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Research papers

A rank-based approach for correcting systematic biases in spatial disaggregation of coarse-scale climate simulations

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ABSTRACT

Use of General Circulation Model (GCM) precipitation and evapotranspiration sequences for hydrologic modelling can result in unrealistic simulations due to the coarse scales at which GCMs operate and the systematic biases they contain. The Bias Correction Spatial Disaggregation (BCSD) method is a popular statistical downscaling and bias correction method developed to address this issue. The advantage of BCSD is its ability to reduce biases in the distribution of precipitation totals at the GCM scale and then introduce more realistic variability at finer scales than simpler spatial interpolation schemes. Although BCSD corrects biases at the GCM scale before disaggregation; at finer spatial scales biases are re-introduced by the assumptions made in the spatial disaggregation process. Our study focuses on this limitation of BCSD and proposes a rank-based approach that aims to reduce the spatial disaggregation bias especially for both low and high precipitation extremes.

BCSD requires the specification of a multiplicative bias correction anomaly field that represents the ratio of the fine scale precipitation to the disaggregated precipitation. It is shown that there is significant temporal variation in the anomalies, which is masked when a mean anomaly field is used. This can be improved by modelling the anomalies in rank-space. Results from the application of the rank-BCSD procedure improve the match between the distributions of observed and downscaled precipitation at the fine scale compared to the original BCSD approach. Further improvements in the distribution are identified when a scaling correction to preserve mass in the disaggregation process is implemented. An assessment of the approach using a single GCM over Australia shows clear advantages especially in the simulation of particularly low and high downscaled precipitation amounts.

1. Introduction

Climate change is likely to have major impacts on human and natural ecosystems and in particular water resources systems. The current generation of General Circulation Models (GCMs) have reasonably coarse spatial resolutions that precludes their use in many impact assessments (Gutmann et al., 2014). For better planning and management of water resources, climate projections are required at spatial scales that are finer than the GCM resolution. To reduce the gap between policy relevant information and climate model data, downscaling is used to transfer large-scale GCMs output to regionally relevant scales (Christensen et al., 2008; Mejia et al., 2012). Downscaling aims to retain all the large-scale information provided by the climate model, and to add finer-scale information that climate model could not resolve (Kanamaru and Kanamitsu, 2007).

Because computational requirements prohibit the widespread use of dynamic downscaling, for long term simulations statistical downscaling approaches are very common (Fowler et al., 2007; Wilby et al., 1998; Wood et al., 2004). This is particularly the case when multiple GCMs and/or multiple greenhouse gas emission scenarios need to be considered (Ahmed et al., 2013; Maurer et al., 2013). The Bias Correction Spatial Disaggregation (BCSD) method (Wood et al., 2004) is a popular approach that has been used in a number of studies to assess the hydrological impacts of climate change (Christensen et al., 2008; Maurer and Hidalgo, 2008; Payne et al., 2004; Shrestha et al., 2014; VanRheenen et al., 2004; Vicuna et al., 2007).

BCSD uses a three step approach for the downscaling. Monthly GCM simulations are bias corrected at the GCM grid scale using Quantile Mapping (QM) (Ines and Hansen, 2006; Wood et al., 2002). The simulations are then spatially disaggregated to match

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the fine-scale resolution of the observation data. Finally the monthly data is temporally disaggregated to produce a daily time series. Due to the popularity of the BCSD approach, a number of modifications have been proposed suggesting the bias correction step followed by spatial disaggregation of raw GCM output (Abatzoglou and Brown, 2012; Ahmed et al., 2013). These have generally focused on improving the final daily time series. It was found that this provided better performance for both daily maximum and minimum temperatures as well as precipitation (Ahmed et al., 2013). Abatzoglou and Brown (2012) used a 15-day moving window to define the probability distribution for bias correction, leading to improvements in the resulting daily time series.

An aspect of BCSD that has received limited attention is whether the spatial disaggregation step interferes with the bias correction at the coarse scale. Ahmed et al. (2013) comment on the sensitivity of the downscaled results to the initial coarse spatial resolution at which the bias correction is applied. This sensitivity is demonstrated in Fig. 1 where the GCM and BCSD simulations are compared to observations at coarse and fine spatial scales. For a single grid cell, Fig. 1a demonstrates that before applying the quantile mapping the probability distributions of the GCM and observations are very different. This bias is completely removed (as expected) following the bias correction. Once the GCM is bias corrected, then the simulations are spatially disaggregated. This step ensures that the spatial variability at the fine scale is appropriate (Wood et al., 2004). However it is clear from Fig. 1b that the spatial disaggregation leads to biases in the simulations at the finer scale, even though at the GCM scale the precipitation simulations are unbiased. Simple solutions to address this issue are developed in this paper.

The BCSD method was originally developed for downscaling monthly precipitation and temperature with the temporal disaggregation step as described above to generate daily time series. In principle, daily GCM output could also be downscaled directly using the BCSD approach. The modified BCSD method by Abatzoglou and Brown (2012) has already been used for daily data to improve the downscaling skill in reproducing fine scale temporal statistics. However spatial variability of daily precipitation is much higher than for monthly data and the interpolation scheme is unlikely to be able to represent this variability (Hwang and Graham, 2013). Hence, this paper will focus on the BCSD applied to month data. Although it is not often the case that hydrologic simulations are made with monthly climate data, there are important implications of improving the monthly BCSD simulations for applications such as drought assessments where retaining the spatial and temporal characteristics of precipitation events is paramount.

This research thus examines the assumptions behind the BCSD method and highlights possible improvements to the approach. The approach adopted here is based on the BCSD algorithm detailed in Wood et al. (2004). Different versions of this algorithm have been reported in Wood et al. (2002) and (Maurer, 2007), which result in subtle differences in the downscaled field obtained. It should be noted that, although the original BCSD is applied for both temperature and precipitation, here the focus is on precipitation because the spatial variability of monthly precipitation data is much larger than for temperature data. Nevertheless, any improvement in the BCSD method could be used for temperature as well. The outline of the paper is as follows. Section 2 provides information about the observed and model data. In Section 3 details of the BCSD method are presented along with the proposed modifications to address the spatial disaggregation problems highlighted above. Results are provided in Section 4, with a discussion and conclusions in Section 5.

2. Data

Fine scale gridded monthly observed precipitation data were used to correct the precipitation simulations from a single GCM from the Coupled Model Inter-comparison Project 5 (CMIP5), namely CSIRO-MK3.6 model. Twenty years (1980–1999) precipitation from current climate was used for the analyses as per Wood et al. (2004). A single GCM is appropriate for use here because the bias correction step will ensure a perfect match in the distributions between the GCM and observed data at the GCM scale, allowing the focus to be on the spatial disaggregation step, rather than addressing uncertainties of climate model simulations.

The observed precipitation data is provided by the Australian Bureau of Meteorology and the monthly product has a spatial resolution of 0.25°. This gridded dataset is produced using an optimised Barnes successive correction technique that applies a weighted averaging process to the station data (Jones et al., 2009).

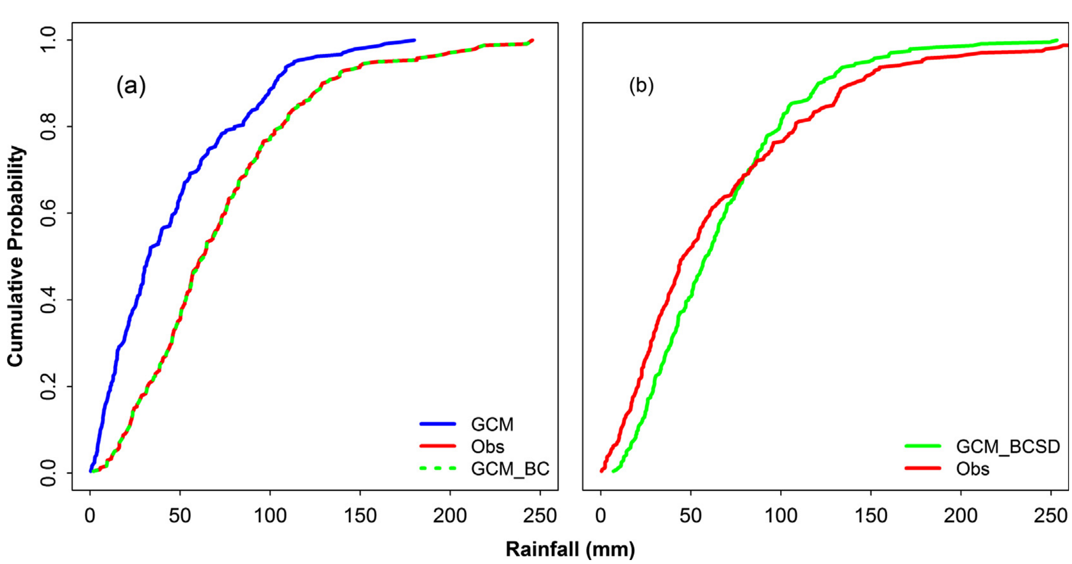

Fig. 1. CDFs of monthly precipitation from a single grid comparing the observations and GCM simulations at a) coarse and b) fine scale. At the coarse scale, QM matches the GCM simulations with the observations. At the fine scale the BCSD simulations do not match the observations.