FUTURE CLIMATE PROJECTIONS FOR COASTAL NSW

J.P. Evans, D. Argueso, A. Di Luca, R. Olson, F. Ji, C. Lee, M. Riley, Y. Scorgie

Abstract

NARCliM (NSW/ACT Regional Climate Modelling project) is a regional climate modelling project for southeastern Australia produced in a collaboration between the NSW Office of Environment and Heritage (OEH) and the University of New South Wales (UNSW). It will provide a comprehensive dynamically downscaled climate dataset for South-East Australia at a resolution of 10km. NARCliM data will be used by the NSW and ACT governments to design their climate change adaptation plans. OEH will be making the NARCliM data available to the public in 2015.

NARCliM uses WRFv3.3 regional climate model (RCM) to perform an ensemble of simulations for the present (1990-2009) and the projected future climate (2020-2039 and 2060-2079). WRF is run in three different model configurations (different combinations of physical parameterizations) that have been shown to perform well in South-East Australia and were chosen based on performance and independence. We use four GCMs (MIROC-medres 3.2, ECHAM5, CGCM 3.1 and CSIRO mk3.0) from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset as initial and boundary conditions for the WRF simulations. These GCMs were chosen through a process that considered model performance, independence and projected future changes. Thus an ensemble of 12 simulations for each period was obtained. In addition, each RCM is run for the period 1950-2009 forced by NCEP/NCAR reanalysis.

The 10km resolution allows the eastern seaboard of NSW to be resolved and climate projections to be of direct relevance to coastal NSW. While future sea level rise is a significant impact of climate change, future changes in coastal precipitation, winds and temperatures may be just as important. In this talk, we will present the NARCliM projected changes in these climate variables of most relevance for coastal NSW.

Introduction

Future climate change has been recognised as one of the largest issues facing the world in the coming century. The Intergovernmental Panel on Climate Change (IPCC) has been tasked with compiling the state of knowledge in relation to climate change on a regular basis. To date they have produced five such. These assessments are the basis of knowledge used by most governments to establish climate change related policy, including the ongoing debates around the introduction of a price on greenhouse gas emissions.

Global Climate Models (GCMs) are the main tools used to project the extent of future climate change. The Coupled Model Intercomparison Project 3 (CMIP3, Meehl et al., 2007) was the international collaborative effort of GCM groups to produce projections that directly informed the IPCC fourth assessment report (IPCC, 2007). This database of global climate projections has been widely used to investigate global climate system processes (e.g. Diffenbaugh et al., 2008; de Szoeke and Xie, 2008) as well as large scale climate change projections (Marriotti et al., 2008; Evans, 2009; Vavrus et al., 2009; Evans 2010). This construction of a multi-GCM ensemble is vital for dealing with the uncertainty associated with future projections. Every GCM, which performs adequately for the recent past, provides a plausible projection of future climate and it is difficult to know which of these plausible futures is more likely. Hence the use of a multi-model ensemble is required to provide some measure of likelihood of the projected future climate.

As the risks associated with large scale climate change have become better understood, more impact and adaptation studies have been performed. A significant spatial scale problem exists between the scale of the processes that GCMs can represent (larger than about 300km) and the scales of interest for impacts and adaptation studies which are often only tens of kilometres or less. In order to address this spatial scale problem various methods have been developed to downscale the GCM output. These downscaling methods can be generalised into two types: statistical and dynamical. Statistical downscaling involves deriving statistical relationships between some large scale predictors and a local variable of interest. An example would be to use the GCM predicted mean sea level pressure or 500hPa geopotential height to predict precipitation at a station location. It is then assumed that this statistical relationship remains true in a future changed climate and hence can be used to downscale both the present and the future climate. Dynamical downscaling uses mathematical representations of the physical processes that create the climate system, similar to GCMs, applied at a higher spatial resolution than the GCMs. In this way they are able to capture climate phenomena not resolved by the GCMs including the influence of mountains, coastlines and local land-atmosphere feedbacks (Zaitchik et al., 2007a,b). Dynamical downscaling is done with a Regional Climate Model (RCM). When downscaling future climate projections RCMs assume that the physical laws remain the same. Statistical downscaling techniques can also be applied to RCM output in order to provide information at point locations.

One advantage of statistical techniques is that they are less computationally intensive and hence can be used to downscale many GCM (or RCM) climate projections. This allows the statistical techniques to be applied to many climate models and hence they can span the range of plausible future climates. RCMs, on the other hand, are quite computationally intensive. To date this has prevented them from being used to downscale many GCMs, hence they have not sampled the full range of plausible future climates. This issue has been addressed in a number of large international projects focused on Europe (PRUDENCE - Christensen and Christensen (2007), ENSEMBLES - van der Linden and Mitchell (2009)) and North America (NARCAP - Mearns et al. (2009)) that produced large ensembles of RCM simulations. PRUDENCE was the first attempt to produce a RCM ensemble through a large cooperative international program. In this case several RCMs were used to downscale the same GCM thus providing a measure of the uncertainty associated with RCM simulations but not placing this within the context of plausible future climates simulated by GCMs (Deque et al., 2005). Both ENSEMBLES in Europe and NARCAP in North America have attempted to address this issue by using a collection of RCMs to downscale a collection of GCMs. While these projects have found significant spread amongst the RCMs it has generally been smaller than the spread found in the full GCM ensemble (Fowler et al., 2007). Thus, an emphasis on sampling the GCM ensemble more comprehensively has been recommended (Kendon et al., 2010).

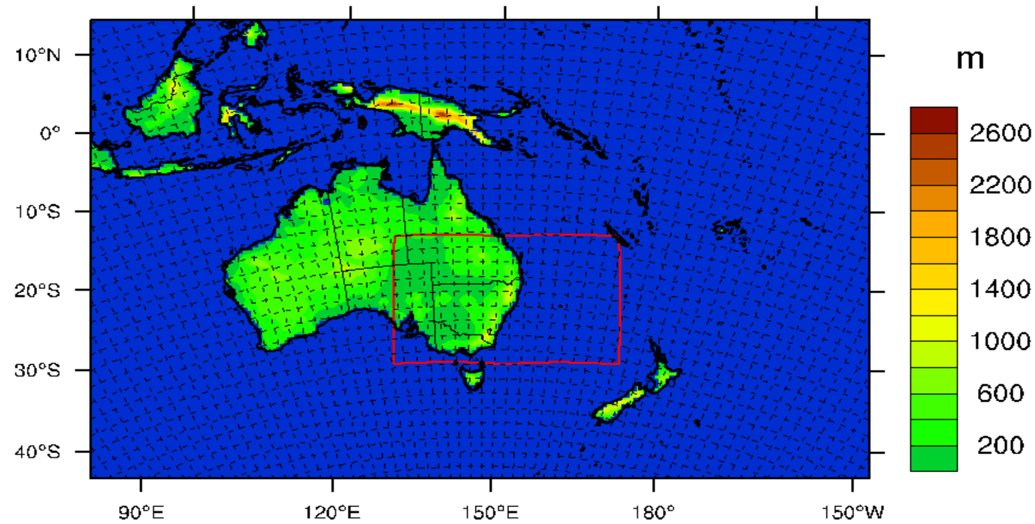

Figure 1: AustralAsia domain and topography. The red rectangle outlines the high resolution south-east Australia NARCliM domain.

Uncertainty about future climate projections comes from several sources. Here these sources of uncertainty are broken down into three main categories, a different but similar way to categorise these sources of uncertainty can be found in Foley (2010). The first source, and one of the largest unknowns, is the future emissions of greenhouse gases and aerosols. Since this uncertainty is impossible to quantify mathematically, it is presented as a series of possible emission scenarios or projections. These scenarios are then used in GCM simulations to study the impact on climate.

The second and the third sources of uncertainty deal with the response of the physical system to the increase in greenhouse gases and aerosols. Specifically, the second source is a large scale response to changes in atmospheric constituents. It can be sampled by using different GCM ("model structural uncertainty"), and different parametrizations within a single GCM ("model parametric uncertainty"). The third source is a local response given a large-scale response. In the case of RCMs this includes the uncertainty in model physics and structure similar to issues associated with GCMs, while for statistical downscaling this includes uncertainties associated with the statistical technique used. In combination these sources of uncertainty provide a limit to the confidence that can be placed in any particular projection of future regional climate.

Quantifying this uncertainty is done by creating a collection, or ensemble, of climate simulations that sample various parts of the uncertainty described above. Emission scenario uncertainty is addressed by running simulations from more than one scenario. To quantify the structural uncertainty associated with GCMs an ensemble of many GCMs should be used and similarly for RCMs (or dynamical downscaling) many RCMs should also be used. Ideally these GCMs and RCMs would be independent of each other ensuring they are sampling different parts of the plausible future climate space. Once an ensemble sampling these uncertainties has been established there are multiple methods for combining the information to establish a probabilistic future climate change prediction. Déqué and Somot (2010) used a technique that weighs a frequency distribution based on model performance. Bayesian analysis has also been used in a number of ways (Tebaldi et al., 2004,2005; Buser et al., 2010) and is an area of active research.

NARCliM Project Plan

The NARCliM ensemble has been designed to produce 12 regional climate model simulations (Evans et al, 2014). Twelve RCM runs were selected as a minimum number of runs to improve the probability of capturing the range of possible future climates. The process of developing the 12 RCMs first included the selection of the GCMs that were to be downscaled. The project was run using four independent GCMs to provide the boundary conditions for three RCM simulations each, for a total of 12 runs. The GCM selection process included evaluation of GCM performance in simulating actual climate for South-East Australia. Other criteria were that the model estimates of future climate should be independent and span the range of future climate change projections from the full CMIP3 GCM ensemble. The second step involved selecting the RCMs to perform the downscaling. The RCMs chosen are three most independent configurations of the Weather Research and Forecasting (WRF) model that have been shown to perform well over the region across a range of time scales (Evans et al. 2012; Evans and Westra, 2012; Evans and McCabe, 2013).

Three 20 year simulations were performed with each of the 12 GCM/RCM combinations, for the present day (1990-2010) and two future periods, 2020-2040 and 2060-2080. In addition to the GCM driven simulations, another set of the RCM runs

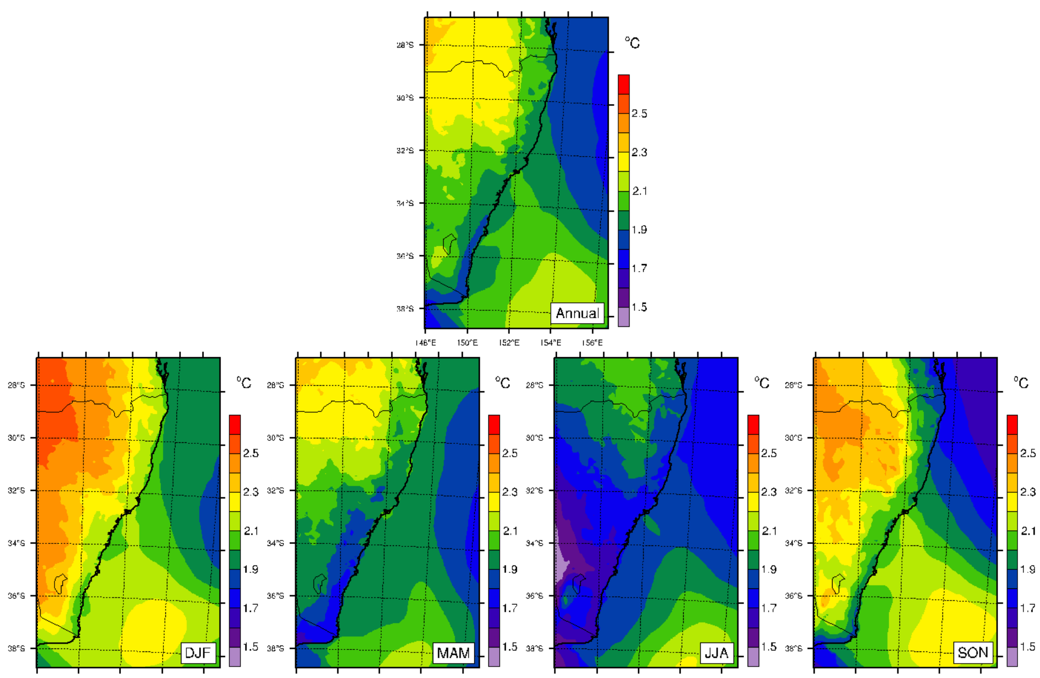

Figure 2: Projected future changes in ensemble mean 2m temperature (2070 - 2000).

used boundary conditions from NCEP/NCAR reanalysis to produce long (60-year, 1950-2009) historical simulations. The NARCliM domain is shown in Figure 1. The large outer domain has a ~50km resolution while the inner high resolution domain has a ~10km resolution. The resolution is chosen in order to capture important local land-atmosphere coupling feedbacks (Evans et al. 2011).

Results

Here projected future changes from the present-day period of 1990-2009 (referred to as 2000) to the future period of 2060-2079 (referred to as 2070) are shown. The changes in mean temperature (Figure 2) indicate that generally the land warms more in spring and summer than autumn and winter. In summer this warming generally leads to an increase in the land-sea temperature gradient, while in winter there is generally a decrease. Over the Tasman Sea the strongest warming occurs in the south, particularly in spring and summer. This southern Tasman Sea warming is amongst the largest projected in any non-Arctic ocean.

Projected changes in precipitation are shown in Figure 3. On an annual basis, most of coastal NSW is projected to see only small changes. However, this masks some larger seasonal changes with much of the coast likely to experience increases in precipitation in summer and autumn, and decreases or little change in winter and spring. The changes along the northern NSW coast are dominated by likely increases in summer and autumn, while the southern NSW coast is projected to see a decrease in spring. Figure 4 shows the spring (SON) rainfall change for each individual model giving an example of the variability that can be found between models.

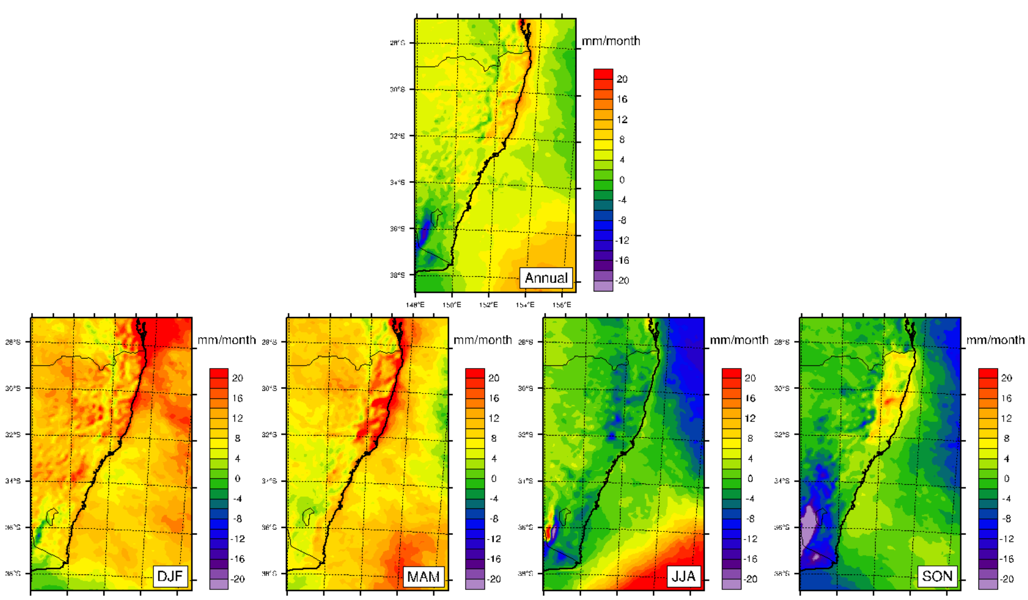

Figure 3: Projected future changes in the ensemble mean precipitation (2070-2000).

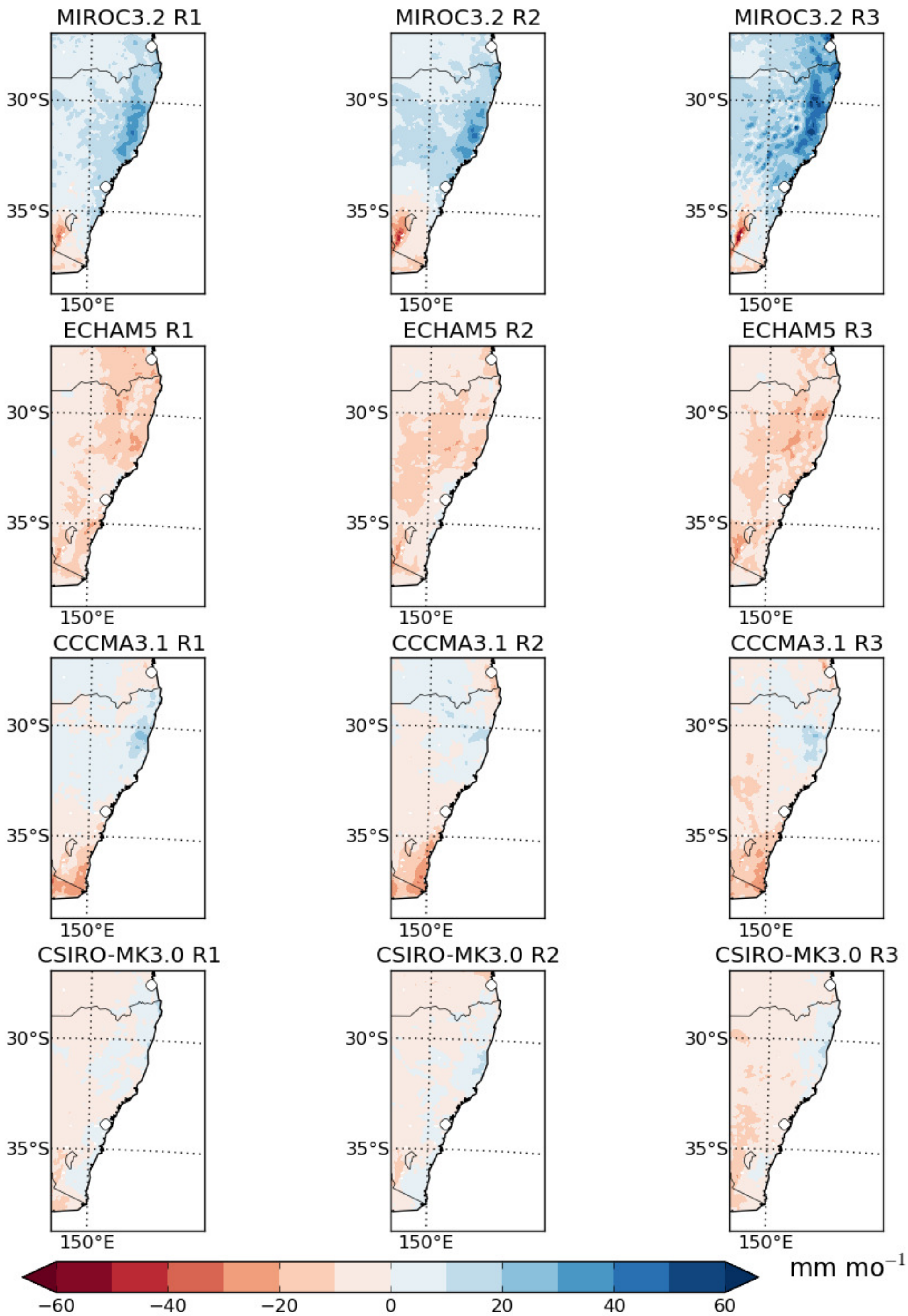

Figure 4: Spring (SON) precipitation changes for each of the ensemble members.

In this case 9 (or 10) of the 12 models project a decrease on the south coast in spring while the remaining project little or no change.

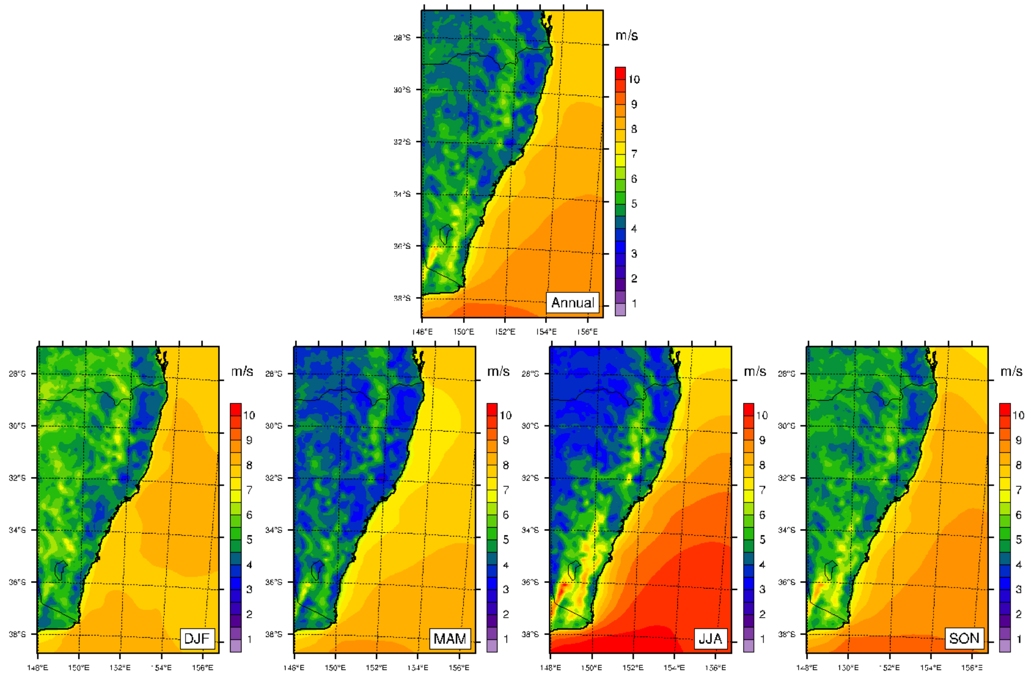

Figure 5: Present-day ensemble mean 10m wind speed.

The mean seasonal wind speed at 10 meters for the region is shown in Figure 5. Clearly the ocean winds tend to be stronger than the winds over land, and are strongest in winter in the southern Tasman Sea. On the northern NSW coast the winds tend to be stronger in spring and summer, while for the southern NSW coast they are much stronger in winter followed by spring. The projected future changes in these winds are shown in Figure 6. No change or small decreases in wind speed are

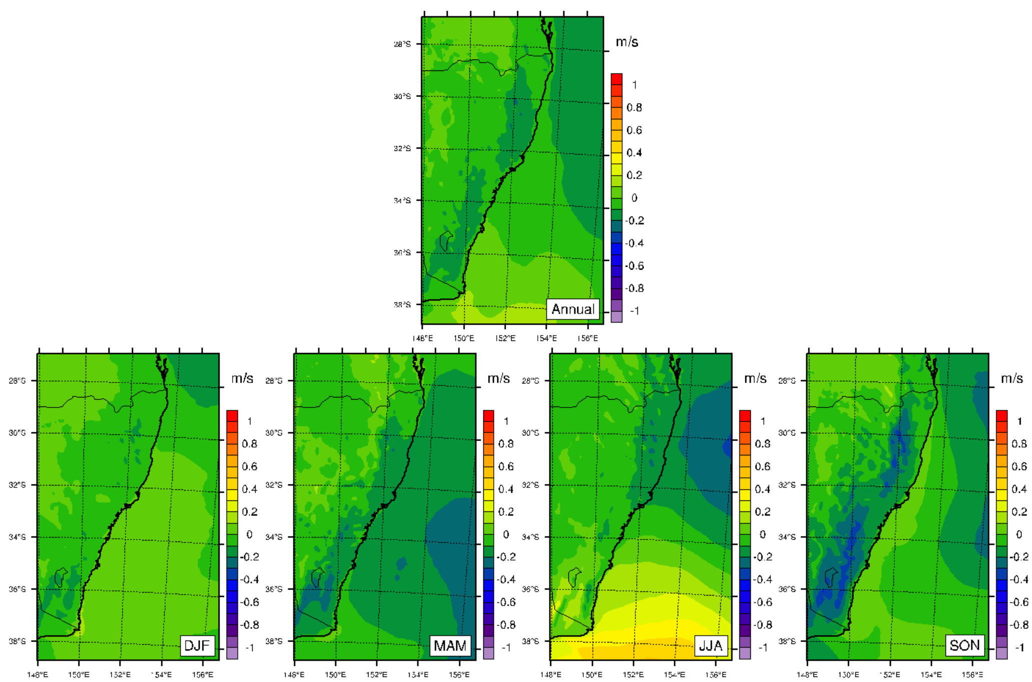

Figure 6: Projected future changes in the ensemble mean 10m wind speed (2070-2000).

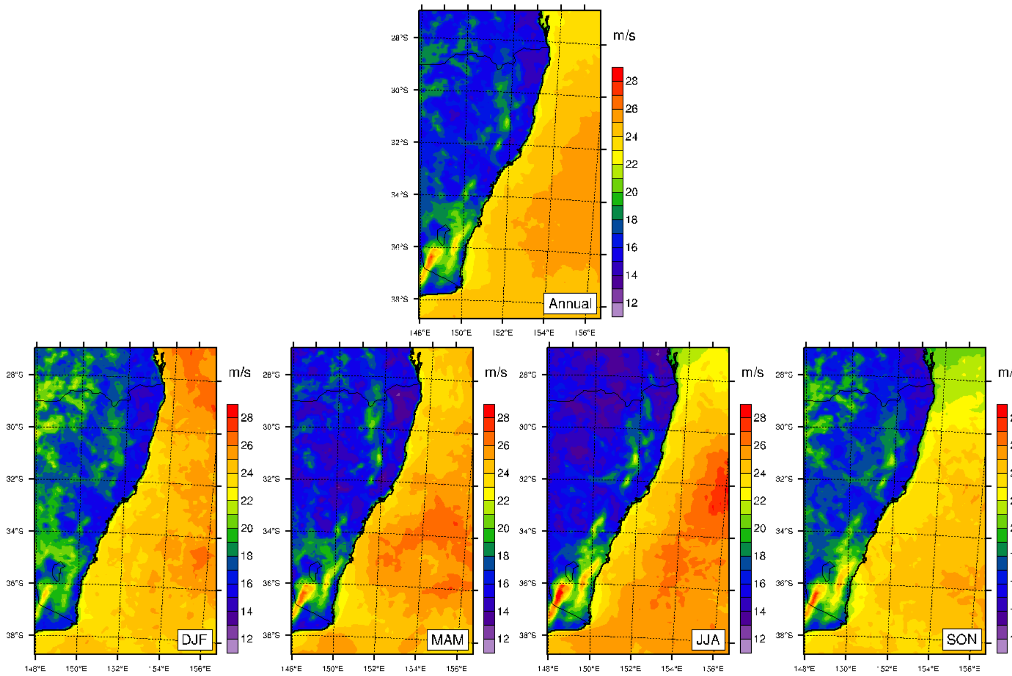

Figure 5: Present-day ensemble mean maximum 10m wind speed.

generally projected throughout the region except for winter when the southern Tasman Sea is projected to experience an increase in the mean maximum wind speed.

Next we investigate changes in maximum wind speeds as these are often associated with coastal impacts. Figure 7 shows the present-day ensemble seasonal mean

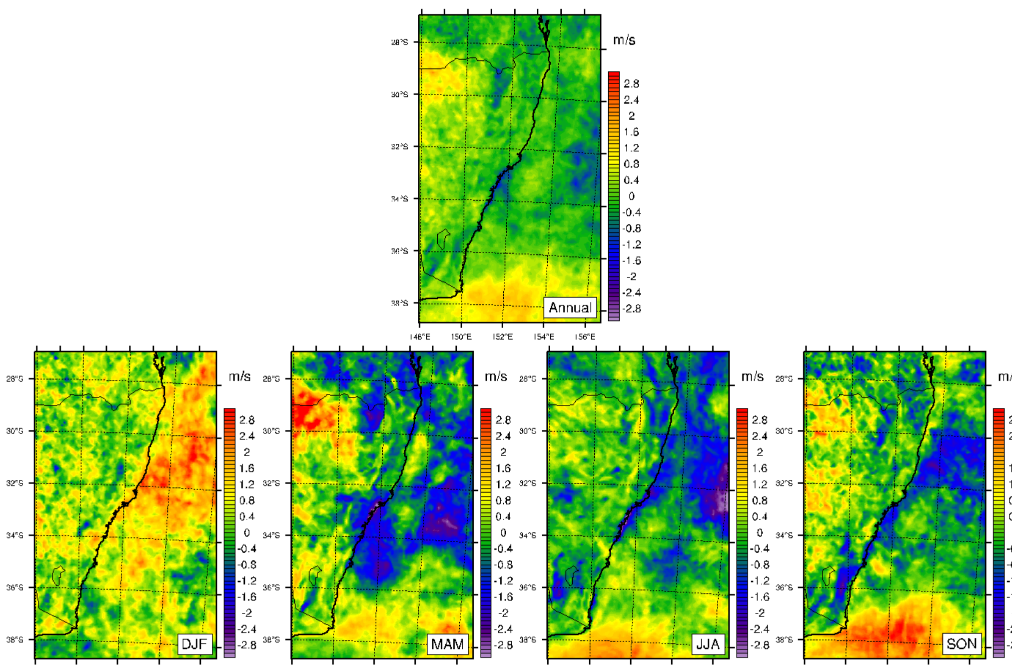

Figure 6: Projected future changes in the ensemble mean maximum 10m wind speed (2070-2000).

maximum wind speed. That is, the mean of the maximum recorded wind speed in that season, in each of the 20 years. Again, much higher wind speeds are found over the Tasman Sea than over land, however the area with the highest maximums is not confined to the southern Tasman as it is for the mean winds. On land it can be seen that the southern NSW coast experiences notably higher maximum wind speeds compared to the northern coast, particularly in winter and spring. Future changes in these maximum wind speeds are shown in Figure 8. In summer, increases in maximum wind speeds are found in the northern Tasman Sea and along much of the NSW coast (especially the north). In winter the largest increases occur in the southern Tasman Sea, though only the southernmost coastline is affected by these increases. In all seasons other than summer, most of the NSW coast is projected to see little change or decreases in maximum wind speeds.

Conclusions

By modelling the regional climate at 10km resolution the NARCliM regional climate projections are able to provide significant detail to future climate changes for coastal NSW. This detail can be largely attributed to better resolving the coastline and nearby mountain ranges, as well as small-scale processes captured by RCMs but unresolved in coarse resolution models. Projected changes include: temperature increases of more than 2ºC in summer but less than this in winter; precipitation increases particularly on the northern coast in summer and autumn, and decreases on the southern NSW coast in spring; small decreases in mean wind speed; and increases in maximum wind speeds in summer but decreases in other seasons. In all cases we have reported the ensemble mean changes here. The variability within the ensemble provides a measure of the confidence level associated with these changes and should be considered together with the ensemble mean change.

References

Christensen, J., and O. Christensen (2007), A summary of the PRUDENCE model projections of changes in European climate by the end of this century, Climatic Change, 81, 7-30, doi:10.1007/s10584-006-9210-7.

de Szoeke, S., and S. Xie (2008), The tropical eastern Pacific seasonal cycle: Assessment of errors and mechanisms in IPCC AR4 coupled ocean - Atmosphere general circulation models, Journal of Climate, 21(11), 2573-2590, doi:10.1175/2007JCLI1975.1.

Deque, M. et al. (2005), Global high resolution versus Limited Area Model climate change projections over Europe: quantifying confidence level from PRUDENCE results, Climate Dynamics, 25(6), 653-670, doi:10.1007/s00382-005-0052-1.

Deque, M., and S. Somot (2010), Weighted frequency distributions express modelling uncertainties in the ENSEMBLES regional climate experiments, Climate Research, 44(2-3), 195-209, doi:10.3354/cr00866.

Diffenbaugh, N., F. Giorgi, and J. Pal (2008), Climate change hotspots in the United States, Geophysical Research Letters, 35(16), doi:10.1029/2008GL035075.

Evans, J.P. (2009), 21st century climate change in the Middle East, Climatic Change, 92(3-4), 417-432.

Evans, J.P. (2010) Global warming impact on the dominant precipitation processes in the Middle East. Theoretical and Applied Climatology, 99 (3-4), 389-402.

Evans, J. P., F. Ji, C. Lee, P. Smith, D. Argüeso, and L. Fita (2014), Design of a regional climate modelling projection ensemble experiment – NARCliM, Geosci. Model Dev., 7(2), 621–629, doi:10.5194/gmd-7-621-2014.

Evans, J.P, M. Ekström, and F. Ji (2012) Evaluating the performance of a WRF physics ensemble over South-East Australia. Climate Dynamics, 39(6), 1241-1258, DOI 10.1007/s00382-011-1244-5.

Evans, J.P., and M. F. McCabe (2010), Regional climate simulation over Australia's Murray-Darling basin: A multitemporal assessment, J. Geophys. Res., 115(D14114), doi:10.1029/2010JD013816.

Evans, J.P. and M.F. McCabe (2013) Model resolution impact on regional climate and climate change using WRF over south-east Australia. Climate Research, 56(2), 131-145, doi:10.3354/cr01151.

Evans, J.P., A.J. Pitman and F.T. Cruz (2011) Coupled atmospheric and land surface dynamics over South East Australia: A review, analysis and identification of future research priorities. International Journal of Climatology, 31, 1758-1772.

Evans, J.P. and S. Westra (2012) Investigating the Mechanisms of Diurnal Rainfall Variability Using a Regional Climate Model, Journal of Climate, 25, 7232–7247, doi:10.1175/JCLI-D-11-00616.1.

Foley, A. (2010), Uncertainty in regional climate modelling: A review, Progress in Physical Geography, 34(5), 647-670, doi:10.1177/0309133310375654.

Fowler H.J., S. Blenkinsop, C. Tebaldi (2007) Linking climate change modelling to impacts studies: Recent advances in downscaling techniques for hydrological modelling. International Journal of Climatology 27:1547–1578.

IPCC (2007), Climate Change 2007: The Physical Science Basis, edited by S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor, H.L. Miller, Cambridge University Press, Cambridge, United Kingdom.

Jones, D. A., W. Wang, and R. Fawcett (2009) High-quality spatial climate data-sets for Australia. Australian Meteorological Magazine, 58, 233–248.

Kendon, E., R. Jones, E. Kjellstrom, and J. Murphy (2010), Using and Designing GCM-RCM Ensemble Regional Climate Projections, Journal of Climate, 23(24), 6485-6503, doi:10.1175/2010JCLI3502.1.

Mariotti, A., N. Zeng, J. Yoon, V. Artale, A. Navarra, P. Alpert, and L. Li (2008), Mediterranean water cycle changes: transition to drier 21st century conditions in observations and CMIP3 simulations, Environmental Research Letters, 3(4), doi:10.1088/1748-9326/3/4/044001.

Mearns, L. O., W. J. Gutowski, R. Jones, L.-Y. Leung, S. McGinnis, A. M. B. Nunes, and Y. Qian (2009), A regional climate change assessment program for North America, EOS, 90(36), 311-312.

Meehl, G. A., C. Covey, T. Delworth, M. Latif, B. McAvaney, J. F. B. Mitchell, R. J. Stouffer, and K. E. Taylor (2007), The WCRP CMIP3 multimodel dataset - A new era in climate change research, Bull. Amer. Meteor. Soc., 88(9), 1383-1394.

Tebaldi, C., L. Mearns, D. Nychka, and R. Smith (2004), Regional probabilities of precipitation change: A Bayesian analysis of multimodel simulations, Geophysical Research Letters, 31(24), doi:10.1029/2004GL021276.

Tebaldi, C., R. Smith, D. Nychka, and L. Mearns (2005), Quantifying uncertainty in projections of regional climate change: A Bayesian approach to the analysis of multimodel ensembles, Journal of Climate, 18(10), 1524-1540.

van der Linden, P., and J. Mitchell (Eds.) (2009), ENSEMBLES: Climate change and its impacts. Summary of research and results from the ENSEMBLES project, Met Office Hadley Centre, Exeter, UK.

Vavrus, S., D. Waliser, A. Schweiger, and J. Francis (2009), Simulations of 20th and 21st century Arctic cloud amount in the global climate models assessed in the IPCC AR4, Climate Dynamics, 33(7-8), 1099-1115, doi:10.1007/s00382-008-0475-6.

Zaitchik, B.F., J.P. Evans and R.B. Smith (2007a) Regional impact of an elevated heat source: The Zagros plateau of Iran. Journal of Climate, 20: 4133-4146.

Zaitchik, B.F., J.P. Evans, R.A. Geerken and R.B. Smith (2007b) Climate and vegetation in the Middle East: inter-annual variability and drought feedbacks. Journal of Climate, 20: 3924-3941.