncertainty that resembles a probability but that does not meet all the necessary requirements. Probabilistic statements can be qualitative e.g. “It is almost certain that rising  $CO_2$  concentrations will contribute to global warming” or quantitative e.g. expressing the likelihood of events as odds that do not sum to one (break the Second Kolmogorov Axiom of probability).

**Regional** In this thesis, refers to an area relating to one of the regions as defined in Giorgi & Mearns (2000).

**Scenario** An emissions scenario used as a basis for forcings in a climate projection. Also see SRES.

**Sea Surface Temperature (SST)** The temperature close to the surface of a large body of water.

**Skillful** In the context of forecasting, a forecast is said to be skillful if it can beat some simple straw-men that are tantamount to guessing.

**Special Report on Emissions Scenarios** Emissions scenarios first developed by Nakicenovic *et al.* (2000) to be used as a basis for climate projections. These scenarios are based on story lines that follow particular demographic, societal, economic and technical changes.

**Straw-man** A naïve test for quality of information. Straw-men for forecast skill can include simple statistical techniques such as persistence or climatology.

**Trajectory** The time-ordered path of states taken by a simulation of a dynamical system.

**Transient Experiment** A climate modelling experiment run using time-varying forcings, usually as a simulation of Earth's climate system.

**Verification** The target values for a model. Not necessarily verifying the model itself Oreskes *et al.* (1994) but targets that we would like the model to get close to, in some sense. In perfect model experiments verifications are the values from the a model simulation itself. In the case of climate models, that are imperfect, observations of the Earth's climate can be used as verifications.

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