CHAPTER SIX

CLIMATE CHANGE PROJECTION METHODS

MACQUARIE RIVER, TASMANIA, ISTOCK

CHAPTER 6 CLIMATE CHANGE PROJECTION METHODS

The Australian climate change projections are based on the full body of knowledge of the climate system and the most up to date view of how the current climate may change under enhanced greenhouse gas emissions. This view of future climate is informed by sophisticated global climate models, simulating the climate response to a range of plausible scenarios of how greenhouse gases and aerosols may change throughout the 21st century. This chapter outlines the methods for producing projections and accompanying confidence ratings. Note that methods unique to the marine projections will be covered where those projections are presented in Chapter 8.

The key sources of uncertainties in climate change data from global climate models are discussed in Section 6.1, followed by a description of the method used to summarise their outputs (Section 6.2). An outline of downscaling and how it is used to provide additional and complementary insights to global climate model simulations is described in Section 6.3. The final section describes how model evaluation, process understanding, attribution of observed trends and consistency with simulated recent changes, and downscaled projections are used to derive confidence statements for climate change projections. These confidence statements give guidance about the robustness of the projections, and act to support users when implementing these projections in further analysis, impact assessment and adaptation planning.

6.1 LIMITATIONS AND UNCERTAINTIES IN CLIMATE CHANGE DATA

6.1.1 SOURCES OF UNCERTAINTY

Uncertainties in regional climate change projections can be grouped into three main categories: scenario uncertainty, due to the uncertain future emissions and concentrations of greenhouse gases and aerosols; response uncertainty, resulting from limitations in our understanding of the climate system and its representation in climate models; and natural variability uncertainty, the uncertainty stemming from unperturbed variability in the climate system. Figure 6.1.1 illustrates the relative contributions of these three broad sources of uncertainty to regional climate projections as estimated from 28 CMIP5 simulations for two variables, mean temperature and rainfall in winter (Hawkins and Sutton, 2009). The plot shows the contribution to uncertainty for a projection of decadal mean climate for different times in the future. Please note that the relative contributions also depend on the climatic variable, spatio-temporal aggregation and location (see discussion below).

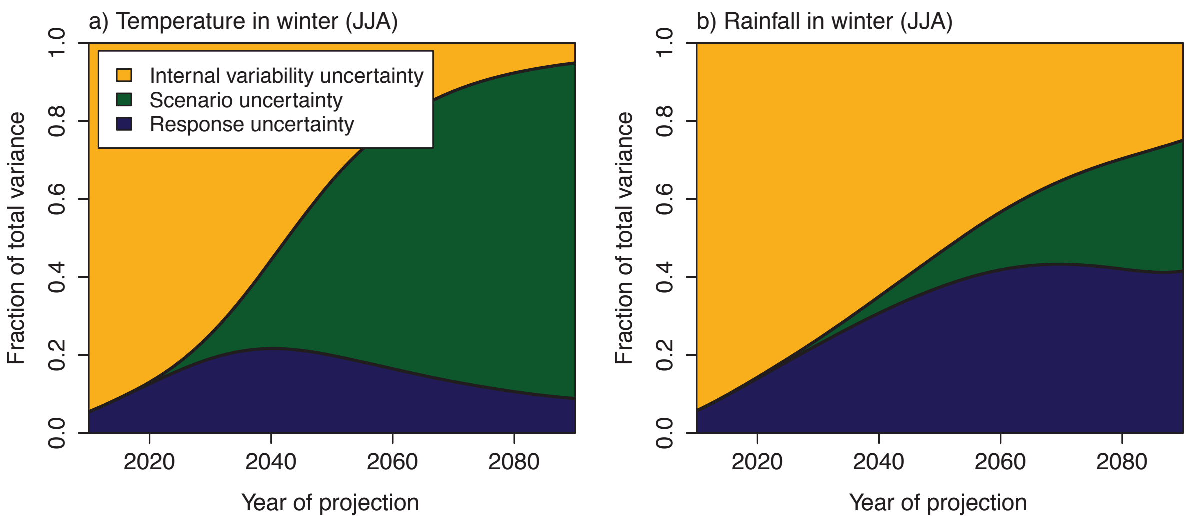

FIGURE 6.1.1: FRACTIONAL CONTRIBUTION OF INTERNAL VARIABILITY (ORANGE), SCENARIO (GREEN), AND RESPONSE UNCERTAINTY (BLUE) TO TOTAL UNCERTAINTY IN PROJECTED CHANGE IN TEMPERATURE (A) AND PRECIPITATION (B) IN SOUTHERN AUSTRALIA IN WINTER (JJA) BASED ON 28 CMIP5 MODELS (PRODUCED USING THE METHODS OF HAWKINS AND SUTTON, 2009).

Scenario uncertainty results from the range of possible, but also unknown, future concentrations of greenhouse gases and aerosols in the atmosphere, due to emission rates by human activities, and their complex interactions with the biosphere and hydrosphere. This source of uncertainty is commonly characterised by simulating the climate change response to a range of concentration scenarios that encompass different possible futures. In these projections, scenario uncertainty is considered through the use of Representative Concentrations Pathways (RCPs, see also Section 3.2). Each of the RCPs considered here represent a different pathway of greenhouse gas concentrations and associated enhanced greenhouse effect, but all are treated as plausible. Up to around 2030, greenhouse gas concentrations in the various RCPs differ only marginally and therefore scenario uncertainty is small. Its relative contribution to the total uncertainty increases over the future decades, becoming the dominant source of uncertainty for temperature by the end of the 21st century (green shading in Figure 6.1.1).

Response uncertainty results from limitations in our understanding of the climate system, our ability to simulate it and how it may evolve under different RCPs. While climate models are all based on the same physical laws, they have different configurations and use somewhat different components and parameterisations, which lead to differences in their simulation of climate feedbacks and in long-term changes (also see Section 3.2 and 3.3). The largest differences between models are from cloud feedbacks and the impact of aerosols on clouds and precipitation (Myhre *et al*. 2013), oceanic heat uptake (Kuhlbrodt and Gregory, 2012) and carbon cycle feedbacks (Friedlingstein *et al*. 2014). Further, uncertainty in future changes in the Greenland and Antarctic ice sheets is particularly important for sea level projections (Church *et al*. 2011b). We estimate response uncertainty from examining the range of climate simulations from global climate models with different, but equally acceptable, model configurations for a given RCP. While response uncertainty increases over the 21st century its relative contribution to total uncertainty generally peaks or plateaus around the middle of the century (blue shading in Figure 6.1.1).

Projected change in mean climate will be superimposed on natural climate variability. Natural variability uncertainty stems both from internal climate variability (*e.g.* the state of ENSO, see also Section 3.1.1) and natural external forcing mechanisms including future volcanic eruptions and changes in incoming solar radiation. Natural forcing mechanisms such as volcanic eruptions are typically not predictable into the future and are not included in simulations of the future so their contribution to the total projection uncertainty is not quantified in this Report. Similarly, internal variability (*e.g.* the timing of El Niño events) cannot be predicted beyond a few months into the future. Model simulations do include these sources of natural variability, but their timing is not tied to those in observations. Instead, natural internal variability contributes to the total projection uncertainty and we quantify and display its contribution. This internal variability uncertainty is estimated from model experiments with varying initial conditions to reflect the range of possible future combinations of forced change and internal variability (see also Section 6.2). The relative importance of internal variability uncertainty generally decreases with time, as response and scenario uncertainty increase (Figure 6.1.1, orange shading). However, the relative contribution of internal variability uncertainty strongly depends on the location, on the spatio-temporal aggregation, and on the climatic variable analysed. In particular, internal variability uncertainty is generally larger at smaller spatial scales and for shorter averaging periods. Consequently, for regional climate change and variables with pronounced internal variability such as rainfall, internal variability uncertainty is always the largest source of uncertainty from one year to the next and can remain an important source of uncertainty for the long-term change (*e.g.* 10-year average) even at the end of the 21st century (Figure 6.1.1b).

6.1.2 INTERPRETATION OF RANGES OF CHANGE IN PROJECTIONS

In this Report, ranges of projected climate change for a given RCP are reported to indicate the range of plausible future outcomes. It is important to note, however, that not all sources of uncertainty are captured in the CMIP5 ensemble, and the ensemble does not sample *response uncertainty* in a systematic way (Parker, 2013). Also, climate change projections are made for late in the century, for unobserved (novel) states of the atmosphere, which means that it is not possible to demonstrate their reliability. The ranges of change reported in this Report therefore do not relate directly to the probability of the real world changing under a given RCP. Rather, the projected range of change from model simulations can often give an indication of a lower bound of uncertainty, as not all sources of uncertainty are quantified. However, in some particular cases where certain aspects of *response uncertainty* are uncertain the range of model changes may be larger than the physically plausible range of change. Additional lines of evidence, including model evaluation (Chapter 5) and processes driving change are used to assess the confidence in the model range, as a guide to future change for a given scenario (Section 6.4).

6.2 REGIONAL PROJECTION METHODS

6.2.1 OVERVIEW AND COMPARISON OF EXISTING REGIONAL PROJECTION METHODS

Climate projections are typically based on the output of climate models combined with knowledge about climate processes that help to contextualise and supplement the climate model outputs. Combining several model simulations into a model ensemble allows for an assessment of uncertainty (as outlined in previous section). However, several approaches exist to convert an ensemble of model simulations into climate change projections; some using model selection/weighting (based on model evaluation against observations) in an attempt to produce more 'reliable' projections. Many recent studies based on CMIP3 models have attempted to reduce uncertainty in projected climate change in Australia by only focusing on the better performing models (Charles *et al*. 2007, Perkins *et al*. 2007, Suppiah *et al*. 2007, Maxino *et al*. 2008, Moise and Hudson, 2008, Watterson, 2008, Chiew *et al*. 2009b, Grose *et al*. 2010, Kirono and Kent, 2011, Smith and Chandler, 2010, Vaze *et al*. 2011). There is an assumption that the better performing models will give a narrower and more plausible range of projected change than the entire ensemble. However, there is considerable disagreement regarding the relative merits of the various models (Chiew *et al*. 2009b, Smith and Chandler, 2010), making it difficult to justify a reduced set (Vaze *et al*. 2011).

There are some cases where researchers have selected a set of strong performing CMIP3 models based on a particular evaluation metric, with the range of uncertainty in projections narrowed in a potentially robust way. For example, Perkins *et al*. (2009) found less warming of extreme temperatures in models with stronger skill. However, sometimes different preferred models can provide opposing signals of climate change, *e.g.* where Smith and Chandler (2010) found a tendency for stronger rainfall decrease in the Murray-Darling Basin in better performing models, but Cai *et al*. (2011) and Pitman and Perkins (2008) found tendencies for increase when using a different set of preferred models. Other studies demonstrate cases where model selection had limited impact on the range of projected changes (Chiew *et al*. 2009b, Kirono and Kent, 2011).

An alternative to picking the best few models is to reject the models that have particularly poor performance. There is, for example, some agreement on a small set of CMIP3 models with consistently poor performance across a range of studies and metrics (Smith and Chandler, 2010, Cai *et al*. 2011, Frederiksen *et al*. 2011, Vaze *et al*. 2011). For CMIP5, some poor-performing models have been identified for Australia (Chapter 5).

For Australia, we can consider the impact on projections when excluding models identified as poor performers (Table 5.6.1 of Chapter 5). Figure 6.2.1 illustrates the effect for rainfall projections for the four large super-clusters.

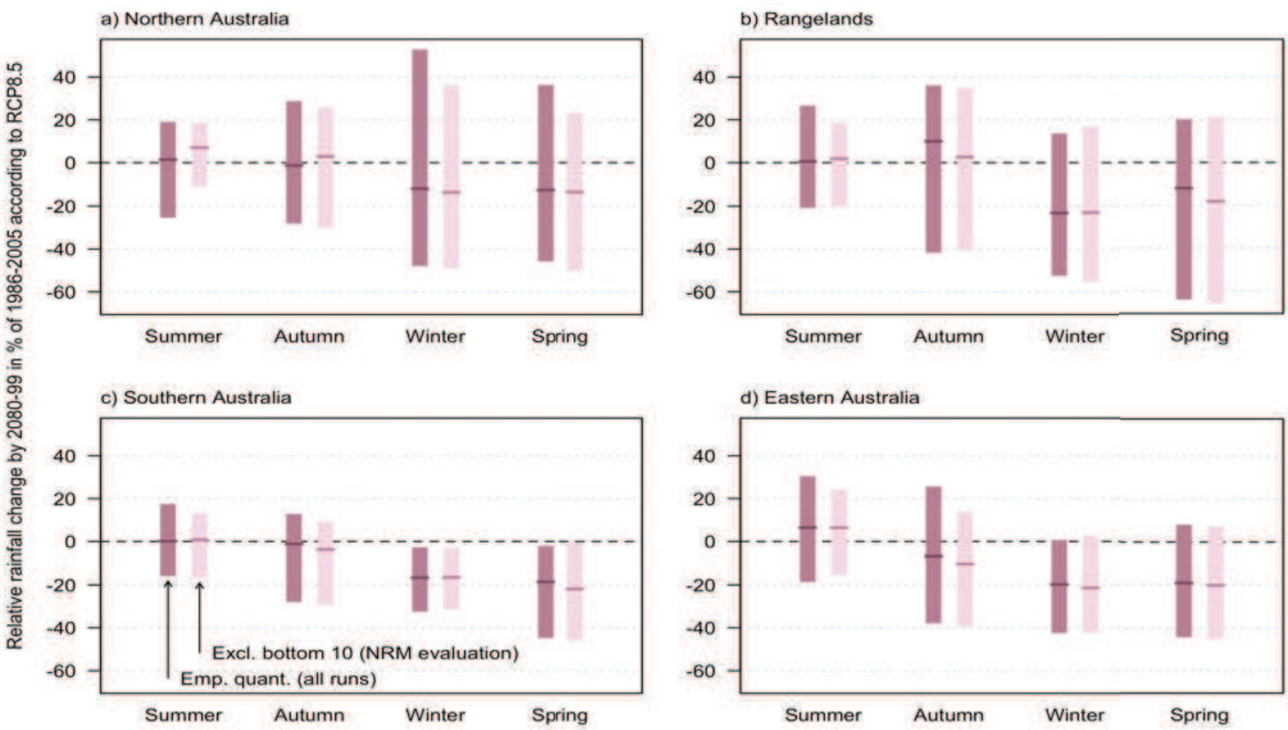

FIGURE 6.2.1: COMPARISON OF PROJECTED SEASONAL RAINFALL CHANGES ACCORDING TO RCP8.5 FOR FOUR SUPER-CLUSTERS IN AUSTRALIA WITH THE EMPIRICAL QUANTILES (EMP. QUANT.) OF THE FULL SET OF CMIP5 GCMS (DARK SHADED BARS) AND THE SUBSET EXCLUDING THE 10 MODELS THAT SCORE LOW ON A VARIETY OF EVALUATION METRICS IDENTIFIED IN CHAPTER 5 (LIGHT SHADED BARS).

Projections using the empirical quantiles (median and percentiles of the model range) of the full set of CMIP5 models are compared with projections from the better performing models (10 models being excluded due to low scores on at least 3 different evaluation metrics; no projections data are available for CESM1-WACCM) (Fig. 6.2.1). Noteworthy differences are a somewhat reduced occurrence of strong rainfall increases in summer and autumn in Eastern Australia (and to a lesser extent in Southern Australia), and less evidence for strong summer drying in Northern Australia in the reduced set of models.

However, overall differences between projections, including and excluding low-scoring models, are slight in most regions and seasons. Perhaps most importantly, selecting a subset of better performing models in this instance did not provide more clarity on the direction of the expected rainfall response.

In addition, performance-based weighting of models in regional projections has been widely used (Christensen *et al*. 2010). In many cases, however, performance in the current climate and future projections are only

BOX 6.2.1: THE EFFECT OF DIFFERENT PROJECTION METHODS

Projections can be generated using several different methods. Figure B6.2.2 demonstrates the effects of some of these methods, namely that of:

1. Spatial resolution: projections in some regions depend on the spatial resolution of the climate models. This applies in particular to the smaller regions with complex terrain, such as Tasmania, for which coarse resolution GCMs cannot represent potential small-scale differences in the climate change signal. The importance of spatial resolution is further analysed in this Report using downscaled data (see Section 6.3).
2. Selecting the 'best' models: selecting a subset of 'best' models can have an impact on regional climate change projections, but the effect strongly depends on the metric and feature used to evaluate the models (see also Figure 6.2.1). For example, the 10 models that best represent the average rainfall, surface temperature and mean sea level pressure in Australia (Watterson *et al*. 2013a) indicate stronger drying for southern Australia, whereas the 10 models that best represent important modes of circulation variability in the southern hemisphere (Grainger *et al*. 2013, 2014) indicate less drying.
3. Constrained by observations: the effect of using observations (climatology or trends) as constraints is mostly small at the regional scale or is dependent on the specifics of the weighting method used.

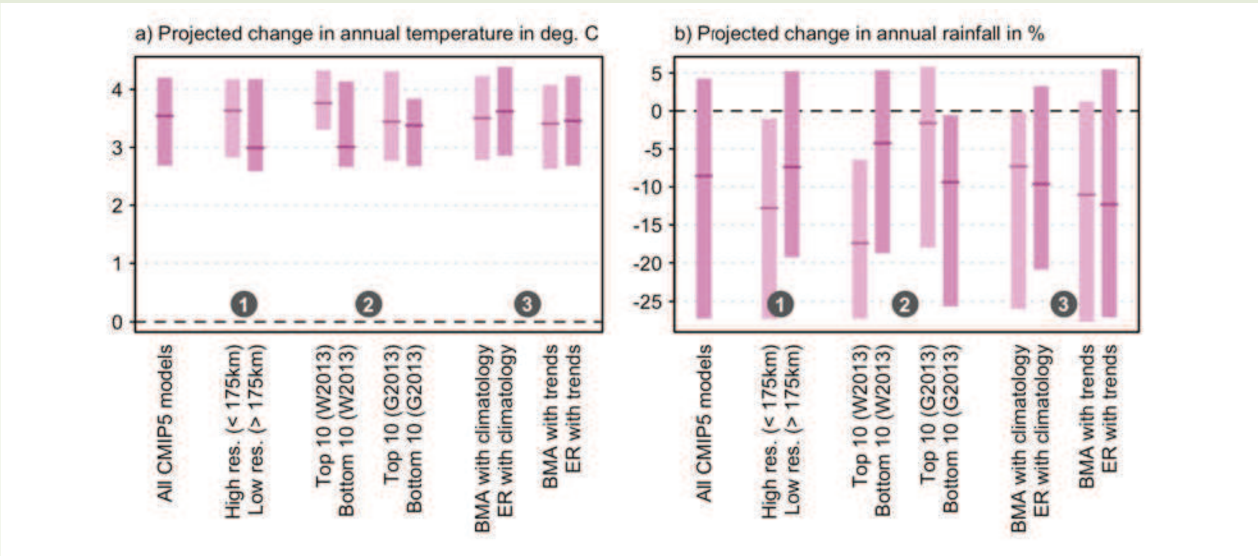

FIGURE B6.2.2: COMPARISON OF DIFFERENT METHODS TO PRODUCE PROJECTED CHANGES IN SOUTHERN AUSTRALIAN (A) ANNUAL TEMPERATURE AND (B) ANNUAL RAINFALL FOR 2080-99 WITH RESPECT TO 1986-2005 ACCORDING TO THE HIGHEST EMISSION SCENARIO (RCP8.5). FROM LEFT TO RIGHT THE PROJECTIONS USE ALL CMIP5 MODELS, HIGH- AND LOW-RESOLUTION MODELS ONLY, THE 10 TOP AND BOTTOM SCORING MODELS ACCORDING TO AN EVALUATION OF WATTERSON *ET AL*. (2013, DENOTED W2013) AND AFTER GRAINGER *ET AL*. (2013, DENOTED G2013), AND WEIGHTED BY HOW CLOSELY THE MODELS REPRESENT THE ANNUAL TEMPERATURE AND RAINFALL CLIMATOLOGY AND RECENT TRENDS FROM 1956-2005 RESPECTIVELY. IN THE LATTER CASES, TWO DIFFERENT WEIGHTING SCHEMES HAVE BEEN USED NAMELY BAYESIAN MODEL AVERAGING (BMA: MIN *ET AL*. 2007) AND ENSEMBLE REGRESSION (ER: BRACEGIRDLE AND STEPHENSON, 2012).

-20° -10° 0° 10° 20° 30° 40° 50°

weakly related (Knutti *et al*. 2010), and therefore using performance-based weights will have little effect on projections. Using non-optimal weights is more often than not worse than not weighting models at all (Weigel *et al*. 2010).

Against this background, a number of scientists are taking the view that using the full range of available models, rather than a performance-based selection or weighting, is the most appropriate course of action for regional applications (Chiew *et al*. 2009b, Kirono *et al*. 2011a). Model evaluation results, however, may influence the choice of individual models in some applications (Chapter 9).

Attempts have been made to infer a probability distribution of future climate change from projections of multiple models. Such probabilistic projections for Australia have been prepared using the 'Reliability Ensemble Averaging' (REA) approach (Moise and Hudson, 2008) and using a fitted Beta-distribution (Watterson, 2008, Watterson and Whetton, 2013), where Watterson's approach (Section 6.2.3) was used in *Climate Change in Australia* 2007 (CSIRO and BOM, 2007). Other approaches have been used to produce regional probabilistic projections elsewhere. These include fully probabilistic statistical models used to interpret the diversity of projected changes in multi-model ensembles, such as CMIP3 and CMIP5 (Tebaldi *et al*. 2005, Buser *et al*. 2009, Smith *et al*. 2009, Chandler, 2013). Indeed the growing number of methods to produce probabilistic projections reflects the lack of consensus on how best to interpret diversity in model results (Parker, 2013).

In the absence of clear guidance on how best to form probabilistic projections from multiple climate models, and because the effect of different projection methods is generally small (Box 6.2.1), we adopt a simple method to produce the projections presented in this Report. The specific choices and details are discussed in the following section. In the interest of comparing model results using the CMIP3 and CMIP5 models across Australia, the method used to generate the 2007 projections (based on the CMIP3 models) is further applied to the CMIP5 dataset (Section 6.2.3).

6.2.2 PROJECTION METHODS USED IN THIS REPORT

Climate refers to the statistics of weather and therefore long-term averages are often used to characterise climate for a specific period and location. In this Report, 20-year averages of CMIP5 outputs are used to characterise change in the future climate.

The model-based projections are generally presented as the model ensemble median (50th percentile) and the 10th to 90th percentile range (see Box 6.2.2). That is, less than 10 per cent of the models project changes that are smaller than the lower bound (10th percentile) and less than 10 per cent project changes that are larger than the upper bound (90th percentile). The median projected change (50th percentile) is the middle value of the simulated changes with half the models showing changes larger/smaller than the median.

In accordance with results reported in the latest Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2013), the primary reference period used in this Report is 1986-2005. This period is used to demonstrate change in bar charts, maps, and tables; note that this is different from the 1980-1999 period used in *Climate Change in Australia* 2007 (CSIRO and BOM, 2007). The more recent period is chosen partly because this period has more comprehensive observational data sets (aided by satellite measurements), which is important as the CMIP5 models are run with observed forcings as opposed to forcings based on different RCPs from 2005 onwards. It is important to note, however, that natural internal variability does not fully average out in 20-year averages, as some sources of natural variability manifest on time scales greater than 20 years. This has to be taken into account when relating simulations (or projected change) to recent observations.

The time series plots, however, use a different reference period, 1950-2005. The selection of a different reference period is due to technical reasons in producing a visually representative time series plot where simulations of the historical and future time periods are merged into one long series. The use of a longer reference period more

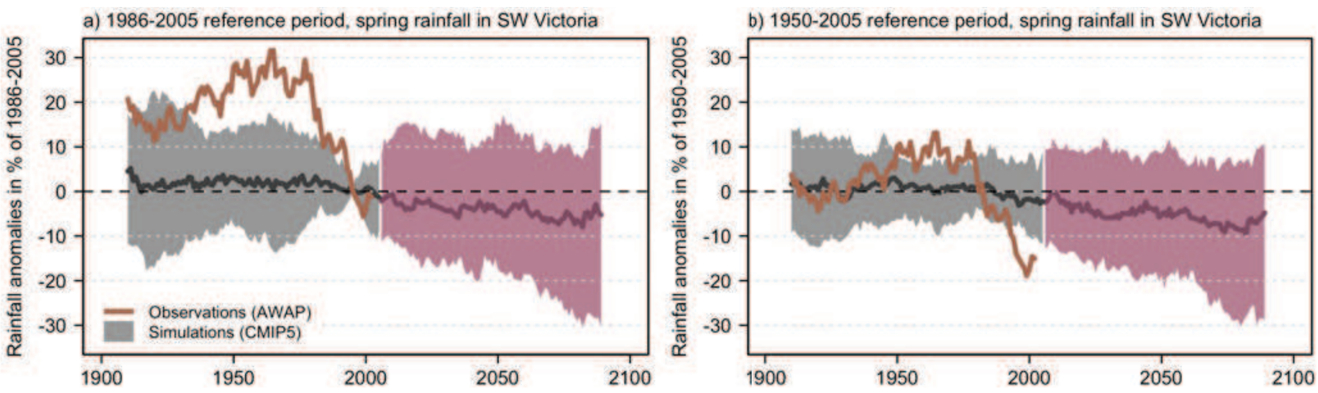

FIGURE 6.2.3 THE EFFECT OF USING DIFFERENT REFERENCE PERIODS WHEN RELATING SIMULATED AND OBSERVED CLIMATE TIME SERIES ILLUSTRATED WITH SPRING (MAM) RAINFALL IN SOUTH-WESTERN VICTORIA (SSVW). 20-YEAR AVERAGES OF SIMULATED AND OBSERVED RELATIVE ANOMALIES IN PER CENT OF THE 1986-2005 MEAN (A) AND OF THE 1950-2005 MEAN (B) ARE SHOWN. SHADING INDICATES THE 10TH TO 90TH PERCENTILE RANGE OF THE CMIP5 SIMULATIONS, THE SOLID LINE INDICATES THE MEDIAN.

truthfully reflects our scientific understanding how these periods relate to each other. For example, the longer reference period is particularly important in cases when natural internal variability leads to a large deviation of the 1986-2005 mean from the 'underlying' (but unknown) climate (*e.g.* spring rainfall in western Victoria as shown in Figure 6.2.3). In this situation, the observations may appear to lie outside the simulated range for most of the 20th century with a 1986-2005 reference period, whereas adopting a long reference period highlights the anomaly of the recent past with respect to the long-term mean. The change to a longer reference period is also necessary to avoid the false impression that the climate in 1986-2005 is known exactly and thereby much more certain than the climate in 20-year periods earlier in the 20th century (Figure 6.2.3). As a consequence of the different reference periods, quantitative changes in time series plots differ slightly from the corresponding changes reported in tables and bar plots. This difference illustrates the influence of the choice of reference period in climate change projections.

WEIGHTING OF CLIMATE MODELS

Since there is no strong evidence to weight models, the possible detrimental effects of weighting and the small impact of model rejection (see above), we do not weight or exclude models.

NATURAL INTERNAL VARIABILITY

Projected regional warming has been shown to differ considerably across simulations when using different initial conditions (Deser *et al*. 2012a, b). Hence, natural internal variability is an important contributor to the spread of projected climate change (see also Figure 6.1.1). The contribution of natural internal variability is illustrated in this Report by showing the range (10th to 90th percentile) of changes due to natural internal variability only (*e.g.* right-hand panel in Figure B6.2.4). This range is estimated from the spread of simulations for the 2080–99 time period using different initial conditions (*i.e.* simulations that differ only in their state of internal variability). All available simulations are used to estimate projected change. Some models provided multiple simulations, each with different initial conditions and a distinct natural variability. To ensure that models get equal weight in the final projection, individual simulations of the same model are weighted with the inverse of the number of simulations.

MAPS OF PROJECTED CLIMATE CHANGE

Chapter 7 also uses maps, showing the 10th, 50th, and 90th percentile of projected climate change. Instead of using empirical quantiles, the method based on pattern scaling used in *Climate Change in Australia* 2007 (CSIRO and BOM, 2007) has been adopted to illustrate the spatial pattern in projected climate change (Watterson, 2008). The two different approaches are compared in the following section.

6.2.3 COMPARISON WITH CLIMATE CHANGE IN AUSTRALIA 2007

The *Climate Change in Australia* 2007 (CSIRO and BOM, 2007) approach for generating probability density functions (PDFs) for climate change relies on 'pattern scaling' based on the assumption that the local change (on the scale resolved by the GCMs) is proportional to the amount of global warming. To represent uncertainty, a PDF for both the global warming (for each scenario and time in the future) and the local sensitivity to the warming (for each variable) is derived. The PDF for the global warming is derived from RCP8.5 simulations over the 21st century; consistent with the *Fifth Assessment Report*'s assessment for global warming, as noted in Section 3.6. The local PDF is derived by regression of values of the variable against the global mean temperature, using yearly data from the RCP8.5 simulation for CMIP5 (or scenario A1B for CMIP3). For consistency with the 2007 report, the overall skill scores for Australia presented in Table 5.2.2 are used as model weights using the baseline period 1986-2005 for both CMIP3 and CMIP5 projections. This provides a 'change per degree' field for each model, variable, season, and grid cell, which is then interpolated to a common 1-degree grid over Australia. The product of the global and local PDFs gives the combined PDF for the forced local change from which percentile changes are estimated.

The pattern scaling approach has been further developed by Watterson and Whetton (2011) to include the contribution of natural decadal variability to the forced signal, and by Watterson and Whetton (2013) to allow for a time series representation of forced and random components matched to a long-term observed series. This is illustrated for the case of eastern Victorian temperature, shown in Figure 6.2.5b. It can be compared to the equivalent time series for the Southern Slopes Victoria East (SSVE) cluster in (a), derived using the present method (described in Box 6.2.2) from GCM simulated change. The span in (b) for the forced or underlying climate is similar to the shaded band in (a), and in this respect the PDFs provide similar results. Differences may indicate local effects of aerosols (included in (a) but not (b) as the PDFs are scaled from the long-term forced change) or limitations to the pattern-scaling theory. In this case the CMIP5 models are well calibrated in that each observed series falls within the 10th to 90th percentile ranges approximately 80 per cent of the time. In (b), an indication of how the observed series may link to the future span is provided, and a similar inference could be made in (a).

BOX 6.2.2: PRESENTATION OF PROJECTED AREA-AVERAGE CHANGES

Time series plots and bar plots both illustrate projected climate change and how the simulated change relates to the current climate. The following paragraphs explain how to interpret each of the two plot types.

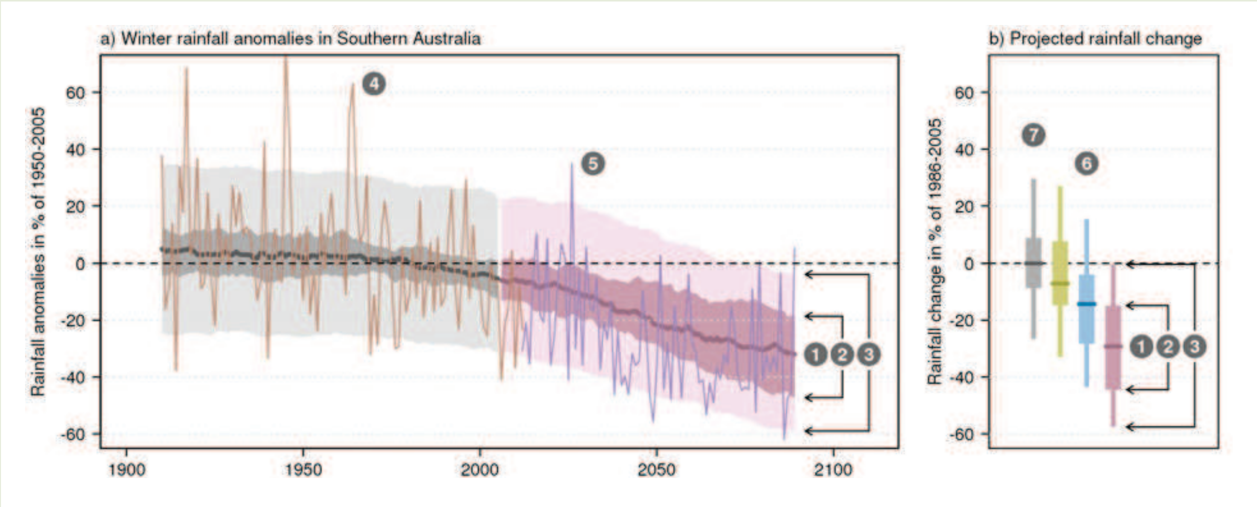

FIGURE B6.2.4: TIME SERIES OF OBSERVED AND SIMULATED CHANGE (A) AND PROJECTED CHANGE ACCORDING TO DIFFERENT SCENARIOS (B) FOR WINTER (JJA) RAINFALL IN SOUTHERN AUSTRALIA. PLEASE NOTE THE DIFFERENT REFERENCE PERIODS USED IN A AND B (SEE DISCUSSION IN SECTION 6.2.2). FOR EXPLANATIONS REGARDING THE KEY ELEMENTS SEE TEXT BELOW.

Time series plots: the range of model results is summarised using the median (1) and 10th to 90th percentile range of the projected change (2) in all available CMIP5 simulations. The change in mean climate is shown as 20-year moving averages (Figure B6.2.4a). Dark shading (2) indicates the 10th to 90th percentile range for 20-year averages, while light shading (3) indicates change in the 10th to 90th percentile for individual years. Where available, an observed time series (4) is overlaid to enable comparison between observed variability and simulated model spread. When CMIP5 simulations reliably capture the observed variability, the overlaid observations should fall outside the light-shaded range in about 20 per cent of the years. To illustrate one possible future time series and the role of year to year variability, the time series of one model simulation is superimposed onto the band representing the model spread (5). Note 20-year running average series is plotted only from 1910 to 2090.

Bar plots: similar to time series plots, bar plots also summarise model results using the median (1) and 10th to 90th percentile range of the projected change (2) in all available CMIP5 simulations. The extent of bars (2) indicates the 10th to 90th percentile range for difference in 20-year averages (reference period to a future period), while line segments (3) indicate change in the 20-year average of the 10th and 90th percentile, as calculated from individual years. The projection bar plots enable comparison of model responses to different RCPs (6), where RCP2.6 is green, RCP4.5 is blue and RCP8.5 is purple (Figure B6.2.4b). The range of natural internal variability without changes in the concentration of atmospheric greenhouse gases and aerosols as prescribed by the RCP scenarios (see Section 6.2.2) is shown in grey (7). This range is estimated from the spread in projections for the period 2080-99 amongst simulations differing only in their initial conditions. In the above case, the median projection in all RCPs is for a decrease in winter rainfall. The models agree well on the magnitude of the decrease and therefore the spread in projected changes (coloured bars) is only slightly larger than due to natural internal variability alone (grey bar). In cases where the models do not agree on the magnitude and/or sign of the projected change, the range of projections is much larger than that due to natural internal variability.

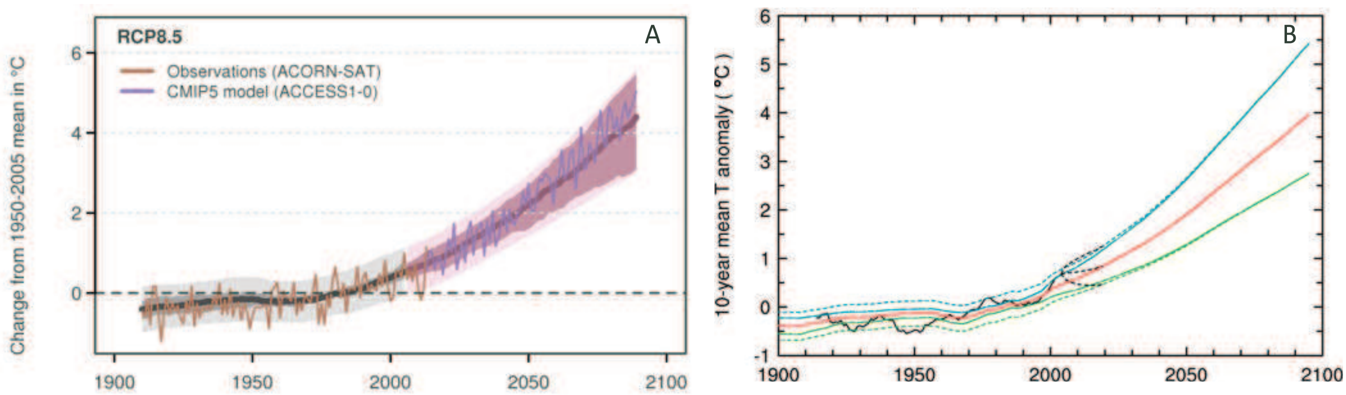

FIGURE 6.2.5: ANNUAL TEMPERATURE CHANGE FOR SSVE SHOWN AS TIME SERIES BASED ON THE PROJECTION METHOD FOR TIME SERIES USED IN THIS REPORT (A) AND THE PROJECTION METHOD USED IN *CLIMATE CHANGE IN AUSTRALIA* 2007 (CSIRO AND BOM, 2007). THE DARK SHADED AREA IN (A) INDICATES THE 10TH TO 90TH PERCENTILE RANGE OF MOVING 20-YEAR AVERAGES, THE SOLID LINE IS THE MEDIAN OF THE CMIP5 SIMULATIONS. OVERLAID ARE THE OBSERVATIONAL SERIES AND MODELLED SERIES (AS IN BOX 6.2.2). THE BLACK LINE IN (B) IS THE DECADAL MEAN OBSERVED VALUES FOR EASTERN VICTORIA. THE OTHER SOLID LINES ARE THE 10TH, 50TH (MEDIAN) AND 90TH PERCENTILE SERIES FOR THE 'UNDERLYING' CLIMATE, BOTH IN THE PAST AND INTO THE FUTURE, AS FORCED BY RCP85, AND USING CMIP5 SENSITIVITY RANGES. THE DASHED LINES SHOW THE CORRESPONDING RANGE WHEN TAKING INTO ACCOUNT NATURAL INTERNAL VARIABILITY OF DECADAL MEANS IN ADDITION TO FORCED CHANGES.

Under pattern scaling, the projected changes for a specific time depend on the global warming and hence the RCP. In CSIRO and BOM, (2007), projections were given for forced change in 2030, 2050 and 2070, under the SRES scenarios. This Report uses mainly the periods 2020-2039 and 2080-2099, under the RCPs (estimates for other times will be available from the corresponding website, see Chapter 9). There is also a six-year difference in the base period (the 2007 projections using the 1980-1999 period). Typically, a later base period results in a slightly smaller projected change (see Figure 6.2.5). As a result of these various differences, the 2007 projections cannot be directly compared with those presented here. However, with regard to the response to global warming, scaling allows a comparison of the Australian projections based on the CMIP3 and CMIP5 ensembles under a common global warming case, as described further in Appendix A.

6.3 DOWNSCALING

This section gives a brief introduction to methods of downscaling, their advantages and limitations, how these methods are used in the report, where in Australia downscaling might provide most additional insight to complement global climate model (GCM) projections, and advice on availability of downscaled datasets in Australia. For more information about downscaling principles and practice, there are several useful reviews (Giorgi and Mearns, 1999, Wang *et al*. 2004b, Fowler and Wilby, 2007, Foley, 2010, Maraun *et al*. 2010, Rummukainen, 2010, Feser *et al*. 2011, Paeth and Mannig, 2013), and guidance material on selection and evaluation of downscaling methods for impact and adaptation planning is given in Ekström *et al*. (accepted).

6.3.1 WHAT IS DOWNSCALING?

Downscaling as it is applied here is the process by which GCM outputs, with a typical spatial resolution of 100-200 km, are translated into finer resolution climate change projections. There are a number of reasons for downscaling, the most common ones being:

- GCMs may not be able to adequately represent the current climate of a particular region, or the change to the regional climate (*e.g.* because landscape features or weather systems are not well represented by GCMs),
- there may be an interest in studying potential impacts on atmospheric processes that are not well resolved by GCMs (*e.g.* convective storms),
- because of a desire for climate change projections with greater detail and fine spatial resolution in impact assessments, guidance for decision making or adaptive planning.

There are many different ways in which GCM outputs can be translated to finer resolutions or even point locations. Some methods are nearly as complex as the GCMs themselves, while others merely involve adding the mean change, as given by the GCM, to observed data. As a general guide, downscaling methods can typically be categorised into three groups: *dynamical downscaling, statistical downscaling* and *change factor methods*. Dynamical downscaling means running a dynamical model also known as a Regional Climate Model (RCM) using output from a GCM as input, and statistical downscaling is doing the same but with a statistical model. Change factor methods are techniques of combining the change signal from GCM outputs with observed datasets and are therefore a simple form of downscaling.

Dynamical and statistical downscaling produce a projection with new information in the simulation of climate processes and the pattern of climate change (termed the climate change 'signal'). Change factor methods don't produce new information in the climate change signal (so don't meet the somewhat stricter definition of downscaling). Downscaling will almost certainly create datasets that more closely match observations at the local scale (what we term *climate realism*). Depending on the method used, the downscaling method may also produce new information in the climate change signal that is more physically plausible than the host GCM (what we term *physically plausible change*) (Ekström *et al*. submitted). While *climate realism* is important in terms of practical applicability, *physically plausible change* is the crucial requirement for credible projections (Figure 6.3.1). Note, high *climate realism* does not equate with ability to show *physically plausible change*.

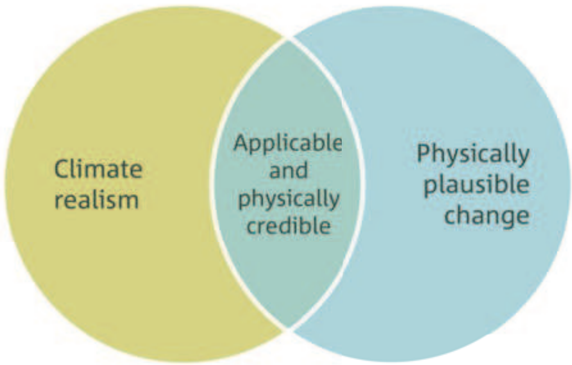

FIGURE 6.3.1: THE REALMS OF DOWNSCALING. IDEALLY, A DOWNSCALING METHOD SHOULD BE SKILFUL IN TERMS OF GENERATING DATA WITH HIGH CLIMATE REALISM AND HIGH PHYSICALLY PLAUSIBLE CHANGE, PRODUCING DATA SETS THAT ARE APPLICABLE TO REAL WORLD STUDIES AND PHYSICALLY CREDIBLE.

The merits of downscaling must be assessed in the context of what information about change is inherited from the host models (in this case, global climate models), and what is added. The degree of *climate realism* can be assessed by comparing downscaled data to observed climate characteristics, and downscaling often performs very well in this regard. However, assessing physically plausible change is more challenging and comprises an assessment of the plausibility of large-scale change inherited from the host GCM and the regional-scale change produced in the downscaling. The physical plausibility that may be added by downscaling can be broken down into approach capability and approach bias, where the former represents the theoretical ability of a particular approach to estimate certain aspects of change and the latter concerns the approach-specific bias that any particular method may exhibit due to its theoretical formulation (Ekström *et al*. accepted) (Figure 6.3.2).

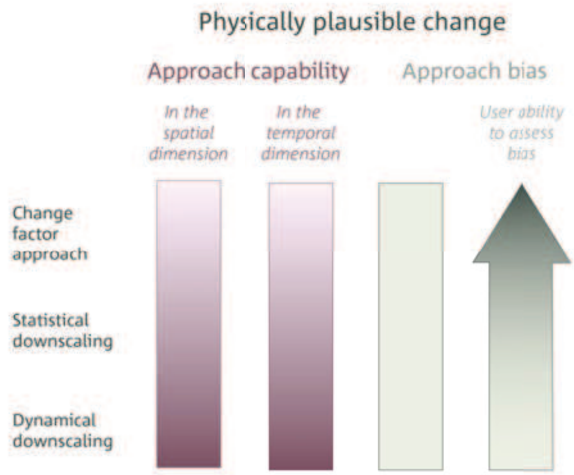

FIGURE 6.3.2: CONCEPTUAL MODEL SHOWING THE RELATIONSHIP BETWEEN DOWNSCALING APPROACHES OF DIFFERENT COMPLEXITY WITH APPROACH CAPABILITY AND APPROACH BIAS. DARKER SHADING DENOTES HIGHER CAPABILITY/ABILITY (EKSTRÖM *ET AL*. ACCEPTED).

It would be reasonable to expect increasing ability to depict physically plausible change in the spatial and temporal dimension for downscaling methods of higher complexity. Unfortunately, while more complex methods may give richer information about climate change, a user's ability to assess presence and characteristics of approach bias becomes much more difficult simply due to the vast number of ways in which data can interact with model dynamics and parameterisation schemes (a similar argument could be made for more complex statistical methods). To avoid over-reliance on any particular method and minimise exposure to potential approach biases, users of downscaling data are often asked to consider a range of different downscaling methods when possible and to give the context from the GCM projections at the scale of the intended application. The process of choosing downscaling methods is discussed further in Chapter 9.

6.3.2 COMBINING INSIGHTS FROM DOWNSCALING AND GCM PROJECTIONS

A set of GCM projections is an informal 'ensemble', and the range of results between acceptable models gives some measure of the uncertainty in the projected climate change signal (see also Section 6.2). Downscaling may reveal additional regional detail in the climate change signal, but different methods of downscaling produce different results, so in fact reveal further uncertainty within climate change projections. Also, since many forms of downscaling are computationally demanding or require specific inputs, they are often run with a limited subset of GCMs and emissions scenarios. Therefore, to fully sample the uncertainties from all available global modelling and downscaling, some systematic experimental design is required.

Such a design should use multiple downscaling methods and adequately sample emission scenarios and the range of GCM projections. This has been attempted in the upcoming set of projections in the North American Regional Climate Change Assessment Program (NARCCAP), sampling a representative set of runs from a GCM-RCM 'matrix' (Mearns *et al*. 2009). A similar approach was taken in the European ENSEMBLES program (Christensen *et al*. 2009, Kendon *et al*. 2010). Of regional interest is the Coordinated Regional Climate Downscaling Experiment project (CORDEX) for Australasia (http://wcrp-cordex.ipsl.jussieu.fr/), which will provide a sampling of a GCM-downscaling 'matrix' (both dynamical and statistical) for all of Australia when complete (Evans, 2011).

There is currently no set of systematically produced GCM-RCM climate projections available that covers the entire continent. However, two different downscaled projections were produced for this project and there are several regional climate change studies that have produced valuable insights (listed below). These outputs do not represent a systematic sampling of GCM and downscaling uncertainty. Therefore the CMIP5 ensemble is the primary tool for examining projected climate change in Australia in this Report, and downscaling data is used as a complementary source of information; reported only where and when it is felt that it provides compelling 'added value' about the climate change signal. We particularly look for cases where the downscaling shows higher *physical plausible* change than GCMs due to regional influences.

Most of the content in this Report discusses the regional insights that downscaling provides under a high emissions scenario (RCP8.5) for the end of the century, when the climate change signal is at its strongest. This emphasises the regional scale patterns that are revealed by downscaling, which is useful for qualitative interpretations. However, currently there is no fully representative and complete GCM-RCM dataset suitable for quantitative analysis to accompany these regional insights.

6.3.3 STATISTICAL AND DYNAMIC DOWNSCALING METHODS USED

Statistical downscaling is not a change factor method of the variable itself, it refers to a model that utilises a statistical relationship between the local-scale variable of interest and larger-scale atmospheric fields. This is achieved through regression methods (e.g. multiple regression statistics, principal component or canonical correlation analysis, neural networks), weather typing or through the use of weather generators calibrated to the large atmospheric fields. We report results from the Bureau of Meteorology analogue-based Statistical Downscaling Model (SDM) for Australia (Timbal *et al*. 2009).

Dynamical downscaling is the use of a numerical climate model operating at a finer spatial resolution (compared to GCMs), using the broad-scale climate change from a GCM as input. There are various configurations of dynamical downscaling models, but most are atmosphere-only models (using the SSTs from the 'host' GCM), and have fine resolution only over the area of interest. There are two main types used for downscaling in Australia: variable resolution global models and limited area models. We report on results from the CCAM variable resolution global model (McGregor and Dix, 2008) plus other downscaled outputs where available.

6.3.4 PROS AND CONS OF STATISTICAL AND DYNAMICAL DOWNSCALING

Statistical downscaling (such as the BOM-SDM) will almost certainly produce greater *climate realism* than the host model, but may still have some level of approach bias compared to an observed dataset, both in spatial and temporal distributions. In terms of *physically plausible* change, statistical downscaling is likely to produce more spatial and temporal detail in the climate change signal compared to the GCM. This change signal could be more plausible compared to that of the host model, especially around areas of important topography and coastlines. The outputs may also have greater *physically plausible change* in the simulation of temporal distributions, both in the current climate and in the projected change in variability. However, many statistical techniques are not suited to simulating extremes, especially those extremes for which there are no historical precedent. Also, statistical downscaling does not produce a full suite of internally-consistent variables; it is generally done for a limited set of variables (typically temperature and rainfall).

Dynamical downscaling produces a suite of internally-consistent variables that have the potential to show a complete spatial and temporal response in the climate to the scenario, including events without historical precedent. The *climate realism* in dynamical models can be relatively high, but outputs will contain some inevitable approach biases compared to observations. This means that the outputs are not suitable for direct use into sophisticated impact analysis models and therefore require bias correction. Dynamical downscaling has great potential to produce *physically plausible* change on the regional-scale, in terms of spatial distribution (particularly in areas with a strong influence of topography or coastlines on the climate), and in temporal distribution, including extremes (*i.e.* the method has high approach capability). However, this potential for extra realism in the change signal needs to be critically assessed in the actual outputs for any region.

6.3.5 AREAS OF GREATEST POTENTIAL ADDED VALUE

In Australia, there are a few compelling cases where downscaling may produce more *physically plausible* change compared to the GCM hosts. Hence there is an argument for using downscaled data in preference to GCM outputs for impact analysis at the regional scale in these cases. These are the regions with the greatest influence of topography and coastlines, and also the regions where there are distinct climatic zones within a relatively small area. These areas include Tasmania, south-east mainland Australia, the Australian Alps, the Eastern Seaboard between the coast and the Great Dividing Range and south-east Queensland, as well as some regions within southern South Australia and south-west Western Australia. For example, downscaling was shown to reveal different projected rainfall changes in western compared to eastern Tasmania in some seasons, according to plausible regional climate boundaries based on the relationships of rainfall to mean westerly circulation (Grose *et al*. 2013). For climate change projections in the tropics, the largest source of uncertainty is often from processes such as convection and clouds, therefore a different projection in downscaling may be due to a different simulation of convection and clouds and can be harder to attribute to finer resolution of surface features. Without such a firm basis to identify the added value, we place less emphasis on downscaling in the tropics, but emphasise the 'added value' from downscaling primarily in southern Australia.

6.3.6 AVAILABILITY

This project has produced two sets of downscaled climate projections for Australia that are reported on here. These outputs are produced using the CCAM model using six CMIP5 host GCMs as input (ACCESS-1.0, CCSM4, CNRM-CM5, GFDL-CM5, GFDL-CM3, MPI-ESM-LR and NorESM1-M). These six models were chosen to cover a representative range of projected changes for Australia and the wider region, chosen from the better performing set of CMIP5 models. CCAM data will be available through the *Climate Change in Australia* website. We also report on outputs from the Bureau of Meteorology Analogue-based SDM of Timbal *et al*. (2009) with 22 CMIP5 GCMs as input (see Table 3.3.1 for models used). Outputs are produced for RCP4.5 and the RCP8.5. Along with this new downscaling work, reference is made to regional studies that produced downscaled projections for particular sub-regions of Australia, including:

- Climate Futures for Tasmania (http://www.acecrc.org.au/Research/Climate%20Futures) and further work on the Australian Alps to be released in 2015
- South Eastern Australian Climate Initiative (SEACI; http://www.seaci.org/)
- Queensland Climate Change Centre of Excellence project for South-east Queensland
- Indian Ocean Climate Initiative (IOCI, http://www.ioci.org.au/)
- Goyder Institute South Australia (http://goyderinstitute.org/)
- Consistent climate scenarios project (Burgess *et al*. 2012) (http://www.longpaddock.qld.gov.au/climateprojections/about.html)
- NSW and ACT Regional Climate Modelling (NARCLIM, http://www.ccrc.unsw.edu.au/NARCliM/)

Please note that while these sites provide information about the relevant data, it may not necessarily provide access to datasets.

6.4 ASSESSING CONFIDENCE IN PROJECTIONS

Assessing climate projections is quite different to assessing weather forecasts. Weather forecasts are initialised with current observations and provide predictions of the next 1-10 days that can be continually assessed against observations. Climate is the average weather. Climate projections are simulations that are largely independent of the initial conditions, designed to show the long-term response of the climate system to hypothetical, but plausible, scenarios of external forcings into the future. Climate projections are not expected to give accurate predictions of individual weather events into the far future.

However, it is expected that the projections will show a plausible change to multi-decadal climate statistics if a particular RCP is followed and natural climate variability is taken into account. Confidence in projections can be assessed by comparing simulations of the current climate and past climate changes with observations, assessing the agreement between climate model simulations, and by considering our understanding of the physical processes driving projected changes (see Chapter 5). In reality, projections for 2030 and beyond can never be fully assessed against observations, the concentrations of greenhouse gases in the atmosphere will probably not play out exactly as specified any one RCP, and there is likely to be unpredictable natural forcing factors such as volcanic eruptions. These factors affect what constitutes confidence in climate projections, and how it is assessed.

Confidence in a climate projection statement represents the authors' assessment of its reliability. Confidence comes from multiple lines of evidence including physical theory, past climate changes and climate model simulations. Here confidence language specified by the IPCC for their *Fifth Assessment Report* is used (see Mastrandrea *et al*. 2010), which considers factors along two dimensions; evidence (type, amount, quality and consistency), and agreement between those lines of evidence (Figure 6.4.1) to assign a confidence rating using calibrated language based on expert judgment of the various lines of evidence. As in IPCC (2013), confidence is expressed using the qualifiers '*very high*', '*high*', '*medium*', '*low*' and '*very low*'. Though in practice, only four qualifiers were used as '*very low*' confidence was never assigned to a variable.

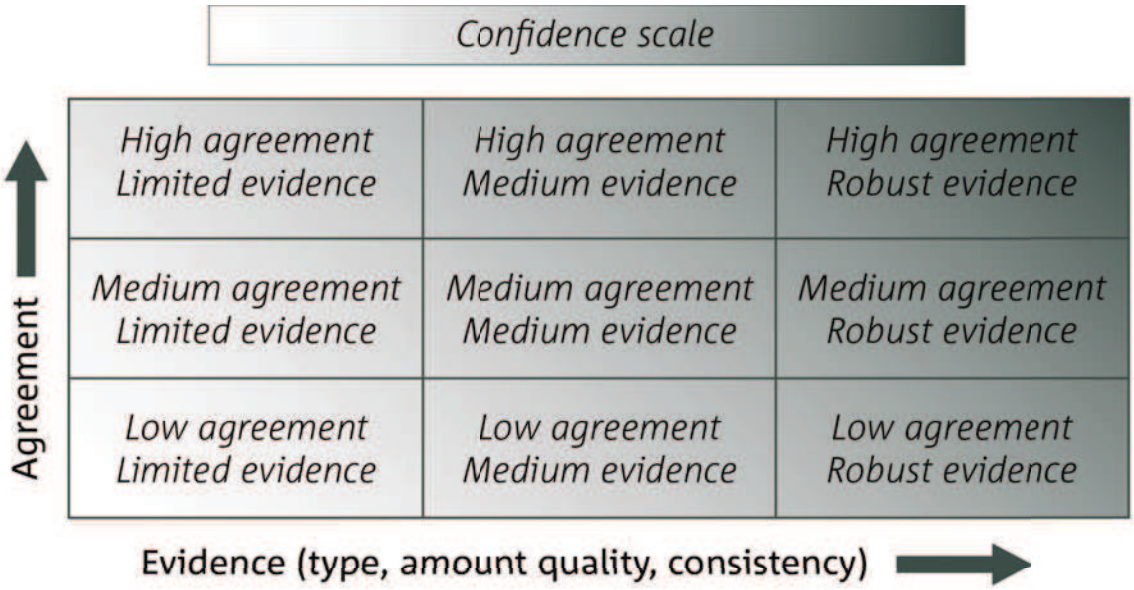

FIGURE 6.4.1: A DEPICTION OF EVIDENCE AND AGREEMENT STATEMENTS AND THEIR RELATIONSHIP TO CONFIDENCE. CONFIDENCE INCREASES TOWARDS THE TOP RIGHT CORNER AS SUGGESTED BY THE INCREASING STRENGTH OF SHADING. GENERALLY, EVIDENCE IS MOST ROBUST WHEN THERE ARE MULTIPLE, CONSISTENT INDEPENDENT LINES OF HIGH QUALITY EVIDENCE (ADAPTED FROM: MASTRANDREA *ET AL*. 2010).

In setting confidence for projections in this Report, the simulated range of change from CMIP5 models and any consistency on the simulated direction of change was considered. This is supplemented by the following lines of evidence: model reliability at simulating relevant aspects of the current climate, results from relevant downscaled projections, evidence for a plausible process driving the simulated changes, and the level of consistency with emerging trends in the observations. For rainfall change, all of these lines of evidence were considered in some detail (see Section 7.2, Table 7.2.2). Some other variables did not always permit or require this full approach, but in all cases confidence is assessed, and reasons and evidence are given.