

# Forecasts of Seasonal Irrigation Allocations in the Goulburn Catchment, Victoria

Rebgetz, M.D.<sup>1</sup>, F.H.S. Chiew<sup>2</sup> and H.M. Malano<sup>1</sup>

<sup>1</sup> Department of Civil and Environmental Engineering, The University of Melbourne, Victoria

<sup>2</sup> CSIRO Land and Water, GPO Box 1666, Canberra, ACT 2601, Australia

Email: m.rebgetz@pgrad.unimelb.edu.au

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## EXTENDED ABSTRACT

There is a very high interannual variability in streamflows, and hence irrigation allocations, across much of Australia. Irrigation allocation forecasts, particularly in the form of continuous exceedence probabilities, may thus assist irrigators in qualifying the climatic risk they take in their decision making. The exceedence probability is the probability that the actual outcome will equal or exceed a specified outcome during a given time period (Piechota et al. 2001).

This paper compares the results obtained from five different approaches to obtaining continuous exceedence probability forecasts of the irrigation allocation at the end of the irrigation season (May) for gravity irrigators in the Goulburn catchment of northern Victoria. These forecasts were obtained at the start of the irrigation season (August). Irrigation allocations in the Goulburn catchment are primarily dependent upon the volume of water in the various reservoirs at the beginning of the season, and the inflows to the reservoirs during the season.

The first approach (DF) was to use the reservoir levels at the beginning of the irrigation season, as well as a climatic indicator, to directly obtain a forecast of the final irrigation allocation. The second approach (ISF) was to forecast the individual inflows, based on antecedent inflows and a climatic indicator, and then use a hydrological simulation model to obtain the irrigation allocations based on these forecast inflows and the actual reservoir levels at the beginning of the irrigation season. The third approach (ICS) was the same as the second, except that climatological values of the inflows were used. The fourth approach (TSF) was to forecast the total inflow to the system, then disaggregate this into the individual inflows according to the typical distribution, and then use the hydrological model to obtain the forecasts of irrigation allocations based on these forecast inflows and the actual reservoir levels at the beginning of the

irrigation season. The fifth approach (TCS) was the same as the fourth except that the total climatological inflow was used.

It was found that using an El Niño / Southern Oscillation (ENSO) indicator as well as the initial reservoir levels as predictors did not improve the skill of direct forecasts (DF). However, using ENSO indicators as predictors did improve the skill of the inflow forecasts. For most inflows, the use of the Darwin mean sea level pressure anomaly, along with antecedent flow, was found to give the highest skill, as measured using the Nash-Sutcliffe coefficient of efficiency (E) and the modified Linear Error in Probability Space (LEPS). The correlation between the various inflows and ENSO indicators was not significantly improved by the addition of indices of the Pacific Decadal Oscillation, The Quasi-Biennial Oscillation, or the Southern Annular Mode.

The skill level of the irrigation allocation forecasts was measured using E and the Ranked Probability Skill Score (RPSS). The irrigation allocations obtained using all five forecasting approaches were found to give significantly better skill than climatological irrigation allocations.

Although the DF approach gave the highest E and RPSS skill level, this method was unsatisfactory at low risk levels, as the forecasts were often less than the allocations that would actually be obtained even if there was no streamflow in the coming season.

Irrigation allocation forecasts obtained using streamflow forecasts (ISF and TSF approaches) showed higher skill than those obtained using climatological streamflows (ICS and TCS approaches). There was little difference in skill between irrigation allocation forecasts obtained using individual streamflow forecasts (ISF), and those obtained from disaggregating forecasts of the total inflow (TSF).

## 1. INTRODUCTION

The Goulburn catchment is the largest irrigation district in Victoria, in terms of both the area of land irrigated and the volume of irrigation water applied. Although irrigators have a legally defined entitlement to irrigation water, their actual allocation can be highly variable from year to year. Goulburn-Murray Water provides a probability that the allocation will reach a certain level, based on the probability that the inflows will be sufficient to satisfy that allocation. However forecasts of the actual allocations are currently not available. Forecasts in the form of continuous exceedence probabilities would allow irrigators to take a known risk in their decisions relating to water availability for the forthcoming irrigation season.

### 1.1. Irrigation allocations

Irrigation water in the Goulburn region is available from the 15<sup>th</sup> of August through to the 15<sup>th</sup> of May the following year (i.e. Spring – Autumn). Irrigation water is allocated in two parts, generally referred to as water rights and sales water. Up to 100% of an irrigator's water entitlement can be allocated as water rights. When determining the allocation of water rights it is assumed that there will be no inflows for the remainder of the irrigation season. Water rights are thus based only on the volume of water currently in the reservoirs, taking into account set losses, and water that will be available from recession baseflows. If there is additional water available after 100% of water rights have been allocated, then this water is put towards the following year's allocation of water rights. When 100% of water rights have been allocated for the following year (allowing for inflows with a 99% probability of exceedence (p.o.e.)) then further water, known as "sales" water, is allocated for the current year. Currently sales water of up to 100% of water entitlement may be allocated. The water right and sales water percentages are usually added together to give the allocation as a single figure of up to 200% of a farmer's water entitlement.

In general, irrigation allocations thus depend upon both the initial reservoir levels, and the inflows over the forthcoming season. However forecasts of irrigation allocations will be independent of inflows if the volume of water in the reservoirs at the beginning of the irrigation season is such that:

- it is already nearly sufficient to provide 200% of irrigation allocations, in which case the irrigation allocation is already at a maximum, or

- it is just sufficient to provide 100% of irrigation allocations, in which case, unless the inflow is unusually high, any inflow will go towards meeting the next year's water rights, and the allocation for the current year will remain at 100%.

A complex interconnection of channels and reservoirs in north-western Victoria enables water from the Goulburn River to also be used to supplement irrigation water supplies in both the Campaspe and Loddon catchments, as shown in Figure 1. Thus, while irrigation allocations are given separately for irrigators in each of the Goulburn, Broken, Campaspe and Loddon systems, these are not independent of each other.

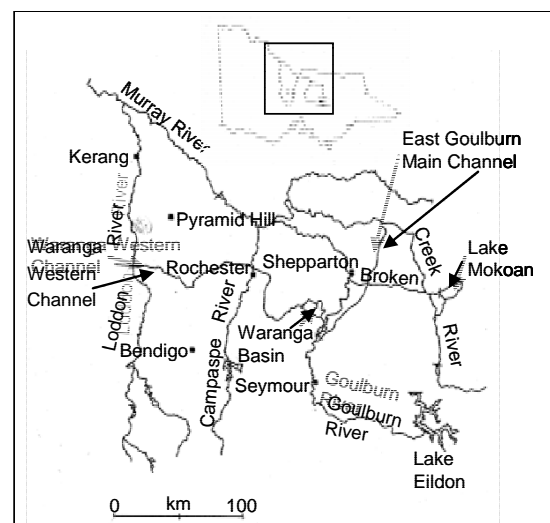


Figure 1. Goulburn-Murray Catchment

### 1.2. Factors influencing hydroclimate

The El Niño/ Southern Oscillation (ENSO) is probably the most significant of the phenomena affecting seasonal hydroclimate in northern Victoria. The influence of ENSO on seasonal precipitation and streamflow patterns across eastern Australia is well documented (e.g. Chiew and McMahon (2003)). The ENSO-streamflow teleconnection is generally stronger than the ENSO – rainfall teleconnection. This is probably because, while precipitation is often highly variable over a catchment, streamflow in effect spatially integrates the precipitation, resulting in a less variable quantity (Chiew and McMahon 2003).

A number of different indices can be used to define the phase and strength of ENSO events. The Southern Oscillation Index (SOI), the Multivariate ENSO Index (MEI), and Pacific sea surface temperatures (SSTs) are the most common of these. Of the SST data sets available, the NINO3

(Latitude 5°N - 5°S, Longitude 150° - 90°W) and the NINO3.4 (Latitude 5°N - 5°S, Longitude 170° - 120°W) regions are most commonly used for forecasting seasonal hydroclimatic variables across eastern Australia. It is also possible to use the mean sea level atmospheric pressure for a single location such as Darwin (DMSLP) as an ENSO indicator.

Other factors that affect Victoria's seasonal hydroclimate over the spring-autumn period, independently and/or by modulating the effects of ENSO, include the Pacific Decadal Oscillation (PDO) / Interdecadal Pacific Oscillation (IPO) (e.g. Verdon et al. (2005)), the Quasi-Biennial Oscillation, (e.g. Kiem (2003)), and the Southern Annular Mode (SAM) (e.g. Carleton (2003)).

While it is not actually a determinant of hydroclimate, there is also a strong serial correlation in streamflow for many Australian rivers (e.g. Chiew and McMahon (2003)). For short lags, this is generally as strong as, and often stronger than, the ENSO teleconnection. However at longer lags, when the temporary runoff storages have emptied, this serial correlation no longer exists (Chiew and McMahon 2003).

## 2. METHOD

In this research, five different approaches are taken to obtain forecasts of the irrigation allocations at the end of the irrigation season. The first (DF) uses the reservoir levels at the beginning of the irrigation season, as well as a climate indicator, to directly obtain a forecast of the final irrigation allocation. The second approach (ISF) is to forecast the individual inflows, based on antecedent inflows and a climate indicator, and then use a hydrological model to obtain the forecasts of irrigation allocations based on these values and the actual reservoir levels at the beginning of the irrigation season. The third approach (ICS) is the same as the second, except that climatological values of inflows are used in the hydrological model. The value relating to the  $x\%$  p.o.e. is taken to be that corresponding to the  $(100-x)\%$  percentile of the historical data set. The fourth approach (TSF) is to forecast the total inflow to the system, then disaggregate this into the individual inflows according to the typical distribution, and then use the hydrological model to obtain the forecasts of irrigation allocations based on these values and the actual reservoir levels at the beginning of the irrigation season. The fifth approach (TCS) is the same as the fourth except that the total climatological inflow is used.

The hydrological model used to determine the irrigation allocations from given streamflow forecasts was the Goulburn Simulation Model (GSM). The GSM is a monthly model of the water distribution system of the Goulburn-Broken, Campaspe and Loddon catchments using the REsource ALlocation Model (REALM) (Department of Sustainability and Environment (Victoria) 2003). The inputs required for the calibration used here (system file GOULA749.SYS) are rainfall totals for six stations, evaporation totals for seven stations, twenty-eight inflows (two of which are repeating annual series and hence are not forecast), and unrestricted water demand data for sixty-two nodes (sixteen of which are repeating annual series and hence are not forecast) (Department of Sustainability and Environment (Victoria) 2003). The rainfall and evaporation data are primarily used to calculate the water balance in the reservoir.

Two different methods were used for calculating the water demands. Major irrigation demands were calculated using the Program for Regional Irrigation Demand Estimation (PRIDE) (Hydro Technology 1995), using forecast evaporation and rainfall data. Climatological percentiles were used for the remainder of the demands, with the  $x\%$  p.o.e. taken to be that corresponding to the  $x\%$  percentile of the historical demand data.

The Non-parametric Seasonal Forecast Model (NSFM) (Chiew and Siriwardena 2005) was used to obtain continuous exceedence probability forecasts. The NSFM uses two predictors, antecedent conditions and/or a climate indicator, to give a continuous relationship between the predictand and predictor(s). Linear discriminant analysis is used to empirically fit the historical data, and a kernel function to calculate the probability density function. In the NSFM the value of each predictor can be considered for two, three or four months of data, but the last month must be the same for both predictors.

The two measures used in the NSFM to assess the skill of the exceedence probability forecasts are the Nash-Sutcliffe coefficient of efficiency,  $E$ , and the modified linear error in probability space (LEPS) score. The  $E$  value assesses the goodness of the mean prediction, while the modified LEPS is a measure of the goodness of exceedence probability forecasts compared with the measured values. A model is generally considered to have some / good forecasting skill if the  $E$  value is greater than 0.1, and the LEPS value is greater than 10% (Chiew and Siriwardena 2005). In this research, the skill values were only considered for the cross-verification mode, whereby each year of data is

left out in turn, and the model is developed using the remaining data (Chiew and Siriwardena 2005).

E and the Ranked Probability Skill Score (RPSS) are used to assess the goodness of the irrigation allocation forecasts. The RPSS is a simpler measure of the spread of the probability distribution than the LEPS score, and is suitable for categories with different widths. As the RPSS is sensitive to the number and choice of categories it is not possible to say that a particular RPSS value indicates “good” skill.

The historical inflow, rainfall, evaporation and demand data used to obtain the irrigation allocation forecasts was that supplied with the GSM. These records extend from the 1891-92 season through to the 2001-2002 irrigation season, giving 111 years of data. When obtaining the various forecasts, the year for which the forecast was to be obtained was not included in the calibration.

The volume of water in the reservoirs at the start of the season was taken from annual GSM runs of the preceding years. “Historical” values of the irrigation allocations, used for comparison purposes, were obtained from runs of the GSM using historical data.

SOI values, which date from 1876, were obtained from the Australian Bureau of Meteorology (<http://www.bom.gov.au/climate/current/soihtml1.shtml>). MEI values, which date from 1950, were obtained from the Earth System Research Laboratory of the National Oceanic and Atmospheric Administration (<http://www.cdc.noaa.gov/people/klaus.wolter/MEI/table.html>). The various SST values, which also date from 1950, were obtained from the National Weather Service Climate Prediction Centre of the National Oceanic and Atmospheric Administration (<http://www.cpc.ncep.noaa.gov/data/indices/>). DMSLP data, dating from 1892, was obtained from the National Weather Service Climate Prediction Centre (<http://www.cpc.ncep.noaa.gov/data/indices/>). The anomalies were calculated using 1892-2005 as the base period. The PDO data, dating from 1902, was obtained from the Joint Institute for the Study of the Atmosphere and Ocean (<http://jisao.washington.edu/pdo/PDO.latest>). The QBO data, dating from 1953, was obtained from the Institute of Meteorology of the Free University Berlin (<http://strat-www.met.fu-berlin.de/products/cdrom/html/data.html>) for a pressure height of 30 hPa. The SAM data, dating from 1957, was obtained from the British Antarctic Survey data sets ([\[bas.ac.uk/icd/gjma/sam.html\]\(http://bas.ac.uk/icd/gjma/sam.html\)\). A monthly base period was used for all climatic data.](http://www.nerc-</a></p></div><div data-bbox=)

### 3. FORECASTS

#### 3.1. Rainfall and evaporation

Forecasts of rainfall and evaporation totals for the Goulburn catchment up to ten months in advance did not show significant skill for any predictor and lag combinations considered. Climatological percentiles of rainfall and evaporation, obtained from the entire historical data set, were thus used where required. For rainfall, the value relating to the  $x\%$  p.o.e. was taken to be that corresponding to the  $(100-x)\%$  percentile. For evaporation the best case corresponds to the lowest value, so the  $x\%$  p.o.e. was taken to be that corresponding to the  $x\%$  percentile.

#### 3.2. Individual inflows

The seasonal influence of the PDO, QBO and SAM, over and above the influence of ENSO, was determined for the August-May totals for each of the inflows. This was undertaken by comparing the correlation coefficient calculated for the linear regression of the historical inflows with an ENSO indicator, with the coefficient for multiple linear regression calculated for the historical flow with the same ENSO indicator and a non-ENSO indicator. The Southern Oscillation Index (SOI) and the DMSLPa (Darwin Mean Sea Level Pressure anomaly) were used as ENSO predictors. The ENSO and non-ENSO predictor were considered for a range of lags, and averaged over two, three and four months.

For the twenty-six inflows considered, the  $r^2$  values for the ENSO indicator ranged from 0.1 to 0.32, with most being around 0.25. For the same time periods, including a non-ENSO indicator only increased  $r^2$  values by an average of 0.01, with a range of 0 – 0.04. It is thus apparent that, for the inflows considered, there is a teleconnection between streamflow and ENSO, but incorporating the non-ENSO climate indicators did not significantly improve the correlation.

The combination of ENSO index and antecedent flow predictor types resulting in the highest overall cross-verification skill levels was determined for each inflow for the August-May period. The GSM requires monthly flows, but most monthly forecasts obtained at the beginning of the irrigation season did not have a reasonable skill level. As forecasts of the inflow during the entire irrigation season had an acceptable skill level, these were disaggregated into monthly totals for input to the

GSM. The historical data was divided into nine categories, for low, medium and high ranges of both the antecedent flow and the ENSO category. For each forecast of seasonal inflow, the monthly distribution was determined according to the average percentage distribution for the category to which the antecedent conditions belonged.

For the twenty-six inflows considered, the predictor combinations resulting in the highest overall forecasting skill for the August-May period are given in

Table 1.

**Table 1.** Summary of predictor combinations giving highest forecasting skill for various inflows.

Predictors giving highest skill	DMSLPa and antecedent flow			DMSLPa	SOI and antecedent flow			MEI and antecedent flow		NINO3-4 and antecedent flow	NINO3 and antecedent flow
	June -July	May -July	April -July	June-July	May -July	June -July	April-July	May-June	May-July	May-July	May-July
ENSO prediction period giving highest skill											
No. of inflows	13	1	1	1 <sup>1</sup>	4	1	1	1	1	1	1 <sup>2</sup>
	15				6			2			
Skill	E: 0.18 - 0.43 LEPS: 20 - 30			E: 0.12 LEPS: 11	E: 0.27 - 0.34 LEPS: 17 - 28			E: 0.24 - 0.29 LEPS: 16 - 22		E: 0.26 LEPS: 20	E: 0.54 LEPS: 37
<b>Inflow prediction period giving highest skill</b>				<b>May-July</b>	<b>June-July</b>			<b>April-July</b>			
<b>No. of inflows</b>				15	6			4			

1. This was for an ephemeral stream, so it is unsurprising that antecedent flow was not a predictor, and that the resulting skill was much lower than for any other inflow.

2. However for most other inflows, NINO3-4 gave a better correlation than NINO3.

As the SSTs and MEI are not available prior to 1950, for the purposes of comparing historical irrigation allocations with forecast values it was necessary to use the SOI or DMSLPa to obtain the forecast inflows. For the four cases for which SSTs or the MEI gave the best forecasts, the DMSLPa was found to give a better forecast than the SOI.

When comparing the historical inflows with the forecast inflows, it was found that, for twenty-three inflows, over 50% of the forecasts (up to 63%) were less than the 50% p.o.e.; for twenty-three inflows, over 10% of the forecasts (up to 20%) were less than the 90% p.o.e.; and for twenty-three inflows, over 1% of the forecasts (up to 8%) were less than the 99% p.o.e. The forecasts of individual inflows clearly have significant skill, but are biased towards higher than observed values at high exceedence probabilities.

The cross-correlation between the individual flows and the total flow should be similar for the historical and forecast flows. The average historical  $r^2$  correlation is 0.72, with a maximum of 0.93 and a minimum of 0.43. The smallest difference in  $r^2$  between the historical and forecast cross-correlations was only 0.03, while the largest was 0.46, with an average difference of 0.15. For fourteen of the twenty-six streamflows, there was a significant difference between the cross-correlations for the historical and forecast cases at a 0.05 confidence level. This places some question around the validity of some of these forecasts.

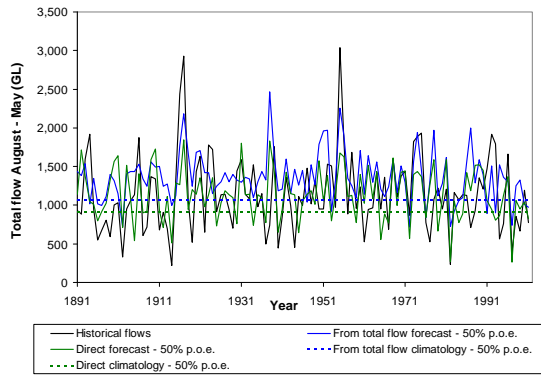
However disaggregating the total inflow into individual flows will also be of questionable validity, as this will overestimate the correlation between the various inflows.

### 3.3. Total inflows

The DMSLPa and antecedent flow for May – July was found to give the best skill in forecasting the total inflow to the GSM for the August-May period. This gave an E score of 0.29, and a LEPS of 22. The total flow was disaggregated into individual monthly inflows according to the average value for the preceding conditions, using lower, middle and upper thirds for each of the DMSLPa and total antecedent inflow.

### 3.4. Comparison of inflows obtained using different methodologies

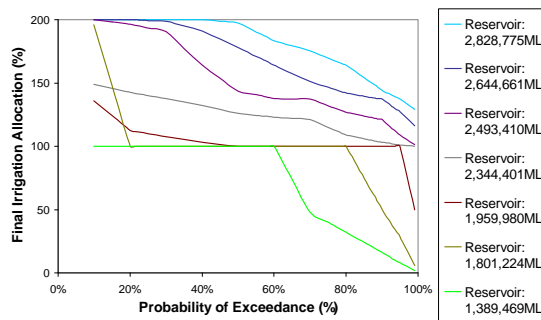
The forecast inflows generally replicate the basic pattern of the historical data moderately well, as can be seen in Figure 2 for Eildon inflow, although the actual values are not well predicted. The forecasts obtained from disaggregating the total inflow are generally significantly higher than those obtained by forecasting the inflows individually. The climatological values obtained from the total inflow are also generally greater than those obtained from the individual inflows, except at low p.o.e.s. At high p.o.e.s the climatological values are much more conservative than forecast values, but the opposite is true at low exceedence values.



**Figure 2.** Forecasts of Eildon inflow obtained using different methods, for 50% p.o.e.

### 3.5. Direct forecasts of irrigation allocations (DF)

A variety of combinations of reservoirs, as well as ENSO indicators, prediction periods and lags were investigated to determine the combination giving the forecast with the highest skill level. Compared with the skill resulting from using only the initial reservoir levels, the inclusion of ENSO predictors often decreased the skill of the forecasts, and never increased it by more than 2%. The best forecasts were obtained using the total volume of water in the Eildon Reservoir and Waranga Basin at the end of July as the only predictor. They gave cross-verification E and LEPS scores of 0.85 and 72% respectively. These results, which do not incorporate any indicator of the hydroclimatology for the coming year, show the influence of initial reservoir levels in determining irrigation allocations for the coming season. Example probabilities of exceedence for a range of reservoir levels are shown in Figure 3.

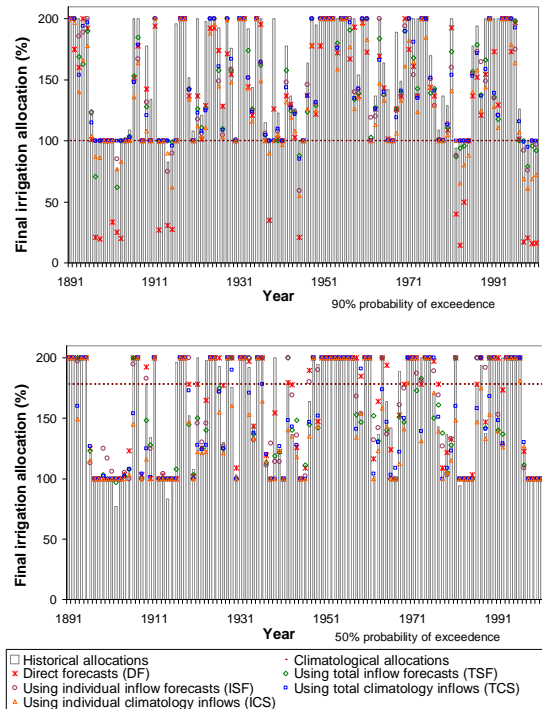


**Figure 3.** Probabilities of exceedence using direct forecasting, for a range of reservoir levels.

## 4. COMPARISON OF IRRIGATION ALLOCATION FORECASTS

The forecasts of irrigation allocations obtained using the five different approaches are compared

graphically in Figure 4 for 90% and 50% p.o.e. In a number of years, and for several exceedence probabilities, the irrigation allocations determined from streamflow forecasts using the ISF, TSF and TCS approaches actually decreased with decreasing p.o.e. This was due to the rainfall, evaporation and demand increasing disproportionately with the streamflow at successive p.o.e.s.



**Figure 4.** Irrigation allocation forecasts obtained by various approaches for 90% and 50% p.o.e..

The E skill score (calculated for the 50 percentile forecast) and the RPSS (calculated using the climatological irrigation allocations as the reference) for the various forecasting approaches are given in Table 2. These measures clearly indicate that all five forecasting methods are superior to climatological values of the irrigation allocations.

**Table 2.** Skill of irrigation allocation forecasts.

	DF	ISF	ICS	TSF	TCS
E	0.82	0.74	0.59	0.71	0.65
RPSS	0.36	0.30	0.31	0.33	0.24

Based on E and RPSS scores, the direct forecasts (DF) appear to have the highest level of skill. However, in almost all years, direct forecasts gave the lowest forecasts at 99% p.o.e. In many years these were less than the allocation that would have resulted even if there had been no inflow in the

coming season. This was because the reservoir levels were treated as a predictor, not as a given. Irrigation allocation forecasts obtained using inflow forecasts entered into the GSM did not suffer from this problem. This shows the limitations of the RPSS as a measure of skill.

Irrigation allocations obtained using forecasts of individual streamflows (ISF) gave slightly higher E and RPSS skill levels than those obtained using individual climatological streamflows (ICS), and using disaggregated streamflows obtained from forecasts of the total streamflow (TSF) gave slightly higher E and RPSS skill levels than using total climatological streamflows (TCS). The differences in skill between forecasts obtained using forecasts of individual streamflows (ISF), and total streamflows (TSF), were minimal, despite the differences in the streamflow forecasts.

## 5. CONCLUSION

Five different approaches were used to obtain continuous exceedance probability forecasts of the final irrigation allocations in the Goulburn catchment. The forecasts obtained from all five approaches were found to give significant E and RPSS skill, and were superior to climatological irrigation allocations.

Obtaining the forecasts directly from antecedent reservoir levels (DF) gave the highest E and RPSS skill. However these forecasts were unsatisfactory at high exceedance probabilities as the forecasts were often less than the allocations that would actually be obtained even if there was no streamflow in the coming season. Furthermore, including the ENSO conditions did not improve these forecasts, and hence they are independent of climatic conditions for the coming season.

The other four approaches (ISF, ICS, TSF, TCS) used forecasts of inflows to the various reservoirs in the system as inputs to the GSM, which was then used to determine the irrigation allocations. Most studies of streamflow forecasting undertaken in Australia have only been for three or four monthly totals (e.g. Chiew et al. (1998), Piechota et al. (2001)). This study showed that totals can be forecast with some skill for the forthcoming ten months. For most of the inflows considered, the use of the DMSLP anomaly, along with antecedent flow, was found to give the highest skill. The inclusion of the PDO, QBO and SAM, in addition to a single ENSO indicator, was not found to significantly improve correlations with streamflows. The irrigation allocations obtained from these forecasts gave superior E and RPSS skill to those obtained using climatological

streamflows. It was not possible to differentiate between the skill of the irrigation allocations obtained using forecasts of individual streamflows, and those obtained using disaggregations of the forecast total inflow.

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