Consistent Climate Scenarios: projecting representative future daily climate from global climate models based on historical climate data

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Abstract: As part of the Commonwealth Department of Agriculture, Fisheries and Forestry's (DAFF's) 'Australia's Farming Futures Climate Change Research Program' (CCRP), the Queensland Government undertook a project to support the climate data requirements for nine climate adaptation studies. The project, known as Consistent Climate Scenarios (CCS), delivered climate change projections data, in consistent model-ready formats, enabling project teams to undertake climate change adaptation studies for various primary industries across Australia, in particular within the grazing, cropping and horticultural sectors. Statistical approaches were developed to transform historical climate data from the Queensland Government's SILO climate database using climate projections modelling from the Intergovernmental Panel on Climate Change (IPCC), Fourth Assessment Report (AR4). All IPCC AR4 models from the Third Climate Model Intercomparison Project (CMIP3) were ranked by an Expert Panel overseeing the CCS project. Ranking was based on model performance over the Australian region using, as a guide, methods developed by Suppiah, et al. (2007) and Smith & Chandler (2010). Of 23 available models, four were omitted as underperforming, and the remaining models were used to develop the CCS projections data. Over 1 million data files were delivered to the CCRP project teams. These projections data are now available to the wider research community as an adjunct to SILO. Registered users can obtain 'CCS data' at http://longpaddock.qld.gov.au/climateprojections.

Two different techniques are used to modify the daily observed climate values extracted from the SILO database (http://longpaddock.qld.gov.au/silo) using trends obtained from global climate models (GCMs). The two techniques are monthly change factors (CF) derived by pattern scaling from GCMs, and quantile matching (QM). The CF technique projects trends in mean values whereas the QM technique projects both the mean and internal variability within climate sequences. The initial CF trend data were obtained from CSIRO and constituted the monthly trends interpolated to 25 km grids by OzClim ™ (http://www.csiro.au/ozclim). This set included trends in maximum and minimum temperatures for only seven required GCMs, and did not include specific humidity for five GCMs, or solar radiation for two. Estimation techniques, using the combination of machine learning and regression techniques (Ricketts&Carter 2011) were used to estimate missing variables. The UK Met-Office has also made available maximum and minimum temperature, and specific humidity files for the HadCM3 and HadGEM1 models, which had not been available to CSIRO from the IPCC's repository at PCMDI (http://www-pcmdi.llnl.gov/). The QM methodology (Li, Sheffield & Wood 2010, Kokic, Jin & Crimp 2012, Kokic, Jin & Crimp 2013) was developed in conjunction with CSIRO. Two variations of QM are described in these papers, one which requires daily data from the GCM (which is only available from a very small subset of GCMs) and one which uses monthly GCM data.

Data generated by the methods described may be downloaded after registration, currently at no additional cost from the web site. Users may request up to ten datasets at a time, selected from SILO's 4759 available patched point stations, projected to either 2030 or 2050, based on six SRES scenarios and two stabilization scenarios, and three different climate sensitivities. They receive projection files in a choice of two formats, plus additional data (e.g. CO_2 concentrations, diagnostic plots and a comprehensive user guide). In addition to the nine CCRP projects, more than 120,000 files have been downloaded from this web site in the 2012/13 financial year to eight Australian universities and a number of state bodies and consultancies.

Keywords: *climate change projections, SILO, consistent climate scenarios (CCS), pattern scaling, quantile matching*

1. INTRODUCTION

Biophysical modelling of the type performed for agricultural modelling may require detailed, daily weather information, both for calibration and for predictive/projective explorations. Rainfall, temperature, and water vapour related variables are, in general, the most crucial variables. Explorations of the range of potential impacts of climate change in the agricultural sector are often performed by comparing the outputs of a biophysical model driven by daily climate from a selected historical period, to those of the same model driven by simulated climate as it may be in the future. It was thus seen as beneficial to make data available to all related CCRP projects, from a single source, using a common suite of methods. This relieved the projects of the need to independently develop methods, at the same time increasing inter-project consistency.

An Expert Panel was formed from stakeholders, QCCCE, and CSIRO staff to consider the range of possible approaches to the task of estimating future daily climate suited to input into biophysical modelling. The approach agreed on was to provide historical daily climate from SILO, and to derive information about possible future climates from a selected suite of global climate models (GCMs) taken from those made available via the Intergovernmental Panel on Climate Change (IPCC) for the IPCC Fourth Assessment Report (AR4) as part of the Third Climate Model Intercomparison Program (CMIP3).

This paper outlines: 1) the rationale for the design and methods chosen (Section 2); 2) how these methods were employed to develop projections data within the CCS framework (Section 3); and 3) how the project addressed the issues of GCM selection (Section 4).

2. SELECTION OF METHODS AND DATA

2.1. The SILO Database

The SILO climate database (Jeffrey et al. 2001) was developed during the 1990s by Queensland Government in conjunction with the Bureau of Meteorology (BoM) in order to provide historical climate data to biophysical modellers in ready to use formats. Currently SILO is hosted, maintained and made available through Queensland Government, at http://longpaddock.qld.gov.au/silo. Fifteen observed and derived climate variables are available, including temperature, rainfall, water vapour variables, and estimates of a number of Morton's evapotranspiration functions (Morton 1986). Wind related variables are not currently available. Five climate variables from SILO are currently used by the CCS system.

2.2. Climate Models

Models were selected and ranked by the expert panel using two model comparison papers (Suppiah, Hennessy & Whetton 2007) and (Smith & Chandler 2010) which both assigned scores to GCMs based on their performance in providing representations of features of broad-scale climatology over Australia (e.g. El Nino Southern Oscillation index ENSO). Of 23 available models, four were omitted as underperforming.

2.3. SRES Scenarios

21st century runs for all of the GCMs in AR4, were forced by the prescribed forcings described in the Special Report on Emissions Scenarios (SRES) (Nakićenović & Swart 2000). Six SRES scenarios are commonly used, and provide a range of emission trajectories based on broad assumptions about regional versus global economic growth and economic versus environmental focus. GCM runs available via CMIP3 generally only include output one or two of the six SRES scenarios, so a method known as pattern scaling is used, based on two assumptions explained below.

Since every GCM develops its own global responses, a simple climate model (SCM) is used to estimate a standardised global temperature response for each SRES scenario. As implemented, pattern scaling uses an SCM called MAGICC (http://www.cgd.ucar.edu/cas/wigley/magicc/). Although each scenario produces different trajectories especially in the second half, at the end of the 21st Century the six scenarios produce a range of mean global temperatures, with medians ranked from lowest to highest as, B1, A1T, B2, A1B, A2, A1FI. Another parameter, known as "climate sensitivity", is also computed from MAGICC output to cover the range of uncertainties in the response of the SCM to emissions. Temperature curves computed by MAGICC for three climate sensitivities (median, 10th and 90th percentile) from forcings prescribed in the six SRES scenarios above, plus two stabilization scenarios (WRE450 and WRE550) are used to provide mean global warming values for each year in the 21st century.

2.4. Pattern Scaling

Pattern scaling was introduced by Santer et al. (1990) for the first IPCC assessment report, and has been refined ever since (Mitchell et al. 1999, Mitchell 2003). According to Mitchell (2003) pattern scaling is based on two assumptions. "*Assumption 1. The SCM accurately represents the global climate response of the GCM, even when the response is non-linear. … Assumption 2. The responses to radiative forcing – as represented by a GCM – of a wide range of climatic variables, at local and seasonal scales, are a linear function of the amount of global warming – as represented by the same GCM*". The form of pattern scaling used in this work is identical to CSIRO's OzClim™ product, previously documented in Whetton & Hennessy (2001) and Ricketts & Page (2007). The term "pattern" refers to the spatial pattern of change shown by a GCM, derived by estimating a trend in a climate variable against some time dependent variable (and not necessarily time itself). In this work the regressed independent variable is mean annual global temperature for each individual GCM for the matching scenario (A1B chosen for completeness) and the dependent variables are the monthly averages of climate variables of choice. The analysis is taken over the 21st Century, where a separate regression is performed at every grid-point in the GCM. One pattern of change is produced for each month, for each GCM, and for each variable. Thus we can project a pattern of deltas (change factors), simply by multiplying the pattern of change by the mean global temperature projected at some future date. Since mean rainfall over continental Australia shows enormous variation across GCMs it is usual to normalise the pattern of change by the mean rainfall for a reference period, in this case years 1975-2004 (see Figure 1).

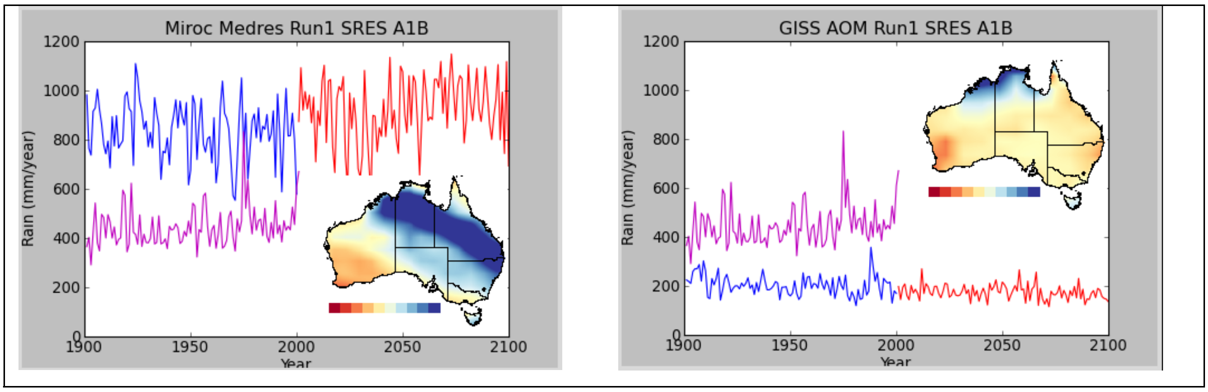

Figure 1: Illustrating the inter-GCM variation in mean annual rainfall over continental Australia. The GCMs shown MIROC_Medres (left pane) and GISS_AOM (right pane) on common axes. Observed rainfall is plotted in magenta, 20th century modelled rainfall in blue and 21st century modelled rainfall in red. Maps are normalised patterns (red to blue represents changes of -40% to +40% of 1975 to 2004 mean) of annual 21st century rainfall trends for the GCMs.

2.5. Quantile matching

A considerable number of reports have utilised pattern scaling to obtain long term trends in monthly climatology and then apply this to either monthly mean, or daily observations, to produce estimates of climate change impacts. Li et al. (2010) proposed a method of quantile matching (QM) to map the probability distribution function (PDF) of a target variable onto a projected future PDF, and then replacement of each observed value with the value from the same quantile in the perturbed PDF. Using both a pattern scaling based approach and QM, information from the observations is blended with information from GCMs to produce plausible future climate. Where they differ is in precisely which statistical components are derived from GCMs and which from observations.

3. DEVELOPING PROJECTIONS FOR 'CONSISTENT CLIMATE SCENARIOS'

The decision on *how* to combine present day observed climate with model based projections of future climate considered the requirements of the range of likely client biophysical models. Important factors identified included: (a) the need to consider the detailed relationship between rainfall, water vapour variables, solar radiation and temperature variables; (b) the fact that for most GCMs only monthly values were available; and (c) that for all GCMs climate variables are represented as coarse scale spatial averages (typically 100-200 km per grid point). Thus, the problem is one of imputing changes in fine scale daily climate, given changes in coarse scale monthly climate, in such a way that the resulting outputs are plausible and weather-like. It is highly desirable that such results have both spatial and temporal integrity, and coherence, and especially that the present to future transitions contain no discontinuities. Since the observational record is the only source of information about daily temporal and spatial weather coherence, these patterns represent the best available source of plausible future climate patterns. Under the pattern scaling approach used, known as the change factor (CF) approach, all observed values within a month are shifted by a single, uniformly applied value derived from a GCM. Thus, the mean is altered, but the variance and shape of the probability distributions (PDFs) are unaltered from the historical observed data. Under QM, an attempt is made to estimate the change in shape of the PDFs in the future. Changes in means are derived from GCMs as per the CF approach, but changes in variance and PDFs can be derived either by extrapolation of the observations or calculated from the GCMs.

3.1. Change Factors

The CF approach uses pattern scaling to estimate change factors which are then used to adjust the observed climate variables to produce projected climate. The initial CF trend data were obtained from CSIRO and constituted the monthly trends interpolated to 25 km grids by OzClim ™ (http://www.csiro.au/ozclim). This set included trends in maximum and minimum temperatures for only seven required GCMs, and did not include specific humidity for five GCMs, or solar radiation for two. Estimation techniques, using the combination of machine learning and regression techniques (Ricketts&Carter 2011) were used to estimate missing variables. The UK Met-Office has also made available maximum and minimum temperature, and specific humidity files for the HadCM3 and HadGEM1 models, which had not been available to CSIRO from the IPCC's repository at PCMDI (http://www-pcmdi.llnl.gov/).

3.2. Quantile Matching

The quantile matching methodology (QM) (Li, Sheffield & Wood 2010, Kokic, Jin & Crimp 2012, Kokic, Jin & Crimp 2013) was developed in conjunction with CSIRO. Two variations of QM were produced, one which uses monthly GCM data and one which requires daily rainfall from the GCM (which is only available for the required dates from a very small subset of GCMs, and even then, not for all the desired climate variables).

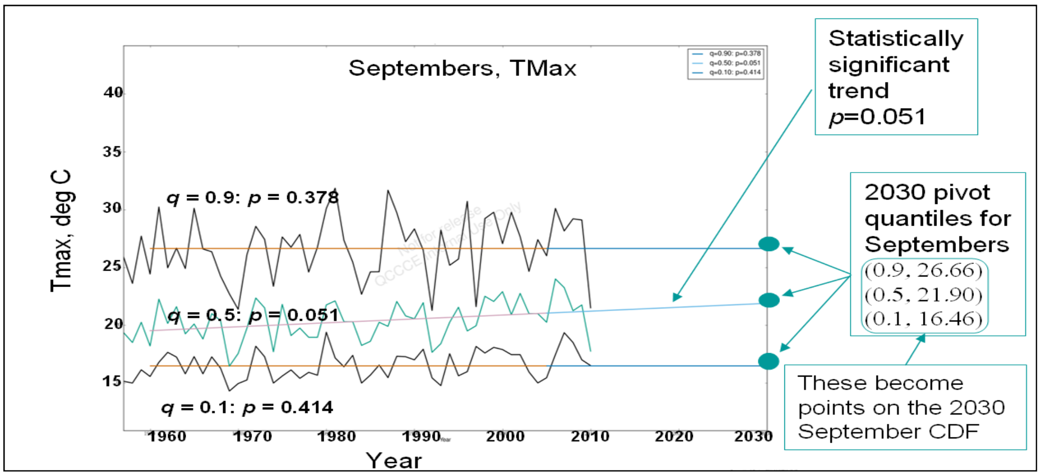

Figure 2: Quantile trend plot for September daily maximum temperature, showing how quantiles 0.1,0.5 and 0.9 are computed for 2030 (the computed quantiles are referred to here as the pivot quantiles).

The main points of the QM approach are explained in Sections 2.1 to 2.2 of Kokic et al. (2013), however the approach used in CCS varies from this paper by not using bootstrapping. Instead, a single simulation of projected daily climate is produced by sequentially processing the training data using the QM algorithm. The QM method produces projected daily data for the future by mapping historical cumulative distribution functions (CDFs), sourced from a 1957 to 2010 training period, to a projected future CDF. A variation in the QM method is used, depending on whether projections for 2030 or 2050 are required. Different methods are required as there is almost no daily data for GCMs around 2030. In addition, even where data do exist, no GCM daily data for surface water vapour and solar radiation are available.

For 2030, the future CDF is estimated by the forward projection of historical trends in monthly quantiles out to that year (Figure 2). There is a risk that historically-based quantile trends may meet or cross each other at some point in time which is dealt with in code but reduces precision. Beyond 2030 the effect was found to be unacceptable. Therefore, to acquire 2050 projections datasets, future CDFs for rainfall and temperature variables have been computed differently, using daily data obtained from GCMs instead of extrapolating historical quantile trends. Once the projected quantiles are determined, daily observations are projected by ‘matching’, month by month, their quantile ranks in the future with their quantile ranks in the training period. A residual correction also needs to be applied because of the difference between the quantiles obtained from the linear trend line and the empirical quantiles (Kokic, Jin & Crimp 2013). Finally the projected data is shifted so its monthly mean levels match those obtained by the CF approach. While the approach for 2050 rainfall and temperature projections uses daily GCM data, QM 2050 projections for other climate variables use the QM 2030 method extended to 2050.

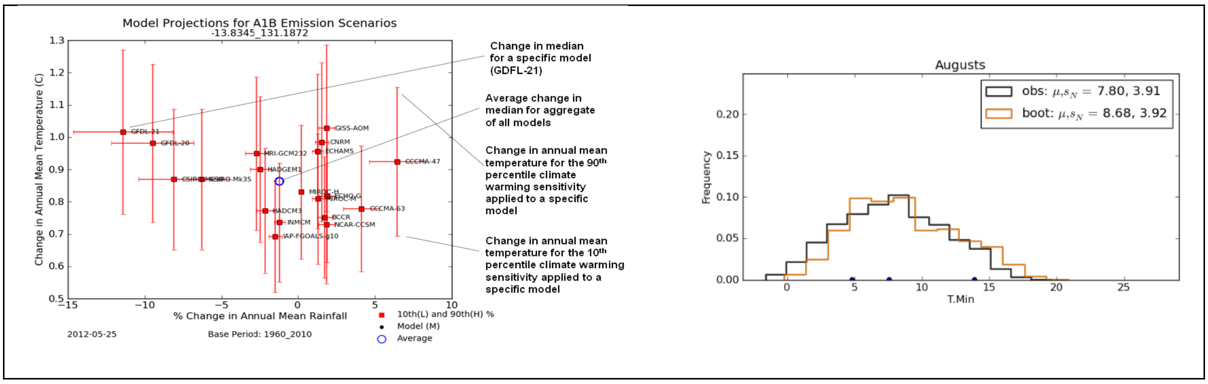

Figure 3: Two sample diagnostic plots. **Left:** Comparison of model projections plot for 2030 for Douglas River (Location Code 014901) in Northern Territory. Plot generated using Version 1.2 projections data climate ‘Change factors’ for GCMs forced by the A1B emissions scenario. **Right:** Minimum temperature information displayed in a histogram of ‘Quantile-matched’ (QM) projections data for Augusts for a specific location, showing differences between the observed 1957 to 2010 baseline climate and 2030 QM projection of the data. This plot shows a positive shift in the QM frequency distribution. The blue semi circles on the x-axis represent projected 10^{th}, 50^{th} and 90^{th} percentile values of the mean daily minimum temperature for 2030, using QM trends. Observed 1957-2010 and projected 2030 means and corresponding standard deviations are presented in the top right panel.

3.3. Composite Models

The issue of Global Climate Model (GCM) selection is an important one and various views exist as to the best approach to take. It is desirable that end-users can relate their results, based on their choice of GCMs, to the results from another user who has chosen a different set of GCMs - particularly if the results differ. The CCS system potentially produces a large number of outputs (any combination of 19 models, eight scenarios and three climate sensitivities) which can be difficult for modellers to process and communicate. To reduce the number of models needing to be run a model compositing approach based on the work of Watterson (2012) was adopted. This approach describes how projected Australian 21^{st} Century rainfall responses for the range of CMIP3 GCMs may be clustered according to, global warming sensitivity, and East Indian versus West Pacific Ocean temperature responses. The GCM responses can be split into four Representative Future Climate (RFC) partitions:

- HI: A high level of global warming, where the Eastern Indian Ocean warms faster than the Western Pacific Ocean.
- HP: A high level of global warming, where the Western Pacific Ocean warms faster than Eastern Indian Ocean.
- WI: A low level of global warming, where the Eastern Indian Ocean warms fasters than Western Pacific Ocean.
- WP: A low level of global warming, where the Western Pacific Ocean warms fasters than Eastern Indian Ocean.

Four composite models composed from the members of the 19 preferred GCMs (see Figure 4) that fall into each group have been provided for users who wish to sample a diverse range of possible climate futures without necessarily requiring specific models.

3.4. Diagnostics

When ordering projections data, the user has an option to select ‘diagnostics’. If diagnostics is selected, the user will receive the following plots, which can also be used with or independently of the projections datasets:

- historical time series plots;
- comparison of model projections plots (showing change in rainfall and temperature at 2030 for 19 GCMs based on 'Change factors');
- monthly quantile trend plots, for selected climate variables (QM only); and
- histograms showing historical and 'Quantile-matched' distributions for each climate variable (QM only).

Sample frequency distribution plots (based on CF projections) can be requested by contacting us directly.

4. WEB INTERFACE

User registration is performed via (http://longpaddock.qld.gov.au/climateprojections/registration.php). The data request process is a guided one. One innovative control is the GCM selection control (Figure 4) which provides considerable feedback. The GCMs are shown clustered according to Watterson (2012), GCMs are also show in a checkbox list as ranked by the expert panel with the four composites at the bottom. Patterns of change and summary statements are shown dynamically on the right hand side.

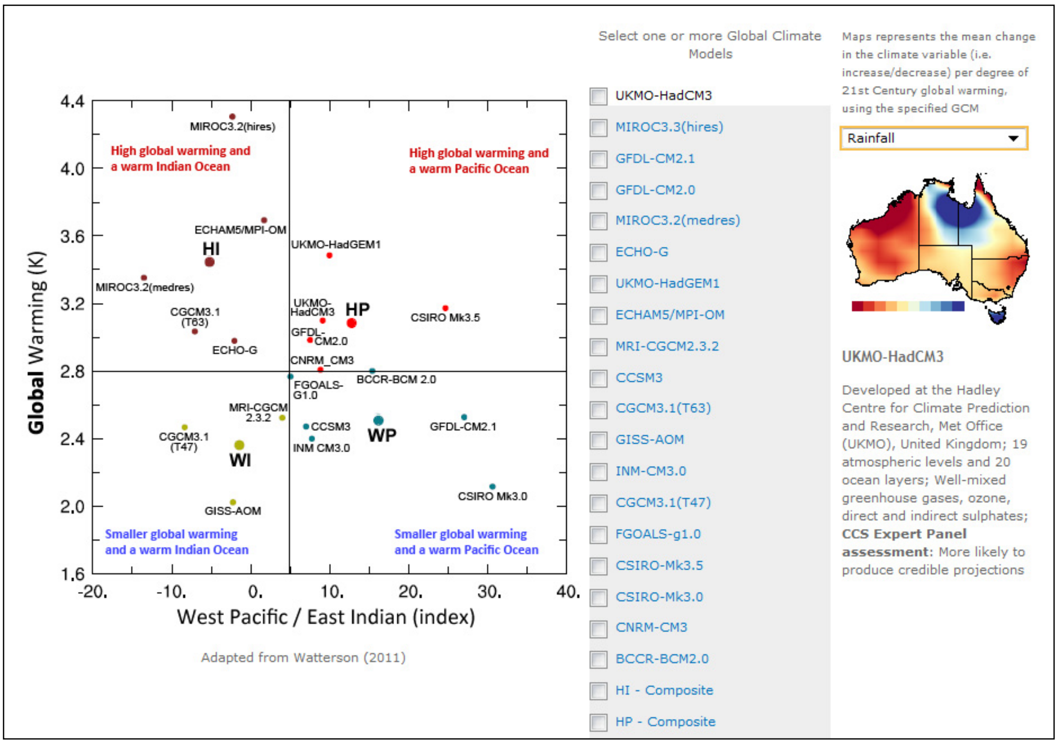

Figure 4: Selection of GCMs. The left hand panel is a control adapted with permission from (Watterson 2012) and allows users to select a GCM, or one of the composites, whilst viewing an annual pattern of change in the right hand panel. It acts as a combination of selection tool and review tool. Users may select GCMs from the check boxes.

5. DISCUSSION AND CONCLUSIONS

This framework is believed to be the first of its kind in Australia. The aim of the CCS project was to provide ready to use consistently prepared climate change data sets for use in biophysical modeling. While there are many possible methodologies available for providing daily data we have chosen simple methods that preserve historical weather-like patterns and thereby possibly preserving calibration parameters in some crop and pasture models. In the future the challenge will be to produce similar datasets from AR5 GCM runs and elaborate the QM methodology. However, we caution that limits inherent in the assumption of pattern scaling methodologies may in some cases have significant impact on data integrity.

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