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Statistical downscaling of CMIP5 outputs for projecting future changes in rainfall in the Onkaparinga catchment

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HIGHLIGHTS

• A generalized linear model was used for multi-site daily rainfall downscaling.
• Rainfall was downscaled from CMIP5 GCM outputs.
• Two multi-model ensemble approaches were used.
• Bias was corrected using the Frequency Adapted Quantile Mapping technique.
• Future changes of hydrologically relevant metrics were estimated.

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ABSTRACT

A generalized linear model was fitted to stochastically downscaled multi-site daily rainfall projections from CMIP5 General Circulation Models (GCMs) for the Onkaparinga catchment in South Australia to assess future changes to hydrologically relevant metrics. For this purpose three GCMs, two multi-model ensembles (one by averaging the predictors of GCMs and the other by regressing the predictors of GCMs against reanalysis datasets) and two scenarios (RCP4.5 and RCP8.5) were considered. The downscaling model was able to reasonably reproduce the observed historical rainfall statistics when the model was driven by NCEP reanalysis datasets. Significant bias was observed in the rainfall when downscaled from historical outputs of GCMs. Bias was corrected using the Frequency Adapted Quantile Mapping technique. Future changes in rainfall were computed from the bias corrected downscaled rainfall forced by GCM outputs for the period 2041–2060 and these were then compared to the base period 1961–2000. The results show that annual and seasonal rainfalls are likely to significantly decrease for all models and scenarios in the future. The number of dry days and maximum consecutive dry days will increase whereas the number of wet days and maximum consecutive wet days will decrease. Future changes of daily rainfall occurrence sequences combined with a reduction in rainfall amounts will lead to a drier catchment, thereby reducing the runoff potential. Because this is a catchment that is a significant source of Adelaide's water supply, irrigation water and water for maintaining environmental flows, an effective climate change adaptation strategy is needed in order to face future potential water shortages.

1. Introduction

Human activities, and particularly the burning of fossil fuel, have a significant influence on warming of the atmosphere and oceans. This results in changes in the global water cycle, mean sea level rises, changes in some climate extremes, and eventually changes in the global climate (Stocker et al., 2013). Continued emissions of greenhouse gases will cause further warming and changes in all components of the climate system. These changes of climate are identified in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5). According to that report, the global mean temperature change for the period 2016–2035 will likely be within the range of 0.3 °C to 0.7 °C relative to 1986–2005 and it is likely to exceed 1.5 °C by the end of the 21st century relative to 1850–1900 (Stocker et al., 2013). These changes in the climate will have impacts on the local rainfall and hydrological regimes, which will eventually affect the society, economy and environment. For example, according to the AR5 report, the annual mean rainfall is likely to be increased by the end of this century in many mid-latitude and subtropical dry regions.

Projections of future changes in the climato-meteorological variables such as rainfall due to a changed climate are vital for sustainable management of catchment scale water resources. General Circulation

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Models (GCMs) are a widely used tool to project future climate change under different greenhouse gas emission scenarios (Chu et al., 2010; Hu et al., 2012; Huang et al., 2011; King et al., 2012; Sachindra et al., 2014a). Hydrological and water resource management studies require fine resolution climate data (Arora, 2001; Timbal et al., 2009). But due to the coarse resolution of GCM outputs, their direct application for catchment scale hydrological modelling is limited. So, downscaling methods are often used to resolve this problem by relating coarse-resolution GCM outputs to local hydro-climatic variables such as rainfall, temperature and evapotranspiration. Fu et al. (2013) downscaled the GCM outputs of IPPC CMIP3 to rainfall for the periods 2046–2065 and 2081–2100 in the southern Murray–Darling basin in south-eastern Australia using the Nonhomogeneous Hidden Markov model (NHMM). They found suitability of stochastic model to project Australian rainfall. Heneker and Cresswell (2010) downscaled rainfall from GCM (CSIRO MK3.0) outputs under A2 and B2 emission scenarios for the period 2035–2065 in the Western Mount Lofty Ranges region in Australia. They observed that there is a possibility of a 13.3% reduction in annual mean rainfall under an A2 scenario and 12.3% under a B2 scenario in the Onkaparinga catchment in South Australia.

Downscaling methods are broadly divided into two groups, dynamic downscaling and statistical downscaling. The latter is more widely and frequently used because it is easy to implement and is generally less expensive (Fowler et al., 2007; Jeong et al., 2012; Sachindra et al., 2014b). The Generalized LInear Modelling of daily CLImate sequence (GLIMCLIM) is a multi-site stochastic downscaling model based on a GLM (Chandler, 2002), which has been used around the world (Beecham et al., 2014; Frost et al., 2011; Kigobe et al., 2011; Liu et al., 2012; Mehrotra et al., 2009; Mirshahi et al., 2008). Although application of GLMs for multi-site stochastic rainfall simulation is relatively new in Australia, successful application of this model in Australia is available in recent studies (Beecham et al., 2014; Frost, 2007; Frost et al., 2011). Beecham et al. (2014) used GLIMCLIM to downscale multi-site daily rainfall from NCEP reanalysis outputs in the Onkaparinga catchment in South Australia for the present climate (1981–2010). They concluded that the model has the ability to statistically downscale GCM outputs to catchment scale rainfall. Abaurrea and Asín (2005) used a GLM to statistically downscale the future projections of the coupled GCM of the Canadian Centre for Climate Modelling and Analysis (CCCma) to local rainfall in the area of Zaragoza (Spain) for the period 2090–2100. The model was found useful for obtaining long-term projections for daily rainfall patterns at a local scale. Rashid et al. (2013) used a GLM to downscale daily rainfall from the Coupled Model Inter-comparison Project 5 (CMIP5) model (CSIRO MK.3.6) and projected the changes in the annual maximum rainfall under RCP4.5 and RCP8.5 scenarios for the period 2041–2060 in the Onkaparinga catchment in SA.

New climate projections for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) are now available from a number of CMIP5 climate models. CMIP5 includes a broader variety of experiments, more reasonable scenarios and application of more comprehensive models compared to CMIP3. The fifth phase of the Coupled Model Intercomparison Project (CMIP5) is the result of the continuing activities of the World Climate Research Programme's Working Group on Coupled Modelling (WGCM) and builds on the successes of the earlier phases of CMIP such as CMIP3 and CMIP4. In CMIP5 GCMs, the Earth System Models (ESMs) incorporate additional components describing the atmosphere's interactions with land-use and vegetation, and can explicitly consider atmospheric chemistry, aerosols and the carbon cycle (Taylor et al., 2012). According to Teng et al. (2012), the median spatial resolution of CMIP5 GCMs is finer than that of CMIP3 GCMs. In CMIP5 roughly half of the GCMs have an average longitudinal resolution finer than 1.3° whereas in CMIP3 only one model fell into this category.

Recent studies show that CMIP5 models perform better than the CMIP3 ones to reproduce the observed rainfall variability. For example Wang et al. (2014) observed that CMIP5 models are more skilful than CMIP3 models in reproducing the Asian-Australian monsoon (AAM). Sillmann et al. (2013) observed that the CMIP5 models are generally able to adequately simulate climate extremes and their trend patterns. They concluded that CMIP5 ensembles provide some improvement to CMIP3 ones in the representation of the magnitude of precipitation indices and this improvement is partly due to the higher spatial resolution of CMIP5 models compared to CMIP3 models. CSIRO and BOM (2015) assessed the performance of CMIP5 GCMs to simulate historical rainfall and compared the changes in the CMIP3 and CMIP5 projections for different regions of Australia. They observed that in general CMIP5 GCMs were better able to reproduce major climate features (SAM, monsoon, pressure systems, subtropical jet, circulations) and modes of variability (seasonal cycle, ENSO and Indian Ocean Dipole). The CMIP5 models reasonably simulated the recent observed rainfall trends and extreme rainfall such as annual maximum daily rainfall for different regions of Australia. RCP4.5 (medium radiative forcing scenario) corresponds to the case of radiative forcing after 2100 of approximately 4.5 W/m^2, which is equivalent to approximately 650 ppm CO_2. Similarly, RCP8.5 (high radiative forcing scenario) is defined as the case where the radiation is assumed to exceed 8.5 W/m^2, which means the equivalent CO_2 exceeds 1370 ppm (Moss et al., 2010).

Due to structural differences in the GCMs, climate projections vary from one GCM to another leading to different projections when downscaled to catchment scale rainfall (Sachindra et al., 2014a; Yu et al., 2002). Ensemble projections become more popular in decision making as they are produced from multiple GCMs to a single projection (Krishnamurti et al., 1999; Tebaldi and Knutti, 2007; Zhang and Huang, 2013). Although there are several techniques for developing multi-model ensembles, according to Zhang and Huang (2013) averaging is the most widely used technique. The advantages of using averaging are also reported in several earlier studies (Fealy and Sweeney, 2008; Kharin et al., 2001; Knutti et al., 2010; Warner, 2011). As the accuracies may vary from one ensemble to another, some researchers have proposed to assign weights to each model in the ensemble based on their performances. Different methods are available in the literature to assign weights to each model (Ingol-Blanco, 2011; Zhang and Huang, 2013). However, there is still quite some subjectivity on the selection of parameters for the assessment of GCM performance and also how the final weights are derived from the model assessment (Christensen et al., 2010). Another technique for multi-model ensembles is the regression of GCM outputs against observed datasets (for example using NCEP reanalysis) and eventually producing a single set of predictor series to use in the downscaling model (Krishnamurti et al., 1999; Sachindra et al., 2013). Sachindra et al. (2013) regressed outputs of ensemble members (HadCM3, ECHAM5, GFDL2.0) against NCEP reanalysis datasets to prepare multi-model ensemble predictors and used these as inputs to a downscaling model to simulate monthly rainfall in Victoria, Australia.

Bias is defined as the disagreement between the GCM outputs and observations. Bias in the GCM outputs is common as the GCM structures are based on various assumptions and approximations which cause the outputs to deviate from the observations (Charles et al., 2007; Frost et al., 2011; Sachindra et al., 2014b). These biases need to be considered carefully before applying these data for future projections. Otherwise, the projections could be misleading (Charles et al., 2007; Ojha et al., 2012; Rashid et al., 2013; Sunyer et al., 2012). There are two main approaches to correct the bias: (1) the correction of bias in the raw GCM predictor variables (i.e. geopotential height) before downscaling and (2) the correction of bias in the downscaled outputs (i.e. rainfall) forced by the GCM predictors. In the former process, bias in the raw GCM predictors are corrected against the reanalysis datasets (such as NCEP reanalysis data), but there are a number of reanalysis outputs available from different organizations and these may have their own bias as well (Brands et al., 2012; Hofer et al., 2012; Yang and Wang, 2012). This method is also computationally expensive whereas bias correction of the downscaled outputs is computationally inexpensive and correction