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Modelling Extreme Events in a Changing Climate using Regional Dynamically-Downscaled Climate Projections

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Abstract: The ability of regional dynamically-downscaled general circulation models (GCMs) to assess changes to future extreme climatic events was investigated by comparing hindcast model outputs with observations. Projections were generated on a 0.1° grid across Tasmania using the CSIRO Conformal Cubic Atmospheric Model (CCAM). Two future SRES emission scenarios (A2 and B1) and multiple boundary conditions from GCMs were used for the period 1961-2100. A bias-adjustment procedure was employed to spatially correct extreme magnitudes. Events were fitted to a Generalised Pareto Distribution (GPD) using an automated threshold selection procedure developed for gridded precipitation datasets. Estimates of precipitation average recurrence intervals (ARIs) were calculated using extreme value analysis and compared to gridded observations. Spatial patterns were found in gridded precipitation extremes that closely matched observations. Projections of future changes to precipitation extremes were found to vary spatially between models, correlating with projected changes to regional climate drivers. Results demonstrate that dynamical downscaling captures regional climate variability (particularly relevant for precipitation) and displays significant ability in modelling future changes to the intensity, magnitude and frequency of extreme events at the local scale for use in adaptation and emergency planning applications.

Keywords: extremes; regional downscaling; precipitation; climate change; extreme value analysis.

1. INTRODUCTION

The Antarctic Climate and Ecosystems Cooperative Research Centre (ACE CRC), Hobart, has produced high-resolution climate change projections for the Australian state of Tasmania as part of the *Climate Futures for Tasmania* project. A key component of the project is to establish possible changes to climatic extreme events as a consequence of climate change up to the end of the 21st Century. Natural climate variability produces extreme climatic events in Tasmania including heat waves, flooding, droughts and severe storms. These events can have devastating and wide-ranging costs to all sectors of society, including agriculture, water resources and emergency planning. Six general circulation models (GCMs) have been dynamically-downscaled to a 0.1° grid for the period 1961-

2100. The hindcast ability of the downscaled GCMs at capturing extreme precipitation events is investigated and a bias-adjustment procedure introduced using observations. An automated extreme value distribution fitting procedure is developed for large gridded observational and modelled datasets and its performance evaluated through changes to magnitudes for given average recurrence intervals. The change to frequency, magnitude and duration of extreme events across Tasmania due to anthropogenic interference of the climate through the enhancement of the greenhouse effect is assessed.

2. DYNAMICALLY-DOWNSCALED REGIONAL CLIMATE PROJECTIONS

2.2 Tasmania's Climate

Tasmania is an island state of Australia that lies to the south-east of the mainland between 40° and 43.5° south and has a varied temperate maritime climate. Tasmania is mountainous in the western, central and north-eastern parts of the state, affecting the flow of air overland and precipitation distribution. The principle characteristic of the Tasmanian climate is the interaction between prevailing westerly winds and the mountain ranges near the west coast and the central plateau. This interaction strongly influences the spatial variation of precipitation across the state [Langford, 1965].

2.2 Modelling

GCMs are typically of relative coarse resolution and do not have the necessary skill to capture Tasmania's varied topography and climate (e.g. convection, land-sea interactions) accurately. A regional downscaling approach was required to model the state's climate variability. The *Climate Futures for Tasmania* project made the technical and financial commitment to undertake an extensive downscaling process involving multiple GCMs and SRES scenarios [Corney et al., 2010]. Six GCMs were dynamically-downscaled using the CSIRO Conformal Cubic Atmospheric Model (CCAM) [McGregor, 2005] using the high-resolution 0.1° grid for the period 1961-2100. The GCMs selected were CSIRO-Mk3.5 (Australia), GFDL-CM2.0 and GFDL-CM2.1 (USA), ECHAM5 (Germany), UKMO-HadCM3 (UK) and MIROC3.2(medres) (Japan). The model selection was based on an assessment by Smith and Chandler [2009] that assessed the ability of selected models at reproducing the present-day climate of the Australian region. Two SRES emission scenarios were used to provide a range of likely projected futures, from a low (B1) to a high (A2) increase in atmospheric greenhouse gas emissions.

The CCAM dynamical downscaling process [Katzfey et al., 2009] uses a stretched-grid global model with forcing data taken from a host GCM. The result is a fine-scale dynamical model over the area of interest (often referred to as a regional model). To achieve a desired final resolution of 0.1°, a two stage downscaling process was required. The first stage (intermediate model) involved downscaling from the host GCM to a grid with the high-resolution face of the cubic conformal grid covering all of Australia at a resolution of approximately 0.5°. The second stage placed the high-resolution face over Tasmania and the Bass Strait islands at an approximate resolution of 0.1°.

Figure 1 shows the average annual precipitation totals for the state at three resolutions; a typical GCM and the two stages of downscaled results (here demonstrated by GFDL-CM2.1). A typical GCM resolution (left panel) only has two or three grid cells covering the state, suggesting the average state-wide annual total precipitation to be ~746 mm. The 0.5° resolution model (centre panel) shows an improved spatial pattern of precipitation, with the predominantly dryer eastern and wetter western regions starting to be defined, and an average annual total of ~1006 mm. The finest 0.1° resolution model (right panel) has an average annual total of 1385 mm, closely resembling the observed spatial patterns and total of 1390.4 mm. It was concluded that the high-resolution 0.1° dynamical downscaling process had the ability to model the local climate of Tasmania accurately across the downscaled models, including seasonality, spatial variance and relationships between the different climate variables [Corney et al., 2010].

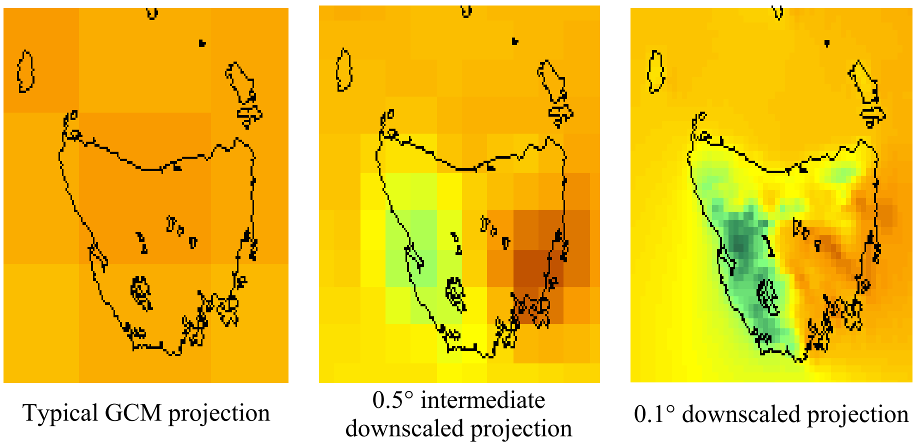

Figure 1. Average annual precipitation totals for Tasmania projected on typical GCM, 0.5° and 0.1° grids [Corney et al., 2010]. Precipitation scaled from 0-3000 mm per annum.

2.3 Bias-adjustment

Whilst capturing the correct spatial pattern of total annual precipitation in the downscaled models is important, when attempting to project future changes to extreme precipitation events, the correct magnitudes of events are also of key importance. Extreme precipitation events are a result of the complex interaction between temperature, moisture, winds and orography, and are typically localised phenomena. As such, the magnitudes of extreme precipitation events can vary greatly over relatively short distances and elevations. To enable the modelling output to be used for the extreme value analysis, five key climate variables (daily maximum temperature, daily minimum temperature, daily precipitation, daily potential evaporation and daily solar radiation) from the 0.1° model output were bias-adjusted using observations. The bias-adjustment process was based on a percentile binning method [Corney et al., 2010], using the Australian Water Availability Project (AWAP) [Jones et al., 2009] interpolated observed dataset for Tasmania. The adjustment process was applied on a daily, cell-by-cell basis, for each of the land grid cells. The overlap period between the 0.1° modelling output and the AWAP observed dataset (1961-2007) formed the training period where the required adjustments for each percentile bin were calculated. The adjustments were then applied to the entire modelling dataset (1961-2100).

3. EXTREME VALUE ANALYSIS

3.1 Methods

A simple way to assess extreme events in natural phenomena is through the concept of average recurrence intervals (ARIs), often referred to as 'return periods'. The ARI allows climatologists, engineers and planners to estimate both the magnitude and frequency of extreme events occurring. Formally, the ARI is the average *interval* or *period* between exceedances of a given value (e.g., precipitation total or wind gust speed). Commonly, the ARI is approximated from the inverse of the annual exceedance probability (AEP) of an event exceeding a given value in any one year (for example, if the probability of exceeding a given event in a single year has an AEP of 0.02, we can say that the event may be exceeded, on average, once in every 50 years):

$$\text{ARI} = 1/(1 - \text{AEP}) \tag{1}$$

where: AEP is the annual exceedance probability
ARI is the average recurrence interval, expressed in years^{-1}

The reason for the popularity of ARI in natural phenomena studies is the possibility of extrapolating the ARI curve beyond the range of the observations. This is achieved by using extreme value analysis and specialised extreme value distributions (EVD). There are two basic methods to fit an EVD to a given climatic dataset: a) the block maxima method where an EVD (typically the Generalised Extreme Value family of distributions) is fitted to an annual maxima series; b) the 'peaks-over-threshold' method where the Generalised Pareto Distribution (GPD) is fitted to values exceeding a selected threshold (typically applicable to daily time series). As maximum daily data were available from the CCAM model runs, the GPD method was selected as the preferred method for this study.

The fundamental problem when fitting a GPD is the selection of an appropriate threshold for the 'peaks-over-threshold' calculation. The parameters of the GPD are very sensitive to the threshold selection. Most methods developed to solve this problem are difficult to implement, especially for large-scale gridded model output as was available for the *Climate Futures for Tasmania* project. These kinds of problems require efficient methods to find the appropriate threshold.

In this study, the automated threshold selection method developed by Sanabria and Cechet [2007] for wind speed datasets was altered for precipitation data in the R programming environment [R Development Core Team, 2009]. This procedure is based on the extreme statistical theory introduced by Coles [2001] and developed in the R programming environment by Stephenson [2004]. The procedure has also been adapted for selected extreme events in the Sydney region of Australia by Abbs and Rafter [2009]. The procedure generates all feasible ARIs for each grid cell in the study area (2856 cells, including 721 land cells) using a continuous algorithm with thresholds increasing in steps of 0.25 mm from a selected starting value. The algorithm is automatically stopped when the remaining number of observations available exceeding the threshold falls below 25. The threshold that produces the highest ARI of precipitation is then selected. Feasible thresholds are those that produce convex curves (e.g., curves that tend to a limiting value). These type of curves have been shown to be appropriate to model naturally bounded phenomena including precipitation, wind speed and temperature.

3.2 Data Preparation

Unlike other climate variables such as wind speed or temperature, precipitation requires careful preparation of the data before it is submitted to the extreme value algorithms. Precipitation weather systems can track slowly, thus the same event may span several days at any given location. It was therefore necessary to sort the precipitation data into independent events – a fundamental condition of extreme value analysis. Two parameters were defined: the threshold above which daily precipitation events were extracted (typically this can be relatively low), and the number of consecutive observations below the threshold such that the event may be considered to have ended and a new event may occur. The final value of each independent event is then given by the maximum daily precipitation value in the window. The package 'EVD' [Stephenson, 2004] in the R programming environment was employed to sort the gridded daily precipitation data.

Figure 2 illustrates an example of the technique using 250 daily precipitation records (mm) observed at Sorell, a Bureau of Meteorology recording station about 25 km east of Hobart, Tasmania's capital. Here, the threshold value for an event was selected as 5 mm. In this example, when the algorithm locates a daily precipitation value greater than 5 mm the event window starts, and only ends when 3 (or more) events below the threshold occur consecutively (standard event window of +/- 3 days). Figure 2a shows that there are 10 event windows (grey bands) in the 250 daily precipitation series. Figure 2b shows that by selecting the maximum value from each window, only 10 independent precipitation events are found that exceed the threshold in this daily time series.

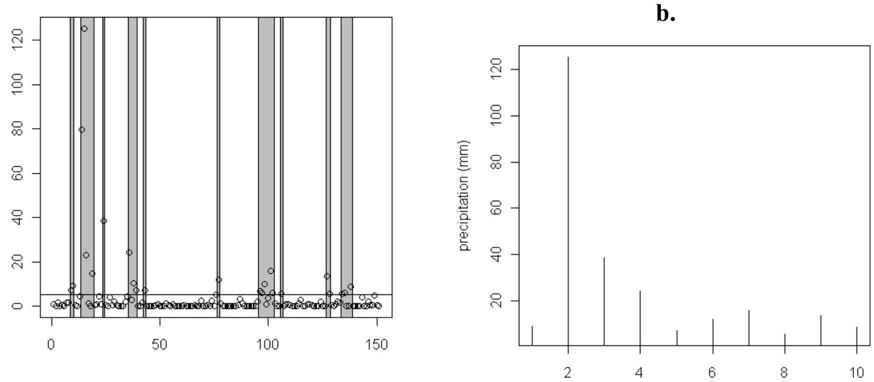

Figure 2. Illustration of the automated independent precipitation event selection process at a single location (Sorell, Tasmania): **a.** grey bands show the automatically selected event windows; **b.** independent maximum daily precipitation values selected from each window.

3.3 Confidence Intervals

A confidence interval (CI) shows the range of values in which the value of the ARI lies for a given probability. The CI depends on the amount and structure of the data samples, which measures the spread of the samples around their mean.

Gillelland and Katz [2005] found that the 'Profile Likelihood' method for the calculation of CI values to extreme value temperature data produced accurate results as it considers the asymmetry of the data. Since precipitation data is also highly asymmetric, the 'Profile Likelihood' method as implemented in the R 'extRemes' package by Gillelland and Katz [2009] was used. Figure 3 shows an example ARI plot of observed precipitation at a single location in Tasmania (Sorell) with calculated 95% CI. Both the upper and lower bounds for the ARI are shown asymmetrically with respect to the calculated ARI. Note that the CI substantially increases as the ARI values increase indicating a higher degree of uncertainty when making inferences substantially beyond the range of the data.

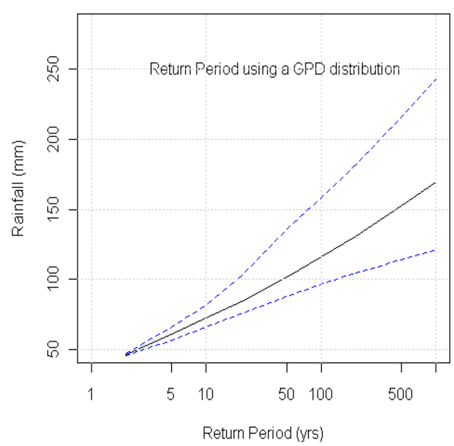

Figure 3. Example of observed precipitation data fitted to a Generalized Pareto distribution with 95% confidence intervals at Sorell, Tasmania

4. RESULTS

4.1 Validation and Performance

The ability of dynamically-downscaled GCMs at capturing the magnitude and frequency of extreme precipitation events was investigated using the automated extreme value GPD fitting procedure. The procedure was applied to the gridded raw and bias-adjusted modelled output generated across the state of Tasmania on a 0.1° grid. The performance of the models was compared against interpolated observations from the AWAP dataset using the same GPD fitting procedure and grid resolution. The validation period was selected as the standard climatology period of 1961-1990.

Figure 4 compares example daily precipitation magnitudes of the 200-year daily ARI for the validation period, generated from the AWAP (observed) gridded observations and the raw and bias-adjusted downscaled CSIRO-Mk3.5 modelled outputs. The automated GPD fitting procedure was found to perform well with all three sets of gridded data across the models. In this example, the most noticeable feature however is the underestimation of the extreme magnitudes displayed by the raw downscaled CSIRO-Mk3.5 data (centre panel) compared to observations (left panel). Although the AWAP observations were found to lie within the CI of the raw downscaled CSIRO-Mk3.5 data (CI not shown), the differential in *magnitudes* can be explained in part by the lack of orography in the CSIRO-Mk3.5 model across Tasmania. The downscaled GCMs do not fully account for the steep mountain ranges inland of the west coast, or the steep drop off from the Western Tiers mountain range in the central west that cast a rain-shadow over this region. In contrast, the bias-adjusted downscaled CSIRO-Mk3.5 modelled data (right panel) showed greater spatial similarity to the AWAP observations, although some magnitudes were found to be slightly too high, mainly in the south-western region of the state where observations are limited. It was concluded that the bias-adjustment applied to the downscaled GCMs had improved the spatial pattern of extreme precipitation magnitudes [White et al., 2010].

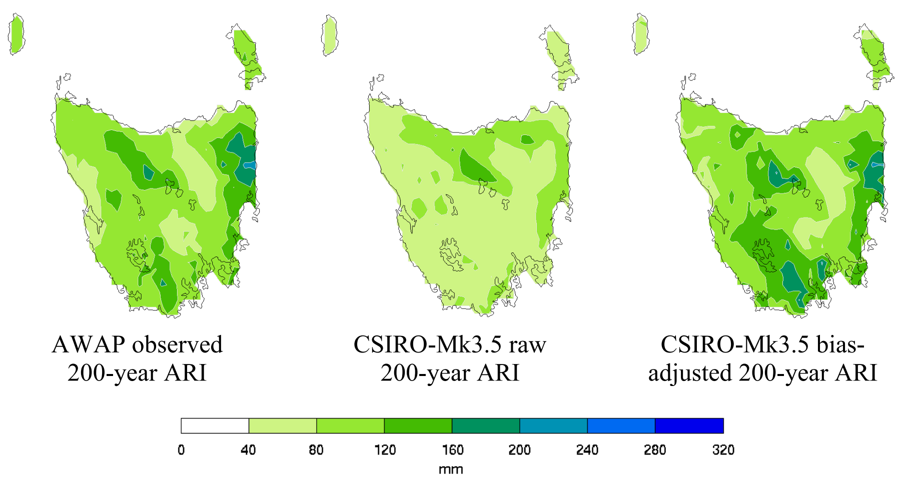

Figure 4. Example validation of the daily precipitation magnitudes of the 200-year ARI for 1961-1990: AWAP (observed); raw CSIRO-Mk3.5 (modelled); bias-adjusted CSIRO-Mk3.5 (modelled). All data for the validation period projected on a 0.1° grid.

4.2 Future Projections

The dynamically-downscaled GCM simulations provide a suite of climate change datasets driven by an increase in atmospheric greenhouse gas composition up to the end of the 21st Century. Modelled precipitation projections from the downscaled projections under the SRES A2 high emission scenario were used to calculate bias-adjusted magnitudes (mm) of the 2, 5, 10, 20, 50, 100, 200 and 500-year ARIs using the automated GPD fitting procedure. Figure 5 shows a panel of the projected percentage change in the magnitude of the 200-year ARI for 2070-2099 relative to 1961-1990 baseline period for each model.

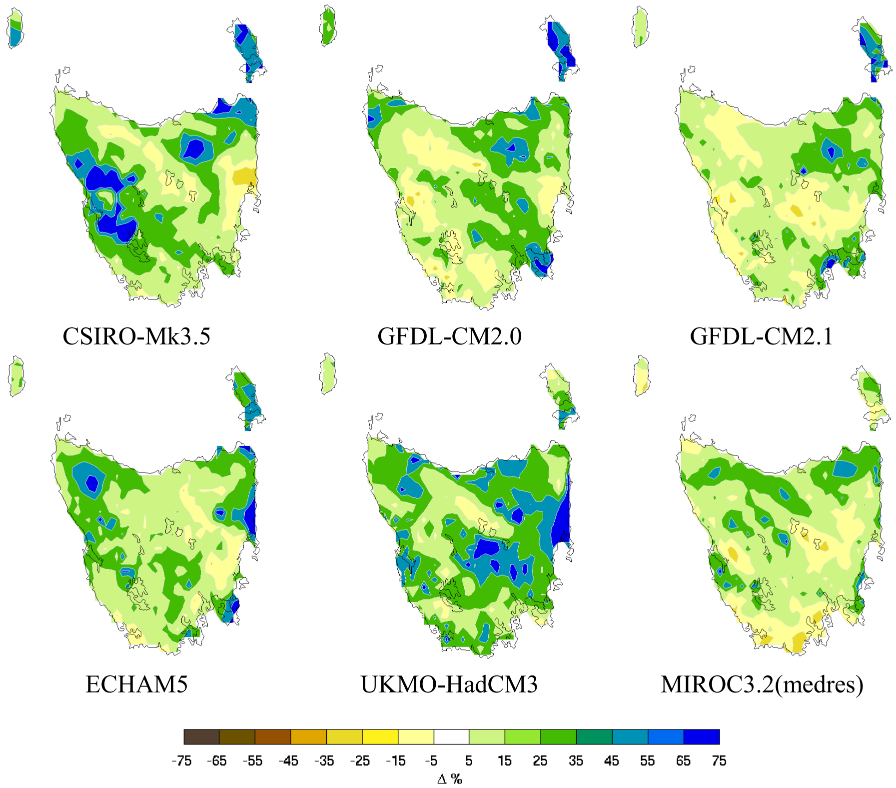

Figure 5. Percentage change magnitudes of the 200-year ARI for 2070-2099, relative to the 1961-1990 baseline across Tasmania. Models: CSIRO-Mk3.5 (Australia); GFDL-CM2.0 and GFDL-CM2.1 (USA); ECHAM5 (Germany); UKMO-HadCM3 (UK); MIROC3.2(medres) (Japan).

Whilst the projection of mean total annual precipitation for Tasmania under SRES A2 displayed no significant trends up to the end of the 21st Century [Grose et al., 2010], significant changes in the frequency and severity of extreme events was found [White et al., 2010]. This was noted to be particularly apparent for the regional extreme precipitation trends that showed a steadily emerging pattern of increased magnitudes of daily extreme events, particularly over the central-eastern and western regions, with reduced magnitudes over central areas and in some areas of north-west Tasmania. The spatial pattern however was not found to be uniform across the six models with notable spatial differences, suggesting that the automated GPD fitting procedure has successfully retained the unique climate change signals from each of the models. The changes in seasonal extreme precipitation events were stronger still with the west coast of Tasmania displaying a pattern of significant increase in precipitation extremes in winter and a significant decrease in summer events that emerge by the end of the 21st Century (not shown).

5. CONCLUSIONS

The bias-adjustment process performed well when correcting the extreme magnitudes whilst preserving the frequency of events from each model. Results displayed a close spatial pattern to the AWAP observational data for the period 1961-1990. Confidence intervals were calculated to assess the accuracy of the results (not shown), with observations found to lie within the confidence intervals of the downscaled data. The automated GPD procedure produced good results for both the observed and modelled gridded datasets over a range of ARIs. The variation between the six downscaled future projections demonstrates that the unique climate change signal from each model has been preserved by the automated GPD fitting procedure for large gridded datasets.

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