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Ensemble forecasts of monthly catchment rainfall out to long lead times by post-processing coupled general circulation model output

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SUMMARY

Monthly streamflow forecasts with long lead time are being sought by water managers in Australia. In this study, we take a first step towards a monthly streamflow modelling approach by harnessing a coupled ocean–atmosphere general circulation model (CGCM) to produce monthly rainfall forecasts for three catchments across Australia. Bayesian methodologies are employed to produce forecasts based on CGCM raw rainfall forecasts and also CGCM sea surface temperature forecasts. The Schaake Shuffle is used to connect forecast ensemble members of individual months to form ensemble monthly time series forecasts. Monthly forecasts and three-monthly forecasts of rainfall are assessed for lead times of 0–6 months, based on leave-one-year-out cross-validation for 1980–2010. The approach is shown to produce well-calibrated ensemble forecasts that source skill from both the atmospheric and ocean modules of the CGCM. Although skill is generally low, moderate skill scores are observed in some catchments for lead times of up to 6 months. In months and catchments where there is limited skill, the forecasts revert to climatology. Thus the forecasts developed can be considered suitable for continuously forecasting time series of streamflow to long lead times, when coupled with a suitable monthly hydrological model.

1. Introduction

Water management agencies require good quality forecasts of streamflow to inform a wide range of water management activities including dam operations, water trading, environmental releases and planning for the future. For many applications, forecasts are required at intra-seasonal and seasonal time scales with lead times of up to one year. Intra- or inter-seasonal streamflow forecasts can be produced using either statistical or dynamical modelling approaches. Statistical approaches forecast streamflow directly, whereas dynamical approaches force a hydrological model with forecast rainfall. Corresponding to the shift to dynamical models within the climate forecasting community, many hydrological forecasting agencies are now operating or experimenting with dynamical models for streamflow forecasting. For example, Tuteja et al. (2011) experimented with dynamical monthly and three-monthly streamflow forecasting in Australia at zero lead time.

A key problem for dynamical streamflow forecasters, across all time scales from hours to weeks to seasons, is sourcing quality and timely rainfall forecasts. For the short time scales, hours to days, hourly or three-hourly rainfall forecasts are available from numerical weather prediction (NWP) models that closely simulate weather patterns by numerically solving physical equations. NWP forecasts are usually run on a high resolution grid (e.g. 12 km) and may resolve topography and other localised rainfall effects sufficiently well for the rainfall to be used directly, or after moderate calibration, in hydrological models. For the longer time scales, weeks to months to seasons, regular daily rainfall forecasts are increasingly becoming available from coupled general circulation models (CGCMs) (Graham et al., 2005; Saha et al., 2006; Wang et al., 2011; Yasuda et al., 2007). CGCMs can be regarded as weather forecasting models that are run on relatively coarse grids (e.g. 250 km). They are intended for forecasting seasonal climate shifts, even though the models are run on a daily time step. Beyond about 10 days of simulations, the sequence of individual weather events is not necessarily realistic, due to the chaotic nature of the ocean–atmosphere system. Rather, useful information can be derived about the climate of the system by analysing the forecasts at large temporal (and spatial) scales. Because of the chaotic nature of the modelled system, CGCMs for seasonal forecasts are nowadays mostly run in ensemble mode, with perturbed initial conditions leading to a range of possible outcomes that are represented by ensemble members.

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The inherent simplifications, coarse grid structures, and ensemble nature of CGCMs give rise to a number of problems that must be addressed before CGCM rainfall can be used to force a hydrological model. Firstly, CGCMs may have difficulty resolving local rainfall patterns, possibly leading to forecasts that correctly simulate local rainfall variability but suffer from biases, or, in some cases, forecast rainfall patterns that bear little resemblance to observed rainfall patterns. Secondly, a CGCM's ensemble generation technique may not produce ensembles that properly characterise forecast uncertainty, manifested by ensembles that are, on aggregate, found to be under- or over-dispersed (e.g. Lim et al., 2011). One way to tackle these problems is to statistically post-process CGCM output (Feddersen et al., 1999).

Taking on this approach, we consider that CGCM rainfall is usually made available on daily and monthly time scales. This raises the question: is it better to post-process daily or monthly rainfall? In Australia, an analogue downscaling method (Shao and Li, 2012; Timbal and Jones, 2008) exists to produce catchment-scale post-processed daily rainfall from a CGCM. However, there are a number of reasons in favour of post-processing monthly rainfall directly. Monthly aggregates should contain greater low frequency climate signals, relative to high frequency weather noise, to be more readily captured for seasonal forecasting. Monthly rainfall is also much simpler to model as a stochastic process, and its processing can therefore be focused on fewer statistics.

Monthly rainfall forecasts can be directly used as input to a monthly catchment water balance model for forecasting monthly streamflow. A recent study by Wang et al. (in preparation) found that the monthly **wa**ter **pa**rtition and **ba**lance model (WAPABA) performed comparably to two of the daily hydrological models most widely used in Australia at simulating monthly streamflow volumes. For intra- to inter-seasonal forecasting of streamflows, it may therefore be sufficient to model at the monthly time step. There are benefits of modelling at the monthly time step; for example, there will be a significant reduction in computing time required, freeing up resources for forecasting to longer lead times with large ensembles and for forecasting at more locations.

In a recent study by Hawthorne et al. (2013), a Bayesian approach was used to post-process monthly CGCM rainfall totals across Australia on the original CGCM grid. The focus of our study here is to extend the approach of Hawthorne et al. (2013), to produce catchment-scale post-processed rainfall forecasts, out to long lead times, which are suitable for input to a monthly hydrological model like WAPABA. We define long lead times as beyond the first three months. The Bayesian approach to post-processing is a conjugation of Bayesian joint probability (BJP) modelling (Wang and Robertson, 2011; Wang et al., 2009) and Bayesian model averaging (BMA) (Hoeting et al., 1999; Raftery et al., 2005; Wang et al., 2012b). BJP models relate predictors, drawn from the raw hindcast datasets of CGMs, to observed rainfall in a probabilistic framework. When the predictor is raw CGCM rainfall, the model is referred to as a calibration model. When the predictor is some other variable, the model is referred to as a bridging model. For example, bridging models may use CGCM forecasts of climate indices based on sea surface temperature as predictors. For some regions, bridging models may have better predictive skill than direct calibration models. Hawthorne et al. (2013) showed that the quality of post-processed monthly CGCM rainfall could be improved by including both calibration and bridging models in the post-processing.

The BJP-BMA approach post-processes forecasts for lead times (and different regions) independently, and the observed temporal (and spatial) correlation structures of the variables are not modelled. If we are to generate, for example, nine months of rainfall forecasts, we expect that corresponding ensemble members will exhibit stable behaviour across lead times. A pragmatic procedure to link the ensemble members is the Schaake Shuffle (Clark et al., 2004). The Schaake Shuffle reorders the ensemble members according to the distribution of historical observed data. After applying the Schaake Shuffle, the temporal correlations in forecast ensembles are implicitly introduced, and individual rainfall ensemble members will be suitable for use in a monthly hydrological model to forecast streamflow to long lead times. The Schaake Shuffle also prepares the ensembles for aggregation to, for example, three-monthly forecasts.

In this study, we produce and assess post-processed forecasts of monthly rainfall, at lead times of 0–6 months, for three catchments of different sizes and in different climatic zones in eastern Australia. Raw simulations of monthly rainfall totals and other variables are obtained from a CGCM known as POAMA (the Predictive Ocean Atmosphere Model for Australia). The Australian Bureau of Meteorology's official seasonal climate outlooks are now produced using a version of this dynamical climate model. Forecast quality is assessed through leave-one-year-out cross-validation for the period 1980–2010. The remainder of the paper is organised as follows. Section 2 provides an overview of Bayesian joint probability modelling, Bayesian model averaging, ensemble sequencing (Schaake Shuffle) and verification methods. Section 3 describes the study catchments as well as the POAMA and observed rainfall datasets. Section 4 presents the results with discussion and Section 5 wraps up the paper with a summary and the main conclusions.

2. Methods

2.1. Overview

There are three main methods applied in sequence in our post-processing approach: (i) Bayesian joint probability modelling (Wang and Robertson, 2011; Wang et al., 2009) for producing calibration and bridging forecasts, (ii) Bayesian model averaging (Hoeting et al., 1999; Raftery et al., 2005; Wang et al., 2012b) for merging the calibration and bridging forecasts, and (iii) the Schaake Shuffle (Clark et al., 2004) for sequencing ensemble members of forecasts for individual months to form ensemble monthly time series. Since we do not significantly modify the listed methods, only the salient features of each method will be described in this section.

2.2. Bayesian joint probability models

The first step in our post-processing approach is to establish multiple statistical models that relate predictor variables, derived from CGCM output fields, to observed catchment rainfall. To do this, we apply a Bayesian joint probability (BJP) modelling approach. We denote a predictor variable as x and a predictand variable as y. The relationship between each x and y is modelled as a transformed bivariate normal distribution. In the context of this study y is always a rainfall variable (catchment average rainfall). If x is also a rainfall variable (i.e. CGCM forecast rainfall), we refer to the model as a calibration model. If x is some other variable (e.g. an index of CGCM sea surface temperature anomalies), we refer to the model as a bridging model. This distinction is merely for convenience, as will become apparent in subsequent sections.

Transformations of the variables may be necessary to satisfy the modelling assumptions of normality and homoscedasticity. In the construction of each model, transformations are applied to each variable independently, and it is assumed that the model follows a bivariate normal distribution in the transformed space.

$$p(\hat{x}, \hat{y}) \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \tag{1}$$

where