NARCliM

NSW | ACT Regional Climate Modelling project

Methodology for Generating Australia-wide Surfaces and Associated Grids for Monthly Mean Daily Maximum and Minimum Temperature, Rainfall, Pan Evaporation and Solar Radiation for the Periods 1990–2009, 2020–2039 and 2060–2079

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1. Introduction

This report describes the methodology used to develop Australia-wide, fine scale, elevation dependent, monthly mean climate surfaces for the period 1990–2009. These surfaces are generated for five standard climate variables: daily minimum temperature, daily maximum temperature, rainfall, pan evaporation and solar radiation. These surfaces support the projection of fine scale gridded climatologies for these variables for the periods 2020–2039 and 2060–2079 using monthly mean change grids generated by the NSW and ACT Regional Climate Modelling (NARCliM) project.

The four main steps in developing these climatologies are:

1. Standardisation of Bureau of Meteorology monthly mean climate data to the 1990–2009 period for the widest possible data network. The standardised means were calculated using robust regression procedures that have been used to calculate monthly mean climatologies underpinning ANUClimate Version 1.0 (Hutchinson et al. 2015). ANUClimate consists of gridded daily and monthly climate data distributed under eMAST (Ecosystem Modelling and Scaling Infrastructure), a facility of the TERN (Terrestrial Ecosystem Research Network).
2. Fitting elevation dependent climate surfaces to these standardised monthly mean data using the ANUSPLIN thin plate smoothing spline package (Hutchinson & Xu 2013).
3. Calculating fine scale gridded monthly mean climatologies for the baseline 1990–2009 period by applying the ANUCLIM package (Xu & Hutchinson 2011) to the elevation dependent climate surfaces using regular grid digital elevation models at nine second and 0.01 degree spatial resolution.
4. Calculating fine scale projected gridded monthly mean climatologies for the periods 2020–2039 and 2060–2079 by applying the ANUCLIM package to the elevation dependent surfaces and the monthly mean change grids at 0.1 degree spatial resolution, as generated by the NARCliM project. These coarser resolution change grids have been developed for an ensemble of 12 CMIP3 GCM-RCM climate simulations based on the IPCC SRES A2 emissions scenario. ANUCLIM employs the 'delta' change factor downscaling method, as described by CSIRO and Bureau of Meteorology (2015), to convert the 1990–2009 climatologies to the projected fine scale future climatologies.

These steps are described in the following sections. The report includes a justification for the change factor downscaling method.

2. Standardisation of monthly mean climate data

The Bureau of Meteorology point observation network contains varying numbers of stations recording the different standard weather variables over the last century. The rainfall data network is the most extensive with around 19,000 stations, while there are around 1800 temperature stations, 575 pan evaporation stations and just 64 solar radiation stations. For the current application, monthly data means are required for the 20 years from 1990 to 2009. As shown in Table 1, the numbers of stations with at least 15 years of record between 1990 and 2009 is considerably smaller than the total network numbers. However, monthly climate values for neighbouring stations are highly correlated, particularly for temperature data. An automated process has been developed (Hutchinson et al. in prep. b) to estimate standard period means from serially incomplete data. The process follows the scheme outlined by Hutchinson (1995) and Hopkinson et al. (2012) by estimating missing monthly values by regressing short-term station data with corresponding data for neighbouring long-term stations. For each short-term station the long-term regressor that gives rise to the least standard error estimate of the standard 20-year mean is chosen. This error estimate takes account of both errors in the regression and any remaining missing values in the calculation of the standard period mean. Thus, depending on the final standard error estimate, a station that estimated more missing values could be chosen in preference to a more highly correlated station that estimated fewer missing values.

The process described by Hutchinson (1995) has been made robust by applying the regressions by season, to increase the number of data points supporting each regression, and by applying reasonable thresholds on correlation coefficients and final standard error estimates. Estimated standard period means exceeding these thresholds were rejected. Moreover, regression estimates were rejected when the total number of observed and estimated monthly values used to calculate the standard period monthly mean was fewer than 15 years. These conditions removed relatively small numbers of stations with poor quality data for each climate variable. In the case of precipitation, the process has been further modified by applying the linear regressions to the square roots of the monthly rainfall values, in recognition of the strongly skewed nature of temporal distribution of monthly rainfall. These regression processes have been used, with minor modifications, to estimate the 30-year standard period means supporting ANUClimate (Hutchinson et al. 2015).

Table 1: Summary of regression estimation of standard period (1990–2009) monthly means from serially incomplete monthly Bureau of Meteorology data

Climate variable	Average number of stations with at least 15 years of record for 1990–2009	Average number of stations with monthly mean estimates for 1990–2009	Average number of observed and estimated values for each standard period estimate	Average standard error of the estimated standard period means
Minimum temperature	452	1,535	19	0.16°C
Maximum temperature	450	1,545	19	0.14°C
Pan evaporation	184	443	19	2.5%
Rainfall	4,830	11,627	19	6.2%

Notes: Averages in the columns are taken over the 12 calendar months. Percentage errors are defined as a percentage of the network means.

The summary results of the regression process for daily minimum and maximum temperature, pan evaporation and rainfall are shown in Table 1. The regression process has increased the numbers of stations with standard period mean estimates by a factor of around three for the temperature means, and by more than a factor of two for the pan evaporation and rainfall means. The estimated 20-year standard period means were supported on average by a total of 19 (out of a maximum possible 20) observed and estimated monthly values. The accuracy of the regression process is indicated by the small average standard error estimates. The expanded monthly mean network also significantly improved the predictive errors of the interpolated surfaces described in the next section.

A different process was used to estimate standard period means for solar radiation in view of the much smaller solar radiation network. Estimates of monthly solar radiation have been obtained by a spatial interpolation process that incorporates both the strong astronomical controls on solar radiation and its dependence on rainfall occurrence at the monthly time step. This method has been developed by Hutchinson et al. (in prep. a) to support ANUClimate and is a significant improvement on the method developed by Hutchinson et al. (1984) that incorporated a dependence on monthly mean rainfall. The new method estimates individual monthly solar radiation values with a standard error of around 5% and monthly mean values for the 1990–2009 period with a standard error of around 3%.

3. Fitting elevation dependent climate surfaces

Elevation dependent thin plate smoothing spline surfaces were fitted to the standardised monthly mean data using the ANUSPLIN package (Hutchinson & Xu 2013). This package has underpinned continent-wide interpolation of climate variables for Australia and other continents since the early 1990s (Hutchinson 1991; New et al. 2002; Hijmans et al. 2005; Hutchinson et al. 2009; McKenney et al. 2011). For the temperature, evaporation and rainfall data the elevation dependence was fitted directly using trivariate spline functions of longitude, latitude and appropriately scaled elevation. Elevation was scaled to be 100 times larger than the horizontal variables, in keeping with the relative horizontal and vertical distance scales of atmospheric dynamics (Daley 1991; Hutchinson 1995). The spline surfaces were fitted to the square roots of the precipitation means, again in keeping with the skewed temporal distribution of rainfall (Hutchinson et al. 2009).

In the case of solar radiation, the elevation dependence was indirect, with the solar radiation means being first estimated for the full Bureau of Meteorology network (19,000 stations) from trivariate spline functions of longitude, latitude and monthly raindays, as indicated above. The rainday surfaces, with mild elevation dependence, have been generated for ANUClimate (Hutchinson et al. 2015). Spline surfaces were then fitted to this extensive network of monthly solar radiation means as bivariate functions of longitude and latitude. The Bureau of Meteorology network is sufficiently dense to represent the broadscale nature of monthly mean solar radiation in bivariate terms. The fitted bivariate solar radiation surfaces were also directly suitable for use by the ANUCLIM package.

The summary of the surface fitting for all five climate variables is given in Table 2. In each case approximate thin plate splines, as defined by appropriately chosen knots (Hutchinson & Xu 2013; Hutchinson et al. 2009), were fitted to each monthly mean data set. The use of knots that equi-sample the area covered by the data ensures robust behaviour of the fitted splines and also provides significant computational savings. It should be noted that this does not imply that any data points were omitted from the analyses. All data points were used to fit the approximate splines. In the case of temperature and solar radiation data, the numbers of knots were set to fixed values that were sufficient to identify the spatial complexity of the data. In the case of pan evaporation all data points were chosen as knots. In the case of rainfall, with many data points and very high spatial complexity, an iterative process was used to efficiently choose knots. This was done, as recommended by Hutchinson and Xu

(2013), by first fitting surfaces using an initial 3500 equi-area sampled knot set and then twice adding 1% (35) knots chosen from the largest residuals of the initial and succeeding fitted surfaces. This gave rise to up to 3570 possible knots for the final fitted monthly mean rainfall surfaces, with the actual knot numbers reduced by missing data values. In each case the number of knots was well in excess of the signals of the fitted splines (Hutchinson & Xu 2013), indicating that the numbers of knots were sufficient to describe the spatial complexity in the data. Quality assurance led to removal of a small number (no more than 10) of questionable temperature and evaporation data means, as identified by significantly large residuals from initial fitted surfaces. No data points with large residuals were omitted from the solar radiation and rainfall surfaces since this made little difference to the fitted surfaces.

Table 2: Summary of thin plate smoothing spline fitting results for all climate variables

Climate variable	Average number of monthly mean data points	Average number of knots	Average signals of the fitted splines	Approximate average standard predictive error
Minimum temperature	1,525	1,000	599	1.0^{o}C
Maximum temperature	1,539	1,000	647	0.6^{o}C
Pan evaporation	438	435	143	15%
Rainfall	11,627	3,543	2,700	15%
Solar radiation	19,088	1,000	779	3%

Notes: Averages in each column are taken over the 12 calendar months. Percentage errors are defined as a percentage of the network means.

Approximate average standard predictive errors for minimum and maximum temperature, pan evaporation and rainfall were obtained from the ordinary cross validation of the fitted spline surfaces over all data points reduced by the square of the estimated data errors given in Table 1. The average standard predictive error for solar radiation was simply taken from the estimated standard errors of the 19,000 monthly mean data points. The relatively small standard predictive error for the daily maximum temperature surfaces reflects the strong direct control of elevation on this climate variable. Minimum temperature is subject to more complex local conditions such as local temperature inversions. The moderate percentage errors for the pan evaporation surfaces reflect the complexity of local conditions and the modest data network. The moderate percentage errors for rainfall reflect the high spatial variability of rainfall, despite the substantially larger data network. The relatively small errors for solar radiation reflect the broadscale nature of this variable.

4. Calculation of gridded monthly mean climatologies for the baseline 1990–2009 period

Gridded monthly mean climatologies for the baseline 1990–2009 period were obtained by grid-based interrogation of the monthly mean spline surfaces described above using the MTHCLIM module of the ANUCLIM package (Xu & Hutchinson 2011). The data flows for the MTHCLIM package are shown in Figure 1. For the 1990–2009 climatologies the climate change grids were not required. MTHCLIM accepts standard elevation dependent monthly mean spline surfaces as produced by ANUSPLIN. It can interrogate these surfaces in point and grid mode. In grid mode, the required elevations are supplied as regular grid digital elevation models (DEMs). For the current project two continent-wide DEMs were supplied – the nine second resolution (approx. 250 m) DEM as distributed by Geoscience Australia (Hutchinson et al. 2008) and a 0.01 degree resolution (approx. 1 km) DEM obtained from the nine second DEM by calculating block averages of the 4x4 nine second cells covering each 0.01 degree grid cell.

The nine second interrogation was performed by the Fenner School and training in ANUCLIM was provided by Tingbao Xu so that NSW OEH could perform the 0.01 degree climate interrogations. This required one run of MTHCLIM for each climate variable to produce the required 12-monthly mean grids.

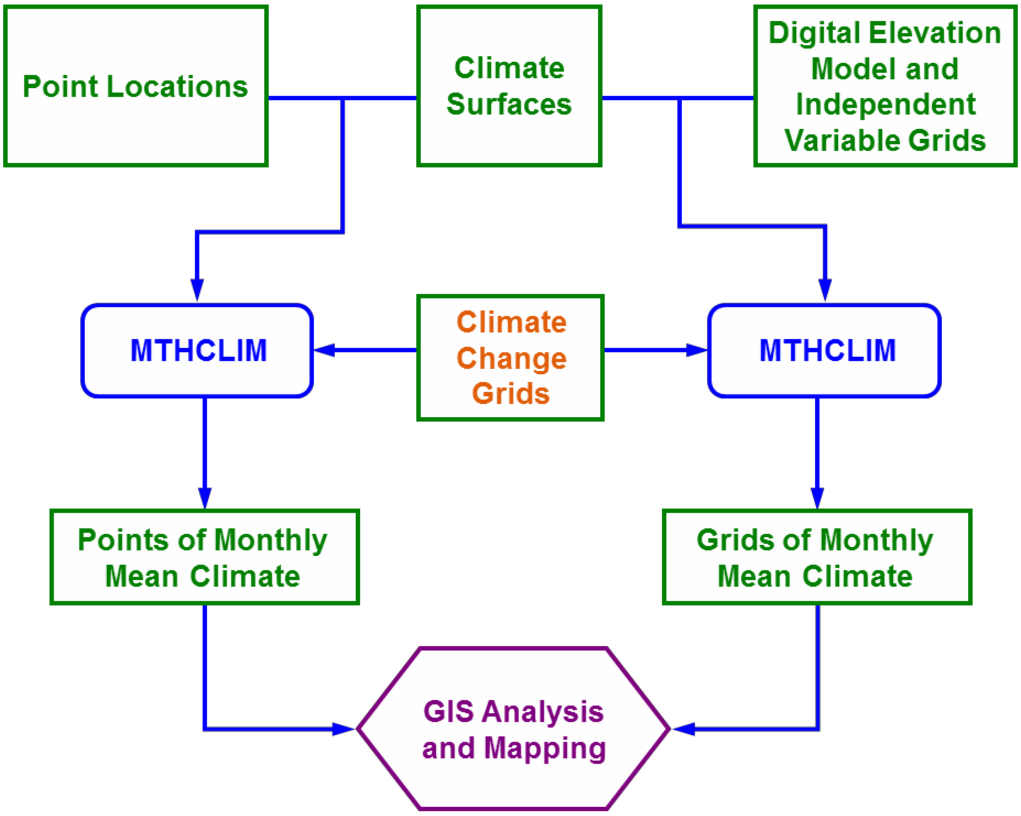

Figure 1: Main data flows through the MTHCLIM module of the ANUCLIM package

5. Calculation of projected gridded monthly mean climatologies for 2020–2039 and 2060–2079

The climatologies for 2020–2039 and 2060–2079 were also calculated by the MTHCLIM module of the ANUCLIM package, using the monthly mean spline surfaces for 1990–2009, nine second and 0.01 degree DEMs and an ensemble of 12 climate simulations at 0.1 degree resolution provided by the NARCliM project for an area covering NSW and Victoria, with approximate longitude limits of 135.7° to 153.7°and approximate latitude limits of –39.5° to –23.6°. NARCliM is an ensemble of 12 RCM (regional climate model) simulations based on the outputs of four GCMs and three configurations of the WRF RCM. The four GCMs used were CCCMA3.1, CSIRO_MK3.0, ECHAM5 and MIROC3.2, as provided for CMIP3, using the IPCC SRES A2 emissions scenario. The three RCMs have different physics parameterisation settings reflecting different combinations of schemes for planetary boundary layer physics, surface layer physics, cumulus physics, microphysics and shortwave and longwave radiation physics. The three RCMs are known as R1, R2 and R3. The nine second and 0.01 degree DEMs were trimmed to the above approximate longitude and latitude limits.

ANUCLIM employs the 'delta' change factor downscaling method, as described by CSIRO and Bureau of Meteorology (2015), to convert the baseline 1990–2009 climatologies to the projected fine scale future climatologies. This involves interpolating the 0.1 degree change grids to the destination nine second or 0.01 degree grid spacing using biquadratic splines. This is carried out automatically within ANUCLIM. The spatially refined change grids are then applied to the baseline grids. The change grids are applied additively to the current temperature grids and multiplicatively to the current naturally non-negative climate variables pan evaporation, rainfall and solar radiation. Thus temperature change grids need to be supplied in degrees centigrade and the multiplicative change grids need to be supplied as percentage changes (Xu & Hutchinson 2011).

As discussed in Chapter 9 of CSIRO and Bureau of Meteorology (2015), the delta change or perturbation method is one of a number of approaches to downscaling. It is well suited to the purpose of downscaling monthly mean climatologies since it involves minimal assumptions about the relationship between broad and fine scale climatologies. It is simple to implement and has been found suitable for many applications. It also facilitates assessments of outputs from many GCMs. Its basic assumption is that the relative changes in monthly mean variables from 1990–2009 to future periods are strongly spatially coherent. This implies that the relative changes can be calculated from relatively coarse 0.1 degree grids and applied with confidence to finer scale monthly mean climatologies. It also removes the need for applying bias corrections to current and future GCM grids. It makes the reasonable assumption that such bias corrections would be largely cancelled out in the calculation of the change grids. The behaviour around complex topography of the projected future grids is then dependent on the behaviour around complex topography of the current 1990–2009 grids. The performance of thin plate smoothing splines in respecting this behaviour for monthly mean climatologies is well accepted in the scientific literature (Hutchinson 1995; Price et al. 2000; Haylock et al. 2008; Hopkinson et al. 2012). It is therefore reasonable to expect the behaviour around complex topography of the future projected grids also to be reasonable.

An indication of the spatial coherence of the temperature and rainfall change grids is provided by the plots in Figures 2, 3 and 4. These figures show particular change grids and associated projected monthly mean grids for daily minimum temperature, daily maximum temperature and rainfall for 2060–2079 using the ECHAM5 and the R2 RCM. In each case the change grids display a strong degree of spatial coherence that is well sampled at 0.1 degree resolution. This is in marked contrast to the projected future grids that show strong dependence on underlying topography.

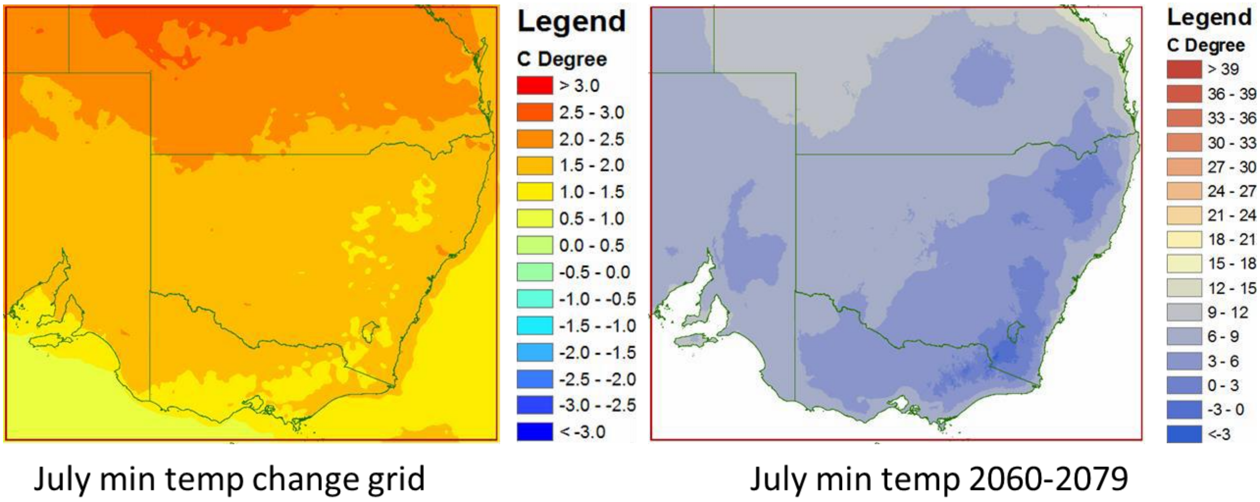

Figure 2: Change grid and projected future grid of mean July daily minimum temperature for 2060–2079 using NARCliM output for ECHAM5 and the R2 RCM

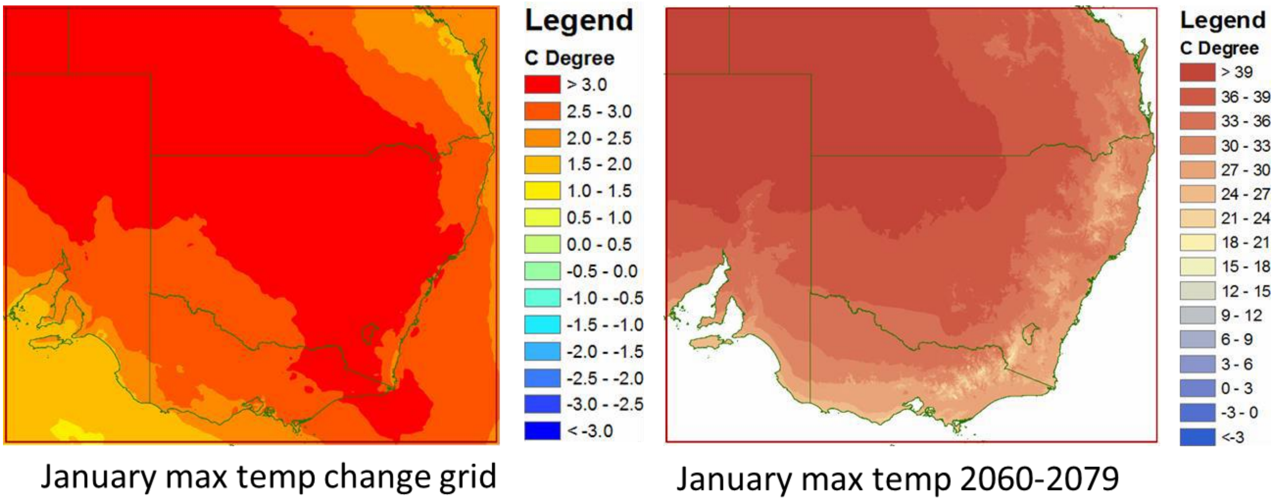

Figure 3: Change grid and projected future grid of mean January daily maximum temperature for 2060–2079 using NARCliM output for ECHAM5 and the R2 RCM

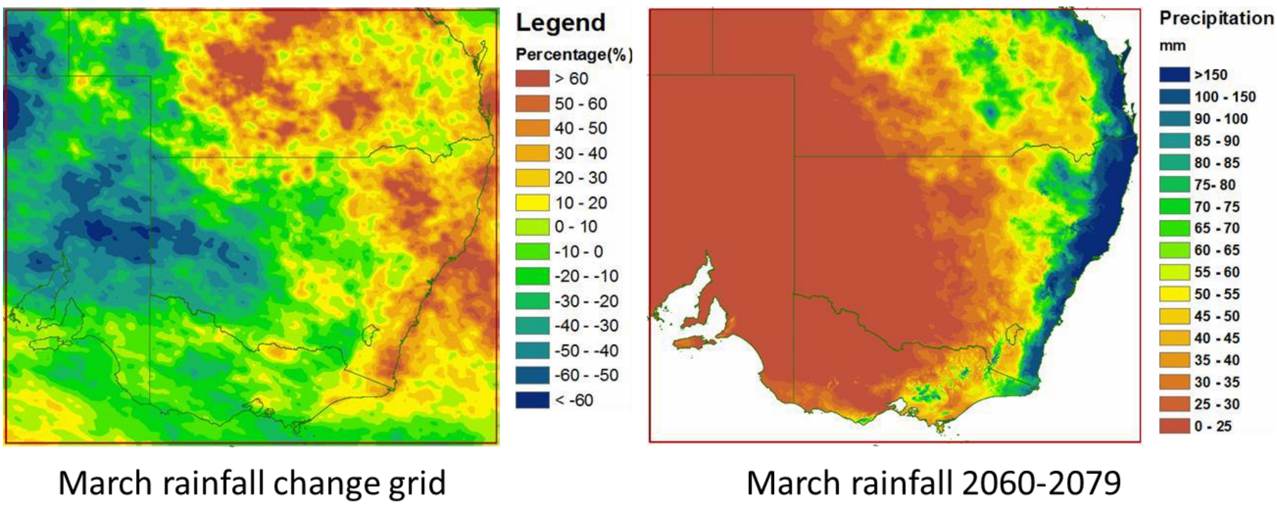

Figure 4: Change grid and projected future grid of mean March rainfall for 2060–2079 using NARCliM output for ECHAM5 and the R2 RCM

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