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Multi-Objective Planning and Operation of Water Supply Systems Subject to Climate Change

B. J. C. Perera, D. A. Sachindra, W. Godoy., A.F. Barton and F. Huang

***Abstract*—**Many water supply systems in Australia are currently undergoing significant reconfiguration due to reductions in long term average rainfall and resulting low inflows to water supply reservoirs since the second half of the 20th century. When water supply systems undergo change, it is necessary to develop new operating rules, which should consider climate, because the climate change is likely to further reduce inflows. In addition, water resource systems are increasingly intended to be operated to meet complex and multiple objectives representing social, economic, environmental and sustainability criteria. This is further complicated by conflicting preferences on these objectives from diverse stakeholders. This paper describes a methodology to develop optimum operating rules for complex multi-reservoir systems undergoing significant change, considering all of the above issues. The methodology is demonstrated using the Grampians water supply system in northwest Victoria, Australia. Initial work conducted on the project is also presented in this paper.

***Keywords*—**Climate change, Multi-objective planning, Pareto optimal; Stakeholder preference, Statistical downscaling, Water supply systems.

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I. Introduction

WATER is a scarce and a precious resource. There are ever-increasing demands for water to satisfy a mix of purposes. Water management is increasingly contested in urban areas due to population growth, rapid urbanisation and the expansion of cities. In rural areas, over-allocation has created major stresses on rivers. The conflicting objectives and expectations of diverse stakeholders have led to increasing interest, and burgeoning complexity, in how best to assess and resolve multiple social, economic, environmental and sustainability objectives in the management of water supply systems, especially during extended dry periods. Climate change and climate variability further exacerbate these problems, affecting people and the environment [1].

Since the second half of the 20th century, many regions of Australia experienced a drop in average rainfall, leading to low inflows to water supply reservoirs. The impact can most easily be observed in the Australian state of Victoria where 13 years of severe drought resulted in reductions to annual average inflows by about 38% to Melbourne's main water supply reservoirs [2] and about 75% to the Grampians water supply system in northwest Victoria [3].

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To address this variability in inflows, many water supply systems are undergoing significant reconfiguration to interconnect catchments to build flexibility and resilience in supply and reduce dependence on rainfall by augmenting with non-traditional supplies. Examples of these reconfiguration efforts in Victoria include Melbourne's proposed desalination plant, the north-south pipeline which transfers water from the Goulburn River system to the Melbourne supply system, and the Wimmera-Mallee pipeline which has replaced over 17,000 kilometres of earthen open channels with an 8,800 km network of pressurised pipelines to reduce seepage and evaporative losses.

When water supply systems undergo change it is often necessary to develop new operating rules. Increasingly this requires water resource system models to be operated at finer time scales, to account for complex daily flow rules associated with sophisticated environmental flow requirements, and complex headworks operations. These new operating rules should also consider forecasts of future climate. Therefore daily hydro-climatic variables, accounting for any climate change and variability, have become essential inputs for the future planning of water supply systems. Droughts, floods, extreme temperatures, sea level changes and poor crop yields are among the results of the climate turmoil. Therefore if the climate of the future can be better understood, this will ultimately lead to more sustainable water supply systems. General Circulation Models (GCMs) are the most advanced and credible tools available for the simulation of future climate considering concentrations of green house gases [4, 5]. However, the coarse spatial resolution of GCMs does not allow for hydroclimatic predictions at the catchment scale, but downscaling methods can be used to generate coarse resolution GCM outputs to surface hydroclimatic variables at finer resolutions.

Water resource systems nowadays are intended to be operated to meet multiple objectives representing social, economic, environmental and sustainability criteria. Any new operating regime derived for a water supply system must increasingly consider complex operating rules at finer temporal and spatial scales, and also climate change. Opimisation techniques can be used to work through these types of problems, but often there is no single optimal solution because of the competing multiple objectives. This can be further complicated by conflicting preferences on these objectives from diverse stakeholders, who have increasing interest in the planning and operation of these systems, especially since water has become a commodity of much interest in recent times. The growing trend is to methodically include stakeholder preferences to aid in decision making on sustainable water resource management [6].

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This paper will describe a methodology to develop optimum operating rules for complex multi-reservoir systems undergoing significant changes, both in configuration and overall water balance. The methods will explicitly account for climate change and variability, a range of social, economic, environmental and sustainability objectives, and stakeholder preferences. The methodology concentrates on the case study of Grampians water supply system in northwest Victoria, Australia. The paper will start with a brief review of literature on two aspects: (1) downscaling GCM outputs to catchment level hydroclimatic variables, and (2) multi-objective optimisation of operation of water supply systems. The next section will describe the case study system, followed by the overall methodology. Current work on the above two aspects will then be described, followed by conclusions of the work.

II. Climate Change and Water Supply System Optimisation – A Review

A. Downscaling GCM Outputs to Catchment Level Hydroclimatic Variables

As outlined earlier, GCMs are incapable of producing outputs at the fine spatial resolution needed for most hydrological and water resource studies. Two downscaling methods, dynamic and statistical methods have been used in the past to link coarse resolution GCM outputs to surface climatic variables at finer resolutions [7]. In dynamic downscaling, a Regional Climatic Model (RCM) is nested within a GCM. The RCM is an atmospheric physics based model to which boundary conditions are provided with the output of a GCM. The major drawback of dynamic downscaling is its complexity and high computational cost [4]. The other problem with dynamic downscaling is the potential for propagation of systematic bias from GCM to RCM [8]. Statistical downscaling methods construct statistical relationships between the large scale GCM outputs (predictors) and the catchment scale climate variables (predictands) [8]. The basic advantage of statistical downscaling is that it is computationally less demanding compared to dynamic downscaling. Statistical downscaling is based on few assumptions [9]. These assumptions are that the predictor-predictand relationships are valid under future climatic conditions, and predictor variables and their changes are well characterised by GCMs. In general, statistical downscaling techniques are classified into three main categories as weather classification, transfer functions and weather generators. Transfer functions are commonly used [5]: for example, linear and nonlinear regression, artificial neural networks (ANN), canonical correlation and principal component analysis.

Statistical downscaling of GCM outputs to catchment scale climatic variables has gained wide application in hydro-climatology. In literature, there are a number of studies performed on downscaling GCM outputs to catchment level climatic variables such as precipitation and temperature. Support Vector Machine (SVM) and Artificial Neural Networks (ANN) were used for forecasting monthly precipitation in [10], while SVM and Multiple Linear Regression (MLR) were used in [7] to predict daily rainfall. Monthly maximum and minimum temperatures were downscaled with the SVM technique in [11], while daily mean temperature using MLR were used in [12]. Generalized Additive Models (GAM) were applied to predict 6 hour mean wind speeds in [13].

In downscaling literature, only a few studies have been done on downscaling GCM predictors directly to streamflow. GAM, Generalized Linear Models (GLM), Aggregated Boosted Trees (ABT) and ANN were used to predict daily streamflows in [14], while SVM and Relevance Vector Machine (RVM) were used to predict monthly streamflows in [5]. ANN model was in [15] for downscaling GCM outputs to 5-day average streamflows, while seasonal streamflows were forecasted in [16] using Canonical Correlation Analysis (CCA) and Perfect Prognosis method. One shortcoming of direct downscaling of GCM predictors to streamflows is that it simplifies the naturally complicated hydrologic cycle to a great extent, neglecting the influences of land use, soil cover, and groundwater storage on streamflow. The other major limitation of this technique is that it can only be used to predict unregulated streamflows in a catchment. This is because the statistical relationships derived between predictors and streamflows will not consider any human influence of on streamflows made by regulating structures such as reservoirs.

B. Water Supply System Optimisation

Water resources systems are characterised by multiple objectives. Most researchers have used classical optimisation methods (such as linear and dynamic programming) to optimise the operation of water resource systems with multiple objectives. They have adopted a weighted approach or a constraint approach, rather than considering all objectives simultaneously [6]. These traditional methods are unable to handle complex environmental flow rules efficiently [17].

During the last decade researchers have used evolutionary algorithms with success, to solve multi-objective optimisation problems [17-19]. Evolutionary algorithms (EA) mimic nature's evolutionary principles to drive its search towards an optimal solution [18]. In simple terms, an optimal solution is characterised as not being the inferior or dominated by any other solution in the search space. Indeed many optimal solutions generally exist for multi-objective problems. These solutions are called 'Pareto optimal' with the entire set of these trade-off solutions presenting themselves as a frontier or 'Pareto front' within the solution space. EA produce populations of solutions whose offspring (or next iteration) search for multiple optimal solutions concurrently in a single run. These algorithms are ideal for multi-objective optimisation as they tend to find global optima more efficiently than classical optmisation methods. Notably, the issue of the testing of EA in terms of their scalability beyond two objectives and their application in complex real-world case

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studies is yet to be addressed [20]. Applications in the field of water resources have mainly focused on small scale multi-reservoir optimisation problems at a strategic planning level as seen for example in [21].

In recent times there has been growing interest in simulation-based optimisation given that EA can be directly linked with simulation models without requiring simplifications in problem specification [22]. Similar to the techniques employed [21, 23-24], the general structure of a simulation-based optimisation model comprises a simulation engine and a search engine. The process is iterative; simulation outputs are used to calculate objective function values which are in turn passed to the search engine to find optimal solutions as described above. For example, a population of 100 candidate solutions requires 100 simulation runs and 100 evaluations per objective function. In the case of a multi-objective problem that seeks to minimise all objective functions, the aim is to find decision variables that yield the lowest values for each objective function.

As stated earlier, for multi-objective optimisation there is often no single solution, but this is further complicated because of diverse stakeholders who have keen interests in water supply planning and operations with different and often conflicting preferences. When high levels of stakeholder conflict beset the management of multiple objectives, multi-criteria decision aiding (MCDA) methods that evaluate stakeholder preferences may be used to facilitate the decision making process [25]. The growing trend is to explicitly include stakeholder preferences in decision making on sustainable water resources management issues [26]. However, there is a premium on consensus-seeking decision making strategies for sustainable water resources management when options for increasing water supplies are limited, existing supplies are becoming exhausted, and preserving eco-systems is at issue [27]. Transparency in decision making is also vital in order for the final outcome to have credibility with the community. In the review of state-of-the-art methodologies for the optimisation of multi-reservoir systems, it is suggested that many of the hindrances to optimisation in reservoir system management are being overcome with the aid of decision support systems (DSS) or decision frameworks [22]. The author of the review believes that this is due to the greater focus that is placed on the decision makers, rather than the computer modellers. There are many examples of DSS's but perhaps the most relevant to water resources management is one that has been developed for urban water decision-making [28]. In this example, the authors discuss the challenges that face sustainable urban water decision-making, and highlight the two main areas of further work as the incorporation of adaptive management, and integrated urban water management. The decision framework proposed by the authors incorporates a process known as *social learning* through effective stakeholder engagement. They argue that such processes provide learning through inclusion, interaction and engagement with stakeholders which assist practitioners in developing more sustainable management practices.

III. Study Area And Data

The Grampians water supply system, which is a large multi-reservoir water supply system located in north-western Victoria, was used as the case study to demonstrate the methodology of this paper. Fig. 1 shows the location of the Grampians water supply system in the Australian state of Victoria, while Fig. 2 shows the area and headworks of the system. This system provides water for many domestic, industrial, irrigation and environmental needs.



Fig. 1 Grampians water supply in north-western Victoria (Australia)

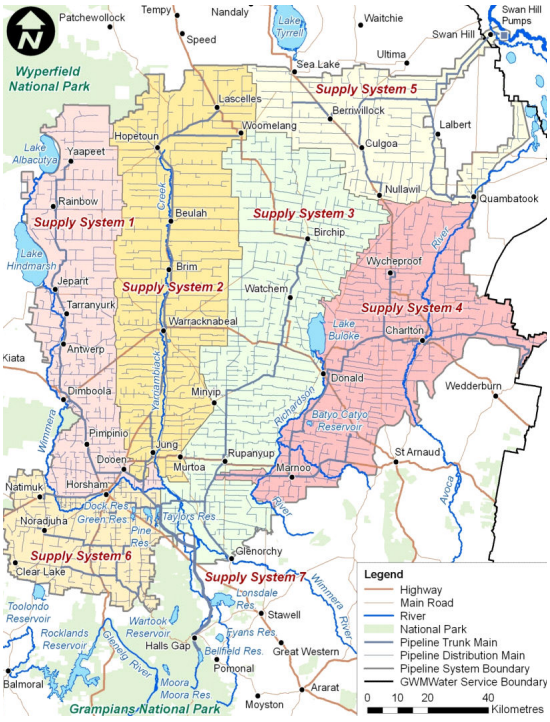


Fig. 2 Grampians water supply system

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The Wimmera-Glenelg REALM model represents all the key characteristics of the water supply system and is used by the Grampians Wimmera Mallee Water Corporation (GWMWater) for strategic planning purposes. The REALM (REsource and ALlocation Model) software package is a generalised computer software package that simulates the harvesting and bulk distribution of water resources, usually at monthly times steps, within a water supply system [29,30]. The Wimmera-Glenelg REALM model represents all the key attributes of the Grampians water supply system including the eleven headworks water storages and five key diversion weirs located in and around the Grampians National Park which divert water from the Wimmera and Glenelg river systems for distribution via the Wimmera Mallee Pipeline. This REALM model is used in this study for multi-objective optimisation process to assess the effectiveness of candidate operating rules for the system considering climate change. Downscaling of hydroloclimatic variables (i.e. streamflows, rainfall, temperature and evapotranspiration) for use in this REALM model for the next 100 years is required, however the current downscaling study described in Section V is limited to a single streamflow site in the study area for the purpose of describing the current work.

For the calibration and validation of the downscaling model, National Center for Environmental Predictions/National Center for Atmospheric Research (NCEP/NCAR) monthly reanalysis data and monthly observed streamflow data at the streamflow site from 1950-2010 were used. These reanalysis data are the outputs of a GCM, corrected and quality controlled at several stages [31]. Therefore, the reanalysis data are considered to be predictions of an ideal GCM [32]. The NCEP/NCAR reanalysis data were downloaded from the website (http://www.esrl.noaa.gov/psd/) of National Oceanic & Atmospheric Administration/Earth System Research Laboratory (NOAA/ESRL) Physical Sciences Division. The quality controlled observed monthly streamflow record at the site concerned was obtained from GWMWater.

IV. Methodology

Fig. 3 shows the broad approach used in this study to determine the optimal operating rules for complex multi-reservoir systems considering climate change. It has two major components: (1) climate modeling, and (2) optimisation of system operation and multi-criteria decision analysis.

A. Climate Modelling

As was done in many previous studies [eg. 33], both different future development scenarios developed by Intergovernmental Panel on Climate Change (IPCC) [1] and outputs of different GCMs, are considered in this study to account for uncertainties associated with climate modelling. First appropriate predictors from the GCM outputs relevant to predictands (i.e. hydroclimatic variables) are considered. Then an appropriate statistical downscaling model is used to downscale monthly hydroclimatic variables. NCEP/NCAR data and present day climate data is used to calibrate and validate the downscaling models. Once the models are developed, calibrated and validated, they are used to produce future catchment level monthly climate variables. Data of these monthly downscaled variables are disaggregated to daily data using an appropriate disaggregation model.

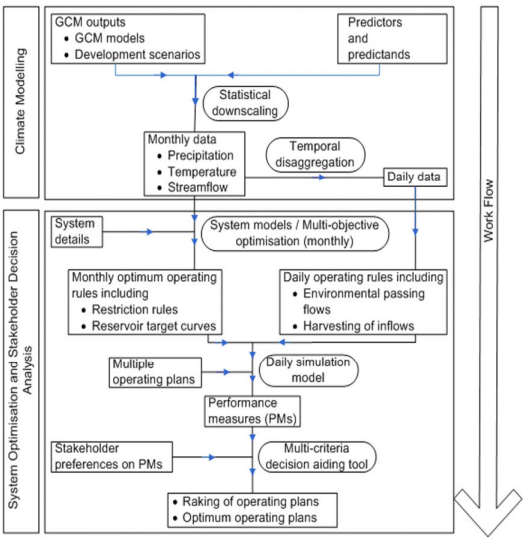


Fig. 3 Flow Chart Showing Broad Methodology

B. System Optimisation and Stakeholder Decision Analysis

This part of the study consists of two components. In the first component, operating rules will be determined through multi-objective optimisation of the water supply system considering the monthly downscaled future hydroclimatic data described in Section IV (A) and identified objective functions related to social, economic, environmental and sustainability objectives. These rules include reservoir targets to optimise water transfers between reservoirs and restriction rules, which optimise the allocation of water over the long term by triggering water restrictions during dry periods. This component will produce several Pareto optimal solutions (i.e. operating rules), which will be used in the second component. These operating rules will be validated and refined using separate daily time-step REALM models of the water supply system, which simulate more sophisticated environmental flow requirements and time lag effects of routing flows throughout the system. Ranking of operating rules will then be done through an appropriate multi-criteria decision making tool, identifying appropriate performance measures which represent social, economic, environmental and sustainability objectives.

C. Current Work

Current work for this project has been progressing on two fronts: (1) downscaling GCM outputs to catchment level hydroclimatic variables, particularly focusing on direct downscaling GCM outputs to streamflows, and (2) development of a generalised procedure for the formulation of

the multi-objective optimisation problem for operation of water supply systems.

V. Climate Modelling

A. Methodology of Statistical Downscaling

In this exercise, LS-SVM regression (LS-SVM-R) was employed to downscale NCEP/NCAR predictors to streamflows. Since the hydroclimatology at a certain point in a catchment is influenced by the atmosphere above and around it, a substantially large atmospheric domain was defined (see Fig. 4).

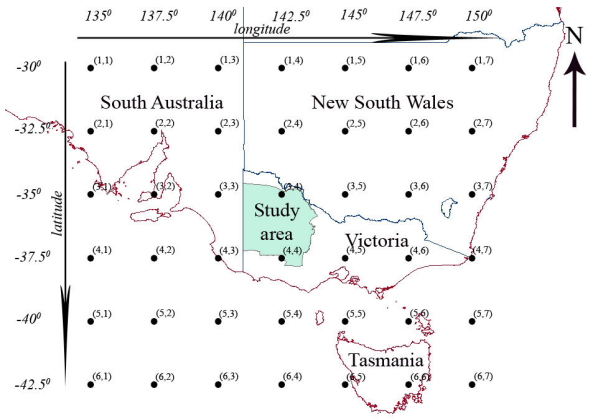


Fig. 4 Atmospheric domain around Grampians water supply system used for downscaling

Based on literature and hydrology, a set of probable predictors corresponding to this atmospheric domain was extracted from the NCEP/NCAR reanalysis variables. The time series of streamflows and the potential predictors for each calendar month were separated into 20 year time slices. For each of these 20 year time slices, the Pearson correlation coefficients were calculated for each calendar month to identify the predictors which are most correlated with the streamflows. The best consistently correlated predictors over the three time slices were selected as potential predictors for the calibration and validation of the model. The consistency of the Pearson correlation between a predictor and streamflow was an important attribute since a good predictor of streamflow should show a consistent relationship over time. These potential predictors for the calibration period were standardised for each calendar month, based on their means and standard deviations for the calibration period. The standardisation of the potential predictors in the validation period was performed with the means and standard deviations corresponding to the calibration period of the data set. The model calibration and validation were performed for each calendar month by introducing the above standardised potential predictors to the LS-SVM-R model. This was done by initially inputting the three best correlated potential variables to the model for a certain month and adding the next best variables one by one, until the model performance is maximised for validation. The model calibration was performed with leave-one-out cross-validation [10] and the validation was done as an independent simulation fixing the optimum model parameters yielded in calibration [4, 10]. The model performances in calibration and validation in each month were monitored with Nash-Sutcliffe efficiency (N-S). The methodology described here was applied to a streamflow site (inflow to the Bellfield reservoir) within the Grampians water supply system as a demonstration.

B. Application of Statistical Downscaling

In past literature, various authors have used different domain sizes for their atmospheric domain. A domain with 5 x 5 grid points around the study area was used for downscaling streamflows in [5], while [10] and [4] used grids with 6 x 6 and 3 x 3 points respectively, for downscaling precipitation. The present study uses a spatially large atmospheric domain of 7 x 6 grid points (each 2.5^0 apart), while maintaining symmetry around the study area as shown in Fig. 4.

C. Probable and Potential Predictors for Downscaling

The selection of probable predictor variables is regarded as the beginning of any downscaling activity. A GCM could produce a large number of different outputs, but only some predictors are more likely to influence the predictand. This subset of all the predictors is called the pool of probable predictors [4]. These probable predictors vary from predictand to predictand. In general, probable predictors for a downscaling study are selected based on past literature. In the present study, for downscaling of GCM predictors to streamflows, probable predictors were selected based on past literature as well as from hydrology principles.

The 23 probable predictors selected for the downscaling exercise included, geopotential height at 200hPa, 500hPa, 700hPa, 850hPa, 1000hPa pressure levels, relative humidity at 500hPa, 700hPa, 850hPa, 1000hPa pressure levels, specific humidity at 2m height, 500hPa, 850hPa, 1000hPa pressure levels, air temperature at surface, 2m height, 500hPa, 850hPa, 1000hPa pressure levels, surface skin temperature, surface pressure, mean sea level pressure, volumetric soil moisture content in the 0-10cm soil layer and 10-200cm soil layer. In this study the above 23 probable predictors were considered to be common for all calendar months of the year, for the streamflow station considered. These probable predictors were selected from the NCEP/NCAR reanalysis data pool. The NCEP/NCAR reanalysis data pool is widely used for the calibration and validation of downscaling models for variety of predictands. Potential predictor variables are a subset of probable variables which vary form streamflow station to station as well as from season to season. The set of potential predictors is the most influential variable set on streamflows, which is a subset of the probable predictor pool. In the current exercise, the Pearson correlation coefficient was used to identify the potential variables for each calendar month. The records of streamflow and NCEP/NCAR probable predictors from 1950 to 2010 were considered under three 20 year time

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slices 1950-1969, 1970-1989 and 1990-2010. The probable variables which displayed the best, statistically significant (95 % confidence level, p = 0.05) correlation with the streamflow, consistently over the three 20 year time slices were selected as potential variables. From the same probable predictor pool, potential predictors for each calendar month were extracted.

D. Downscaling Model Calibration and Validation

The LS-SVM-R model considered in the present study had two tuning parameters γ and σ where γ is the regularisation parameter and σ is the width of the RBF kernel. In this study the LS-SVM-R downscaling model was calibrated for the 40 year period 1950-1989 and validated for the 21 year period 1990-2010. Before the calibration and validation of the downscaling model, the potential predictors used as inputs to the model were standardised. The standardisation of NCEP/NCAR predictors scales down the data and eliminates the units of the variables. For the model calibration, the NCEP/NCAR potential predictors selected for each month were standardised by subtracting the mean and dividing by the standard deviation corresponding to the calibration period 1950-1989. Also in validation, the potential predictors were standardised using the same mean and standard deviation corresponding to the calibration period. In model calibration these standardised potential variables were introduced to the LS-SVM-R model in such way that, initially the three best correlated variables and then the other best correlated variables one by one. The model calibration was performed using the leave-one-out cross validation method and the model parameter optimisation was based on the simplex algorithm. The model validation was done as an independent simulation fixing the optimum values of the tuning parameters, yielded in calibration. The model which displayed the highest performance in validation was considered as the optimum model. By this way the optimum number of inputs to the model was determined. The same calibration and validation process was repeated for each calendar month. Fig. 5 shows the variation of observed monthly flow and LS-SVM-R downscaling model predicted monthly flow for the calibration (1950-1989) and validation (1990-2010) phases. The predictions of the calendar month based models were aggregated to produce a continuous time series of streamflow from 1950-2010. In the model calibration the values of γ and σ varied significantly over the 12 months of the calendar (γ range 7.5-998 and σ range 1.95-99.5). The model displayed overall N-S coefficients of 0.73 and 0.47 in calibration and validation respectively. These overall N-S efficiencies for the calibration and validation, were a bit higher than the seasonal N-S efficiencies shown in Table 1. This occurs when there is a significant difference between the seasonal average streamflows and the overall average of the streamflow time series. To overcome this issue, associated with the traditional N-S efficiency, the seasonally adjusted N-S had been introduced [34]. There, the individual seasonal average streamflow values are considered in calculating the overall N-S efficiency, rather than the overall average of the streamflow. The seasonally adjusted N-S efficiencies for the calibration and validation of the present study were 0.58 and 0.27, respectively.

Fig. 6 shows the scatter plots corresponding to the calibration and validation phase. According to these scatter plots, it was clear that in calibration, the model had a tendency of under-predicting peak flows and in validation tended to over-predict flows. Further, both in calibration and validation zero flows were largely over-predicted by the model. The over-prediction of flow was very evident after 1997, during validation phase which is depicted in Fig. 5.

As given in Table I, performances of the model had a clear seasonal variation. In this table, summer, autumn, winter and spring are defined as periods December-February, March-May, June-August and September-November respectively. Among the four seasons summer and winter had the best N-S coefficient in the validation periods. Meanwhile autumn had the poorest prediction accuracy which was denoted by an N-S efficiency of -2.46. In the seasons of autumn and spring the model performed far better in calibration than in validation.

TABLE I
N-S COEFFICIENTS IN SEASONS

Season	Calibration	Validation
Summer	0.55	0.39
Autumn	0.45	-2.46
Winter	0.56	0.38
Spring	0.62	0.16

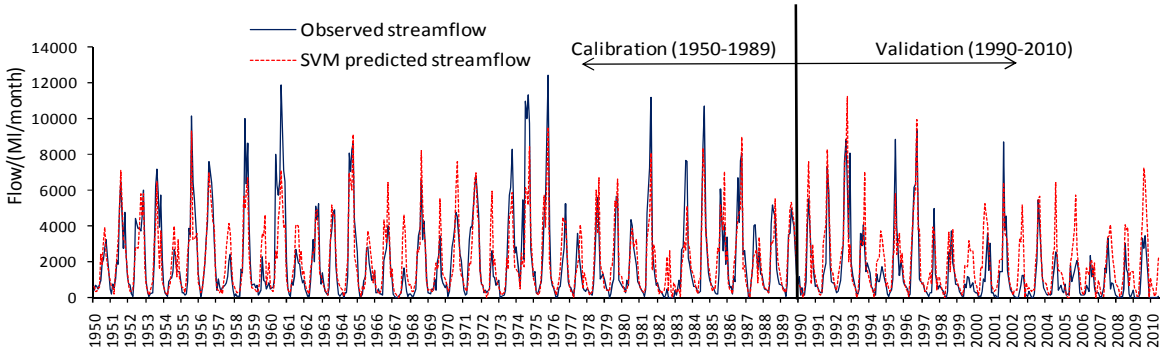


Fig 5 Observed streamflow and SVM predicted streamflow

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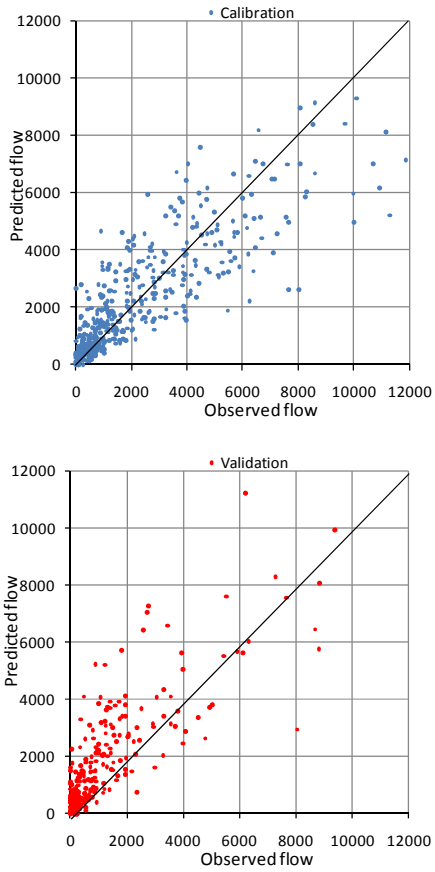


Fig. 6 Scatter plots for calibration and validation of the model

E. Discussion on statistical downscaling

The use of volumetric soil moisture content in the 0-10 cm soil layer and 10-200 cm soil layer for predicting streamflows had not been observed in any of the past studies performed on downscaling GCM outputs to catchment level streamflows. The variations in soil moisture content are highly associated with the atmospheric variability therefore the inclusion of soil moisture in a model could improve the climatic predictions. Further, the soil moisture governs the amount of water retained in soil influencing the rainfall and runoff relationship, and hence streamflows.

The limited forecasting ability of the downscaling model in autumn in the current study was mainly because the catchments in Victoria are usually at a dry state during the period leading to autumn, and during autumn, catchments "wet up" as seasonal rains commence., but this water makes little or at least a variable contribution to streamflow this early in the inflow season.

The over prediction of peak streamflows after 1997 by the model was an evident phenomenon. When the time series plots of the NCEP/NCAR predictors were observed, an obvious change corresponding to this period was not seen. This suggested that the poor performance of the model after 1997 was due to the missing climate change signal corresponding with the drought period in the NCEP/NCAR predictors. The streamflows also displayed poor correlations with the SOI index (El Niño Southern oscillation index) and NINO 3.4 index. Future work will continue the search for possible climate change signals.

The downscaling model developed in the current study showed reasonable capability in predicting the streamflows in summer and winter although it seemed to be less successful in autumn. Downscaling streamflows from the GCMs skips complex hydrologic modeling, saves time and effort in predicting streamflows. In the present investigation, NCEP/NCAR reanalysis data were used for the model calibration and validation meanwhile the future streamflow prediction will be done with the HadCAM3 GCM outputs.

VI. System Optimisation

A. Supply System 6 of the Wimmera-Mallee Pipeline

Before optimisation can begin, it is necessary to develop a common understanding of the problem, of the decisions that have to be made, and of the criteria by which such decisions are measured or evaluated against [35]. Given the complexity of the Grampians water supply system the current work is described in terms of that part of the system that supplies a southwest area of the Wimmera-Mallee Pipeline known as Supply System 6 (SS6) – refer Figs. 2 and 7.

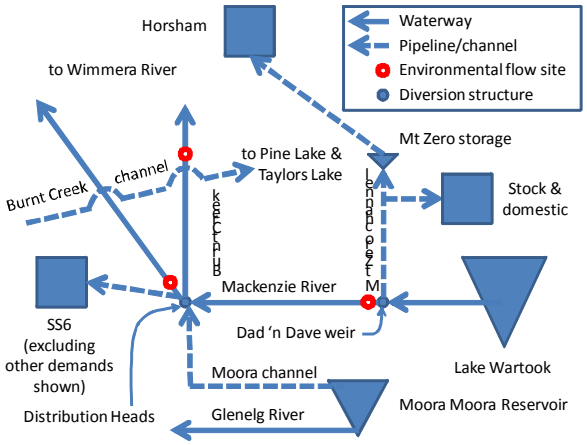


Fig. 7 Schematic representation of Supply System 6 (SS6)

SS6 features two major river systems, namely the Glenelg River and the MacKenzie River and their respective storages Moora Moora Reservoir and Lake Wartook. These storages control the harvest and release of water from the upper reaches of these rivers, and are operated conjunctively to meet the needs of SS6 of the Wimmera Mallee Pipeline. Moora Moora Reservoir is located at the headwaters of the Glenelg River and is used to divert water north-ward across the Great Dividing Range. It is operated as the primary source of supply to SS6 via the Distribution Heads regulating structure situated on the MacKenzie River and its junction with its distributary Burnt Creek.

Lake Wartook was built in 1890 at the headwaters of the MacKenzie River and is the oldest and the highest storage in

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the system [36]. Although it has a spillway, uncontrolled flows downstream are inconvenient and are managed by maintaining a flood reserve volume. The storage was built to provide a reliable supply to the township of Horsham and rural domestic and stock via the Dad 'n' Dave weir and Mt Zero channel (Fig. 7). The system operator, GWMWater, plans to use Lake Wartook as the primary source of supply to Horsham and as a secondary source to SS6. Lake Wartook is also renowned as a popular tourist destination given its location in the Grampians National Park. Whilst data published by Tourism Victoria for 2007-08 shows that the Grampians is one of the least tourism reliant regions in Victoria, the importance of the $115 million local tourism industry can be considerable to the local economy [37].

Environmental flow requirements are specified in the MacKenzie River at Dad 'n' Dave weir and Distribution Heads, and in Burnt Creek at the Burnt Creek channel. The three reaches each have their own water requirements and their relative priorities vary both spatially and temporally. In order of storage operator preference, these environmental demands are satisfied using run-of-river flows that naturally occur overland, followed by regulated releases from Lake Wartook. The composition of these water requirements is based on daily flow recommendations undertaken as part of scientific studies which aim to restore the waterway ecology to near-natural conditions. The most recent state-wide assessments of Victorian streams [38] rates the environmental condition of streams within the study area on a scale from *very poor* to *excellent* over the period 1999 to 2004. This assessment shows that the environmental condition of MacKenzie River upstream of Dad 'n' Dave weir is *moderate* whilst immediately downstream of this point the condition is *very poor* up to Distribution Heads. With the increased overland flow in the lower reach, the environmental condition of the river slightly improves to a status of *poor* downstream of Distribution Heads. Burnt Creek is rated as *poor* for the entire reach from Distribution Heads to its confluence with the Wimmera River. The reason for such low ratings is attributed to the diversions for stock and domestic use which has significantly altered streamflows particularly over the summer period.

B. Formulation of multi-objective problem

The approach used to formulate the multi-objective problem for SS6 is summarised below in four sequential steps:

1) A clear statement of stakeholders' interest to water that form the basis of a multi-objective problem;
2) Identification of decision variables in the simulation model that control the operation of the system;
3) An agreed set of objective functions that are used to guide the search and quantify the performance of each combination of decision variables. It is recommended that the functions be based on step (1) above to ensure all stakeholders' interests are explicitly taken into account; and
4) The inclusion of real-world limits or constraints such as the capacity of storages, channels and pipes.

Whilst stakeholders' interests to water will be specific for any given water supply system, in general they can be classified into any one or a combination of social, economic, and environmental interests, which is often referred to in business parlance as the 'triple-bottom line.' For SS6, work is underway to determine the optimal operating rules that satisfy three conflicting objectives: (1) a social interest which aims to maintain a given volume held in Lake Wartook for recreation purposes, (2) an economic interest which aims to minimise the shortfall in supply to consumptive users, and (3) an environmental interest which aims to minimise the shortfall in meeting environmental flow requirements.

Each REALM simulation will feature a unique set of operating rules which describe different areas of reservoir operation viz. storage targets, storage releases, passing flows and harvesting rules. Thus, each facet of reservoir operation is specified in terms of an input or a 'decision variable' which is used by the optimisation search engine to find optimal operating rules.

In REALM, storage targets are used to describe the broad operation of the system in terms of the sharing of the available resource amongst the various storages at any given month of the year. In addition to their individual target curves, the relative drawdown priority of each storage is also specified so that under a situation of limited resource, water is sourced from the preferred storage. Currently in the REALM model, Moora Moora Reservoir is the first to be drawn down under situations when a choice exists between it and Lake Wartook for supply to SS6, and Lake Wartook is first to be drawn down relative to Mt Zero storage for supply to Horsham. Moreover Lake Wartook is operated to provide some degree of flood attenuation, whilst at the same time ensuring a very good chance of filling over the winter/spring period. Over the long term, a flood reserve volume that is too large may affect the reliability of supply to users downstream, and a reserve volume that is too small may cause the storage to overflow more often and result in more water being lost (in an operational sense) from the system. Environmental water requirements are configured in the REALM simulation model as either explicit environmental demands or passing flows which are firstly satisfied by unregulated river flows and where shortfalls occur, regulated releases from upstream storages [39]. For SS6, the environmental water requirements are configured as explicit demands and are already specified in the setup of the REALM simulation model. As Lake Wartook is an on-stream storage and has the ability to capture all inflows up to the capacity of the storage, a harvesting rule is not required to control the flow rate of water into the storage. Instead, storage targets and a release rule are used in the REALM model to regulate water and to provide a flood reserve volume. Whilst Moora Moora Reservoir is an off-stream storage, it too is operated from the storage outlet [36] and is controlled within the REALM model through storage targets

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In order to determine which combination of these complex rules best meets the specified objectives, each set of operating rules will be modified by the evolutionary processes of selection, crossover, and mutation in preparation for each simulation run. Hence each simulation run will feature a different combination of operating rules which will have a direct effect on the system's performance over the long-term. This effect will be measured by way of the fitness values associated with each candidate solution to assess how well each combination of rules satisfies the stated objective functions.

C. Discussion of system optimisation

Unlike single-objective optimisation problems that have a unique optimal solution, multi-objective problems have a suite of optimal solutions which form a Pareto front. This highlights the importance of on-going stakeholder participation in providing higher level qualitative information as part of both; the problem formulation process and also the optimisation process to enable decision makers to make the necessary trade-offs between choosing one optimal solution over another [18]. Importantly, the procedure for formulation of multi-objective problems will be validated by way of application to the remaining Supply Systems of the Wimmera-Mallee Pipeline. This testing may lead to further refinements of the procedure in light of particular aspects that are not present within the study area. Once the formulation of the multi-objective problem is complete, the intention is to undertake a simulation-based optimisation process to solve a problem concerning the entire Grampians water supply system.

VII. Conclusion

Many water supply systems in Australia are currently undergoing significant reconfiguration due to reductions in average rainfall and resulting low inflows to water supply reservoirs since the second half of the 20th century. Reconfigured water supply systems require new operating rules, since there is limited operator experience to determine their optimum operation. This paper described a methodology that is currently being used by the authors to determine optimum operating rules for complex multi-reservoir systems which are undergoing significant changes, both in configuration and overall water balance. The methods will account for both climate change and variability. They will also evaluate a range of social, economic, environmental and sustainability objectives, and stakeholder preferences about them. The methodology addresses these issues considering a case study of the Grampians water supply system in north-western Victoria, Australia, which is undergoing significant change upon the completion of the Wimmera Mallee Pipeline and off-lining of some currently operational storages. Optimum operating rules that will be derived will enable planners to manage water supply systems efficiently and effectively under a range of short and long term planning conditions, and in drought conditions, while reducing associated environmental impacts and improving sustainability. Results will also demonstrate the impact of climate change on rainfall, streamflow, water demand and system yield, and establish the future vulnerability of water systems.

Currently, work for this project is progressing on two fronts: (1) downscaling GCM outputs to catchment level hydroclimatic variables, particularly focusing on direct downscaling GCM outputs to streamflows, and (2) development of a generalised procedure for the formulation of the multi-objective optimisation problem for operation of water supply systems.

For downscaling work, the current work is concentrated on developing a model that is capable of statistically downscaling monthly GCM outputs to catchment scale monthly streamflows, accounting for any climate change. Support Vector Machine (SVM), a statistical downscaling technique, is used in the current streamflow downscaling exercise. So far, only one streamflow site in the case study area is considered, and only the calibration and validation of the SVM model is tested. It was clear from the results that in calibration, the model had a tendency of under predicting peak flows and in validation it had a tendency to over predict peak flow. Further, both in calibration and validation, zero flows were largely over-predicted by the model. The over-prediction of flow was very evident after 1997 which coincides with the commencement of a long period of drought in Victoria (note that the validation period considered was 1990-2010). Future work will continue the hunt for possible climate change signals to improve the downscaling model.

The second part of the initial work is to develop a generalised procedure for the formulation of multi-objective optimisation problems relating to planning and operation of multi-reservoir systems with complex operating rules. Importantly the procedure is developed for problems that are intended to be solved using simulation-based optimisation techniques. As for current work, the procedure is used to formulate a sample multi-objective problem for the optimisation of operation of part of the Grampians water supply system. The procedure is applied in case study form, detailing the various components of the problem, both in mathematical terms and also the necessary qualitative information derived from stakeholder participation. The procedure is objective and results are promising. As a validation of the procedure, the formulation of multi-objective problem will be extended to the remaining parts of the water supply system. Once the formulation of the multi-objective problem is complete, a simulation-based optimisation process will be used to determine the optimum operating rules.

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