



A comparison of multi-site daily rainfall downscaling techniques under Australian conditions

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ARTICLE INFO

Article history:

Received 16 February 2010

Received in revised form 16 June 2011

Accepted 27 June 2011

Available online 22 August 2011

This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Uwe Haberlandt, Associate Editor

Keywords:

Downscaling

CCAM

Scaling method

Analogue method

GLM

Hidden Markov model

Modified Markov model

SUMMARY

Six methods of downscaling GCM simulations to multi-site daily precipitation were applied to a set of 30 rain gauges located within South-Eastern Australia. The methods were tested at reproducing a range of statistics important within hydrological studies including inter-annual variability and spatial coherence using both NCEP/NCAR reanalysis and GCM predictors, thus testing the validity of GCM downscaled predictions. The methods evaluated, all having found application in Australia previously, are: (1) the dynamical downscaling Conformal-Cubic Atmospheric Model (CCAM) of McGregor (2005); the historical data based (2) Scaling method applied by Chiew et al. (2009) and (3) Analogue method of Timbal (2004); and three stochastic methods, (4) the GLIMCLIM (Generalised Linear Model for daily Climate time series) software package (Chandler, 2002), (5) the Non-homogeneous Hidden Markov Model (NHMM) of Charles et al. (1999), and (6) the modified Markov model–kernel probability density estimation (MMM–KDE) downscaling technique of Mehrotra and Sharma (2007). The results showed that the simple Scaling approach provided relatively robust results for a range of statistics when GCM forcing data was used, and was therefore recommended for regional water availability and planning studies (subject to certain limitations as mentioned in conclusion section). The stochastic methods better capture changes to a fuller range of rainfall statistics and are recommended for detailed catchment modelling studies. In particular, the stochastic methods show better results for daily extreme rainfall (e.g. flooding/low flow) as the simulations are not based purely on temporal/spatial rainfall patterns observed in the past, and a hybrid GLIMCLIM occurrence-KDE amounts model is recommended based on performance for individual statistics. For GCM downscaled simulations, biases in annual mean and standard deviation of $\pm 5\%$ and -30% were observed typically, and no single model performed well over all timescales/statistics, suggesting that the user beware of model limitations when applying downscaling methods for various purposes. A brief demonstration of predictor biases is presented, highlighting that biases observed in GCM predictors can cause poorer performance during GCM validation, and that investigation of these biases should inform choice of GCMs, GCM predictors, and the downscaling methods that use them.

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1. Introduction

Predictions of spatial and temporal variability of rainfall (including climate change effects) on a catchment scale are required for hydrological modelling in many regions throughout the world. Large spatial scale predictions of (typically 125–500 km grids) global

climate scenarios output by General Circulation Models (GCMs) are inadequate for such use as they do not capture the extensive local-scale variability which is characteristic of rainfall. Multi-site or gridded daily rainfall is a required input for modelling complex multi-catchment systems, as small scale spatial variability due to factors such as topography has a large bearing on how much rainfall falls in a given area, and processes such as runoff generation are sensitive to this variability. Thus the large scale climate scenarios output by a GCM are often downscaled to a finer resolution for hydrological impacts studies.

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Multi-site downscaling of rainfall is a maturing field with many recently proposed methods (e.g. Fowler et al., 2005; Haylock et al., 2006; Vrac and Naveau, 2007; Wetterhall et al., 2006) with some methods also finding Australian application (Charles et al., 2004; Hope et al., 2006; Mehrotra and Sharma, 2006; Timbal, 2004; Nguyen and McGregor, 2009). Fowler et al. (2007) provides a thorough review of downscaling methods with an emphasis on hydrological application. As discussed in that review, downscaling methods can usually be classified as either stochastic or dynamical, where either a statistical–empirical or a deterministic relationship between the GCM climate predictors and the rainfall value is modelled respectively. Stochastic methods are based on relatively simplistic empirical relationships between GCM predictors and site rainfall, yet are time consuming to calibrate/specify for specific areas. Deterministic methods, as they are based on parameterisation according to physical laws, do not require calibration and should be applicable widely. However, these deterministic methods suffer from higher computation time, and can suffer from inadequate spatial resolution in particular for identification of convective rainfall events and the effects of orography. This work compares a range of downscaling methodologies in detail, including stochastic and deterministic methods. Although other papers have attempted comparisons of downscaling methods, they often focus on relatively simple methods and there are few if any investigations that assess the relative performance of more modern approaches that might be expected to have superior performance. The methods of interest in this study are those that have found application in Australia.

Typically downscaling techniques are calibrated and validated on an annual or 3–6 month seasonal basis (using large scale test indices), with few papers providing evidence that the daily to monthly spatial correlation and intermittency structure of rainfall is reproduced. It is unclear from the literature whether these models adequately reproduce the total monthly seasonal and site-to-site variations, as required for hydrologic models reliant on such input. It is also rare for downscaling techniques to be validated in reproducing past climate using GCM predictors, as opposed to those from reanalysis data – see Vrac et al. (2007), Schmidli et al. (2007), Wilby and Harris (2006), Charles et al. (2004) and Wilby and Wigley (2000) for some exceptions. Such verification is required to ensure any predictions made using GCM downscaled data might be reasonable, especially in light of biases present within GCM simulations. This work details downscaling multiple site rainfall data using reanalysis data and data from several GCMs.

The intention of this paper is to focus on detailed evaluation of rainfall characteristics (thus allowing improvement of downscaling methods specifically), with discussion of the potential implications when used in hydrological studies. This discussion is subject to certain caveats and uncertainties, such as: (a) inputs other than precipitation (temperature, evapotranspiration) are required for hydrological prediction purposes, (b) rainfall–runoff modelling accuracy and uncertainty will affect outputs; and (c) GCM model accuracy and uncertainty and scenario uncertainty can potentially affect the quality of runoff predictions. In a related paper Chiew et al. (2010) compare the runoff predictions using the simulated downscaled rainfall from the models in this study as input into a calibrated rainfall–runoff model, thus investigating the effect of some of these other uncertainties also.

The paper is organised as follows. Section 2 provides the details on the data and the methodology used in the study. Section 3 describes each of the downscaling models tested, with the results and a brief investigation of the influence of bias in GCM predictors presented in Section 4. The discussion of results, including possible reasons for each model's performance and their wider applicability, are presented in Section 5. Section 5 presents the conclusions and proposed future research.

2. Data and methodology

The purpose of this study is to verify the ability of the six downscaling techniques in reproducing the overall observed rainfall behaviour in the downscaled simulations and thus identify where models are insufficient for hydrological purposes. To achieve this, the techniques are tested by assessing their ability to reproduce observed daily, monthly and annual rainfall statistics using both reanalysis and GCM derived data. This is the first such study to compare the major state-of-the-art downscaling methods currently employed within Australia, thus serving as a future benchmark. An investigation of the effects of the uncertainties in GCM projections and models is considered outside the scope of the work however: the focus is on the accuracy of the methods when downscaling reanalysis data and 20th century scenarios from a small set of GCMs.

2.1. Data

For statistical downscaling, data requirements are: (a) historical multi-station rainfall data for calibration and verification; (b) large spatial scale reanalysis climate data, the historical climate predictors used in calibration of the statistical model; and (c) GCM predictors on the same spatial and temporal scale as the reanalysis predictors, which are used to produce downscaled rainfall projections for various scenarios.

2.1.1. Rainfall data

The study area chosen is part of the Murray–Darling Basin in South-Eastern Australia. This area supplies much of the agricultural produce of Australia, and is under intense demand pressures regarding water allocation for agricultural and environmental purposes (especially given the recent long lasting drought in Southern Australia; for background and management strategy details see www.mdba.gov.au). For details of current/recently completed projects addressing climate variability and change in the Murray–Darling Basin see the Murray–Darling Sustainable Yields Project (www.csiro.au/mdbpsy) and the South Eastern Australian Climate Initiative (www.mdbc.gov.au/subs/seaci/about.html).

Fig. 1 shows the locations of the 30 daily rainfall stations chosen for this study. The sites range from the high altitude Eastern regions (snow in winter) to semi-arid sites in the West, with a range of climatological influences affecting rainfall in the area (e.g. Murphy and Timbal, 2007; Meyers et al., 2007; Hendon et al., 2007). This results in complex seasonal, interannual and spatial variability, thus providing a thorough test of the downscaling techniques. These particular sites (see Table 1), data supplied by the Australian Bureau of Meteorology (BoM), were chosen as they were identified as being of relatively high quality for the calibration time-span used as they: (a) showed little evidence of containing unmarked multiple day accumulations (as identified through the method of Viney and Bates (2004)); (b) had a very low prevalence of marked missing or multiple day accumulated data – see Table 1; and, (c) had been visually buddy-checked with surrounding sites to ensure spatial consistency by BoM Data Management, a measure which has not been undertaken to date on data recorded prior to 1999 (Rod Hutchinson, BoM National Climate Centre, Data Management, *pers. comm*). The calibration period of 1986-01-01–2005-12-31 was chosen due to its higher level of quality control compared with earlier records. Potentially lower quality data spanning the period 1961-01-01–1985-12-31, not retrospectively quality controlled given the time and labour intensive task of checking such data, were reserved for split-sample validation purposes.

To facilitate the smooth application of the methods, site rainfall data was 'patched' on missing days using the spatial interpolation

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