TECHNICAL REPORT

IMPACTS OF CLIMATE CHANGE ON WATER RESOURCES

PHASE 2: SELECTION OF FUTURE CLIMATE PROJECTIONS AND DOWNSCALING METHODOLOGY

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Government of South Australia
Department for Water

IMPACTS OF CLIMATE CHANGE ON WATER RESOURCES

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Matt Gibbs, Graham Green and Cameron Wood

Science, Monitoring and Information Division
Department for Water

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Science, Monitoring and Information Division
Department for Water
25 Grenfell Street, Adelaide
GPO Box 2834, Adelaide SA 5001

Telephone	National	(08) 8463 6946
	International	+61 8 8463 6946
Fax	National	(08) 8463 6999
	International	+61 8 8463 6999
Website	www.waterforgood.sa.gov.au	

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FOREWORD

South Australia's Department for Water leads the management of our most valuable resource—water.

Water is fundamental to our health, our way of life and our environment. It underpins growth in population and our economy—and these are critical to South Australia's future prosperity.

High quality science and monitoring of our State's natural water resources is central to the work that we do. This will ensure we have a better understanding of our surface and groundwater resources so that there is sustainable allocation of water between communities, industry and the environment.

Department for Water scientific and technical staff continue to expand their knowledge of our water resources through undertaking investigations, technical reviews and resource modelling.

Scott Ashby
CHIEF EXECUTIVE
DEPARTMENT FOR WATER

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SUMMARY

Climate Change projections for South Australia indicate that a hotter, drier future climate is generally expected. If these projections are realised, the resulting decrease in rainfall and increase in evapotranspiration will lead to a reduction in water resource availability for the state. General Circulation Models (GCMs) are the best tools available for simulating global and regional climate systems, and simulating the changes that may occur due to increases in greenhouse gas concentrations. Generally, these models provide reasonable representations of past trends over large spatial scales for a number of climate variables, such as temperature and air pressure.

However, GCM results are too coarse to be adopted directly in water resource impact models, and downscaling of the projections to the local weather station scale is required. A number of downscaling studies have been undertaken previously in South Australia (e.g. Charles et al. 2006 and Charles et al. 2009), however they are based on the projections from only one GCM, and do not consider changes to evapotranspiration, only rainfall. Hence, further downscaling of GCM projections is required to provide suitable inputs for the Department for Water Impacts of Climate Change on Water Resources (ICCWR) Project. This report outlines the methods implemented to produce these inputs, including 1) selection of appropriate future GCM projections for South Australia, and 2) the method used to downscale the projections for use in water resource impact modelling.

A total of 23 GCMs were included as part of the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (IPCC AR4, IPCC 2007). Initial studies undertaken as part of the ICCWR project have indicated that Potential Evapotranspiration (PET) projections have a significant influence on the water resource impact analysis, especially the recharge simulation. However, only nine of the 23 GCMs provide an output of changes to evapotranspiration directly. Suppiah et al. (2006) assessed the accuracy of a number of GCMs at simulating observed trends in the South Australian climate, to assess if current GCM climate errors were of a nature that significantly reduced the likelihood that the enhanced greenhouse simulation will be reliable, for example the absence of key climate features in South Australia. Based on the demerit point system implemented by Suppiah et al. (2006), five of the nine GCMs that provide PET projections were deemed unsuitable for South Australian conditions. Hence, the remaining four GCMs, NCAR – CCSM3, LASG – IAP, MRI and CSIRO Mk 3.5, have been selected to provide future projections of the South Australian climate.

The projections provided by the four GCMs have been considered for a number of future time horizons and emission scenarios. In the modelling of future demand and supply for Greater Adelaide up to the year 2050, The Water for Good Plan considered both the A2 and B2 scenarios, to represent high and low emission cases, respectively. However, GCM data is less available for the B2 emission case, and for the purposes of the ICCWR Project emission cases of A2 and B1 have been adopted to represent the potential variation in future emission scenarios. Three forecast time horizons were considered by CSIRO-BoM (2007), 2030, 2050 and 2070. These three time horizons also correspond to the different requirements of water resource managers in South Australia. The 2030 horizon provides a representation of the near future, as is likely to be of most interest to inform water allocation planning. For this time horizon, the climate is largely driven by previous emissions, hence the A2 and B1 scenarios have little impact on the rainfall and PET projections. 2070 is of interest for infrastructure planning, where the design life of infrastructure such as reservoirs is likely to extend up to and to beyond this period. 2050 provides a “middle ground” projection, where the different emission cases begin to influence the projection rainfall and PET series, and was also the time horizon considered as part of the Water for Good Plan. Hence these three time periods have been considered as part of the ICCWR Project.

SUMMARY

A daily scaling method has been selected to apply the projections simulated by the GCMs, for the different time horizons and emission cases selected to the weather station scale. In a comparison of five downscaling approaches of differing complexity, Chiew et al. (2010) concluded that the simple to apply daily scaling method is suitable for hydrological impact assessment studies over large regions, particularly when the main considerations are changes to seasonal and annual catchment water yield. These are exactly the types of assessments that are the focus of the ICCWR Project, hence the daily scaling approach has been deemed suitable. This method allows for variable scaling of rainfall amounts, hence projections that suggest that the largest rainfall events will increase, but the overall average rainfall will decrease, for example, can be incorporated. Adopting an empirical scaling approach such as this allows the range of projections, time horizons and emission scenarios selected to be considered, which would otherwise be unlikely to be feasible if more complex stochastic or dynamic downscaling approaches were implemented.

Two statistical weather generators were considered to derive base times series data to apply the empirical scaling method to. This approach has the ability to produce long time series that preserve the statistics of the observed climate to be generated, allowing rarer wet or dry events to be evaluated with more confidence. However, small errors in the rainfall or PET were found to lead to larger errors in the resulting runoff, which has significant implications when attempting to assess the impacts of climate changes on the water resource availability. In order to avoid errors such as this, a 50 year period of observed data has been used as the base data for the climate projections, as this represents the true rainfall and PET observations for the local weather station, preserves the correlation between the climate variables at each site, and preserves the spatial correlation between weather stations.

The methods outlined in this report allow daily time step rainfall and PET data that are suitable for water resource impact assessment modelling to be generated, incorporating future climate GCM projections appropriate for South Australia. Data generated using the methods described here will form the basis of climate impact modelling in Phase 3 of the ICCWR project, in which the hydrological modelling of climate change impacts will be conducted for water resources in all NRM regions of South Australia.

This report represents Phase 2 of the Department for Water’s ICCWR project. Phase 1 of the ICCWR project reported on a risk assessment and prioritisation of South Australia’s water resources for subsequent modelling of climate change impacts (DFW Technical Report 2011/01, Wood and Green, 2011).

1. INTRODUCTION

Climate Change projections for South Australia indicate that we can generally expect a hotter, drier future climate. For example, the projected change in temperature and rainfall between 1990 and 2090, averaged across multiple climate models, can be seen in Figure 1. The results indicate an increase in the annual temperature of 2.6 degrees, as well as a decrease in the winter rainfall of 11% is expected for southern Australia, averaged across the outputs from the 21 General Circulation Models (GCMs) considered (IPCC, 2007). For southern Australia, there is strong agreement between the 21 GCMs, with a small minority of the climate models projecting any increase in precipitation (Figure 1). If these projections are realised, the resulting decrease in rainfall and increase in evapotranspiration will lead to a reduction in water resource availability for the state.

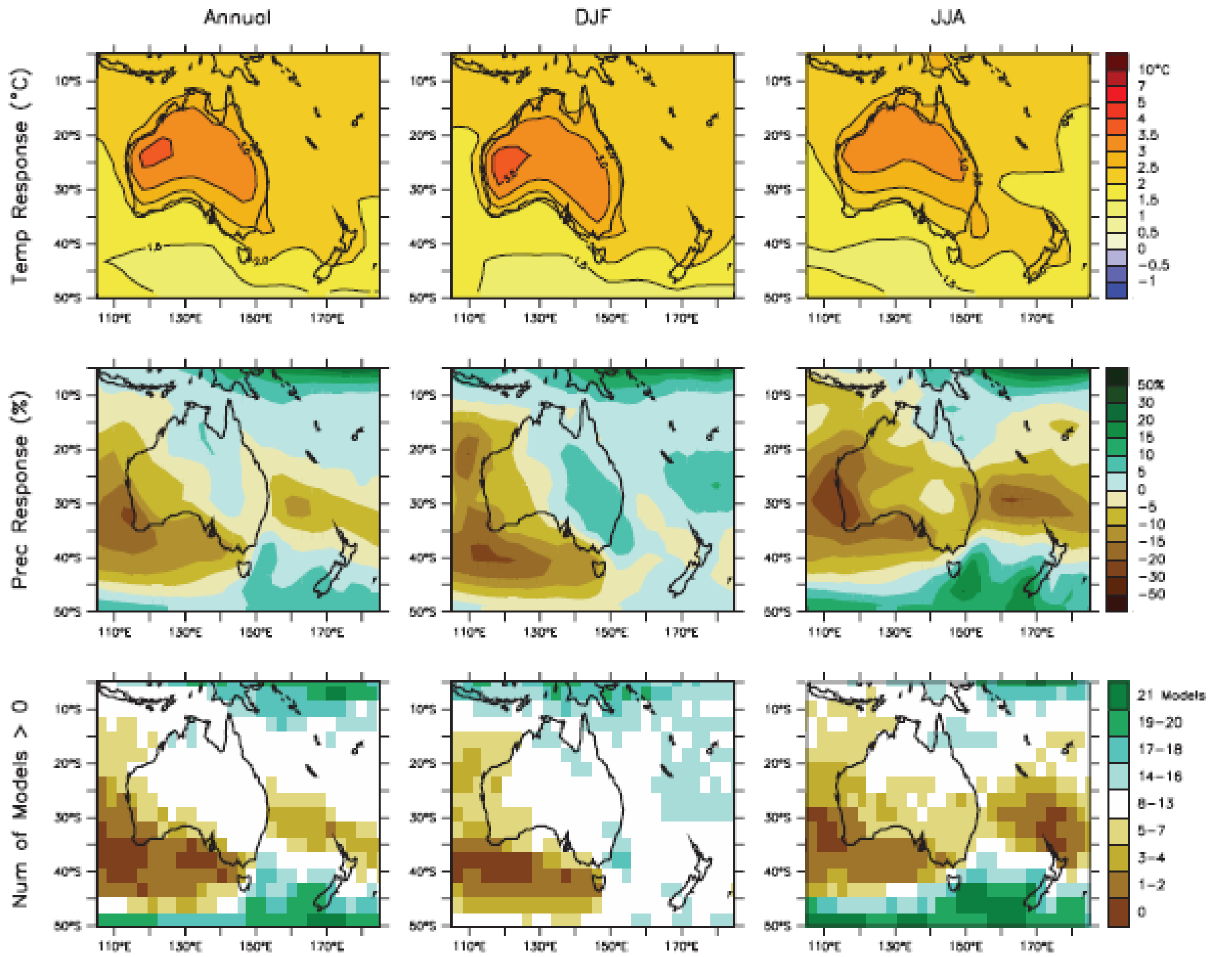


Figure 1. Temperature and precipitation changes over Australia and New Zealand from the Multi Model Dataset for medium (A1B) simulations.

Top row: Annual mean, December, January, February (DJF, summer) and June, July, August (JJA, Winter) temperature change between 1980 to 1999 and 2080 to 2099, averaged over 21 GCMs. Middle row: same as top, but for fractional change in precipitation. Bottom row: number of models out of 21 that project increases in precipitation. (IPCC, 2007)

There is considerable confidence that GCMs provide credible quantitative estimates of future climate change, particularly at continental and larger scales (IPCC, 2007). However, confidence in the estimates produced by these models is higher for some climate variables, for example temperature, than for others, such as rainfall. Unlike seasonal variation in temperature, rainfall variations are also strongly influenced by vertical movement of air, as well as a number of other processes (e.g., evapotranspiration, condensation, transport) that are difficult to evaluate at a global scale (IPCC, 2007). It is influences such as these that lead to the reduced confidence in rainfall outputs produced by current GCMs. Also, GCM simulations are undertaken on relatively large spatial scales, in the order of hundreds of square kilometres, where the scales of interest for water resource impact assessments are generally much smaller. Hence, current GCMs generally fail to reasonably represent the variability in rainfall and PET that occurs at the time scale and spatial extent of interest for impact models. To provide more realistic representation of the projected changes in climate in both time and space, the trends projected by GCMs models must be applied in some way based on observed local datasets, an approach known as downscaling.

There have been a number of downscaling studies undertaken in South Australia previously. Charles and Bates (2006) used Nonhomogenous Hidden Markov Models (NHMMs) to provide daily rainfall projections at selected locations in the Mount Lofty Ranges (MLR) and Upper South East (USE), conditioned on large scale predictors from GCMs, such as temperature, air pressure, dew point or humidity. The projections were produced for a 30 year period around the year 2050, based on the projections of the CSIRO mark 3.0 GCM. Charles et al. (2009) used a similar approach to produce downscaled datasets for a number of other regions in the state, the South Australian Murray-Darling Basin, Eyre Peninsula, Fleurieu Peninsula and Northern and Yorke Natural Resource Management (NRM) regions. These data were based on projections by the CSIRO mark 3.5 GCM, for a continuous time period up to 2100. Both studies considered both high (A2) and low (B2) emission cases.

Suppiah et al. (2006) assessed the performance of 25 GCMs for South Australian conditions based on the representation of historic temperature, rainfall and atmospheric pressure records. The authors noted that a good performance at simulating the current climate does not guarantee that enhanced greenhouse simulation will be accurate, nor do errors in the current climate performance mean that the enhanced greenhouse simulated changes in climate are unreliable. However, judgement was used to assess if the current climate errors were of a nature that significantly reduced the likelihood that the enhanced greenhouse simulation will be reliable, for example the absence of key climate features, such as a high pressure belt, in the region of interest (Suppiah et al. 2006). The CSIRO mark 3.5 GCM was not evaluated as part of the study, and the CSIRO mark 3.0 GCM was rejected as suitable for South Australia. This GCM was used to produce the existing datasets for the MLR and USE, which are key regions of interest for climate change impact analysis in South Australia. Also, these data are limited to 2050 conditions only, and the Department for Water Impacts on Climate Change on Water Resources (ICCWR) aims to consider a range of projection horizons.

Initial studies undertaken as part of the ICCWR project have indicated that Potential Evapotranspiration (PET) projections have a significant influence on the water resource impact analysis, especially the recharge simulation. Bae et al. (2011) also found that PET projections, and the method used to derive PET values, had a significant influence on the simulated soil moisture. These data were not provided as part of the datasets produced by Charles and Bates (2006) or Charles et al. (2009), which considered rainfall alone. Therefore, there is a need to produce future downscaled datasets that consider the correlation between rainfall and PET, based on projections that are suitable for South Australia.

This report outlines the process undertaken to 1) select appropriate projections for South Australia from the available GCMs, and 2) produce daily time step datasets appropriate for impact assessment modelling based on these projections. Further details for each component undertaken are provided in the remainder of this report.

2. SELECTION OF CLIMATE PROJECTIONS

There are a number of options to consider when producing projections of future rainfall and PET time series data, for input to impact assessment models. Firstly, scenarios that have been developed to represent future greenhouse gas emission scenarios must be selected, as well as the future time horizons to consider. Following this, the GCM projections to adopt as a representation of the future climate must be selected. There were 23 GCMs included as part of the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (IPCC AR4, IPCC 2007) and models suitable for the purpose and location of the ICCWR project must be selected.

2.1. EMISSION CASES AND TIME HORIZONS

A number of potential future greenhouse gas emission rates were proposed as part of the Special Report on Emission Scenarios (SRES, 2000). A total of 40 scenarios were proposed, that were summarised into four families for future conditions (A1, A2, B1 and B2). These ranged from the A1 storyline, including the A1B, A1FI and A1T scenarios, which describes a future world of very rapid economic growth and a global population that peaks mid-century, to the B2 story line, which describes a world in which the emphasis is on local solutions to economic, social and environmental sustainability. No predictions were made on which storyline is the most likely to occur. The resulting greenhouse gas emission rates from each storyline are presented in Figure 2.

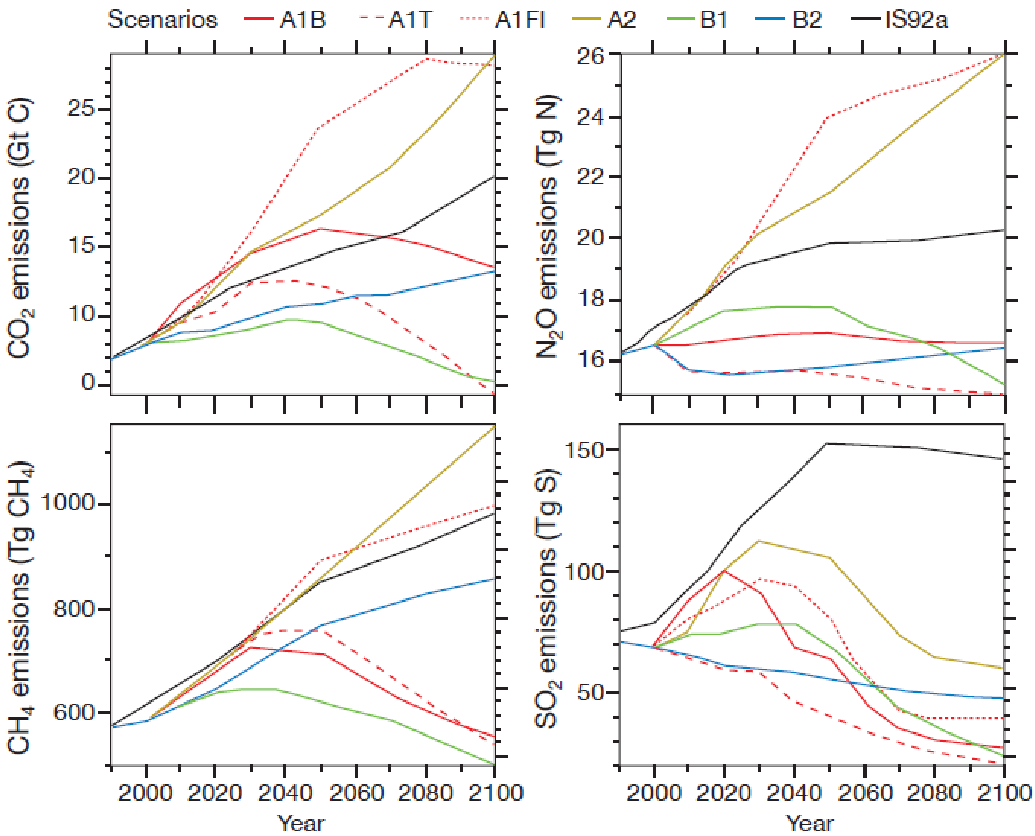


Figure 2. **Anthropogenic emissions of carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and sulphur dioxide (SO_2) for six SRES (2000) scenarios and the IS92a scenario from the IPCC Second Assessment Report in 1996 (IPCC 2001) (CSIRO – BoM, 2007).**

In the modelling of future demand and supply for Greater Adelaide up to the year 2050, The Water for Good Plan considered both the A2 and B2 scenarios. For consistency with the projections considered in Water for Good, the remainder of this section considers A2 and B2 conditions to evaluate the range of GCM projections.

Three forecast time horizons were considered by CSIRO-BoM (2007), 2030, 2050 and 2070. The projections were assessed based on a 30 year period around each horizon (i.e. 2015 – 2044, 2035 – 2064 and 2055 – 2084), and compared to the current climate by considering the 30 year period around 1990 (1975 – 2004). These three time horizons also correspond to the different requirements of water resource managers in South Australia. The 2030 horizon provides a representation of the near future, as is likely to be of most interest to inform water allocation planning. For this time horizon, the future climate is largely driven by emissions that have already occurred, and the various emission scenarios presented in Figure 2 have little impact on the rainfall and PET projections for this period. 2070 is of most interest for infrastructure planning, where the design life of infrastructure such as reservoirs is likely to extend up to and to beyond this period. However, there are large differences between the possible future emission cases (Figure 2), as well as the simulated result of these emission cases by different GCMs, hence projections for a longer time horizon such as this are expected to be largely uncertain and provide a guide only. 2050 provides a “middle ground” projection, where the different emission cases begin to influence the projection rainfall and PET series, and was also the time horizon considered as part of the Water for Good Plan. Hence these three time periods will also be considered as part of the ICCWR Project.

2.2. GENERAL CIRCULATION MODEL PROJECTIONS

23 GCMs are included in IPCC AR4, which provide a vast range of possible future climate scenarios. A summary these models, including the organisations responsible for the development of the model and their spatial resolution can be seen in Table 1. CSIRO-BoM (2007) provides a summary of the range of projections that exist for Australia, for example the range in projected percentage change to winter rainfall for 2030 conditions are presented in Figure 3. The range can be seen to be extremely wide, and irrespective of the emission scenarios, the worse case projections (10th percentile) estimate up to a 10-20% reduction in winter rainfall, while the best case projections (90th percentile) estimate an increase in winter rainfall of up 5 – 10% for the northern part of the state. From Figure 3, the median projections are somewhere between a 2% reduction in the south of the state, up to a 10% reduction in winter rainfall for the north of the state. It is not practical to consider all the projections from all models that exist for the purposes of the ICCWR project, firstly due to the requirements involved in downscaling all 23 GCM outputs, and secondly providing the complete range of projections is unlikely to provide useful guidance for policy and decision making applications. Conversely, selecting a too narrow range of projections may not adequately represent the large uncertainties involved in projections of a future climate. In order to narrow down the GCM projections available, the outputs produced by each model, and the historical accuracy of those outputs, has been considered.

Table 1. GCMs considered as part of IPCC AR4, including the group and country of origin, model acroymn and approximate cell resolution, in kilometers in the horizontal direction. The skill score for Australia (CSIRO-BoM, 2007), demerit points for South Australia (Suppiah et al. 2006) and if the GCM provides evapotranspiration outputs are also provided.

Originating Group	Country	Model	Approx. Grid Spacing	Skill Score	Demerit Points	PET
Bjerknes Centre for Climate Research	Norway	BCCR	175	0.59	6	
Canadian Climate Centre	Canada	CCCMA T47	250	0.518	12	
Canadian Climate Centre	Canada	CCCMA T63	175	0.478	13	✓
Meter-France	France	CNRM	175	0.542	9	
CSIRO	Australia	CSIRO Mk3.0	175	0.601	10	
CSIRO	Australia	CSIRO Mk3.5	175	0.607	-	✓
Geophysical Fluid Dynamics Lab	USA	GFDL 2.0	200	0.671	6	
Geophysical Fluid Dynamics Lab	USA	GFDL 2.1	200	0.672	3	
NASA/Goddard Institute for Space Studies	USA	GISS-AOM	300	0.564	8	
NASA/Goddard Institute for Space Studies	USA	GISS-E-H	400	0.604	14	✓
NASA/Goddard Institute for Space Studies	USA	GISS-E-R	400	0.515	9	
LASG/Institute of Atmospheric Physics	China	LASG-IAP	300	0.639	4	✓
Institute of Numerical Mathematics,	Russia	INMCM	400	0.627	11	✓
Institut Pierre Simon Laplace	France	IPSL	275	0.505	12	
Centre for Climate Research	Japan	MIROC-H	100	0.608	7	✓
Centre for Climate Research	Japan	MIROC-C	250	0.608	9	✓
Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA	Germany/ Korea	MIUB	400	0.632	3	
Max Planck Institute for meteorology DKRZ	Germany/ Korea	MPI-ECHAM5	175	0.7	2	
Meteorological Research Institute	Japan	MRI	250	0.601	4	✓
National Center for Atmospheric Research	USA	NCAR-CCSM	125	0.677	6	✓
National Center for Atmospheric Research	USA	NCAR-OCM1	250	0.506	12	
Hadley Centre	UK	HADCM3	275	0.608	6	
Hadley Centre	UK	HADGEM1	125	0.674	4	

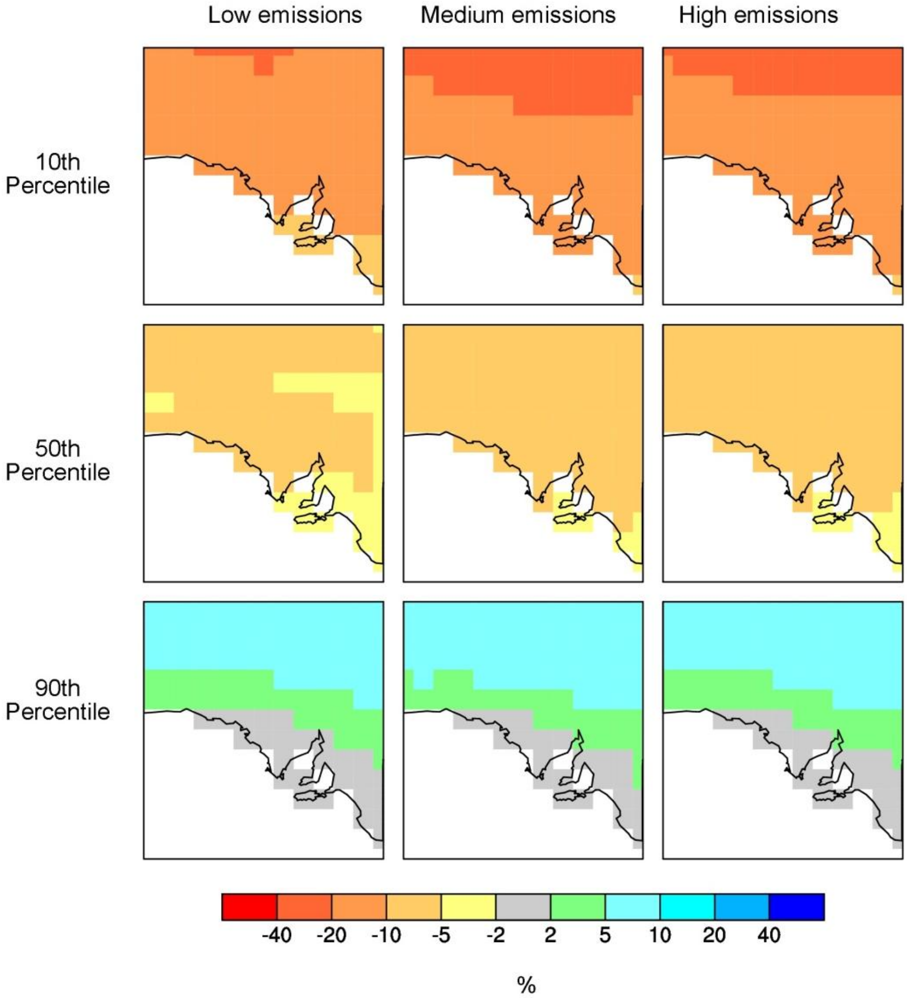


Figure 3. Range in projected changes in winter rainfall for 2030, across the 23 GCMs considered by CSIRO – BoM (2007). Low emissions corresponds to the B1 scenario, medium emissions the A1B scenario, and high emissions the A1FI scenario.

Firstly, PET has been identified as an important variable in the water resource availability for South Australia, particularly the simulation of recharge rates. Care must be exercised to preserve the internal consistency of a GCM's projections of different climate variables (CSIRO – BoM, 2007). Variables such as temperature, rainfall, PET, and humidity are highly interactive, where a change in one variable has an effect on other variables. As such, mixing variables from different models in a single scenario may result in physically implausible combinations (CSIRO – BoM, 2007). From Table 1, it can be see that only 9 of the models provide direct estimates of future changes to PET rates. Due to the need to consider PET changes in the ICCWR project, and to preserve the internal consistency of GCM projections, only the projections from these 9 GCMs are considered further. It is acknowledged that evapotranspiration projections could be derived from other GCM outputs, such as temperature and solar radiation, however downscaling variables such as this has been considered beyond the scope of the ICCWR project.

As noted in the previous section, Suppiah et al. (2006) assessed the performance of a number of GCMs for South Australian conditions, based on the representation of historic temperature, rainfall and atmospheric pressure records. Again, it should be noted that accurate performance when simulating the current climate does not guarantee the same accuracy when applied to future emission scenarios, and vice versa. Considering this caveat, Suppiah et al. (2006) assessed if current GCM climate errors were of a nature that significantly reduced the likelihood that the enhanced greenhouse simulation will be reliable, for example the absence of key climate features in South Australia. There are a range of metrics in the literature for assessing the performance of GCMs, which may result in the selection of a different suite of models, however the demerit points system of Suppiah et al. (2006) has been used for the purposes of this study, as they are specific to the South Australian climate, and are based on an assessment of structural model errors.

Of the 9 GCMs that provide PET outputs, 4 were rejected by Suppiah et al (2006) as suitable to represent the South Australian climate, on the basis of a demerit point system comparing simulated and observed temperature, rainfall and atmospheric pressure. The MIROC-H GCM has also been rejected as part of this project, as it was awarded 7 demerit points. This is a slightly stricter criterion than the used by Suppiah et al. (2006), who adopted a threshold of more than 7 points. The CSIRO Mark 3.5 GCM was not evaluated by Suppiah et al. (2006), however the projections provided by this GCM have been considered appropriate for South Australia, as they were used as the basis for the downscaling undertaken by Charles et al. (2009). As well as the demerit point system, CSIRO – BoM (2007) provides a skill score for each of these GCMs at representing the climate variability in Australia. The demerit points (lower is better) and skill score (higher is better) for the 23 GCMs are presented in Table 1 and Figure 4. The CSIRO Mark 3.5 GCM cannot be plotted on Figure 4 as it was not awarded a number of demerit points by Suppiah et al. (2006).

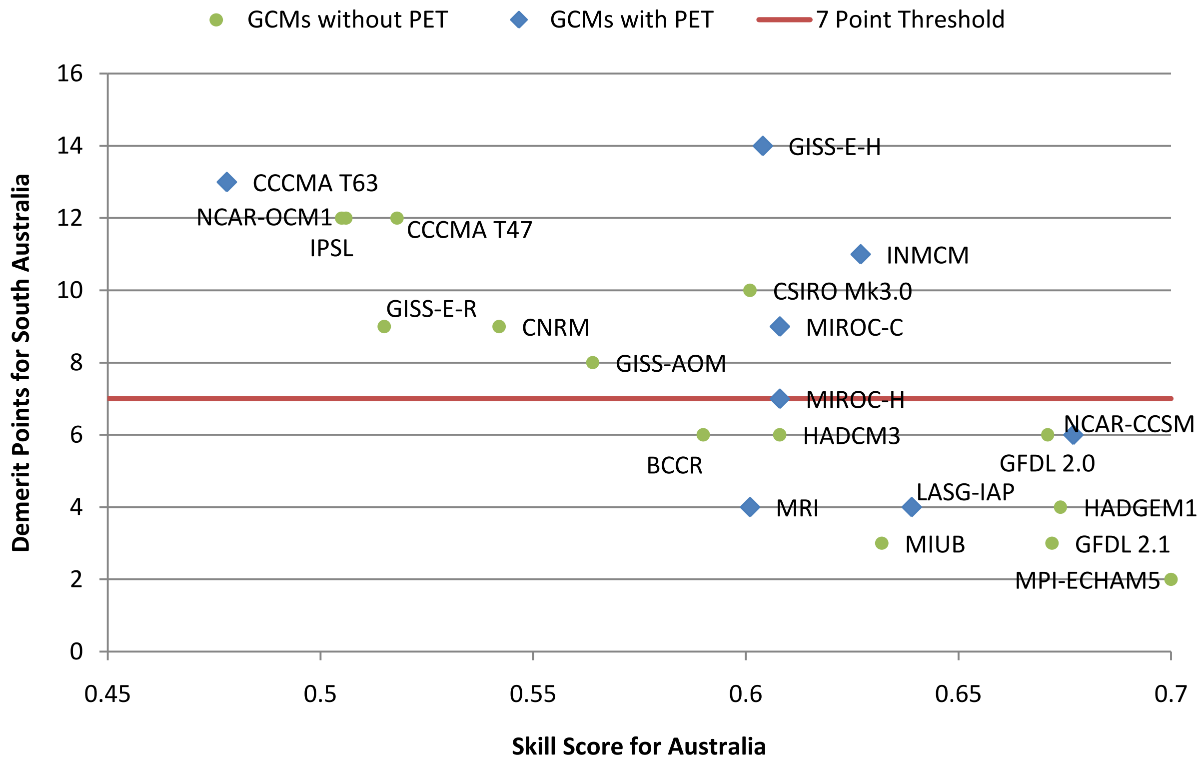


Figure 4. GCM Performance Comparison

The changes in both annual and winter rainfall and areal PET projected by the four remaining GCMs have been interrogated to quantify the range in suitable future projections. Four sites across the state have been selected to assess the spatial range in projections, Mt Gambier (26021) in the South East, Gumeracha (23719) in the Mount Loft Ranges, Clare (21014) in the Northern and Yorke NRM region, and Port Lincoln (18017) on Eyre Peninsula. The projections provided through the CSIRO OzClim website (http://www.csiro.au/ozclim/, accessed 10/3/11) have been used, and the cell corresponding to the location of each station has been extracted for interrogation. The three time horizons (2030, 2050 and

2070) and two emission cases (A2 and B2) identified in the previous section have been considered. The rate of global warming appropriate for the calibration of each GCM was adopted to obtain the relevant projections, namely a low rate for MRI and NCAR-CCSM3 GCMs, and a medium rate for LASG-IAP and CSIRO Mark 3.5 GCMs.

Typical results are presented in Figure 5, and all cases considered in Appendix 1. The CSIRO Mark 3.5 GCM produces by far the most extreme projections of the future climate for South Australia. For rainfall, generally the LASG – IAP GCM results in the smallest change in the future rainfall, with the exception of the site at Clare, where the NCAR – CCSM3 GCM produced the smallest annual percentage changes. However, it is winter rainfall that drives the majority of recharge and runoff in South Australia, and hence the winter projections are likely to have a greatest impact on the water resource availability. For the winter cases, the MRI and NCAR – CCSM3 GCMs are very similar, and fall between the CSIRO Mark 3.5 and LASG IAP GCM projections (e.g. Figure 5).

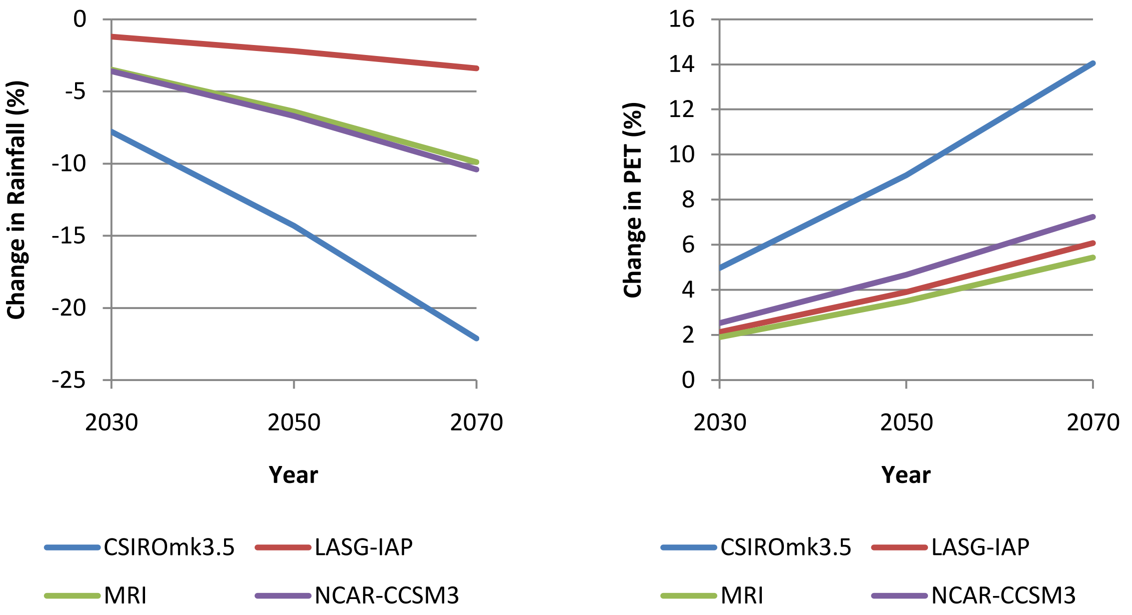


Figure 5. GCM Projections for changes in winter rainfall (left) and winter PET (right) at Mt Gambier for the A2 emission scenario

The MRI GCM generally projects the smallest change in PET for the future scenarios, with the CISRO Mark 3.5 again the highest projections, with the exception of the Clare and Gumeracha sites for the winter case. It is not as clear if one season of PET is more important to the generation of recharge and runoff than another, it may be the annual changes are more influential than the winter projections, which occur outside the winter months when PET exceeds rainfall. For most cases considered, the NCAR – CCSM3 GCM provides projections are close to the middle of the range of projections for both rainfall and PET.

All four GCMs identified in this section have been selected to provide projections of the future climate for generating the rainfall and PET time series for use in the ICCWR Project. This is expected to represent the uncertainty around projections of a future climate, while still remaining suitable for South Australian conditions. The following section outlines the method used to downscale the large scale projections provided by these four GCMs to the local weather station scale required for water resource impact assessment.

3. DOWNSCALING METHODOLOGY

The downscaling methods used to produce catchment-scale future climate series data required to drive hydrological models in impact studies are generally produced by either: (i) empirically scaling the historical data informed by GCM simulations, (ii) statistically downscaling GCM-scale atmospheric predictors to the catchment-scale climate, or (iii) dynamic downscaling to provide higher-resolution climate projections (Mpelasoka and Chiew, 2009).

The statistical downscaling methods relate large synoptic-scale atmospheric predictors to catchment-scale rainfall, while the dynamic downscaling methods generally use high resolution regional climate models nested in a GCM, with the GCM time-dependently driving the regional model at its boundaries. These two approaches may be better than empirical scaling methods that perturb a historical climate series because (i) they directly consider the spatial and temporal scale differences between GCM atmospheric predictors and catchment-scale rainfall; (ii) they take into account changes in the characteristics and relative frequency of synoptic patterns in a future climate; and (iii) GCM simulations of large-scale atmospheric circulation are better than GCM simulations of rainfall (Mpelasoka and Chiew, 2009). However, the application and calibration of the statistical downscaling methods can be laborious, requires expert judgment, and bias corrections to the GCM predictors (Chiew et al. 2010), while dynamic downscaling methods can also be biased, and are constrained by the spatial resolution and computation expenses (Mpelasoka and Chiew, 2009).

Empirical methods are applied by scaling the historical daily rainfall series to represent the future, and therefore these methods do not consider potential changes to other rainfall characteristics including the sequencing and timing of rainfall events (Chiew et al. 2010). Despite this, this approach is simpler to implement and offers a practical solution to constructing future climate scenarios in numerous studies on the effect of climate change on runoff (e.g. Chiew and McMahon 2002; Singh and Bengtsson 2004; Wurbs et al. 2005; Salathe 2005; Fowler et al. 2007; Post et al. 2009, Mpelasoka and Chiew, 2009, Chiew et al. 2010).

Chiew et al. (2010) compared the impact of five different downscaling techniques on eight unimpaired catchments near the headwaters of the Murray River in New South Wales and Victoria. The downscaling models used, in increasing order of complexity, were a daily scaling empirical model, three statistical downscaling models (an analogue statistical model, GLIMCLIM and NHMM models), and a dynamic downscaling model. The authors found similar future simulations were produced by the daily scaling, analogue and NHMM models, and concluded that the simpler to apply daily scaling method can be used for hydrological impact assessment studies over large regions, particularly when the main considerations are changes to seasonal and annual catchment water yield (Chiew et al. 2010). Due to the ease of application while still producing similar results to more complex statistical approaches at the scale of interest for the ICCWR Project, a daily scaling approach has been adopted to be used for the ICCWR Project to produce downscaled rainfall and PET datasets for use in recharge and runoff models across the state. Details of this method are provided in more detail in the remainder of this section.

3.1. DAILY SCALING METHODOLOGY

The simplest and most common scaling approach that has been adopted is a constant scaling approach, where a dataset that represents the historic climate is scaled by a constant factor that represents the projected future, based on GCM output. As the name implies, this constant scaling approach uses the same factor to scale all the data, however different values can be used on a seasonal or monthly basis. This approach has been used to produce the future PET datasets, based on the projected monthly changes provided on the CSIRO OzClim website for a given GCM and emission scenarios combination. A potential inconsistency was considered between the way the GCMs derive PET changes, and the application of these changes to the FAO56 Penman-Monteith PET data from local weather stations. The Penman-Monteith equation is one of the more complex equations available for calculating PET, incorporating wind and humidity information as well as temperature and solar radiation. As the relative changes in PET projected by the GCM are derived from the GCM's projections of the same variables, they were deemed to be appropriate to be applied to the FAO56 Penman-Monteith PET data from local weather stations to generate scaled PET data for input to runoff and recharge models.

The constant scaling approach has been deemed appropriate for PET, which is relatively consistent over a period in the order of a month. However, many GCMs suggest that the extreme rainfall may increase in the future, even in locations where mean annual rainfall is projected to decrease. As high rainfall events generate significant runoff, climate change impact on runoff studies that do not take this into account will underestimate changes in future runoff (Post et al. 2009). In order to accommodate this effect, the daily scaling method (also called quantile – quantile mapping) takes into account changes in the daily rainfall distribution by scaling the different rainfall amounts by different factors. This advantage that the daily scaling method has over the constant scaling method can be important, particularly in studies on changes in extreme runoff (Mpelasoka and Chiew, 2009). However, the difference between the mean annual runoff simulated with future daily rainfall series obtained using the constant scaling and daily scaling methods generally differs by less than 5% (Mpelasoka and Chiew, 2009; Post et al. 2009).

A similar approach to that used by Post et al. (2009) has been adopted to produce the daily scaling adjustments for the ICCWR project. The approach has been applied separately for each of the four seasons, to allow for different adjustments in each period. Firstly, the daily rainfall GCM outputs for a given grid cell and season (in this case corresponding to Mt Gambier in winter) for the simulated historic period are compared to those projected for a future case (in this case 2050 and A2 emissions). To avoid complications with emission scenarios, the period used for the historic conditions in the study was 1970 – 1999, as 1999 is generally the last year for the climate of the 20th century historic GCM runs available. The same 30 year periods used to produce the OzClim data are used for the future datasets (i.e. 2015 – 2044 for 2030 conditions, 2035 – 2064 for 2050 conditions and 2055 – 2084 for 2070 conditions, (CSIRO-BoM, 2007)). The simulated rainfall events are ranked to produce probability of exceedance curves, as seen in Figure 6.

Adjustment factors for the different rainfall percentiles are determined by dividing the future rainfall amount by the past rainfall amount, resulting in the dark circles seen in Figure 7. To obtain a smooth transition in the daily scaling factors, the percent changes are estimated by averaging the rainfall amounts over percentile ranges: 1st percentile (all points smaller than 2.5th percentile), 5th percentile (all points between 2.5th and 7.5th percentiles), 10th percentile (all points between 7.5th to 12.5th percentiles), and every five percentile range upwards (Post et al. 2009). This smoothing process results in the "Daily Scaling" line presented in Figure 7, where it can be seen that the most extreme events, with a probability of occurrence less than 5%, are increased by a small amount, where the remainder of the rainfall events are reduced by more and more as the events become more likely. As a comparison, the equivalent constant scaling factor is represented as the "Constant Scaling" line, which would result in future winter rainfall that are approximately 95% of those experienced historically, irrespective of the daily total.

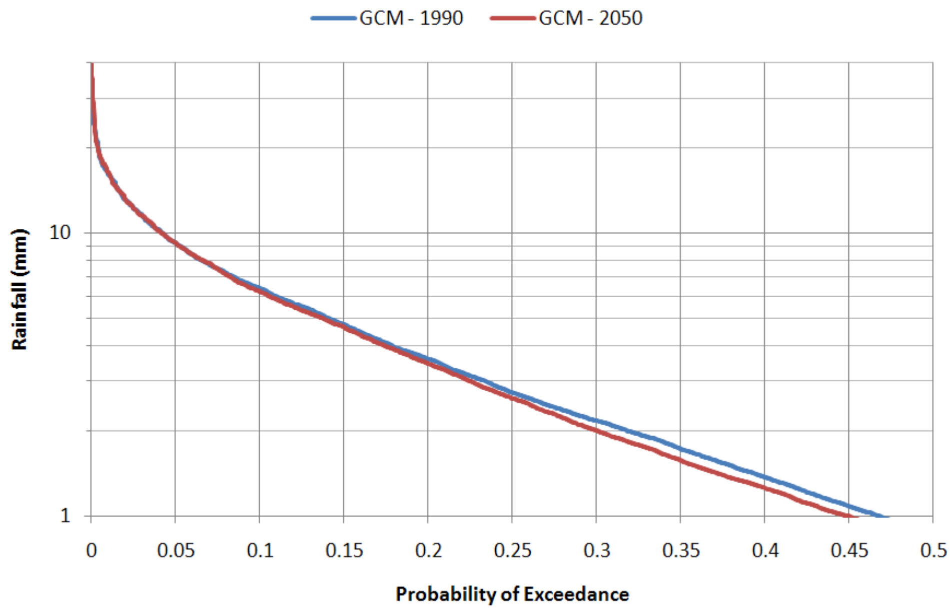


Figure 6. **Comparison of winter rainfall distributions for 1990 and 2050 A2 conditions based on NCAR-CCSM3 GCM projections for Mount Gambier**

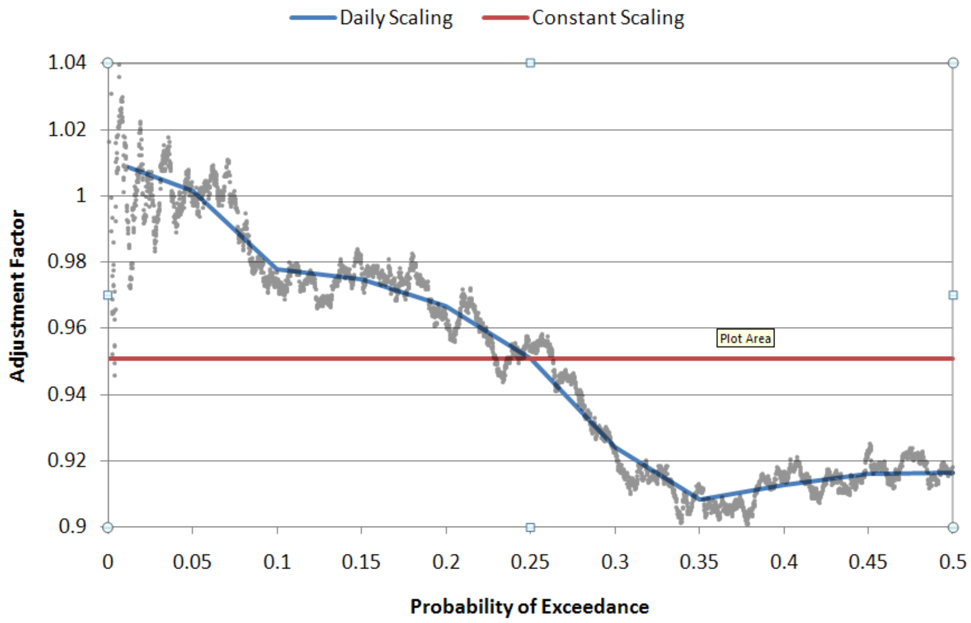


Figure 7. **Adjustment factors used for the daily scaling method, resulting from the distributions presented in Figure 6.**

To apply the adjustment factors, the dataset representing the historic data at the rainfall station of interest are also ranked to provide the probability of exceedance information. The rainfall amounts corresponding to each five percentile interval on the smooth adjustment curve are identified, to enable the correct adjustment factor to be applied to each historic rainfall amount. The historic rainfall amount is finally multiplied by the adjustment factor to produce a daily rainfall dataset which represents the future projections provided by the GCM.

Currently, daily GCM rainfall data are available for only A2, A1B and B1 emission cases on the World Climate Research Programme's (WCRP) Phase 3 of the Computed Model Inter-comparison Project (CMIP3, available online at https://esg.llnl.gov:8443/). Due to the need to include daily GCM outputs in the downscaling approach, A2 and B1 emission cases are adopted to represent high and low emission cases for the ICCWR project.

Some inconsistencies in the GCM results can become apparent due to the natural variability in the simulated climate. For example, the annual rainfall simulated by the NCAR-CCSM3 GCM for the grid cell corresponding to the location of Mount Gambier and B1 emissions can be seen in Figure 8. The linear line of best fit indicates that there is expected to be a decline in rainfall over the next century, as projected by this GCM. However, if the 30 year period around 2050 is considered alone, it happens to provide a lower annual average rainfall (red horizontal line) compared to the average of the 30 year period around 2070 (green horizontal line), even though there is an overall declining trend.

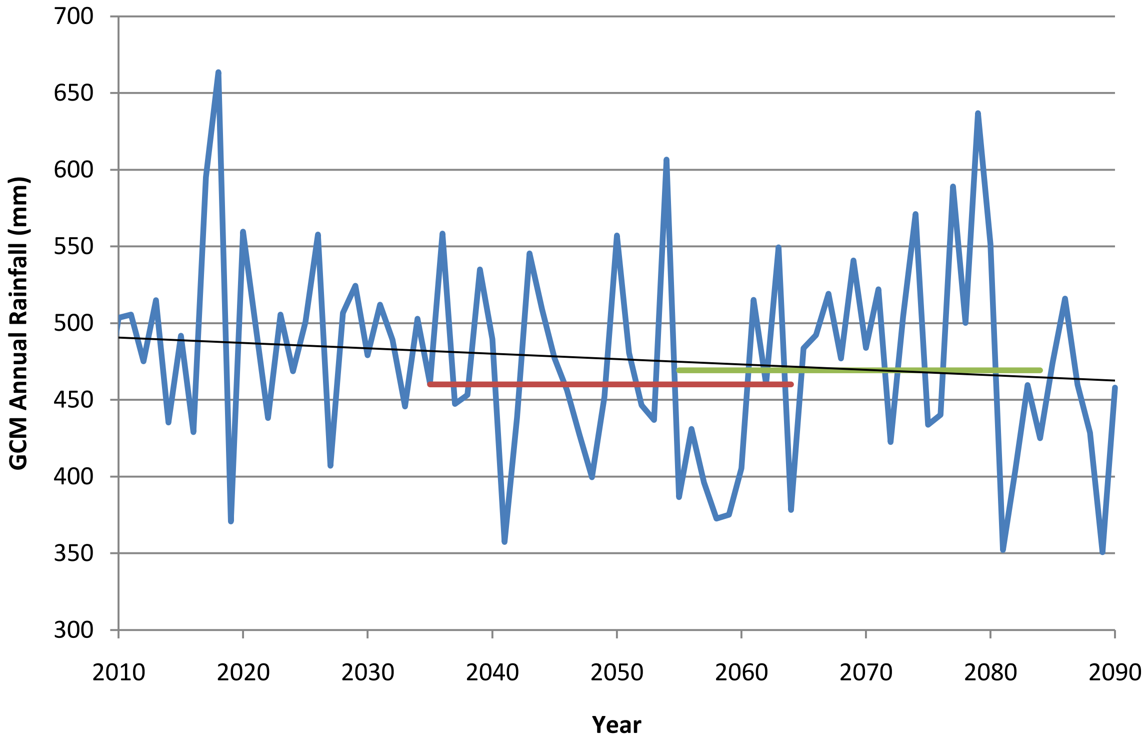


Figure 8. GCM simulated annual rainfall at Mt Gambier for B1 emission case

An ensemble of multiple GCMs runs was considered in an attempt to address variability issues such as that seen in Figure 8. However, consistent results across different time horizons and emission cases are still not guaranteed by this approach. In order to ensure consistency, the daily scaling adjustment factors have been scaled by a factor to produce the same overall change in rainfall for the season as that provided for the same case by the CSIRO OzClim website. For each case provided on OzClim (e.g. GCM, emission case and time horizon) the projections have been produced by developing a linear relationship between the projected change in rainfall (or PET) and the projected change in temperature. This way, trends are provided that avoid the short term influence of annual variability on the projections.

3.2. HISTORIC BASE DATA

The empirical downscaling technique adopted to produce the datasets for the ICCWR Project requires a dataset representing the historic climate to apply the daily scaling adjustments to. The GCM projections available via OzClim are relative to a 1990 baseline period, calculated as the average of the period 1975 – 2004. However, this is a relatively short period, and is likely to include only a few extreme events, of very high or low rainfall for example. Stochastic weather generators can be used to extend the period of data for simulation to include a more complete representation of the distribution of events, based on the statistics of the data used to calibrate the stochastic models.

Two weather generators have been considered to produce this data as a basis for GCM downscaling; LARS-WG, which has been used previously for a study investigating climate change impacts on recharge on Eyre Peninsula, and the Stochastic Climate Library (SCL), developed by eWater. Both approaches have automatic calibration procedures and only require the historic data series to be provided. Both models provide stochastically generated correlated rainfall and PET series, which are required for recharge and runoff simulation. Eight sites in the South East of the state have been considered to investigate the performance of both weather generators in representing the historic South Australian climate. The sites were selected based on possessing high quality historic rainfall record, as well as providing an even distribution across the South East of the state. The stations used can be seen in Figure 9.

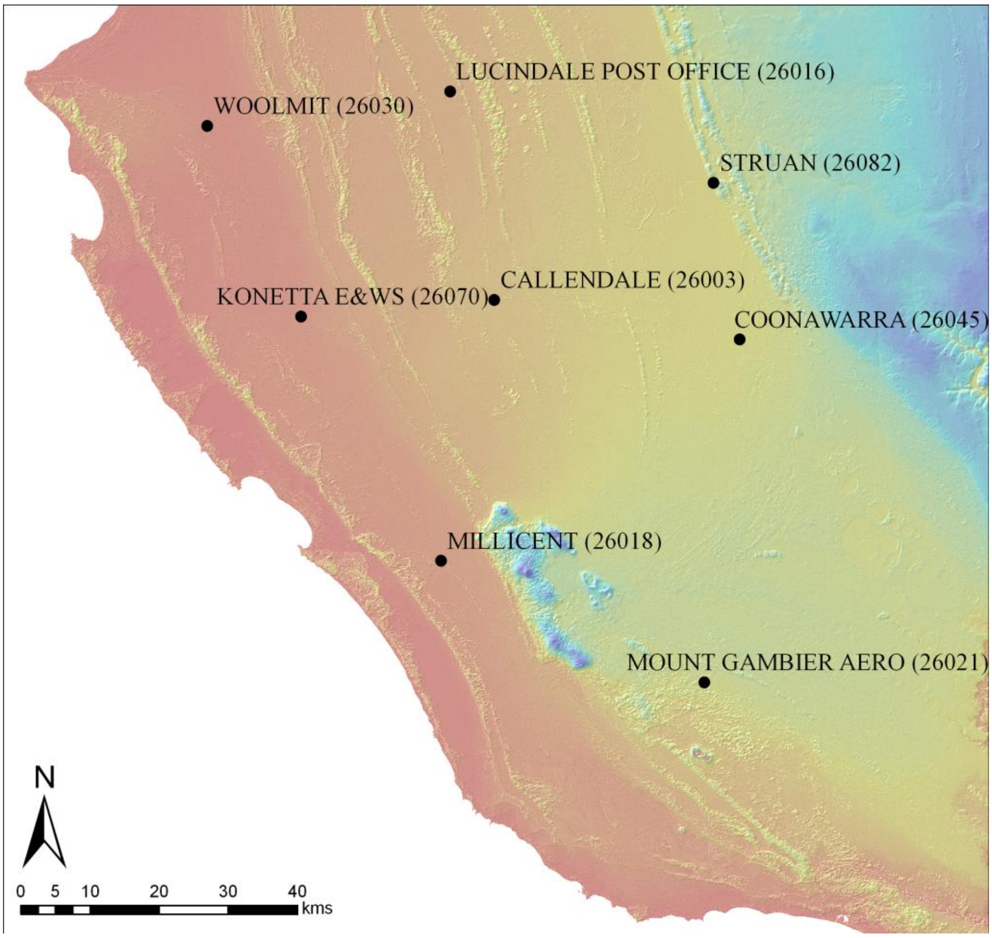


Figure 9. Rainfall sites considered for comparison of stochastic weather generators

The future climate projections provided on OzClim are relative to 1990 conditions, calculated as the average climate for the period 15 years either side, e.g. 1975 – 2004. Hence, data from this 30 year period derived from the SILO Patched Point Dataset (Jeffery et al., 2001) has been used to calibrate the stochastic weather generators for each site. Both weather generators provide output statistics for observed and simulated monthly rainfall and monthly average maximum temperature, and hence these two variables have been used as the basis for comparison.

Table 2 presents the errors in monthly rainfall, averaged across the 12 months for each site, as well as the average across all sites and all months. The performance of SCL can be seen to be much more accurate, with an average monthly rainfall error of 2.2%, compared to 12.1% from LARS-WG. The results for simulated average monthly rainfall for each site can be seen in Appendix 2, as the percentage error from the observed average rainfall over the 30 year baseline period. The SCL adopts an acceptable error tolerance of 7.5%, and only 5 of the 96 months are outside this tolerance across the 8 sites. The performance of LARS-WG is significantly worse on the monthly average rainfall amounts, with 55 of the 96 months outside the 7.5% error tolerance. The results are particularly poor for the summer months with less rainfall, where the error is at times greater than 25% of the observed monthly rainfall.

Table 2. Average Error in Monthly Rainfall Estimates– 1975-2004 Period

Site	SCL	LARS-WG
26003	2.60%	16.33%
26016	2.82%	20.16%
26018	1.76%	6.95%
26021	1.92%	11.60%
26030	1.89%	13.19%
26045	2.10%	9.50%
26070	2.86%	7.19%
26082	1.80%	12.05%
Average	2.22%	12.12%

The simulation of monthly average maximum temperature is more accurate for both stochastic models, with almost all monthly estimates within the 3% acceptable error tolerance suggested by SCL, as seen in Figure 22. However, SCL is again more accurate than LARS-WG, with a monthly average temperature error of only 0.17%, compared to 1.27% for LARS-WG, as seen in Table 3. The results for simulated monthly maximum temperature, average across the 30 year period, for each site can also be seen in Appendix 2.

Table 3. Average Error in Monthly Maximum Temperature Estimates – 1975-2004 Period

Site	SCL	LARS-WG
26003	0.15%	1.35%
26016	0.18%	1.28%
26018	0.17%	1.15%
26021	0.18%	1.37%
26030	0.16%	1.43%
26045	0.18%	1.17%
26070	0.18%	1.22%
26082	0.17%	1.15%
Average	0.17%	1.27%

To quantify the impact of these errors on the resulting simulated runoff, the Mt Hope Drain WaterCress model has been used to translate the stochastic rainfall and evaporation series into simulated flows. The closest SILO station for this model is Millicent, and was used for all catchment nodes with rainfall adjustment factors if necessary, as the stochastic simulations at each station are not spatially correlated to allow multiple sites to be used. A stochastic series of 100 years has been generated using both approaches. A comparison between the simulated and observed rainfall (calculated as the average over the 30 year baseline period) and PET can be seen in Figure 10 and Figure 11, respectively. The SCL model can be seen to follow the historic series slightly better than LARS-WG for rainfall, and is very similar to the observed PET. Conversely, LARS-WG can be seen to significantly underestimate the PET for the drier months of the year.

The impact that these errors in input rainfall and PET series have on the simulated flow can be seen in Figure 12, where the historic series has been simulated by WaterCress using the true historic rainfall and PET data. Both stochastic datasets underestimate the peak in monthly average flow in August. As the SCL input series are more accurate, the resulting flow is also closer to that simulated based on historic data. From Table 2 and Table 3 it can be seen that the site used for the flow analysis, 26018, is the most accurate representation of the historic climate for LARS-WG, and hence the difference in flow would be expected to be much greater for catchments located near the other sites considered.

From Figure 12, it can be seen that adopting a stochastic weather generator can introduce a substantial error into the water resource availability simulated. This error can lead to difficulties when assessing future climate projections, as it cannot be determined if a decrease in the water availability is due to the errors in the generation of the stochastic base data, or due to the perturbations applied to represent a future climate. This can be overcome to some extent by comparing the results representing future scenarios to the base stochastic data calibrated to the historic climate. However, the total available volume is important for many applications, such as water allocation planning and demand supply planning. Therefore, introducing errors into the simulation of the total available volume of a resource by implementing a stochastic weather generator is not preferable.

In order to avoid this issue while still simulating a sufficiently long record of climate variability, a longer period of 50 years of observed data has been used as the base data, spanning 1961-2010. It is assumed that the error introduced by adopting a slightly different base climate period for the projections (compared to 1975 – 2004) is small compared to the errors introduced by adopting a stochastic weather generator to provide a longer time series. Also, the results presented as part of the ICCWR Project are largely concerned with changes to average annual values, which are generally well represented over a 30 to 50 year period. Accurate representation of extreme events is of less interest, which requires long simulation periods to provide sufficient representation of such rare events, and also less suited to be assessed using the empirical daily downscaling approach adopted.

To test this assumption, both stochastic weather generators were applied using the same method to the same sites, but calibrated to data from the longer 50 year period.

Table 4 presents the errors in monthly rainfall, averaged across the 12 months for each site, as well as the average across all sites and all months, and Table 5 the same information for the monthly average maximum temperature. Compared to the results presented in Table 2 and Table 3 based on the 30 year calibration period, the accuracy of the SCL model decreases significantly, with the average monthly error for both variables across all months and sites approximately double that for the 30 year period. While there is variation in the performance of LARS-WG at each site between the 30 and 50 year period, the overall model performance when averaged across all sites is similar for both periods, however still significantly worse than the SCL for the 50 year period. The runoff model was not rerun using these datasets, however given there errors in the input weather data are similar or larger, it would be expected that the errors in simulated runoff based on these datasets would also be similar or less accurate than that seen in Figure 12.

Using observed data as the base data for applying the daily scaling adjustments also has the advantage that the observed climate variables are correctly correlated, both spatially with nearby sites and also across the climate variables. The SCL software has the ability to produce stochastic rainfall series correlated across a number of sites, or correlated weather datasets (rainfall, PET and temperature) at a particular site, but not spatially correlated weather series across a number of sites. Making use of observed values preserves the correlation with both climate variables and spatial sites.

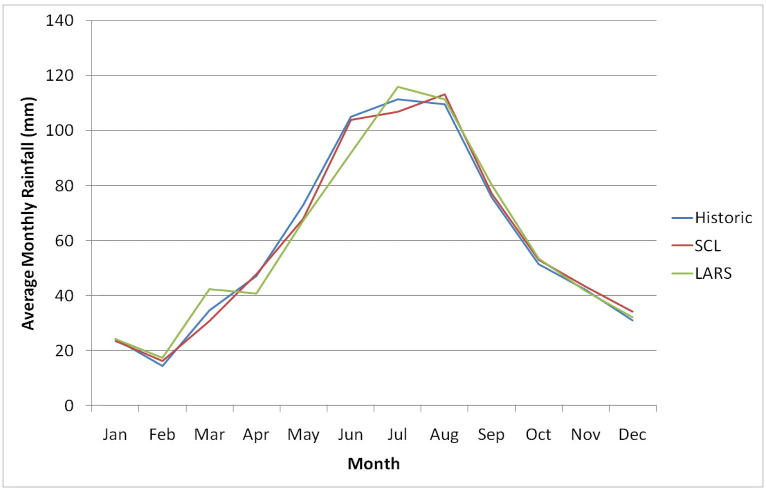


Figure 10. **Simulated average monthly rainfall (26018). The historic series is based on the observed 30 year record, the SCL and LARS-WG series are based on a stochastic 100 year record.**

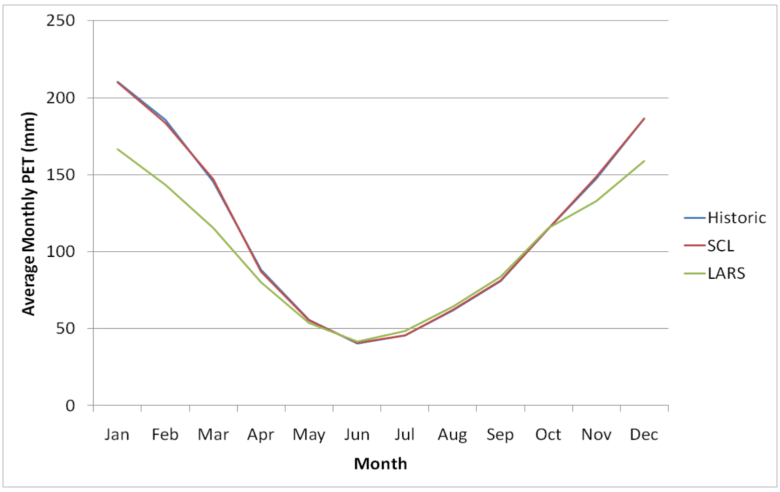


Figure 11. **Simulated average monthly potential evapotranspiration (26018). The historic series is based on the observed 30 year record, the SCL and LARS-WG series are based on a stochastic 100 year record.**

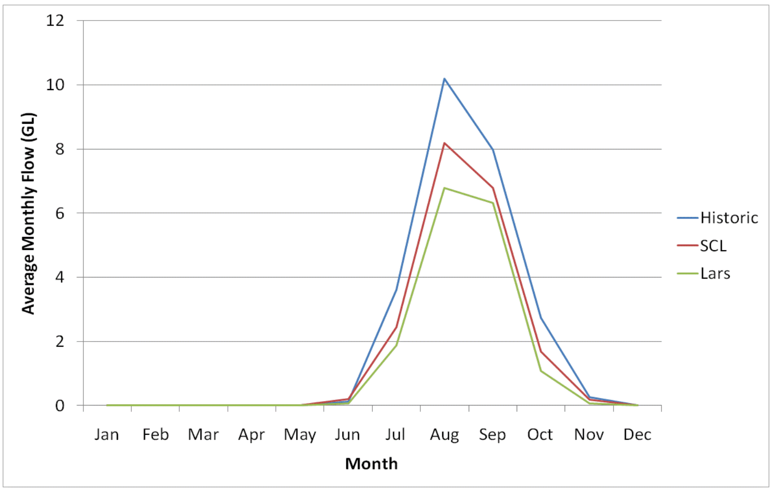


Figure 12. **Simulated runoff for Mt Hope drain, based on the historic and stochastic rainfall and PET inputs**

Table 4. Average Error in Monthly Rainfall Estimates – 1961-2010 Period

Site	SCL	LARS-WG
26003	3.40%	12.09%
26016	5.75%	16.21%
26018	4.15%	10.90%
26021	4.60%	8.31%
26030	4.17%	17.09%
26045	5.35%	10.27%
26070	4.58%	16.73%
26082	4.09%	9.49%
Average	4.51%	12.64%

Table 5. Average Error in Monthly Maximum Temperature Estimates – 1961-2010 Period

Site	SCL	LARS-WG
26003	0.44%	1.10%
26016	0.51%	1.04%
26018	0.41%	1.34%
26021	0.46%	0.81%
26030	0.37%	1.02%
26045	0.48%	1.16%
26070	0.42%	1.18%
26082	0.50%	0.79%
Average	0.45%	1.06%

4. CONCLUSIONS AND RECOMMENDATIONS

The ICCWR Project has identified the need to undertake downscaling of future climate projections for water resource impact studies in South Australia. This need was based on a requirement to consider the correlation between the input data, rainfall and PET, and to adopt the projections that are the most appropriate for the region. In order to achieve this, this report has investigated the currently available (as determined by IPCC AR4) GCM projections, as well as a number of downscaling techniques that are in use to justify the approaches adopted to generate future climate data for the ICCWR Project.

Of the 23 GCMs included in IPCC AR4, only nine provide direct projections of future changes to PET. Of these nine GCMs, five have been deemed unsuitable to represent the climate in South Australia. The annual and winter projections provided by the four remaining GCMs have been considered to quantify the likely range in future climate for both low and high emission cases. All four GCMs have been adopted for application in the ICCWR project for the NRM regions considered. The NCAR CCSM3 GCM was identified as providing a middle projection, between the most extreme and least change cases. For consistency with CSIRO – BoM (2007) and Water for Good, as well as accommodate a range of policy and decision making situations, low (B1) and high (A2) emission cases will be considered by the ICCWR Project, for time horizons of 2030, 2050 and 2070.

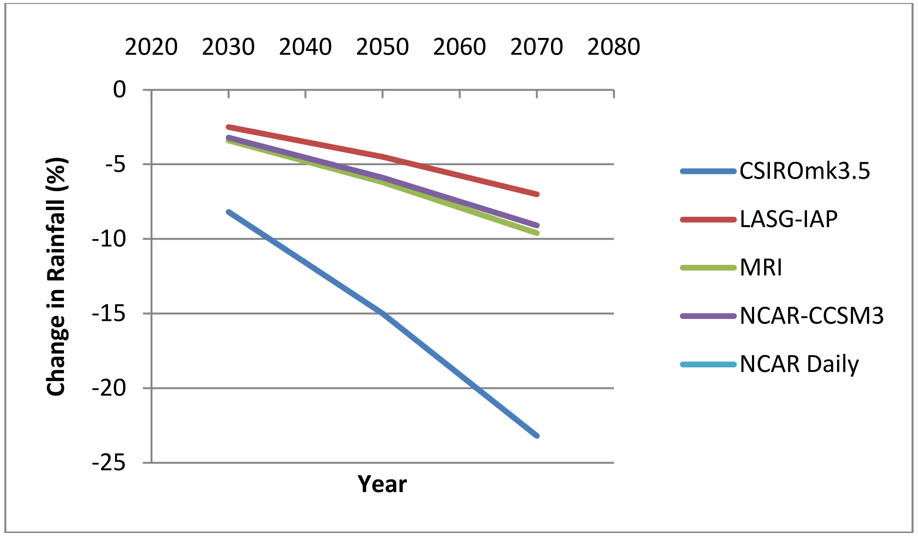
A downscaling technique is required to apply the projections at the local scale for water resource impact analysis. A review of recent studies concluded that simple empirical scaling approaches can provide similar results to more complex statistical approaches when considered at the seasonal or annual scale for large regions. A daily scaling method has been adopted to apply the future rainfall projections, allowing for different adjustments based on the rainfall amount. Hence, this approach can produce increases in extreme rainfall events, even though the average rainfall is expected to decrease for the majority of cases. A constant scaling approach has been adopted on a monthly time step to produce the PET projections.

A base dataset representing the historic climate is required to implement the selected downscaling technique. Two stochastic weather generators were compared to provide this dataset, where the weather generators can be used to extend the climate record at the site to provide a greater representation of the extreme wet or dry events, which occur less often. However, small errors in the rainfall and PET series simulated by the weather generators were found to lead to large (20 to 30%) underestimates in runoff, which may have significant implications if the results are considered in the context of water allocation planning or demand supply planning, for example. To avoid introducing errors via a stochastic weather generator, a period of 50 years of historic data, over the period 1961 to 2010, has been used as the base data for this work. Using observed data also has the advantage of preserving the correlation between rainfall and PET at each site, as well as the correlation in climate variables across a number of weather stations, which may be required for larger water resource impact models.

Subsequent to the work presented in this report, an agreed set of climate projections for South Australia is to be developed by a priority project of the (Government of South Australia) Goyder Institute for Water Research, to be conducted from 2011 to 2014. It is recommended that when the climate projections of the Goyder Institute project become available, the hydrological modelling conducted by the ICCWR project should be revisited, applying the agreed climate projections to generate updated projections of climate change impacts on water resources.

APPENDIXES

A. GCM PROJECTION COMPARISON



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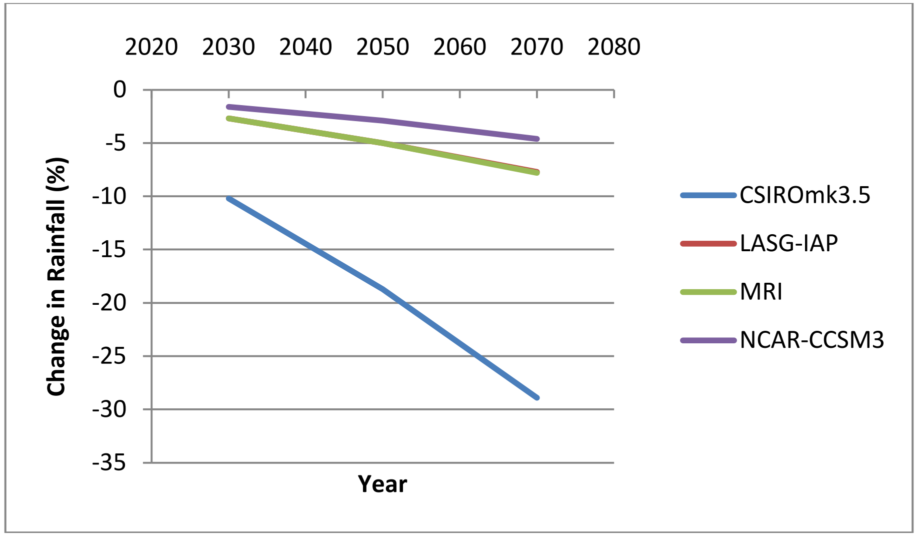
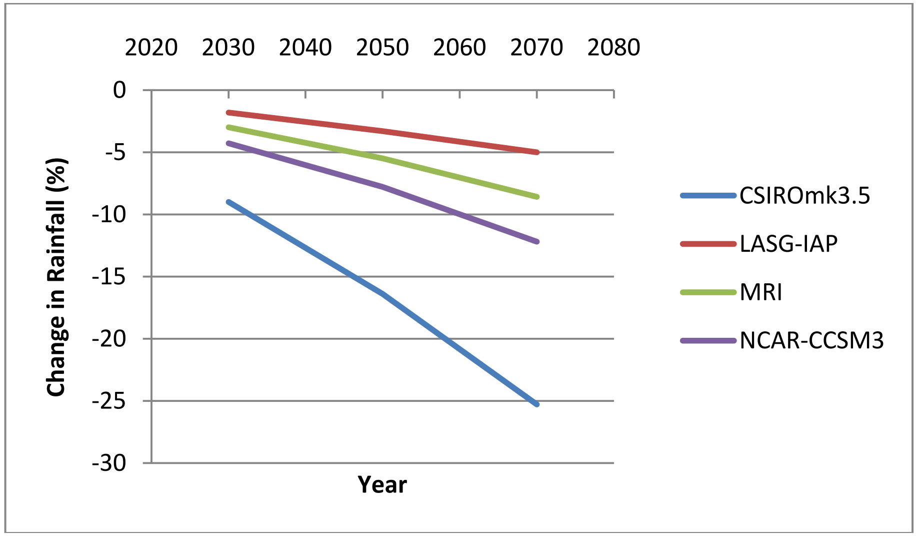


21014 - Clare



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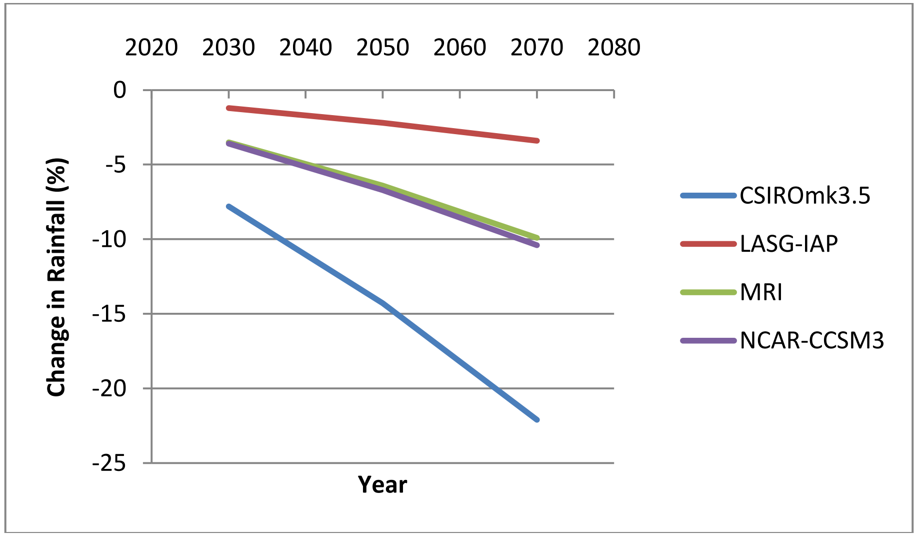
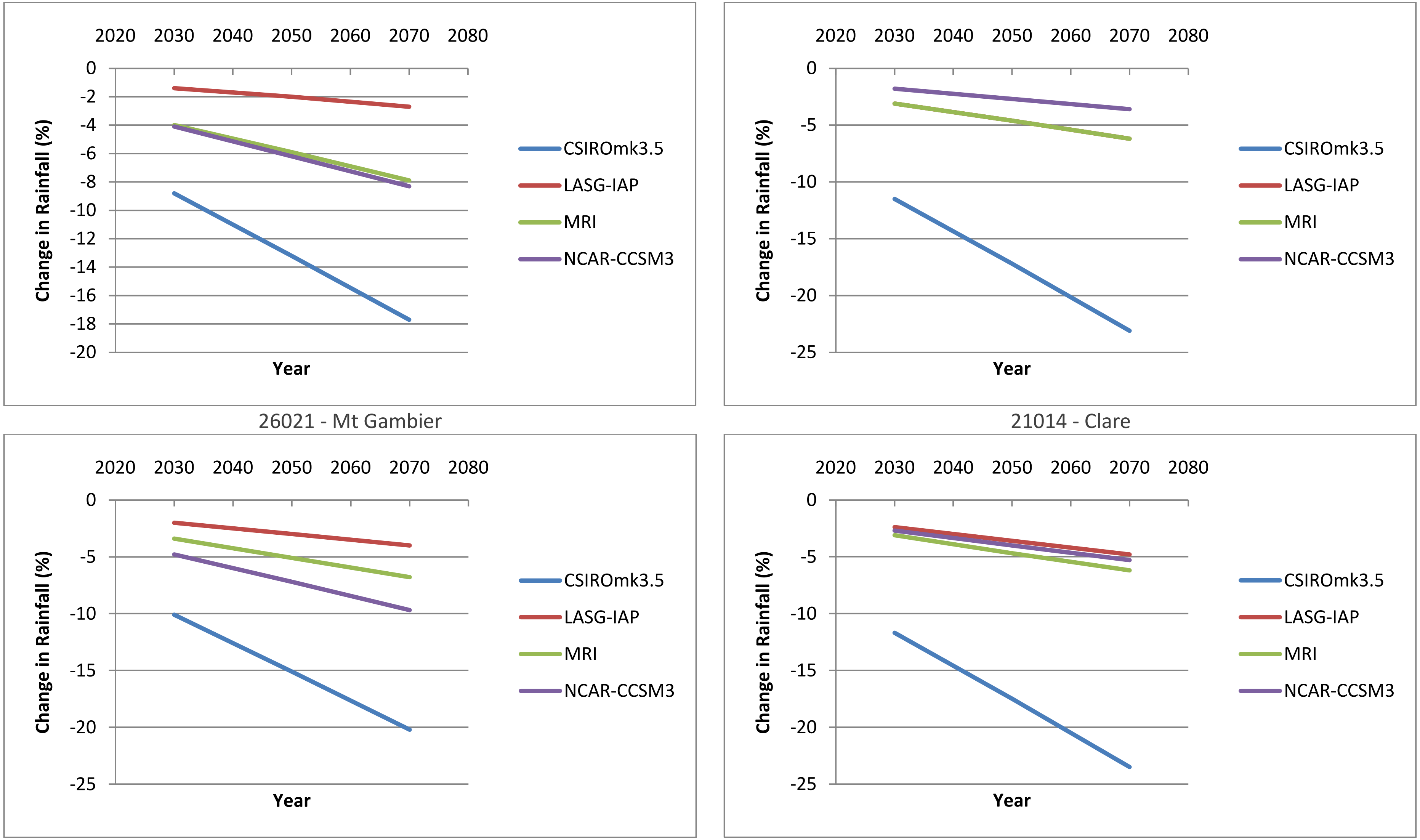


23719 - Gumeracha

Figure 13. Annual Rainfall Projections for A2 Emissions Scenario. For Clare, the LASG-IAP GCM corresponds to the MRI GCM.



26021 - Mt Gambier

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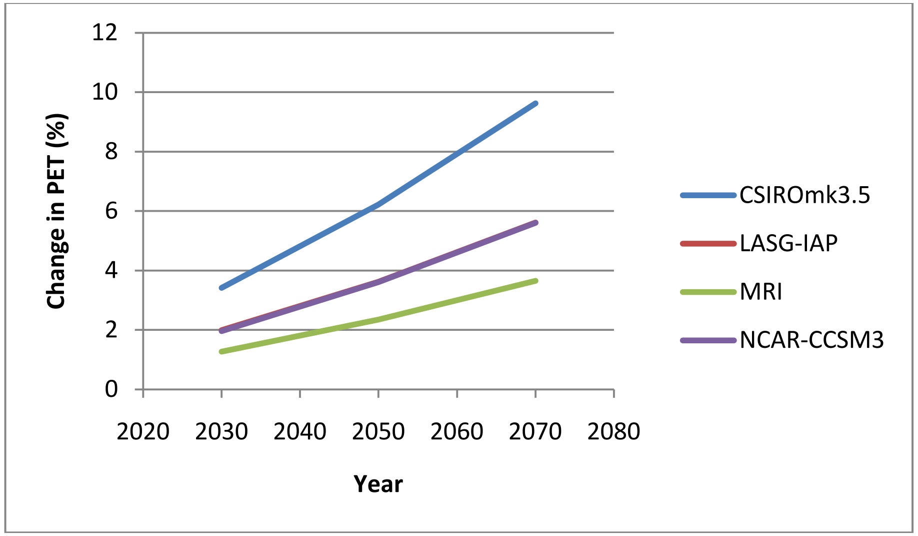
Figure 14. Annual Rainfall Projections for B2 Emissions Scenario. For Clare, the LASG-IAP GCM corresponds to the MRI GCM.



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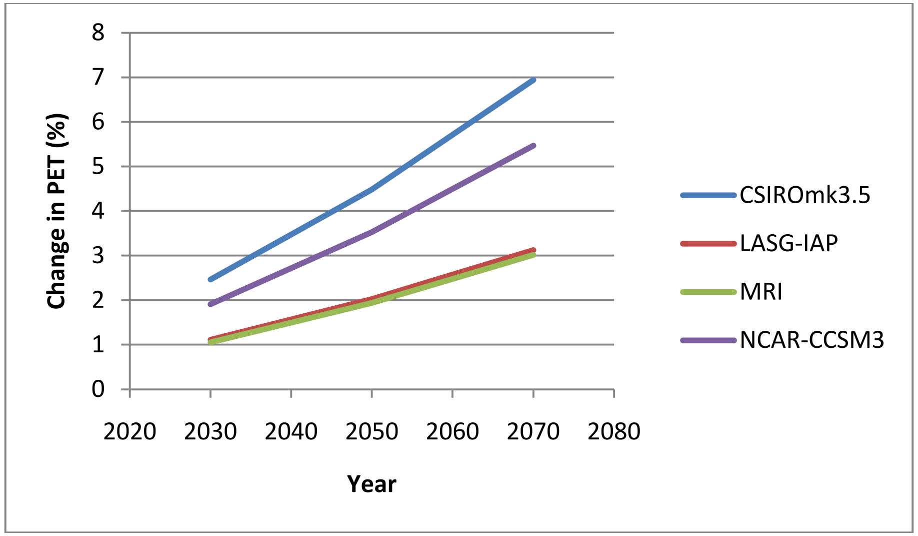

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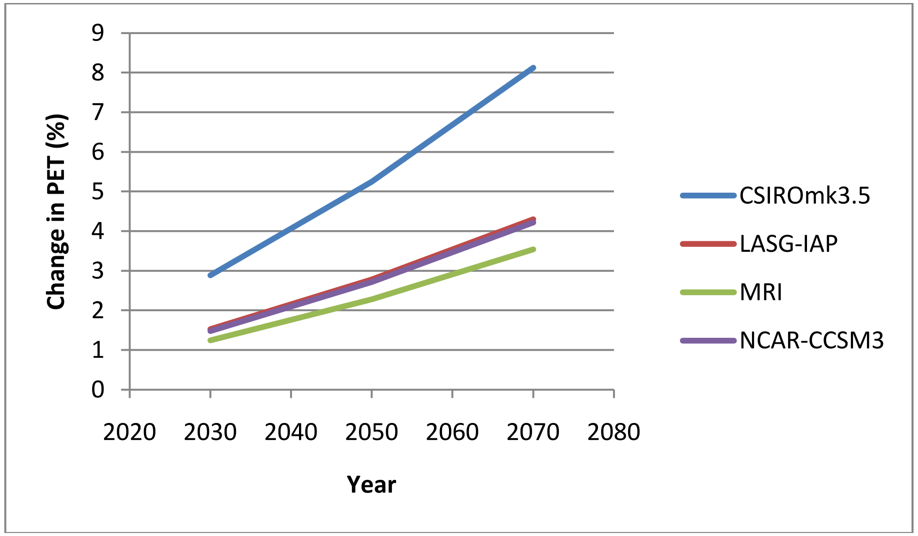

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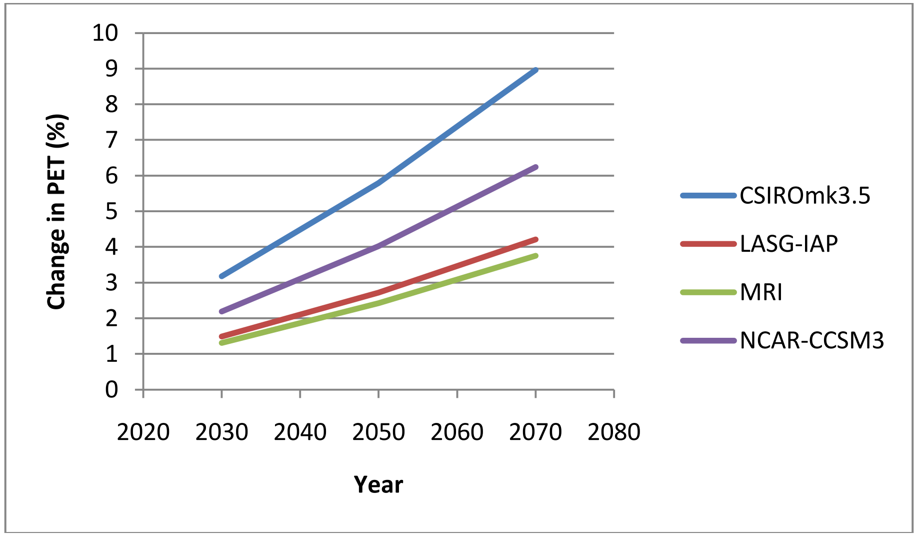

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Figure 15. Annual Evapotranspiration Projections for A2 Emissions Scenario. For Mt Gambier, the LASG-IAP GCM corresponds to the NCAR-CCSM3 GCM

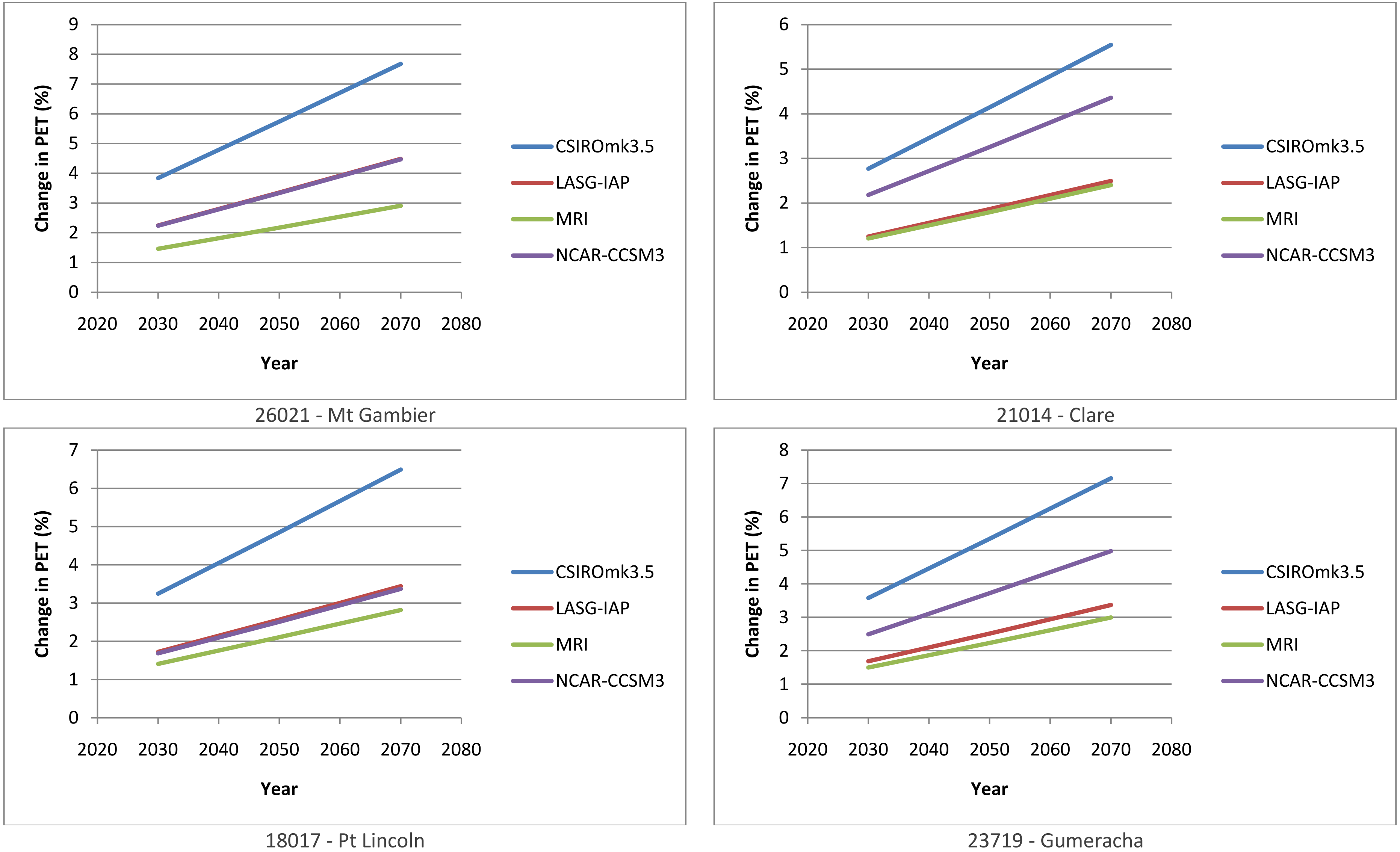
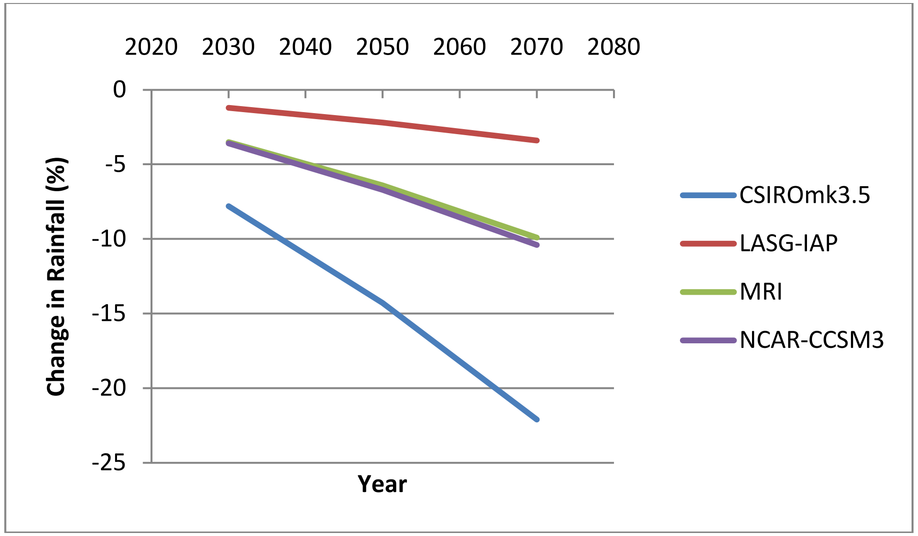
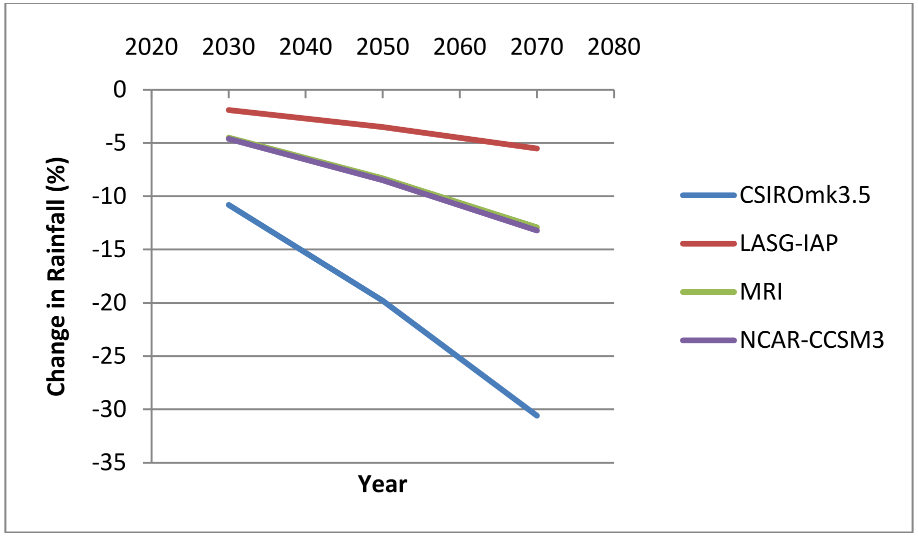


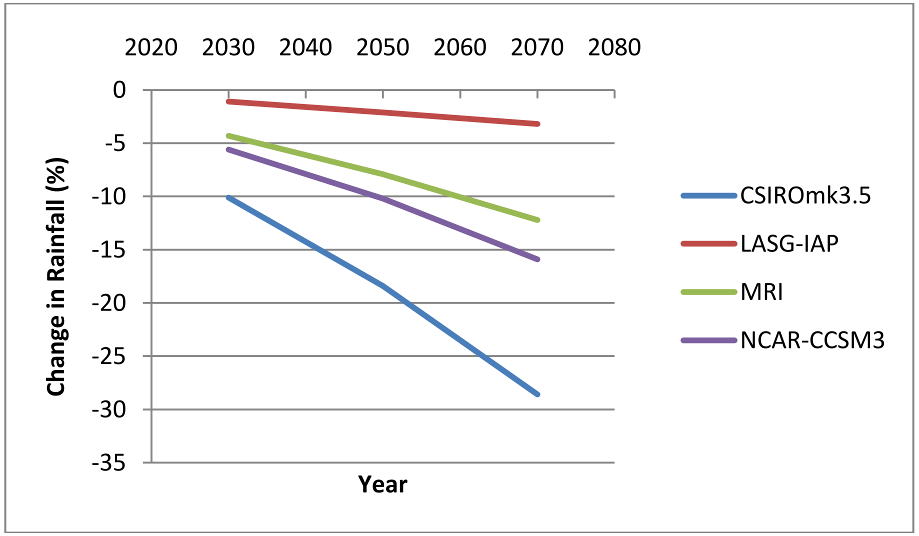
Figure 16. Annual Evapotranspiration Projections for B2 Emissions Scenario. For Mt Gambier, the LASG-IAP GCM corresponds to the NCAR-CCSM3 GCM.



26021 - Mt Gambier



21014 - Clare



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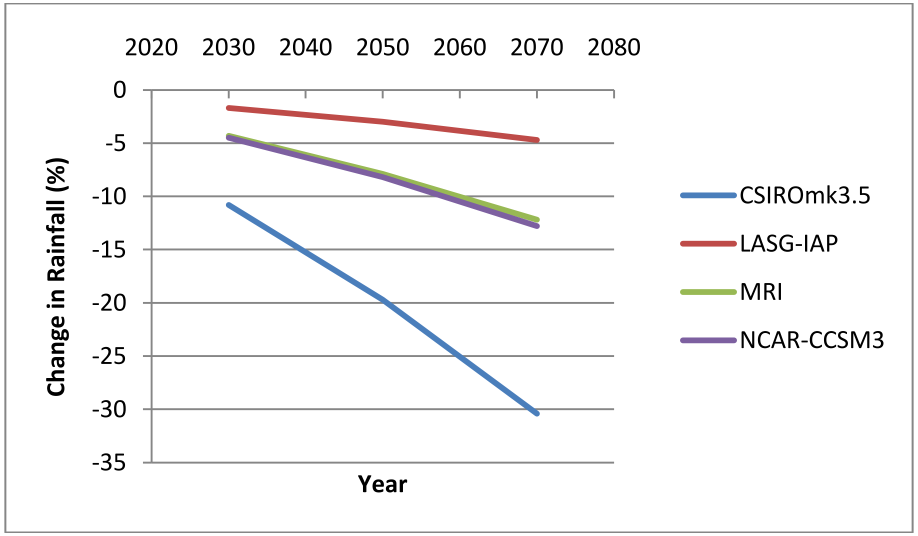

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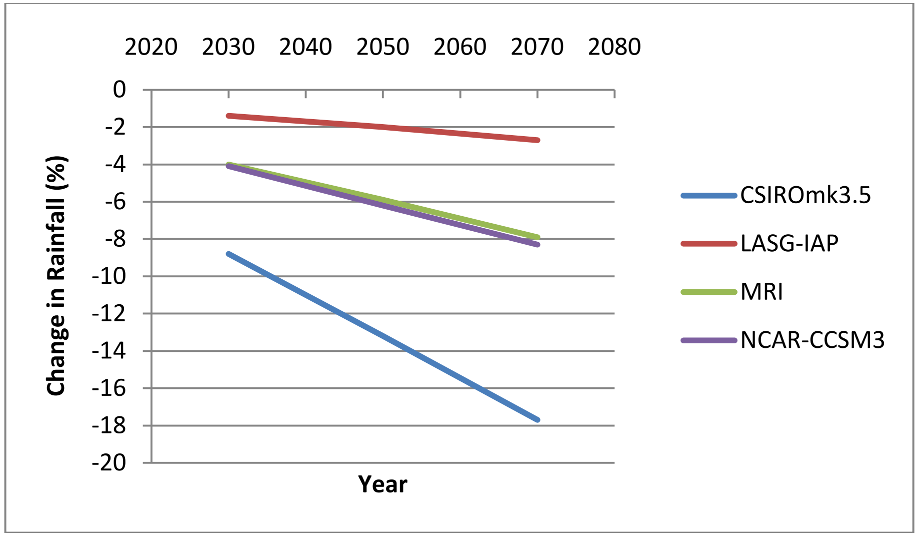
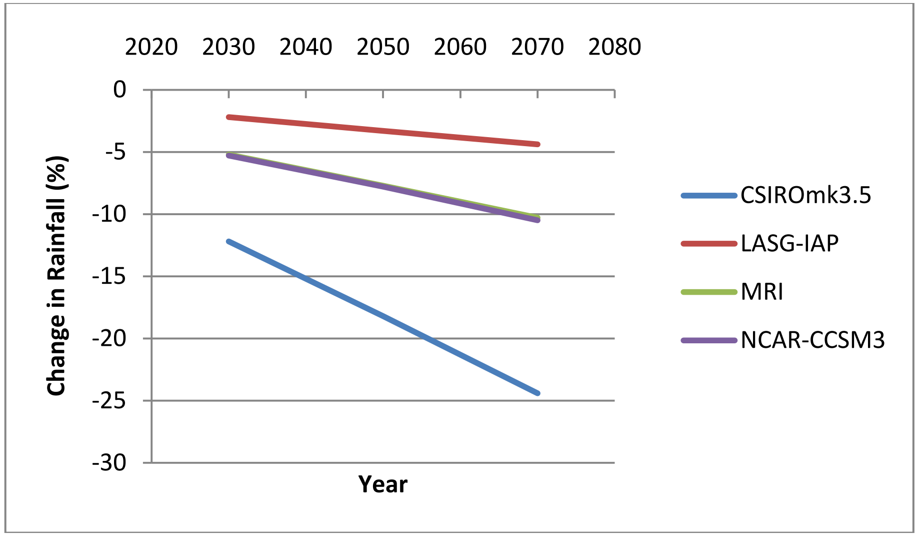
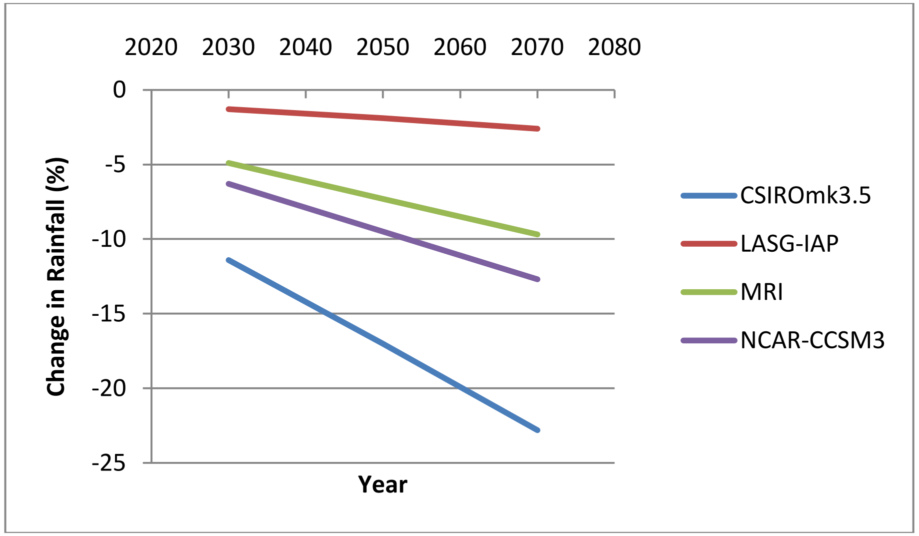
Figure 17. Winter Rainfall Projections for A2 Emissions Scenario. For Clare, the MRI GCM corresponds to the NCAR-CCSM3 GCM.



26021 - Mt Gambier



21014 - Clare



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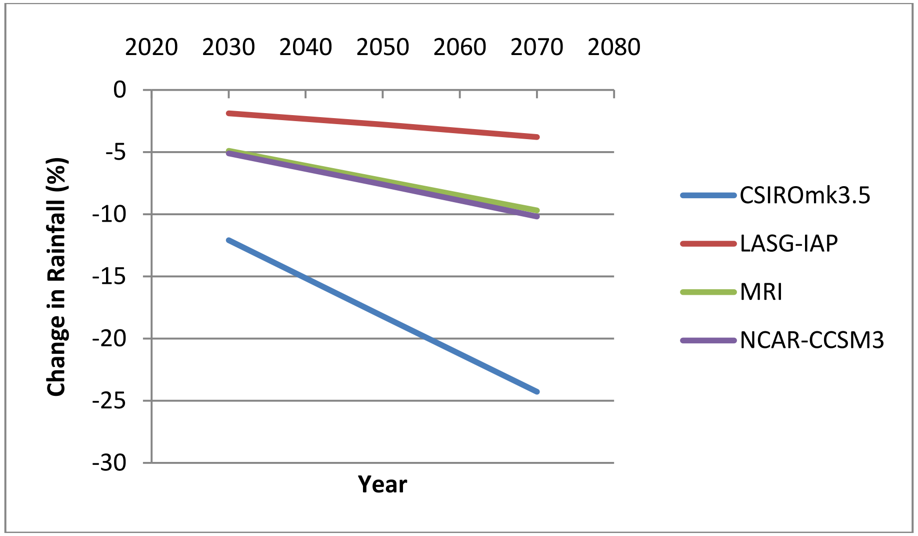

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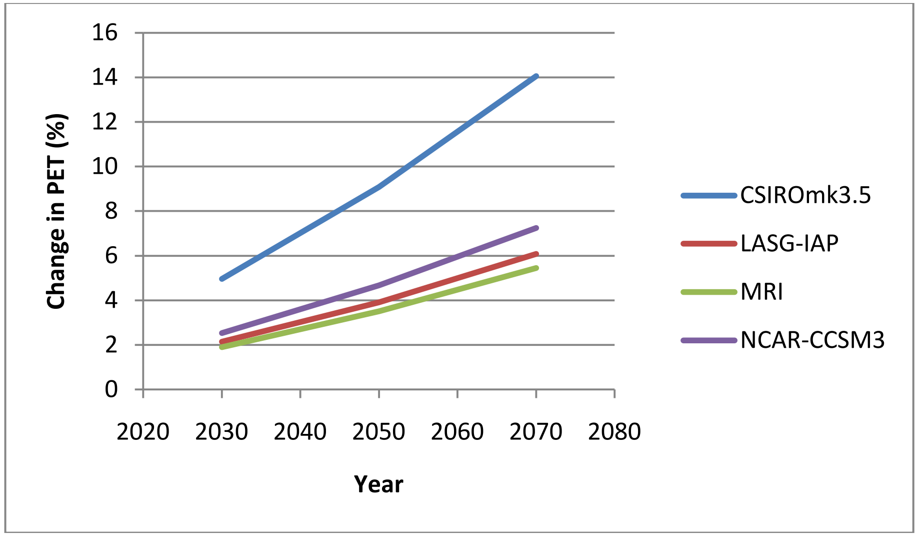
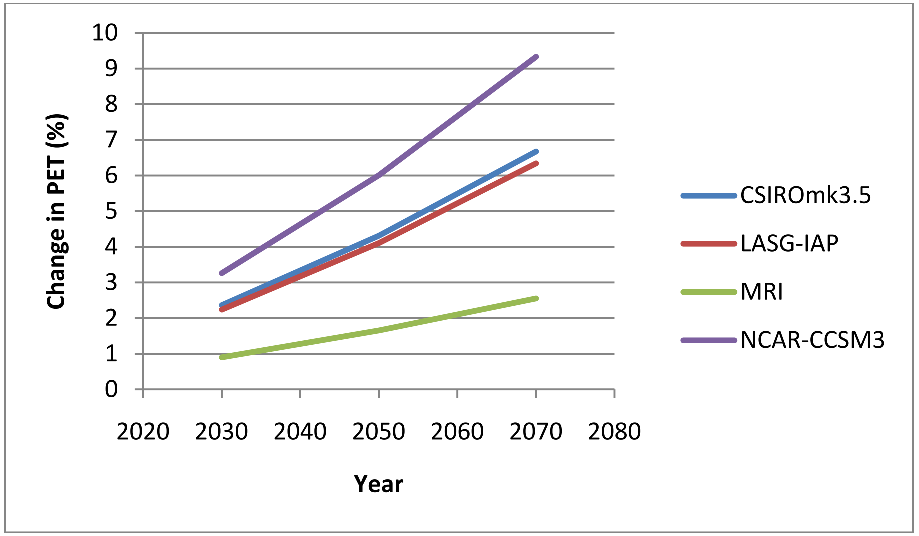
Figure 18. Winter Rainfall Projections for B2 Emissions Scenario. For Clare, the MRI GCM corresponds to the NCAR-CCSM3 GCM.



26021 - Mt Gambier



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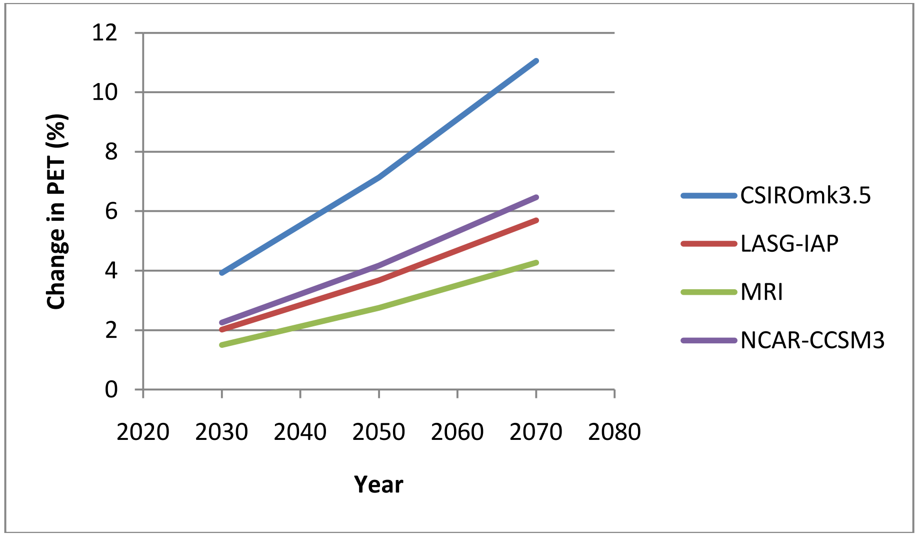

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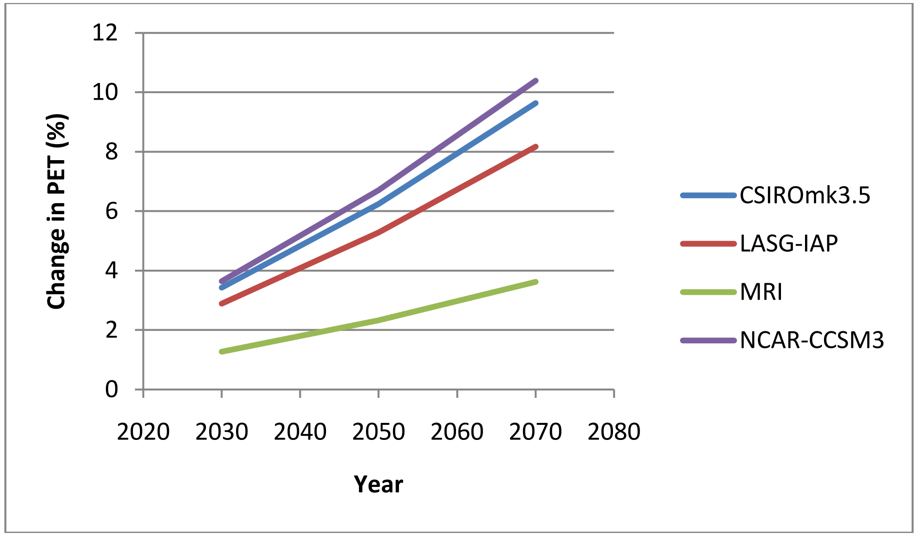
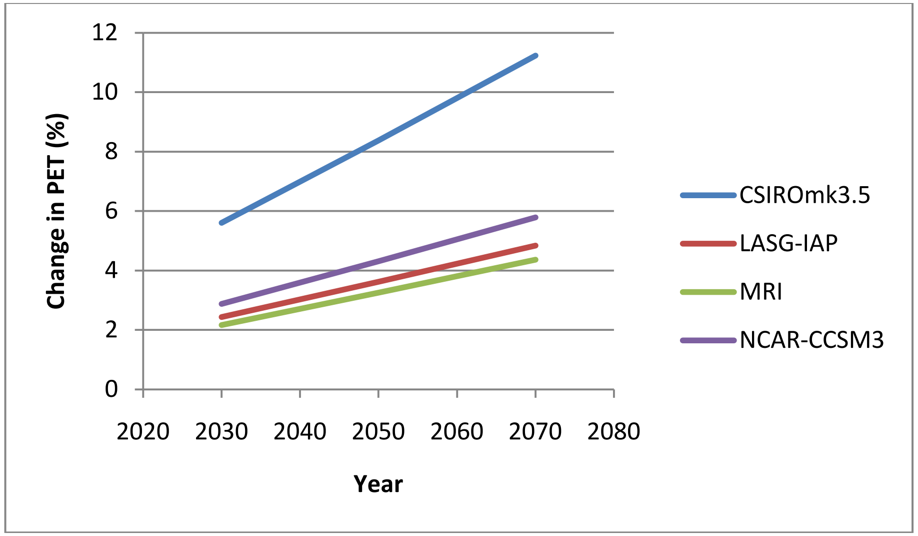
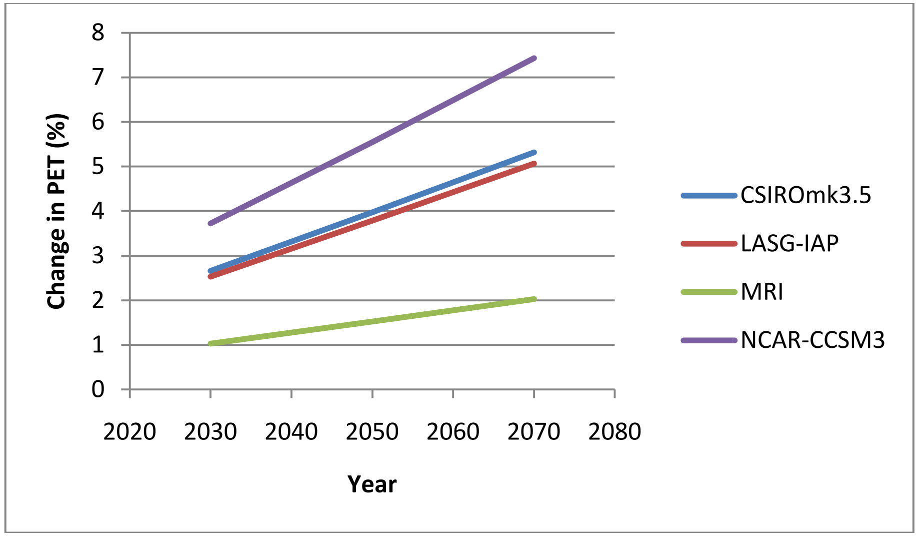


23719 - Gumeracha

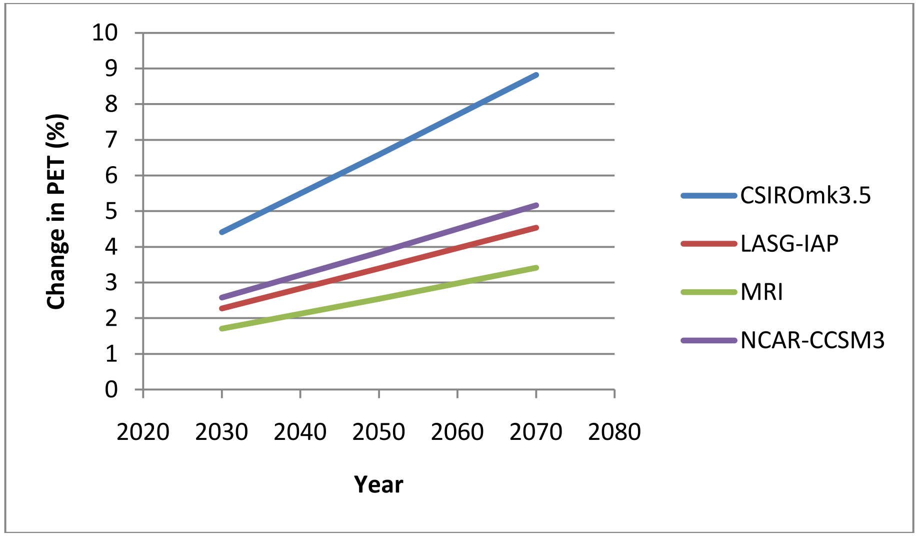
Figure 19. Winter Evapotranspiration Projections for A2 Emissions Scenario



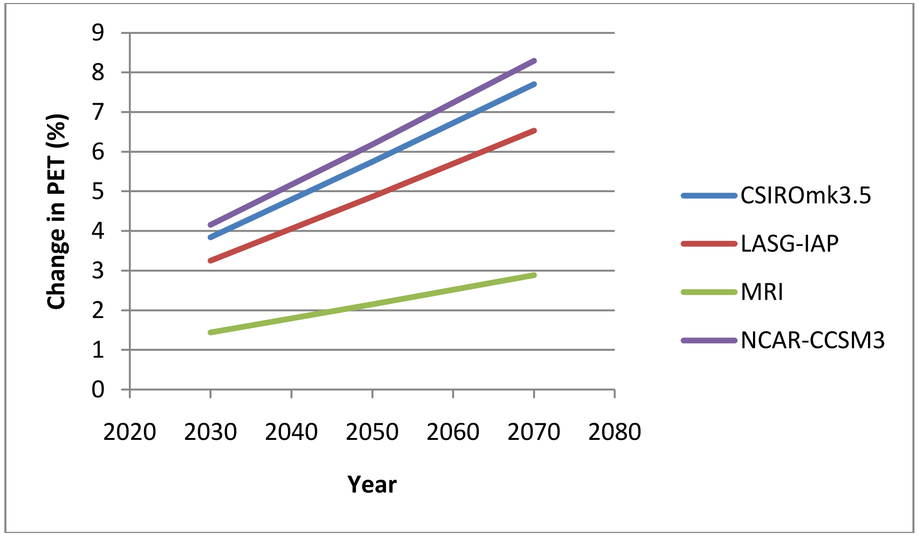
26021 - Mt Gambier



21014 - Clare



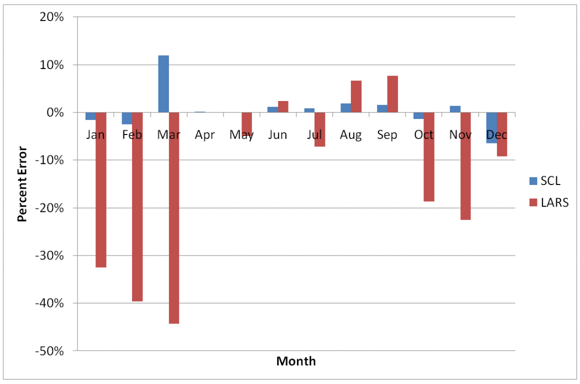
18017 - Pt Lincoln



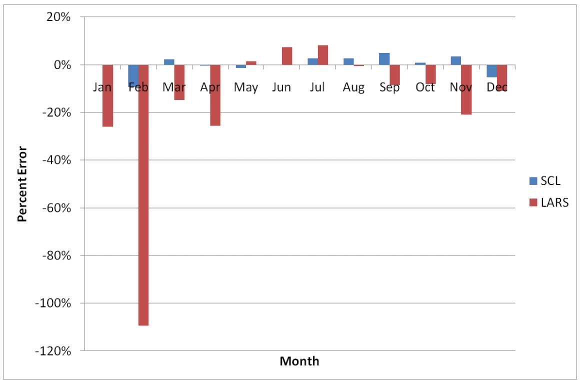
23719 - Gumeracha

Figure 20. Winter Evapotranspiration Projections for B2 Emissions Scenario

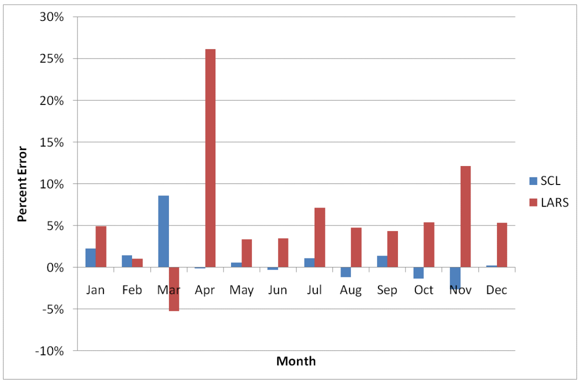
B. ACCURACY OF WEATHER GENERATOR



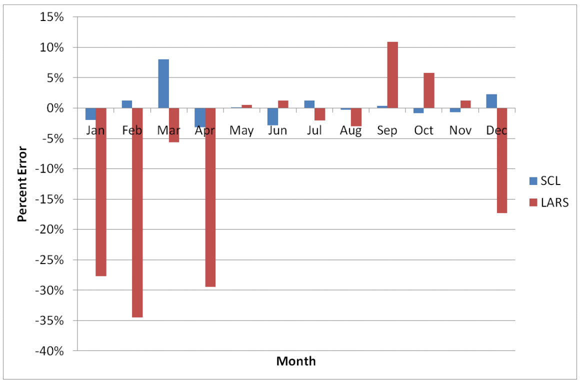
26003 Callendale



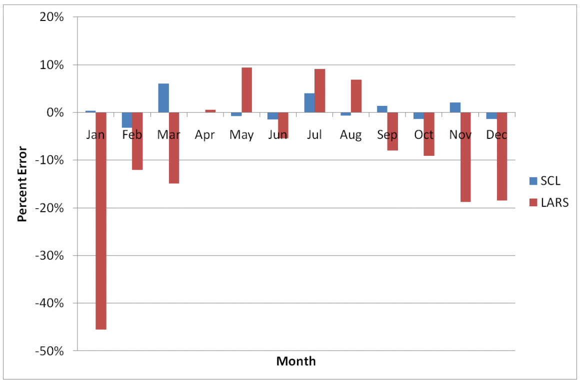
26016 Lucindale



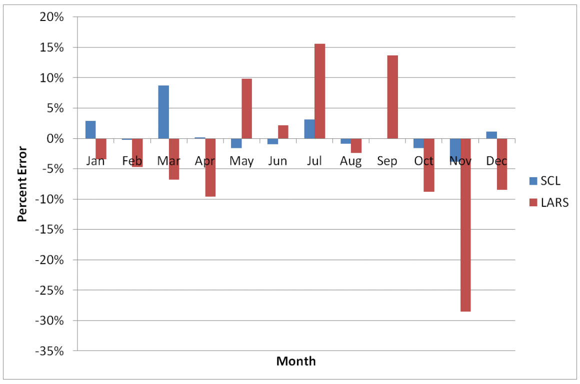
26018 Millicent



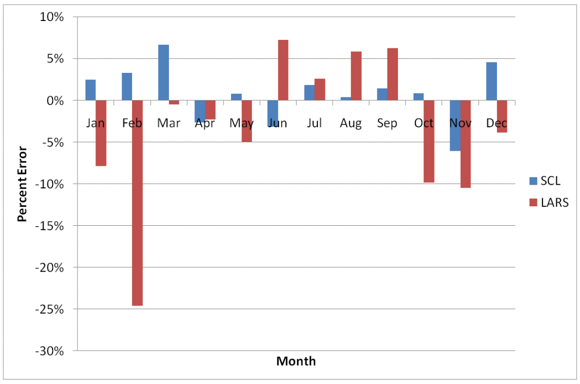
26021 Mount Gambier



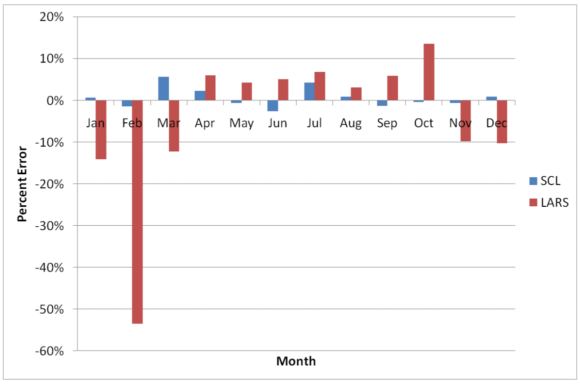
26030 Woolmit



26045 Coonawarra

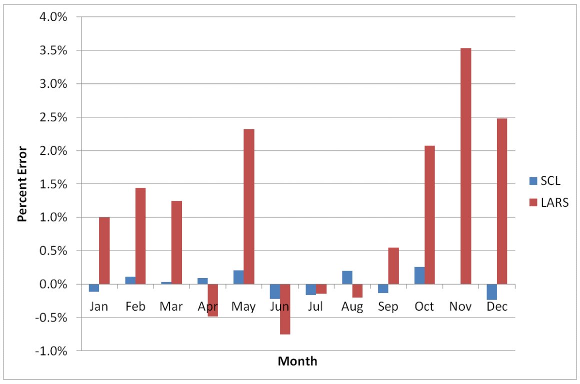


26070 Konetta E&WS



26082 Struan

Figure 21. Errors in simulated mean monthly rainfall, 1975-2004



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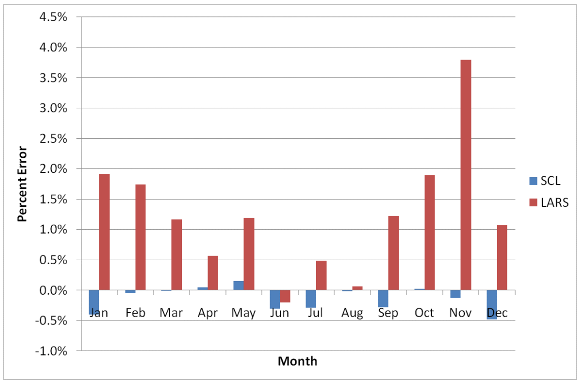

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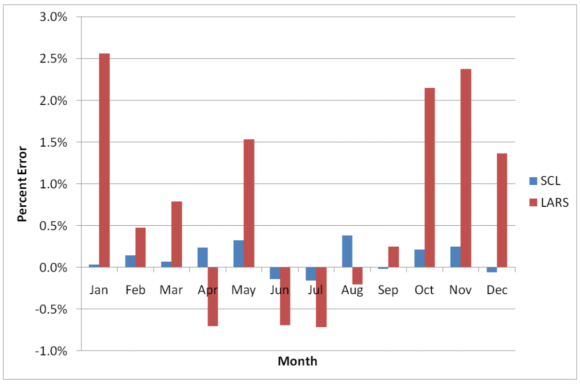

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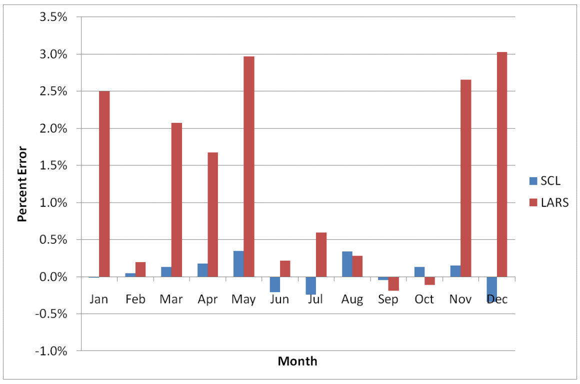
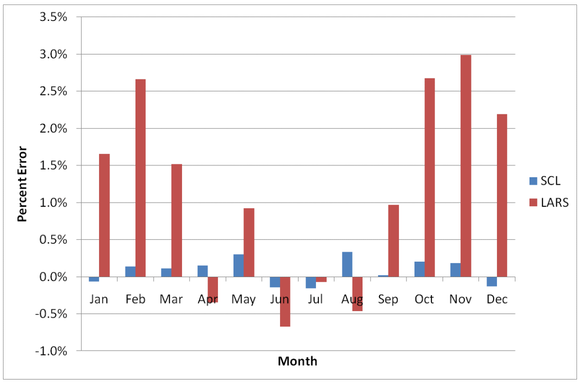


26021 Mount Gambier



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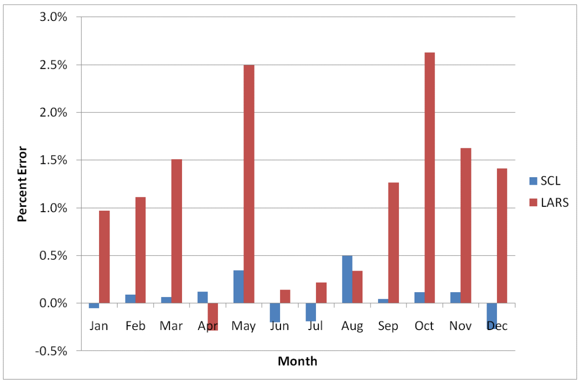

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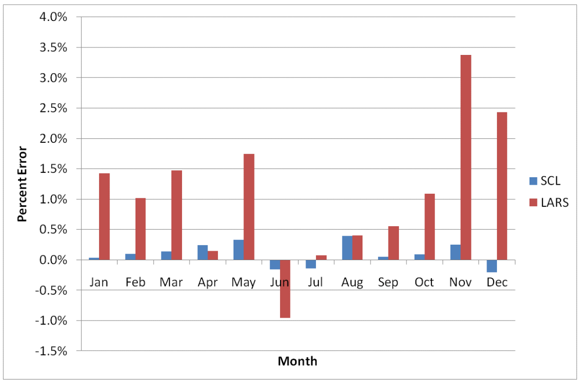
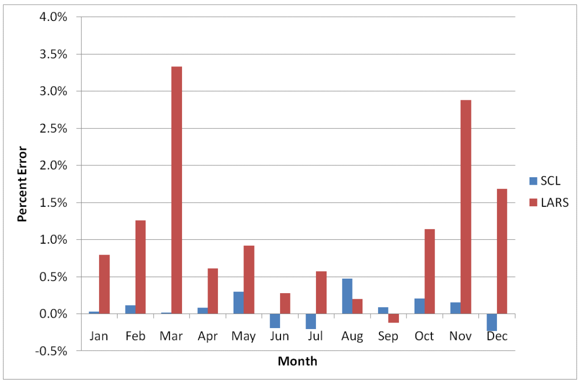


26070 Konetta E&WS



26082 Struan

Figure 22. Errors in simulated mean monthly maximum temperature, 1975-2004

UNITS OF MEASUREMENT

Units of measurement commonly used (SI and non-SI Australian legal)

Name of unit	Symbol	Definition in terms of other metric units	Quantity
day	d	24 h	time interval
gigalitre	GL	10^6 m^3	volume
gram	g	10^{-3} kg	mass
hectare	ha	10^4 m^2	area
hour	h	60 min	time interval
kilogram	kg	base unit	mass
kilolitre	kL	1 m^3	volume
kilometre	km	10^3 m	length
litre	L	10^{-3} m^3	volume
megalitre	ML	10^3 m^3	volume
metre	m	base unit	length
microgram	µg	10^{-6} g	mass
microlitre	µL	10^{-9} m^3	volume
milligram	mg	10^{-3} g	mass
millilitre	mL	10^{-6} m^3	volume
millimetre	mm	10^{-3} m	length
minute	min	60 s	time interval
second	s	base unit	time interval
tonne	t	1000 kg	mass
year	y	365 or 366 days	time interval

Shortened forms

~	approximately equal to
bgs	below ground surface
EC	electrical conductivity (µS/cm)
K	hydraulic conductivity (m/d)
pH	acidity
pMC	percent of modern carbon
ppb	parts per billion
ppm	parts per million
ppt	parts per trillion
w/v	weight in volume
w/w	weight in weight

GLOSSARY

BoM — Bureau of Meteorology, Australia

Catchment — That area of land determined by topographic features within which rainfall will contribute to run-off at a particular point

CSIRO — Commonwealth Scientific and Industrial Research Organisation

DFW — Department for Water (Government of South Australia)

DWLBC — Department of Water, Land and Biodiversity Conservation (Government of South Australia)

Evapotranspiration — The total loss of water as a result of transpiration from plants and evaporation from land, and surface water bodies

Greenhouse effect — The balance of incoming and outgoing solar radiation which regulates our climate. Changes to the composition of the atmosphere, such as the addition of carbon dioxide through human activities, have the potential to alter the radiation balance and to effect changes to the climate. Scientists suggest that changes would include global warming, a rise in sea level and shifts in rainfall patterns.

Groundwater — Water occurring naturally below ground level or water pumped, diverted and released into a well for storage underground; see also 'underground water'

Impact — A change in the chemical, physical, or biological quality or condition of a water body caused by external sources

Model — A conceptual or mathematical means of understanding elements of the real world that allows for predictions of outcomes given certain conditions. Examples include estimating storm run-off, assessing the impacts of dams or predicting ecological response to environmental change

Natural recharge — The infiltration of water into an aquifer from the surface (rainfall, streamflow, irrigation etc). See also recharge area, artificial recharge

NRM — Natural Resources Management; all activities that involve the use or development of natural resources and/or that impact on the state and condition of natural resources, whether positively or negatively

Percentile — A way of describing sets of data by ranking the dataset and establishing the value for each percentage of the total number of data records. The 90th percentile of the distribution is the value such that 90% of the observations fall at or below it.

Pluviometer — An automated rain gauge consisting of an instrument to measure the quantity of precipitation over a set period of time

Surface water — (a) water flowing over land (except in a watercourse), (i) after having fallen as rain or hail or having precipitated in any another manner, (ii) or after rising to the surface naturally from underground; (b) water of the kind referred to in paragraph (a) that has been collected in a dam or reservoir

WAP — Water Allocation Plan; a plan prepared by a CWMB or water resources planning committee and adopted by the Minister in accordance with the Act

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