



Research papers

Ensemble forecasting of sub-seasonal to seasonal streamflow by a Bayesian joint probability modelling approach



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ABSTRACT

The Bayesian joint probability (BJP) modelling approach is used operationally to produce seasonal (three-month-total) ensemble streamflow forecasts in Australia. However, water resource managers are calling for more informative sub-seasonal forecasts. Taking advantage of BJP's capability of handling multiple predictands, ensemble forecasting of sub-seasonal to seasonal streamflows is investigated for 23 catchments around Australia. Using antecedent streamflow and climate indices as predictors, monthly forecasts are developed for the three-month period ahead. Forecast reliability and skill are evaluated for the period 1982–2011 using a rigorous leave-five-years-out cross validation strategy. BJP ensemble forecasts of monthly streamflow volumes are generally reliable in ensemble spread. Forecast skill, relative to climatology, is positive in 74% of cases in the first month, decreasing to 57% and 46% respectively for streamflow forecasts for the final two months of the season. As forecast skill diminishes with increasing lead time, the monthly forecasts approach climatology. Seasonal forecasts accumulated from monthly forecasts are found to be similarly skilful to forecasts from BJP models based on seasonal totals directly. The BJP modelling approach is demonstrated to be a viable option for producing ensemble time-series sub-seasonal to seasonal streamflow forecasts.

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1. Introduction

Informative forecasts can help water management agencies make better decisions and improve water availability outcomes (Chiew et al., 2003; Alemu et al., 2011; Liu et al., 2015). Forecasts at different timescales enable resource management decisions across multiple time horizons (Labadie, 2004). Seasonal streamflow forecasts benefit a range of water resource management activities including drought mitigation (Steinemann, 2006), flood preparation (Ding et al., 2015; Pappenberger et al., 2015) and reservoir operation (Georgakakos et al., 2012). However, many forecast users are also interested in sub-seasonal (e.g., monthly) streamflow volumes (Hamlet et al., 2002; Zhao et al., 2012), because sub-seasonal forecasts can help water managers achieve more efficient short-term decision-making compared to using seasonal forecasts alone (Alemu et al., 2011; Zhao and Zhao, 2014a, 2014b).

Reliable quantification of forecast uncertainty is important for water resource management (Cloke and Pappenberger, 2009; Wang et al., 2009; Shrestha et al., 2015). Over-estimation of

uncertainty may lead to overly conservative decisions, while under-estimation is operationally hazardous (Zhao et al., 2013, 2014). Therefore, it is critical that operational streamflow forecast systems provide reliable forecast uncertainty information by deploying proper ensemble forecasting techniques (Alemu et al., 2011; Georgakakos et al., 2012; Zhao et al., 2015).

In Australia, the Bureau of Meteorology (the Bureau) operates a national, publically-available service that produces seasonal (three-month-total) streamflow forecasts for over 200 gauging stations, in addition to total inflows to reservoirs. The Bureau's forecasts are generated using a Bayesian joint probability (BJP) modelling approach (Wang et al., 2009; Wang and Robertson, 2011), which produces ensemble forecasts. The BJP modelling approach employs multivariate statistical techniques and can handle heteroscedastic data, missing data, non-concurrent data and data with many occurrences of zero flows. It is therefore highly applicable to both perennial and ephemeral rivers (Wang and Robertson, 2011). The BJP modelling approach captures relationships between initial catchment condition predictors, e.g. antecedent streamflow; climate predictors, e.g. climate indices; and future streamflows (Wang et al., 2009, 2012a; Wang and Robertson, 2011; Robertson et al., 2013a, b; Robertson and Wang, 2013; Schepen and Wang, 2014, 2015; Bennett et al., 2014a,b, 2016).

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Forecasts issued on sub-seasonal time scales would better meet the needs of forecasts users and enable better decisions for short-term water use. Although not tested before, the BJP modelling approach can be highly suitable for producing sub-seasonal forecasts. Owing to its multivariate formulation, the BJP modelling approach can theoretically be applied to produce time-series ensemble forecasts of sub-seasonal streamflow by forecasting multiple time periods ahead simultaneously. In this study, we invoke the BJP modelling approach to produce *monthly* sub-seasonal to seasonal forecasts.

We focus on the following three research questions:

- (1) How skilful are monthly sub-seasonal forecasts? To answer this question, month 1, 2 and 3 ahead ensemble forecasts are compared amongst themselves and to climatology reference forecasts.
- (2) Do the monthly sub-seasonal forecasts reliably represent forecast uncertainty? To answer this question, the statistical consistency of ensemble forecasts and observations is analysed.
- (3) Are seasonal forecasts accumulated from monthly forecasts skilful and reliable? To answer this question, the forecast skill and reliability of accumulated seasonal forecasts are analysed and the skill is further compared to the skill of forecasts from BJP models based on seasonal totals directly.

The remainder of the paper is structured as follows. Section 2 introduces the study catchments and hydro-climatic datasets. Section 3 presents an overview of the BJP modelling approach, including data transformation, joint distribution and parameter estimation, and illustrates forecast verification methods. Section 4 evaluates the sub-seasonal to seasonal forecasts, with a focus on forecast reliability and skill. Sections 5 and 6 contain discussions and conclusions, respectively.

2. Catchments and data

This study investigates BJP-based sub-seasonal to seasonal streamflow forecasting for twenty-three catchments around Australia. All of the catchments are current forecasting catchments

in the Bureau's seasonal streamflow forecasting service (<http://www.bom.gov.au/water/ssf/index.shtml>).

2.1. Catchments

The names and areas of these catchments are provided in Table 1. Fig. 1 presents a map of the catchments in the context of climate zones (Peel et al., 2007). The catchments are ordered by latitude from north to south. There are five catchments in northern Australia. Catchments 1 and 2 are in a tropical climate; catchments 3 and 4 are in a sub-tropical climate; and catchment 5 is in a grassland climate. Catchments 6–23 are in a temperate climate. The different climate zones pose varied challenges for sub-seasonal to seasonal streamflow forecasting.

2.2. Streamflow and climate data

Streamflow and sea surface temperature (SST) datasets for the period 1982–2011 are used in this study. They are sourced as follows:

- (1) Streamflow data is provided by the Bureau of Meteorology (<http://www.bom.gov.au/waterdata/>). Monthly flow volume is calculated from daily streamflow. The Bureau provides quality-controlled and partially infilled data; however, some missing values remain. If there is any remaining missing daily data in a given month, the monthly value is treated as missing.
- (2) SST data is downloaded from the National Oceanic and Atmospheric Administration website (<http://www1.ncdc.noaa.gov/pub/data/cmb/ersst/v4/netcdf/>). Subsequently, monthly climate indices, including El Niño Southern Oscillation (ENSO) indices and Indian Ocean Dipole indices are calculated from the SST grids (Risbey et al., 2009; Schepen et al., 2012).

Streamflow seasonality and variability are illustrated using the monthly streamflow data. As is shown in Fig. 2a, flows in the five northern Australian catchments are highest in the austral summer–autumn months (December to April). This pattern

Table 1
Characteristics of 23 case study catchments.

ID	Name	Area (km ²)	Climate
1	Green Ant Creek at Tipperary	416	Tropical
2	Coen River above Coen Racecourse	170	Tropical
3	Barron River above Picnic Crossing	239	Sub-tropical
4	Herbert River above Abergowie	7486	Sub-tropical
5	Burdekin River above Sellheim	36,230	Grassland
6	Stanley River above Peachester	102	Temperate
7	Richmond River above Wiangaree	712	Temperate
8	Wollomombi River above Coninside	377	Temperate
9	Namoi River above North Cuerindi	2532	Temperate
10	Nowendoc River above Rocks Crossing	1893	Temperate
11	Helena River at Ngangaguringuring	316	Temperate
12	Harvey River above Dingo Road	148	Temperate
13	Abercrombie River above Hadley No. 2	1631	Temperate
14	North Para River at Penrice	121	Temperate
15	Goodradigbee River above Wee Jasper (Kashmir)	990	Temperate
16	Goobarragandra River above Lacmalac	668	Temperate
17	Cotter River above Gingera	130	Temperate
18	Murray River above Biggara	1257	Temperate
19	Mitta Mitta River above Hinnomunjie	1518	Temperate
20	Goulburn River above Dohertys	700	Temperate
21	Tambo River above Swifts Creek	899	Temperate
22	Black River at South Forest	319	Temperate
23	Davey River above D/S Crossing Rv	698	Temperate

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