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A seasonal water availability prediction service: opportunities and challenges

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The purpose of this paper is to outline a proposed seasonal water availability prediction service and, in particular, to describe the modelling components behind the service and their future development.

In terms of its climate, Australia has experienced a remarkable decade. The continent has had its warmest period since records began and southern areas have been extremely dry. A seasonal water availability prediction service has been needed in Australia for many years and the Australian Government's recent investment in water information will help address this need. A seasonal climate prediction service has been operating in the Bureau of Meteorology since 1989 but its primary focus has been on rainfall and temperature rather than water availability. Reliable seasonal predictions of streamflows are highly valuable and will have uses for providing water allocation outlooks, informing water markets, planning and managing water use and managing drought.

The seasonal water availability prediction service will rely on the development and integration of a number of modelling systems. A statistical prediction system will be based on a Bayesian Joint Probability modelling approach and is expected to provide reliable predictions of 'seasonal' streamflow at lead times of up to several months. Skill (or accuracy) in these predictions will generally exceed those for both temperature and rainfall. In parallel, a 'dynamical' modelling approach will be developed whereby the outputs from climate models will be downscaled to provide the inputs to hydrological models of various degrees of complexity. The key climate models are the Centre for Australian Weather and Climate Research's (CAWCR) Predictive Ocean Atmosphere Model for Australia (POAMA) and, later, the Australian Community Climate and Earth-System Simulator (ACCESS). All prediction systems will be accompanied with verification systems that will provide information on the skill and reliability for both developers and users. In delivering on these responsibilities, the Bureau will rely on considerable research, particularly through CAWCR and the Water Information Research and Development Alliance (WIRADA) agreement between the Bureau of Meteorology and CSIRO.

The development of a seasonal water availability service must be user driven - it must ultimately lead to changes in decisions that result in improved outcomes in water resource management. Critical to the development of this service will be a modelling infrastructure that will gradually build in complexity. Investment in modelling efforts will, to a large degree, be driven by scientific and technological capability, cost-benefit considerations, and most importantly, the likely incremental benefits of improved predictions and outcomes for water managers.

Keywords: Seasonal water availability predictions, climate predictions, climate and hydrological modelling

1 INTRODUCTION AND PURPOSE

The purpose of this paper is to outline a proposed seasonal water availability prediction service and to describe the modelling components behind the service, including their future development.

In terms of its climate, Australia has experienced a remarkable decade. The continent has had its warmest period since records began and southern areas have been extremely dry (Bureau of Meteorology, 2008a). Rainfall in the southwest of the continent decreased by around 20% in the mid-1970s, compared to the average of measurements from earlier in that century (IOCI, 2002), and never returned. The Murray Darling Basin, located in Australia's inland southeast, generates 39% of the national income derived from agricultural production (Murray Darling Basin Authority, 2008). Catchment runoff in the southernmost parts of the MDB has been the lowest on record and this event would be expected to occur just once in more than 300 years without accounting for climate change (CSIRO, 2008).

While it is still premature to unequivocally link the recent changes in rainfall to global warming the evidence is building (Timbal et al., 2007). Furthermore, the rising temperatures which have exacerbated moisture loss are almost certainly a result of increasing concentrations of greenhouse gases (IPCC, 2007). Future changes are uncertain but surface water availability across the entire MDB is more likely to decline rather than increase (CSIRO, 2008). There have already been severe economic, social and environmental impacts (Drought Policy Review Expert Social Panel, 2008).

A seasonal climate prediction service has been operating in the Bureau of Meteorology since 1989 but has only provided outlooks for rainfall and temperature rather than water availability. Nevertheless, these monthly updated predictions have been highly sought in recent years by Ministers, industry and other government agencies concerned with the possibility of droughts continuing (e.g. Murray Darling Basin Authority, 2009). Reliable seasonal forecasts of streamflows are highly valuable (Chiew et al., 2003) and Wang (2008) lists the following as some of the priority uses: providing water allocation outlooks; informing water markets; planning and managing water use; and managing drought. Chiew et al. (2003) found that predictions were useful in providing indications of the likely increase in available water resources through an irrigation season, allowing irrigators to make informed risk-based management decisions.

The opportunity for the Bureau to expand its seasonal prediction service is a result of its new responsibilities, which largely came about because of the impacts of the prolonged drought. In early 2007 the Australian Government announced ‘Water for the Future’, a $12.9 billion water investment program. This included $450 million for the 'Improving Water Information Program' administered by the Bureau and backed by the Commonwealth Water Act 2007 and key stakeholders. In delivering on its new responsibilities, the Bureau will rely on considerable research, particularly through the Water Information Research and Development Alliance (WIRADA) agreement and the Centre for Australian Weather and Climate Research (CAWCR). The latter is a partnership between the CSIRO and the Bureau while the former is a $50M five-year research collaboration between the two organisations.

The needs of governments, water resource managers and water users will drive developments in an extended hydrological prediction service. Critical to the development of this service will be a modelling infrastructure that will gradually build in complexity. Investment in modelling efforts will, to a large degree, be driven by scientific and technological capability, cost-benefit considerations, and most importantly, the likely incremental benefits of improved predictions and outcomes for water managers.

Section 2 of the paper looks at the seasonal water availability predictions provided in Australia and overseas and Section 3 maps out the various components of an operational service. Those modelling components are given more detailed consideration in Section 4 and the Conclusions section summarises the key challenges for the future.

2 SEASONAL WATER AVAILABILITY PREDICTIONS IN AUSTRALIA AND INTERNATIONALLY

Seasonal climate predictions are now made routinely at a number of operational meteorological centres around the world, but those for seasonal water availability are mainly provided at regional or river basin scale in Australia or overseas.

Seasonal predictions of water availability can be made using dynamical, statistical or hybrid methods. The usual dynamical approach[1] for seasonal water availability prediction is to run dynamical climate models to produce predictions of rainfall and other weather variables, which are then fed into hydrological models to produce predictions of streamflows. The statistical approach is to use statistical relationships derived directly from observed data and derived (predictor) indices. Many climate indicators based on atmospheric pressure and sea surface temperatures (SST) have been linked to future seasonal rainfalls. Such relationships have

[1] The term ‘dynamical climate prediction’ is used in this paper to refer to the application of coupled ocean and atmosphere general circulation models for seasonal prediction purposes. The ‘dynamic hydrological modelling approach’ relies on the downscaled seasonal climate predictions, from the aforementioned models, being input to hydrological models, which can be of varying levels of complexity.

been exploited to predict streamflow several months or seasons ahead (e.g. Glantz et al., 1991; Hammer et al., 2000; Chiew et al., 2003).

In Australia, statistical prediction methods for water availability are more advanced in terms of their stage of development. The Queensland Department of Primary Industries and Fisheries developed the Rainman decision support system, which gives the probability of flow based on phases of both the Southern Oscillation Index (SOI) and SSTs. The predictions are considered skilful out to only one season due to the limited number of predictors (Clewett et al., 2003).

There are several operational and experimental services in operation overseas. The River Forecast Centre of the NOAA National Weather Service (USA), along with federal, state and local agencies, predicts natural or unimpaired runoff volumes (NWS, 2009). One of these agencies is the Natural Resources Conservation Service, which provides water supply forecasts for summer and spring (NRCS, 2009). In the University of Washington, the streamflow predictions were made using the Variable Infiltration Capacity hydrologic model, applied over western the U.S. The daily ensemble outputs of these simulations are summarised as monthly hydrograph distribution plots and as summer runoff period anomalies or seasonal volume forecasts (Wood and Lettenmaier, 2006). New Zealand's National Institute of Water & Atmospheric Research issues seasonal climate outlooks of temperature, rainfall, soil moisture and streamflows (NIWA, 2009).

The Japan Meteorological Agency studied seasonal predictions of water availability based on forcing an atmospheric General Circulation Model (GCM) by observed SSTs. Estimates of seasonal water resources were calculated as precipitation minus actual evaporation (P-E). Potential predictability of the variable P-E was greatest in the tropics, lowest in the extra-tropics and generally lower over land than sea. Seasonal predictions using this method were considered difficult (Nakaegawa et al., 2007).

3 REQUIREMENTS OF A SEASONAL WATER AVAILABILITY SERVICE

A seasonal water availability service will have several components and, most importantly, will need to satisfy its user stakeholders. As Hammer (2000) describes, "An effective application of a seasonal climate forecast is defined as use of forecast information leading to a change in a decision that generates improved outcomes in the system of interest". Producing skilful predictions is a necessary but insufficient requirement to satisfy customers. In short, prediction services need to be developed collaboratively with the users and need to satisfy their decision-making needs. Predictions of streamflow will be a priority and catchment wetness and water demand are also likely to be highly sought. The communication and adoption strategy will have a user needs analysis at its core and, as a priority, will need to consider both the timing and duration period of predictions that best align with water managers' key decisions. Attention will be required as to when and how users receive the predictions and how probabilistic information is communicated.

New science and technologies will underpin this service. Outputs from the Bureau's dynamic climate model have not been used for operational streamflow predictions. An operational downscaling technique for seasonal prediction system will be developed as part of this work. The verification systems proposed do not currently exist. Finally, much new research is required on dynamic hydrological modelling.

The initial prediction system will be based on statistical methodologies (Section 4.3) and will rely on access to good quality historical and real-time climate and hydrological data, especially streamflow. While the Bureau's National Climate Centre has managed the national climate record for decades, the Bureau has only recently begun the development of an Australian Water Resources Information System (AWRIS) to house its hydrological and related geospatial data. AWRIS will provide the backbone for water data management and water information services delivery.

The statistical prediction system will be based on the Bayesian Joint Probability Modelling approach of Wang et al. (2009a) and is expected to provide reliable predictions of 'seasonal' streamflow at lead times up to several months. In parallel, a dynamical modelling approach will be developed whereby the outputs from CAWCR's Predictive Ocean Atmosphere Model for Australia (POAMA, Section 4.2) and, later, the Australian Community Climate and Earth-System Simulator (ACCESS, Section 4.1) prediction models are downscaled (Section 4.4) to provide the inputs to hydrological models of various degrees of complexity (Section 4.5). All predictions will be accompanied with verification systems (Section 4.6) that will provide information on the skill and reliability for both developers and users.

Modelling technologies and frameworks will need to be evaluated and be either adopted, adapted or – as a last resort - invented in transitioning from research into robust operational systems. AWRIS will again be a key consideration here. Prediction products will be developed in close collaboration with users and within the context of a communication and adoption strategy.

Other service considerations include integrating these predictions with both shorter-term streamflow predictions and the traditional seasonal climate predictions and also the extent to which predictions are delivered centrally or through the Bureau's seven regional offices.

4 MODELLING SYSTEMS, CHALLENGES AND FUTURE DEVELOPMENTS

4.1 The Australian Community Climate and Earth-System Simulator and CABLE

ACCESS is a coupled climate and earth system simulator to be developed as a joint initiative of the Bureau of Meteorology and CSIRO in cooperation with the university community in Australia. The main objectives are to:

- Develop a national approach to climate and weather prediction model development;
- Focus on the needs of a wide range of stakeholders and:
  - provide the best possible services;
  - analyse climate impacts and adaptation;
  - make linkages with relevant University research; and
  - meet policy needs in natural resource management.

The design of ACCESS satisfies the so-called 'seamless prediction' modelling approach whereby a unified system is used for prediction at all space and time-scales. Two early recommendations signaled a significant change in the modelling activities at the Bureau and CSIRO. These were that:

- ACCESS should import the Met Office (UK) atmospheric model HadGAM1 to provide the initial atmospheric model for ACCESS; and
- The Met Office 4DVAR scheme should be imported for the atmospheric data assimilation module in ACCESS.

The Met Office model (Unified Model, UM) and the associated data assimilation system, together with components developed at the Bureau and CSIRO, offer considerable advantages for applications to weather and climate prediction . It was recommended that locally developed systems be used for the ocean, i.e. AusCOM, which is based on the Geophysics Fluid Dynamics Laboratory (USA) MOM-4 model and also the CSIRO Atmosphere Biosphere Land Exchange model (CABLE, Kowalczyk et al., 2007) for the land-surface/carbon cycle model.

Significant progress has been made in implementing ACCESS and a number of applications have been successfully developed. These include the completion of a number of climate model intercomparison runs and the successful coupling of CABLE to the UM. Priority has been given to ensuring that ACCESS can replace CAWCR's existing numerical weather prediction models. It is also recognised that ACCESS will be used by a wide group of researchers spread around Australia and the infrastructure will need to be extended in order to meet this requirement.

ACCESS can provide the atmospheric forcing fields (including ensembles[2]) which, after necessary downscaling, could be used to drive a hydrological model. Such a combined system has considerable potential to provide the much needed water availability prediction system for Australia. The transition of the Bureau's dynamical climate prediction model (POAMA) to ACCESS is discussed in 4.2 as well as its implications for hydrological modelling.

4.2 Dynamical seasonal climate and water prediction

POAMA is an intra-seasonal to inter-annual climate prediction system based on coupled ocean and atmosphere general circulation models (Alves et al., 2003). The first version (POAMA-1) was developed

[2] In the context of extended prediction, an ensemble is a collection of different runs of the global climate model with each run tweaked by slightly different initial conditions. The ensemble can be used to infer probabilities of particular events occurring.

jointly between the Bureau, the former division of CSIRO Marine Research and the Managing Climate Variability (MCV) program and became operational in October 2002. The main focus for POAMA-1 was the prediction of SST anomalies associated with the El Niño/Southern Oscillation. A newer version POAMA1.5 was implemented in the Bureau in June 2007, with real-time predictions produced soon after. POAMA-1.5 uses the same coupled model as in POAMA-1 (with some enhancements) and contains a new atmospheric/land initialisation system, developed as part of the SEACI (South Eastern Australian Climate Initiative) project. POAMA-1 and 1.5 are both T47 spectral resolution which is approximately 2.5° x 2.5° or 270km x 270km[3]. The ability of POAMA 1.5 to predict large scale drivers of Australian climate and Australian rainfall (directly) has been analysed in several studies, mostly as part of the SEACI project (Hudson et al., 2009, Lim et al., 2009). Figure 1 illustrates that there is hope for improvements on the Bureau's existing operational prediction system. POAMA-1.5 has been shown to have reasonable skill in large scale regional climate variables (e.g. rainfall), although the predictions of rainfall tend to be too emphatic, i.e. more confident than reality, suggesting that the ensemble spread is not large enough.

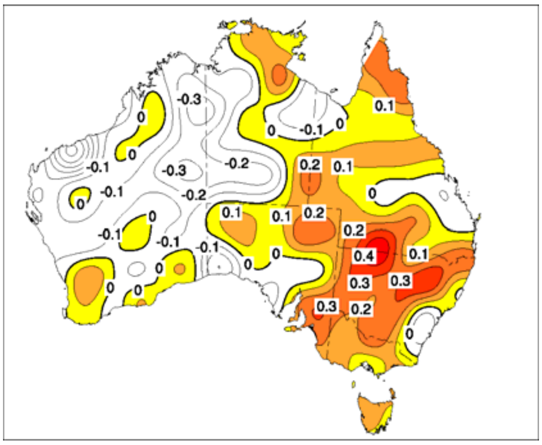

Figure 1. The fractional improvement of Brier skill score (Wilks, 2006) for above median rainfall of POAMA-1.5 rainfall prediction relative to just using climatology. Rainfall skill is for SON based on forecasts starting at the beginning of September, i.e. first season forecasts.

POAMA continues to be developed, as part of the ACCESS project (Section 4.1). One recent significant upgrade is the POAMA Ensemble Ocean Data Assimilation System (PEODAS), which uses the new ACCESS multi-variate ensemble optimum interpolation technique for the assimilation of ocean observations. This major upgrade, in which POAMA predictions are initialised from the new PEODAS assimilation technique, comprises the basis for POAMA-2.0. Wang et al. (2009b) have summarised results from the first major run of POAMA-2.0 and assessed skill including for SST, rainfall and surface temperature based on 5-member ensemble hindcasts[4] over a 22 year period. POAMA-2.0 shares the same configuration as POAMA-1.5, except for ocean initialisation being from PEODAS.

One crucial factor affecting seasonal prediction is model resolution. Although SST skill from previous versions has been skilful, the rainfall prediction over Australia has been less successful. In addition these early versions have large model SST biases, which not only distorts climate variability simulation in the tropics, but also adversely impacts regional climate predictions by altering the teleconnections between tropical SST and regional climate variability, such as in the case for Australian rainfall. A new version, the POAMA-2.1 system has been set-up and uses higher atmospheric model resolution T63 or 200km. This system also includes improved atmospheric physics that leads to smaller systematic biases, an explicit SST bias correction scheme to further reduce systematic biases and an improved version of PEODAS. Hindcasts from this new system are currently being performed. It is expected that these improvements will lead to increased regional skill and POAMA-2.1 will replace POAMA-1.5 as the next operational seasonal

[3] Spatial resolutions for spectral atmospheric GCMs, such as in POAMA, are different from finite grid models. The truncation type is denoted 'T' for triangular here. In simple terms, the truncation number represents the number of waves which are resolved around a latitude zone.
[4] Hindcasts are retrospective forecasts using observed information and are usually applied for model validation

prediction system at the Bureau. One particular feature of POAMA-2.1 and its operational implementation is that it better suits the generation of predictions on weekly time-scales. A study to evaluate skill on these shorter timescales is underway, in part funded by Land and Water Australia.

POAMA-2.1 includes some of the ACCESS modules, in particular those associated with initialisation. POAMA-3 will have all its modules developed as part of the ACCESS project in the next few years and will include the new ACCESS coupled model (Met Office UM atmospheric model, AusCOM ocean model and CABLE land surface model). A new feature of POAMA-3 will be an extension of the PEODAS assimilation system to fully coupled assimilation where the ocean, atmosphere and land will be initialised simultaneously. POAMA-3 will deliver a system to Bureau operations on a time scale of 3 to 5 years.

Issues relevant to water availability prediction range from interfacing the dynamical predictions to improvements of the dynamical model physics. How to best interface these predictions to water availability applications is a key issue and different ways of interfacing the POAMA predictions needs to be explored, e.g. different downscaling approaches (Section 4.4). Another issue is to what extent future POAMA versions based on ACCESS explicitly model the hydrological components, as opposed to interfacing the POAMA predictions to a hydrological model. The approach adopted will at least partly depend on the extent to which enhanced representation of hydrology in the land surface model impacts the prediction of the climate variables, i.e. if there is a feedback. In the foreseeable future, it is likely to be more beneficial in running a more sophisticated and higher resolution hydrological model *a postiori*. Fundamentally, much improved regional prediction skill will come through improvements to basic coupled model physics and initialisation procedures, in particular the representation of the large scale climate drivers[5] and their regional impact.

4.3 Statistical seasonal climate and water prediction

Statistical prediction approaches use historical data to derive relationships between a set of predictands and their predictors. Predictions for future events then use knowledge of the predictor variables to produce estimates of the predictands. For seasonal water prediction, the predictands typically include future inflows into streams, catchment wetness and measures of water demand, while predictors typically include indicators of initial catchment conditions, such as antecedent streamflow or soil moisture, and of ‘current’ or oncoming climate, such as large scale climate indices or climate model predictions.

Underpinning all statistical prediction systems is a database of historical observations of predictors and predictands. To derive reliable statistical relationships, concurrent observations of predictors and predictands are required and the records need to be sufficiently long to include a wide range of conditions. There are several features of hydrological and climate data that present challenges to the derivation of statistical relationships. Streamflow data have long historical records in many cases, but missing observations are common, which reduces the extent of concurrent records. Climate data relevant to seasonal streamflow predictions are not direct observations but derived or modelled indices. These indices have short historical records due to limitations imposed by the number of reliable direct observations or model hindcasts undertaken. Statistical prediction systems therefore need to make best use of all data that are available.

In statistical prediction systems, explicit assumptions are made about the mathematical representation of the relationships between the predictors and predictands and about which predictors are included in the model. Many mathematical representations have been used for seasonal prediction of streamflows and climate throughout the world, including stratified re-sampling, linear regression (Garen, 1992), linear discriminant analysis (Drosdowsky and Chambers, 2001; Piechota et al., 2001), non-parametric fitting (Chiew and Siriwardena, 2005; Sharma, 2000), independent component analysis (Westra et al., 2008) and joint probability modelling (Wang et al., 2009a).

In addition to the mathematical representation of the prediction system, assumptions need to be made about which predictors are included in the prediction system. The selection of predictors is a challenging problem. Ideally only those predictors that have a clear causal relationship with the predictands are to be included. However, statistical methods only assess the strength of correlations rather than causation and therefore judgements about causality are required in addition to statistical tests. Relying solely on statistical tests may

[5] In terms of seasonal predictions, the large scale drivers over Australia are the El Niño Southern Oscilliation, Indian Ocean Dipole, Southern Annual Mode, atmospheric blocking and the Madden Julien Oscillation. An enhanced greenhouse effect is also very likely having an increasing influence.

increase the skill of predictions artificially leading to a prediction system that has poor skill operationally. Predictor selection methods also require assumptions to be made about what constitutes good model performance. While the most appropriate predictors of seasonal rainfall and temperatures have been investigated (Drosdowsky and Chambers, 2001), no systematic investigation of the range of potential predictors has been undertaken for seasonal streamflows in Australia.

To form a model from the assumed mathematical representation and data requires model parameters to be inferred. A range of inferences are available, however many are limited in their ability to handle missing and non-concurrent data and consider the uncertainty of the parameters inferred. Model evaluation assesses the quality of the predictions produced by the system (Section 4.6).

Recently the Bayesian Joint Probability (BJP) modelling approach to streamflow prediction at multiple sites was developed (Wang et al., 2009a). This approach assumes that a set of predictors and predictands is described by a Box-Cox transformed multivariate normal distribution. Bayesian inference of model parameters and uncertainties is implemented using Markov chain Monte Carlo sampling. Continuous probabilistic predictions of future streamflows are produced. This approach overcomes many of the limitations of previous statistical prediction techniques. The Box-Cox transformed multivariate normal distribution has considerable flexibility for modelling a wide range of predictors and predictands. Predictions can be made jointly for multiple sites that ensure inter-site correlations are preserved. The Bayesian inference formulated allows the use of data that contains non-concurrent and missing records. The model flexibility and data handling capability mean that the BJP modelling approach is potentially of wide practical application.

An initial evaluation of the performance of the BJP modelling approach for predicting the 'next' three month streamflows has been undertaken. Procedures for predictor selection are being developed. Preliminary results show a strong seasonal pattern in the predictive skill, most of which arises from knowledge of the antecedent catchment conditions (Figure 2). Given that 'Linear error in probability space (LEPS) scores' of greater than 10% can be considered as indicating useful skill, the results are encouraging. Most of the skill derives from the antecedent conditions but climate predictors can increase the skill of predictions substantially, particularly at times when the skill produced using only antecedent flow predictors is low. This work is being extended to more catchments to examine spatial patterns in selected predictors.

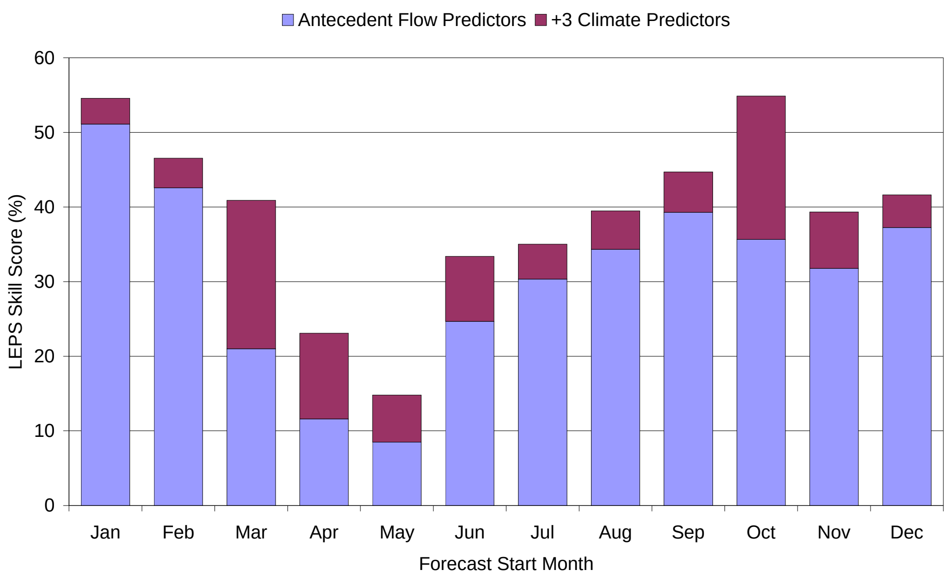

Figure 2. LEPS skill scores for three month streamflow forecasts at station 410057 in the Murrumbidgee catchment.

4.4 Downscaling

Typical coupled global climate models used for dynamical seasonal predictions have resolutions of 100 to 300 km. However, most hydrological models require finer resolutions (of the order of 1 to 5 km) to capture the complex topography of river catchments. Although regional climate models can be nested into the dynamical systems to increase the resolution, they are usually run at coarser resolution than that needed for hydrological application and could prove costly in computing time if pushed to higher resolution and/or run nested within a large ensemble of predictions. The other commonly used alternative for obtaining downscaled information is to develop Statistical Downscaling Models (SDMs).

SDMs are based on the premise that the regional climate is conditioned by two factors: the large-scale climatic state and local physiographic features. From this perspective, regional or local climate information is derived by first determining a statistical model which relates large-scale climate variables (or predictors) to regional and local variables (or predictands). Once this relationship is established, the large-scale output of dynamical prediction systems (e.g. POAMA) can be fed into the statistical model to estimate the corresponding local and regional climate characteristics. There have been numerous applications of SDMs but mostly for climate change impact studies. An extensive comparison of the performance of several of these techniques under Australian conditions has recently been performed (Frost et al., 2009).

Within the framework of a national seasonal hydrological prediction system, while the precise benefits of statistical downscaling prediction remain unproven, a simple technique is best investigated first. The simplest of all forms of downscaling is a simple scaling of the GCM outputs to the local climate. Arguably, since it does not involve synoptic information, this technique does not strictly follow the definition of statistical downscaling. However, it is a simple way to provide local information from climate models, Australia wide. It is also applicable to rainfall as well as other variables for which good observational records exist, and hence could prove a valuable way to provide relevant information for hydrological modelling. Advanced SDMs require a lengthy optimisation and evaluation phase and this will prove challenging in providing national information; the portability and the ease to which the technique can be applied are also important.

One of the simplest forms of SDM is based on the idea of meteorological analogues. Such a method has been developed by the Bureau (Timbal and McAvaney, 2001) and has been extended to a range of variables: rainfall, daily extreme temperature, dew-point temperature and pan evaporation across most of the extra-tropical regions of Australia (Timbal et al., 2008). The technique has been applied nationally for rainfall (Timbal et al., 2009). Although it currently provides downscaled information for a limited number of stations deemed to be of the highest quality, the method is applicable to other observational data and, in particular, to gridded observations such as the newly generated Australian Water Availability Project daily rainfall and temperature 5km grids (Jones et al., 2007). This offers the potential, once linked to the Bureau's existing dynamical systems, to provide 5km resolution outputs for both rainfall and daily temperature extremes.

However, it is important to note that the application of SDM to dynamical systems requires a careful assessment of the suitability of the approach compared to application for climate change impact studies. The focus is on the predictability of the large-scale predictors (atmospheric or surface related fields) which are used to drive the SDM. The purpose here is to translate this predictability for local predictands (e.g. rainfall), for which the model has only limited skill, from the predictability of large-scale forcings for which it is expected that the model has greater predictability.

There are a number of ways in which this can be done. On one hand "bridging" techniques focus on the area of highest predictability in the model but which are remote from the area of interest (such as a SST signal in tropical oceans such as the Pacific). On the other hand, an SDM approach such as the Bureau's technique relies on atmospheric variables in extra-tropical Australia which are known to influence strongly the local climate but are less predictable than, e.g., remote SSTs. In an early attempt to evaluate both methods, it was found that the Bureau's dynamical systems at that time had only low predictability for the predictors and therefore did not translate to useful predictability for the target variables such as rainfall and hence the simpler bridging technique appeared more effective (Voldoire et al., 2002).

As the Bureau's dynamical prediction systems evolve these findings need to be re-evaluated. Recent work performed as part of SEACI and using a more recent version of the POAMA model found that intermediate approaches, such as using empirical orthogonal functions of hemispheric atmospheric patterns, could lead to better results (Lim et al., 2009). Despite these patterns being less predictable than ENSO indices, they relate more strongly to regional rainfall. The opportunity to test if this intermediate approach performs better than using the Bureau's SDM is being considered within the SEACI research program.

The above considerations suggest that specific downscaling methods for seasonal hydrological prediction might need to be developed in the future and are likely to differ from the SDMs being developed for climate change applications. Furthermore, in the case of seasonal water prediction it may be worth considering if an alternative target variable rather than rainfall should be used (e.g. streamflow, river level, soil moisture) as these variables are more relevant to the users and will allow ‘bypassing’ of rainfall - a difficult and ‘noisy’ variable - and also avoid the need to interface with a hydrological model. While its simplicity makes this option attractive, it is unlikely to be a priority.

4.5 Hydrological modelling

Statistical models of seasonal streamflow predictions are developed based on past relationships between streamflow, antecedent streamflow and climate predictors. Such relationships may change into the future particularly with climate change. Against the background of likely improved seasonal climate predictions from dynamical climate models (e.g. Section 4.2), substantial improvements in the SDMs (Section 4.4) and the availability of historical climate data sets at 5 km grid (Jones et al., 2007), dynamical seasonal prediction methods offer an opportunity for improved streamflow predictions at a scale relevant to hydrology.

The dynamic modelling approach (Figure 3) relies on the downscaled seasonal climate predictions as input to a hydrological model which may be a lumped rainfall-runoff model (e.g. SACRAMENTO – Burnash et al., 1973; SMAR – Kachroo, 1992; Tuteja and Cunnane, 1999; SIMHYD – Chiew et al., 2008), a semi-distributed model (PRMS – Leavesley et al., 1983; TOPMODEL – Beven and Kirkby, 1979; CATSALT – Tuteja et al., 2003) or a fully distributed model (SHE – Abbott et al., 1986; TOPOG – Dawes and Hatton, 1993; CLASS – Tuteja et al., 2004). The lumped conceptual rainfall runoff model consists of a model which attempts to represent the transformation of input climate conditions into streamflow using a series of steps representing more or less faithfully, but in a simplified manner, the known hydrological processes. The input data are usually simplified by replacing spatially variable functions by their areal means, a process known as lumping (Kachroo, 1992). Parameters of the lumped conceptual rainfall-runoff models are obtained either manually or automatically by using optimisation algorithms (e.g. Genetic algorithm – Wang, 1991; Back and Schwefel, 1993; Downhill Simplex Descent method – Nelder and Mead, 1965). Conceptual models are robust, numerically efficient and are also amenable to a formal treatment of the uncertainty in hydrological modelling (e.g. the Bayesian Total Error Analysis BATEA framework of Kuczera et al., 2006).

Distributed hydrological models are based on partial differential equations (PDEs) governing flow through the soils (Richards equation, Darcy’s law), overland flow (kinematic and diffusion wave equations), groundwater flow (Boussinesq equation) and open channel flow (Saint-Venant equations) (Freeze and Harlan, 1969). There has been considerable discussion on the strengths and weaknesses of this approach (Beven, 1989; O’Connell and Todini, 1996). Applicability of the point scale PDEs to get deterministic continuum representation of the system in a hydrological context has not reached prediction skills achieved in other fields such as oceanography, limnology or meteorology. This shortcoming is mainly attributable to extreme heterogeneity of the subsurface particularly in the upland catchments, lack of knowledge of the boundary conditions and questionable applicability of the PDEs to commonly encountered ‘non-Darcian’ flow behaviour. Semi-distributed models offer an attractive alternative to the distributed models in that they break-up the catchment into a series of topologically connected Hydrologic Response Units (HRUs) and use these HRUs as a Representative Elementary Watershed (REW) on which the balance laws are applied (Beven, 2002; Khan et al., 2009). These models are numerically very efficient compared to the distributed models and are based on REW-scale conservation laws of mass, energy and momentum.

The research on dynamic modelling to be undertaken by CSIRO to support the Bureau’s seasonal streamflow prediction service will involve: (i) testing the applicability of a series of conceptual rainfall-runoff models streamflow; (ii) development of a methodology for conditional parameterisation/calibration of the hydrological models separately for wet/dry and transitional periods, (iii) development of a method for advanced updating of the parameters and state variables using data-model assimilation approach, and (iv) development of a common procedure to benchmark the skills of dynamic seasonal prediction systems. The approach to be developed will be independent of the structure of the dynamic hydrological model and will be adaptable to better and more physically based models into the future.

The research will focus on the development of a dynamic seasonal prediction modelling capability that satisfies three primary practical requirements – model accuracy (acceptable prediction skills), model consistency (level of accuracy persists through different samples of data) and model versatility (accurate and consistent predictions when subject to diverse applications involving model evaluation criteria not directly based on the objective function used to calibrate the model). Similar to the statistical approach, conventional calibration of the hydrological models is often conducted by using part of the historical rainfall and streamflow data (calibration period) to derive parameter values. The model with the derived parameter values is then tested against the rest of the historical observations (verification period). In that way, calibration of the model is based on 'past' conditions, which may be different from those used in the model verification period. A further question relating to the use of calibrated model under future conditions (e.g. as a result of climate change), which again may be different for streamflow prediction, will be addressed in this research. . The conditional model parameterisation method to be developed aims to solve part of the problem. In this approach, the historical data will be divided into wet/dry/transitional periods (based on rainfall or streamflow) or into different categorical year types (e.g. ENSO years). Different sets of parameter values will be derived for each period or year type using objective functions that account for the ability of the hydrological model to predict both the streamflow volume and the duration curves. Evaluation of the model performance will involve running the model through the testing periods using corresponding parameter sets and issues relating to possible improvements in model predictability will be assessed. In the operational mode, the respective optimised conditional parameter set will be used in conjunction with the downscaled seasonal predictions.

The advanced model updating procedures aim to use all the available information to update model parameters and state variables in order to achieve the highest model performance. A method will be developed using data-model assimilation approach based on Kalman filter type of work (Kalman Filter - Kalman, 1960; Ensemble Kalman Filter - Evensen, 2003). Improvements in prediction capability of the dynamic model by assimilating remote sensing (leaf area index, soil moisture, etc) and other data will be investigated. . The Kalman filter provides an efficient computational (recursive) means to estimate the state of a discrete-time controlled process that is governed by the linear stochastic difference equation, in a way that minimises the mean of the squared (prediction) error. The 'time update' equations of the filter project forward (in time) the current state and error covariance estimates to obtain the *a priori* estimates for the next time step. The 'measurement update' equations account for the feedback by incorporating a new measurement into the *a priori* estimate to obtain a *posteriori* estimate. While the classical Kalman filter provides a complete and rigorous solution for state estimation of linear systems under Gaussian noise, the estimation for nonlinear systems can be obtained using the ensemble Kalman filter which is an ensemble of state estimates that captures the initial probability distribution of the state. These methods are particularly helpful when the models are of extremely high order and nonlinear, initial states are highly uncertain, and a large number of measurements are available.

In order to objectively assess the skill of the dynamic prediction approach, a procedure will be developed to evaluate or benchmark prediction skill in an operational environment which is different to model performance in the calibration mode. Model performance obtained in the conventional model calibration process represents the ability of the model to simulate streamflow given 'known' or 'perfect' climate data. For each observed streamflow value, the model can provide one corresponding simulated streamflow value. However, in prediction mode the model inputs are 'unknown' and 'uncertain'. Therefore, several methods will be explored, which include: the use of streamflow data from historical analogue years to generate probabilistic predictions; the downscaled outputs from POAMA to drive the conditionally calibrated hydrological models to seasonal predictions, and the use of streamflow predictions from the BJP approach.

The dynamic modelling approach for seasonal prediction of streamflow will be set up initially in an operational mode on selected catchments with the objective of eventually extending this service nationally.

4.6 Verification systems

Seasonal streamflow prediction is inherently uncertain and probabilistic predictions are needed to express that uncertainty. Quality probabilistic predictions should have high skill (the predictions are close to the observations) and appropriate spread (the predictions represent the true uncertainty). In addition, the probabilistic predictions should be unbiased (also termed reliable) and sharp.

Because hydrological predictions have mostly been deterministic, verification methods have tended to be developed for deterministic outputs. For weather and climate forecasting, there has been considerable experience in the verification of probabilistic predictions of binary and categorical events (e.g. WMO, 2006; Bureau of Meteorology, 2008b). Seasonal streamflow predictions require probabilistic predictions of continuous variables and thus suitable verification methods.

Much work is still needed in the development of verification methods for probabilistic predictions of continuous variables (Gneiting et al., 2007; Laio and Tamea, 2007; Thyer et al., 2009). Wang et al. (2009a) proposed a suite of methods for such a purpose. Methods for overall verification include the use of prediction skill scores based on the linear error in probability space score (LEPS), the continuous ranked probability score (CRPS) and the root mean-square error of probability (RMSEP), and the use of a PIT (probability integral transform) uniform probability plot. Methods for detailed verification include comparisons of predictions with observed data for individual cases, in terms of both quantiles and PIT values, to assess quality of predictions both over time and over event size. These methods were applied for the verification of streamflow predictions produced using Bayesian joint probability modelling (Section 4.3).

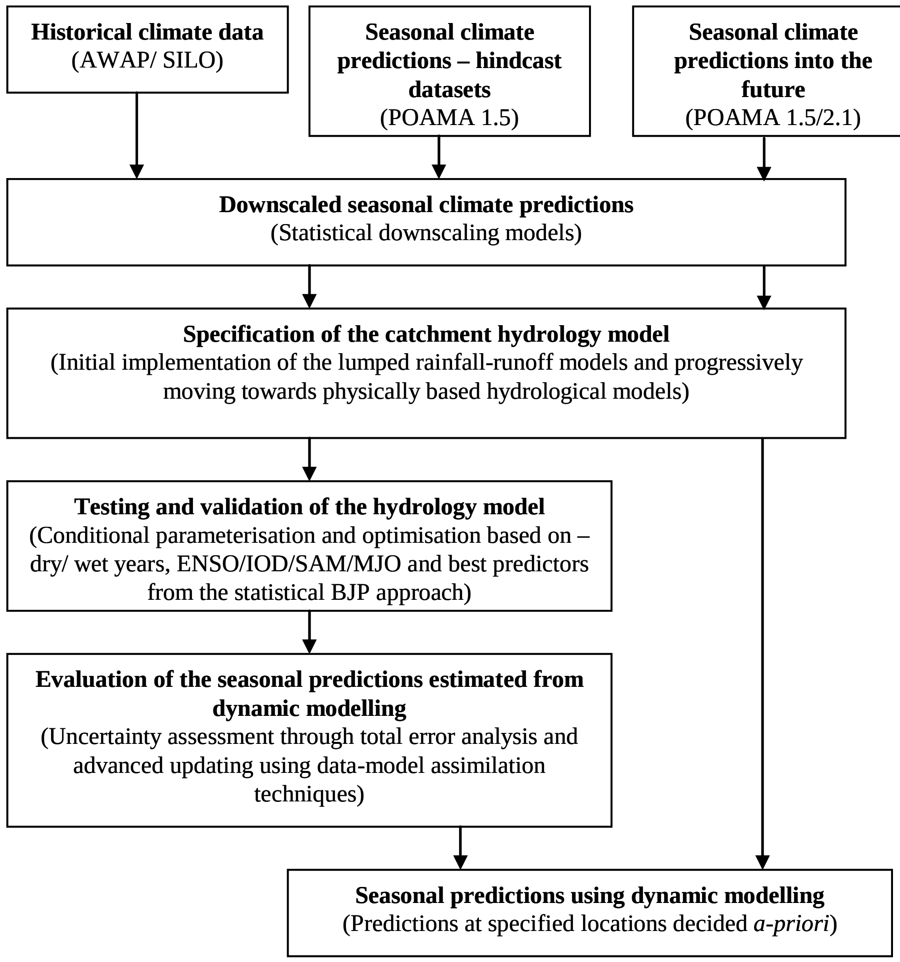

Figure 3. Outline of the methodology for seasonal water availability predictions using the dynamic modelling approach.

5 CONCLUSIONS

Triggered by a long-period of drought affecting many regions of Australia, recent Australian Government investment has provided the opportunity for the Bureau of Meteorology to develop an operational seasonal water availability service. Some of the modelling components for this already exist. The dynamical climate model POAMA has been under development for more than a decade and is already providing seasonal climate forecasts. POAMA-3 will likely have its components developed from the ACCESS model within the next 5 years, leading to ACCESS providing seamless predictions across timescales, from hours to multi-decades. While more effort is required to develop downscaling tools, the work that has been done for climate change impact studies provides a good lead. While more work is also required to develop improved hydrological models for seasonal prediction, existing lumped rainfall-runoff and semi-distributed models can be used initially to interface with global climate models through statistical downscaling.

The first predictions will be derived from the statistical BJP model and early results for predictions of seasonal streamflow are encouraging. These statistical predictions will rely on access to good quality data and the development of the AWRIS information system. Challenges include the effective choice of predictors and the reliance on the stability of past relationships between predictands and predictors. The availability of the CABLE land-surface/carbon cycle model within ACCESS will expand the options for seasonal prediction in the longer-term. Before then, however, improvements in dynamic hydrological modeling are expected from conditional parameterisation/calibration and advanced updating of parameters and state variables. It is very unlikely that ACCESS will replace the need for hydrological models in the foreseeable future. Collaborations between the Bureau, CAWCR, CSIRO and the University sector will be crucial to all of the underpinning research.

With more than one model providing predictions for the same location and time period, work will also be necessary on producing a consensus prediction to present to user stakeholders. The success of a water availability prediction service will, ultimately, not be determined by its accuracy or reliability but by the impact it has on changing the decisions made for water resource management.

REFERENCES

Abbott, M. B., J. C. Bathurst, J. A Cunge., P. E. O'Connell, and J. Rasmussen, (1986), An introduction to the European hydrological system – systeme hydrologique Europeen SHE, 1. History and philosophy of a physically-based distributed modelling system. *Journal of Hydrology*, 87, 45-59.

Alves, O., G. Wang, A. Zhong, N. Smith, F. Tseitkin, G. Warren, A. Schiller, S. Godfrey and G. Meyers, (2003), POAMA: Bureau of Meteorology operational coupled model seasonal forecast system. National Drought Forum, Brisbane, 15 – 16 April 2003, Forum Proceedings, 49-56.

Back, T. and H.-P. Schwefel, (1993), An overview of evolutionary algorithms for parameter optimization. *Evolutionary Computation*, 1(1), 1–23.

Beven, K.J. (1989), Changing ideas in hydrology – The case of physically based models. *Journal of Hydrology*, 105, 157-172.

Beven, K.J. (2002), Towards an alternative blueprint for a physically-based digitally simulated hydrological response modelling system. *Hydrological Processes*, 16, 189-206.

Beven, K.J. and M.J. Kirkby, (1979), A physically-based variable contributing area model of basin hydrology. *Hydrological Science Bulletin*, 24, 43-69.

Bureau of Meteorology (2008a), Long-term rainfall deficiencies continue in southern Australia while wet conditions dominate the north. Special Climate Statement 16, Bureau of Meteorology, Melbourne. http://www.bom.gov.au/climate/current/special-statements.shtml.

Bureau of Meteorology (2008b), Forecast Verification – Issues, Methods and FAQ. Bureau of Meteorology, Melbourne. http://www.bom.gov.au/bmrc/wefor/staff/eee/verif/verif_web_page.html.

Burnash, R. J. C., R. L. Ferral, and R. A. McGuire, (1973), A generalized streamflow simulation system: conceptual modeling for digital computers. Technical report, Joint Fed-State River Forecast Center, Sacramento, U.S.A.

Chiew, F.H.S, J. Vaze, N. Viney, J. Perraud, J. Teng, and D. Post, (2008), Modelling runoff and climate change impact on runoff in 178 catchments in the Murray-Darling Basin using Sacramento and SIMHYD rainfall-runoff models. In Proceedings of Water Down Under 2008, April 2008, Adelaide.

Chiew, F.H.S. and L.W. Siriwardena, (2005), Probabilistic seasonal streamflow forecasting methods. 29th Hydrology and Water Resources Symposium, Institution of Engineers, Canberra.

Chiew F.H.S., S.L. Zhou, and T.A. McMahon, (2003), Use of seasonal streamflow forecasts in water resources management. *Journal of Hydrology*, 270, 135-144.

Clewett, J.F., N.M. Clarkson, D.A. George, S. Ooi, D.T. Owens, I.J. Partridge, and G.B. Simpson, (2003), Rainman StreamFlow (version 4.3): A comprehensive climate and streamflow analysis package on CD to assess seasonal forecasts and manage climatic risk. QI03040, Department of Primary Industries, Brisbane.

CSIRO (2008), Water Availability in the Murray-Darling Basin. A CSIRO report for the Australian Government, CSIRO Land and Water, Canberra, http://www.csiro.au/resources/WaterAvailabilityInMurray-DarlingBasinMDBSY.html.

Dawes, W., and T. Hatton, (1993), TOPOG_IRM - 1. Model description, Technical memorandum 93/5, CSIRO Land and Water, Canberra.

Drosdowsky, W., and L.E. Chambers, (2001), Near-global sea surface temperature anomalies as predictors of Australian seasonal rainfall. *Journal of Climatology*, 14(7), 1677-1687.

Drought Policy Review Expert Social Panel (2008), It's About People: Changing Perspective. A Report to Government by an Expert Social Panel on Dryness. Report to the Minister for Agriculture, Fisheries and Forestry, Canberra, http://www.daff.gov.au/agriculture-food/drought/national_review_of_drought_policy/social_assessment/dryness-report.

Evensen, G. (2003), The Ensemble Kalman Filter: theoretical formulation and practical implementation. *Ocean Dynamics*, 53, 343-367.

Frost A, S. P. Charles, R. Mehrotra, B. Timbal, K.C. Nguyen, F. Chiew, R.E. Chandler, J. McGregor, D. Kirono, E. Fernandez and D. Kent, (2009), A comparison of multi-site daily rainfall downscaling techniques under Australian conditions, *Water Resources Research*, submitted.

Freeze, R.A., and R.L. Harlan, (1969), Blueprint for a physically-based, digitally-simulated hydrologic response model. *Journal of Hydrology*, 9, 237-258.

Garen, D. C. (1992), Improved Techniques in Regression-Based Streamflow Volume Forecasting. *Journal of Water Resources Planning and Management*, 118(6), 654-670.

Glantz M. H., R.W. Katz and N. Nicholls, (1991), Teleconnections linking worldwide climate anomalies. Cambridge University Press, ISBN 0521364752.

Gneiting, T., F. Balabdaoui, and A.E. Raftery, (2007), Probabilistic forecasts, calibration and sharpness. *Journal of the Royal Statistical Society*, Series B-Statistical Methodology, 69, 243-268.

Hammer G. L., N. Nicholls and C. Mitchell, (2000), Applications of Seasonal Climate Forecasting in Agricultural and Natural Ecosystems: The Australian Experience. Kluwer Academic, ISBN 0792362705.

Hudson, D., O. Alves, G. Wang and H. Hendon, (2009), The impact of atmospheric initialization on seasonal prediction in the Indo-Pacific region. Report for South-Eastern Australian Climate Initiative (SEACI).

Indian Ocean Climate Initiative (IOCI) (2002), Climate variability and change in south west Western Australia. General Report, IOCI, Perth, http://www.ioci.org.au/publications/reports.html.

IPCC (2007), Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment. Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)]. IPCC, Geneva, Switzerland, 104 pp.

Jones, D., W. Wang and R. Fawcett, (2007), Climate Data for the Australian Water Availability Project. Final Milestone Report, Australian Water Availability Project, Bureau of Meteorology, Melbourne, http://www.daffa.gov.au/brs/climate-impact/awap.

Kachroo, R.K., (1992), River flow forecasting. Part 5: Applications of a conceptual model. *Journal of Hydrology*, 133, 141-178.

Kalman, R.E. (1960), A new approach to linear filtering and prediction problems. Transactions of the ASME. *Journal of Basic Engineering*, 82(D), 35-45.

Khan, U., N.K. Tuteja, and A. Sharma, (2009), A New Approach for Delineation of the Hydrologic Response Units in Large Catchments. Paper to be presented at MODSIM 2009, Cairns.

Kowalczyk, E.A., Y.P. Wang, R.M. Law, J.L. McGregor, and G. Abramowitz, (2007), CSIRO Atmosphere Biosphere Land Exchange model for use in climate models and as an offline model. CSIRO Marine and Atmospheric Technical report, CSIRO, Aspendale.

Kuczera. G., D. Kavetski, S. Franks, and M. Thyer, (2006), Towards a Bayesian total error analysis of conceptual rainfall-runoff models: Characterising model error using storm-dependent parameters. *Journal of Hydrology*, 331(1-2), 161-177.

Laio, F. and S. Tamea, (2007), Verification tools for probabilistic forecasts of continuous hydrological variables. *Hydrology and Earth System Sciences*, 11(4), 1267-1277.

Leavesley, G.H., R.W. Lichty, B.M. Troutman, and L.G. Saindon, (1983), Precipitation-runoff modelling system: User's manual. U.S. Geological Survey, Denver, Colorado, U.S.A.

Lim, E., H. H. Hendon, D. L. T. Anderson and O. Alves, (2009), Dynamical, statistical-dynamical, and homogeneous multi-model ensemble forecasts of Australian cool season rainfall. Final report for South-Eastern Australian Climate Initiative (SEACI) project 3.1.2., http://www.mdbc.gov.au/subs/seaci/publications_project.html.

Murray Darling Basin Authority (2008), About the basin. Murray Darling Basin Authority, Canberra, http://www.mdba.gov.au/water/about_basin.

Murray Darling Basin Authority (2009), Murray River Drought Update – Issue 17. Murray Darling Basin Authority, Canberra, http://www.mdba.gov.au/media_centre/drought_updates.

Nakaegawa T., S. Kusunoki, M. Sugi, A. Kitoh, C. Kobayashi and K. Takano, (2007), A study of dynamical seasonal prediction of potential water resources based on an atmospheric GCM experiment with prescribed sea-surface temperature. *Hydrological Sciences*, 52(1), 152-165.

Nelder, J.A. and R.A. Mead, (1965), Simplex method for function minimization. *Computer Journal*, 7(4), 308–313.

NIWA (National Institute of Water & Atmospheric Research) (2009), Seasonal Climate Outlook, NIWA, Auckland, New Zealand, http://www.niwa.cri.nz/ncc/seasonal_climate_outlook.

NWS (National Weather Service) (2009), River Forecasts. NWS, Silver Spring, U.S.A, http://www.weather.gov/ahps/forecasts.php.

NRCS (Natural Resources Conservation Service) (2009), Water Supply Forecasts. NRCS, Washington, U.S.A, http://www.wcc.nrcs.usda.gov/wsf/wsf.html.

O'Connell, P.E. and E. Todini, (1996), Modelling of rainfall, flow and mass transport in hydrological systems: An overview. *Journal of Hydrology*, 175, 3-16.

Piechota, T. C., F. H. S. Chiew, J. A. Dracup, and T. A. McMahon, (2001), Development of Exceedance Probability Streamflow Forecast. *Journal of Hydrologic Engineering*, 6(1), 20-28.

Sharma, A. (2000), Seasonal to interannual rainfall probabilistic forecasts for improved water supply management: Part 3 - A nonparametric probabilistic forecast model. *Journal of Hydrology*, 239(1-4), 249-258.

Thyer, M., B. Renard, D. Kavetski, G. Kuczera, S.W. Franks, and S. Srikanthan, (2009), Critical evaluation of parameter consistency and predictive uncertainty in hydrological modelling: a case study using bayesian total error analysis. *Water Resources Research*, Accepted.

Timbal B. and B.J. McAvaney, (2001), An Analogue based method to downscale surface air temperature: Application for Australia. *Climate Dynamics*, 17, 947-963.

Timbal, B., B. Murphy, K. Braganza, H. Hendon, M. Wheeler and C. Rakich, (2007), Compare documented climate changes with those attributable to specific causes. Final report for South-Eastern Australian Climate Initiative (SEACI) project 1.1.2., http://www.mdbc.gov.au/subs/seaci/publications_project.html

Timbal B., E. Fernandez and Z. Li, (2008), Generalization of a statistical downscaling model to provide local climate change projections for Australia. *Environmental Modelling and Software*, 24(3), 341-358.

Timbal B., Z. Li and E. Fernandez, (2009), The Bureau of Meteorology Statistical Downscaling Model Graphical User Interface: user manual and software documentation, Technical Report 4, CAWCR (Centre for Australian Weather and Climate Research), Melbourne.

Tuteja, N. K., J, Vaze, B. Murphy and G. T. B. Beale, (2004), CLASS – Catchment scale multiple-landuse atmosphere soil water and solute transport model. Technical Report 04/12 for NSW Department of Natural Resources and Cooperative Research Centre for Catchment Hydrology (now eWater CRC), Canberra, Australia,
http://www.toolkit.net.au/class.

Tuteja, N.K., and C. Cunnane, (1999), A quasi physical snowmelt runoff modeling system for small catchments. *Hydrological Processes*, 13(12/13), 1961-1975.

Tuteja, N.K., G. Beale, W. Dawes, J. Vaze, B. Murphy, P. Barnett, A. Rancic, R. Evans, G. Geeves, D.W. Rassam and M. Miller, (2003), Predicting the effects of landuse change on water and salt balance – a case study of a catchment affected by dryland salinity in NSW, Australia. *Journal of Hydrology*, 283(1-4), 67-90.

Voldoire, A., B. Timbal and S. Power, (2002), Statistical-Dynamical Seasonal Forecasting, BMRC (Bureau of Meteorology Research Centre) Research Report No. 87, Bureau of Meteorology, Melbourne.

Wang, G, O. Alves, D. Hudson, H. Hendon, G. Liu, and F. Tseitkin, (2009b), Preliminary skill assessment of the POAMA-2 system. Technical report for the South-Eastern Australian Climate Initiative (SEACI).

Wang Q.J. (1991), The genetic algorithm and its application to calibrating conceptual rainfall-runoff models, Water Resources Research, 27(9), 2467-2471.

Wang, Q.J., (2008), Personal Communication.

Wang, Q.J., D.E. Robertson, and F.H.S. Chiew, (2009a), A Bayesian Joint Probability Modelling Approach for Seasonal Forecasting of Streamflows at Multiple Sites, *Water Resources Research*, In press.

Westra, S., A. Sharma, C. Brown, and U. Lall, (2008), Multivariate streamflow forecasting using independent component analysis. *Water Resources Research*, 44(2).

Wilks, D., (2006), Statistical Methods in the Atmospheric Sciences, Academic Press, 592 pp.

WMO (World Meteorological Organization) (2006), Standardised Verification System (SVS) for Long-Range Forecasts (LRF). New Attachment II-8 to the Manual on the GDPFS (WMO-No.485), Volume I, WMO Lead Centre for the Long Range Forecast Verification System, Bureau of Meteorology, Melbourne. http://www.bom.gov.au/wmo/lrfvs/users.shtml.

Wood, A.W. and D.P. Lettenmaier, (2006), A testbed for new seasonal hydrologic forecasting approaches in the western United States, *Bulletin of the American Meteorological Society*, 87, 1699-1712.