Ocean Based Statistical Forecasts for Seasonal Irrigation Allocations

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EXTENDED ABSTRACT

The initial general security water allocation announcements for water users in the New South Wales (NSW) part of the Murray Valley are made during July. The initial water allocation announcement is very conservative as the allocations are based on storage levels and historical minimum inflows statistics to dams during the irrigation seasons. There is a good chance that the water allocations will be increased as the season proceeds. Water availability during the cropping season is a major factor influencing planting decisions made by irrigators and can have a major bearing on the financial viability and irrigation efficiency of irrigation areas. Therefore, increased knowledge on the likely end-of-season allocation by advance predictions can assist in minimising cropping risk and can help optimise farm returns and achieve better irrigation efficiencies.

Seasonal river flow forecasts are used for determining anticipated water allocations; however, this paper presents a more direct approach that forecasts water allocation instead of river flow. The study is based on the hypothesis that the sea-surface temperature (SST) and ocean based climate variability indices (CVIs) are statistically related to water allocation forecasts in a river catchment. Over 100-years data on a global two degree grid SST, CVIs, and water allocations in the Murray Irrigation Area (MIA) were analysed. Statistical techniques including probability analysis and multiple linear regression (MLR) were used to determine the underlying relationships among predictor variables and the end-of-irrigation-season water allocation (February allocation) in the MIA. The SST at three locations around the continent; one lying in the equatorial Pacific, second in the Indian Ocean and third in the Tasmanian Sea, were found highly correlated (Pearson Correlation Coefficient up to -0.83) with February allocation levels in the MIA based on analysis using the CSIRO's SSTman software.

The significant variables identified by the MLR analyses include; SST, SOI, mean sea level pressure, start-of-season (August) and mid-of-season (October) announced allocations and the risk factor. The risk factor can be varied from 0 to 100% and relates the probability of February allocation to announced August allocation and translates degree of risk farmer may take based on known August allocation. The value of the risk factor must be chosen with care because if user/farmer decides a higher value of risk factor, the model will forecast higher allocation suggesting farmer to grow more crops but at the same time involve a higher degree of risk of actually not getting that level of allocation. The model was validated against actual announced allocations for the month of February for ten years (1996/97 to 2005/06). The validation results are presented in Figure 1A. The model underestimated allocations for the years 2001 and 2002. This may be due to borrowing water from future years despite exceptionally low rainfalls during the season and not taking into account then emerging drought conditions.

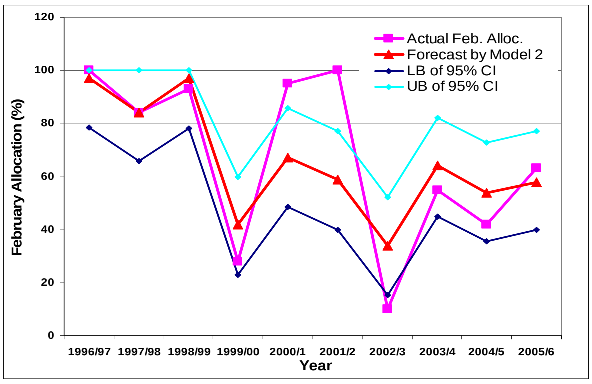

Figure 1A. Comparison of actual and predicted February allocations by regression model

A simple software tool developed based on the findings of this study will provide farmers with risk based crop management options.

1. INTRODUCTION

Climatic variability poses a vital influence on precipitation and ultimately river flows as well as irrigation demand in irrigated agriculture. The short to medium term climate forecast can helps water regulators in determining water availability, water managers in estimating seasonal irrigation demand, and farmers in cropping decisions. Moreover, use of standard climate variability indicators to reduce uncertainty of the water supply can help improve regional and on-farm water use efficiency (e.g. informed cropping decisions rather than later abandoning of crops due to non-availability of water, changed irrigation practices and irrigation demand management in an environmental context) and better management of end of irrigation area's salinity levels through reduced drainage volumes. This will lead to savings in irrigation water and improved irrigation demand patterns which could bring beneficial economic and environmental impacts to irrigation areas. A water allocation in the New South Wales is defined as the percentage of the water user's licensed entitlement available for use in a given year depending on the level of storage and priority order of the given entitlement.

In the past a range of studies have been made to investigate connections between Australian rainfall and the sea surface temperatures (SST), climatic indices and prevailing atmospheric circulation patterns. For example see, Smith et al. (2000), Ansell et al. (2000), Drosdowsky and Chambers (2001), and Verdon and Franks (2005). Smith (1994) examined the capability of PCA in predicting Australian winter rainfall using Indian Ocean SSTs with principal components regression to find relationships between SST and rainfall components. Smith et al. (2005) analysed the hindcast results of CSIRO COCA2 climate model and estimated the skill of the model at predicting large scale climate variability that arises due to El Nino Southern Oscillation (ENSO) events. Khan et al. (2005) conducted a similar study about the Murrumbidgee River Catchment and found significant relationship of only two parameters; the SST and Southern Oscillation Index (SOI) with the water allocation in the valley. The abovementioned references have found that winter rainfall in Australia is generally correlated with seasonal SST and other climate variability indices and have explained the underlying synoptic reasons. The rationale of research work presented in this paper is based on these previous studies however; the target area of the problem has been reduced to an irrigation system level as well as more climate variability indices are included into the analysis. The water allocation levels for irrigation are decided each season based on available storage and the anticipated river inflows to the reservoirs. The rainfall in the catchment is the source of river inflows and storage volumes and respondent to climatic variability. Therefore, a more direct and non-traditional approach has been assumed in the current study by linking irrigation system water allocation levels with the SST and other climate variability indices.

This paper explains the method of development and validation of output of a seasonal general allocation forecast model for irrigated agriculture in the Murray River Catchment (Figure 1). The model is implemented with a simple graphical user interface which is not discussed in this paper

2. STUDY AREA

The Murray is the major river in Murray Darling Basin (MDB) which drains about one-seventh of Australia's land mass and comprises three-quarters of New South Wales (NSW), over one-half of Victoria, a small portion of South Australia, and an area of Queensland greater than the total area of Victoria (Figure 1). From its source in the Australian Alpines in NSW, the Murray River flows 2,530 kilometres west then south to meet the Southern Ocean in South Australia (MDBC, 2005). Since gauging began at Swan Hill in 1909, the Murray ceased to flow at that point for short periods in 1914, 1915, and 1923. Since the Hume Reservoir was built in 1936 a flow has been maintained throughout the length of the Murray at all times, despite several severe drought periods. The catchment of the upper Murray above Albury contributes more than one-quarter of the total flow in the Murray system, from an area which is less than two per cent of the catchment area. Of the above area of Murray catchment, only five percent has an average rainfall in excess of 760 mm and the average rainfall over the Murray basin is 430 mm. As a whole, the Murray Darling Basin has an average annual runoff, combined with inter-basin transfers, of 23,850 GL. Approximately 11,576 GL is extracted for consumptive use and 95.5% of that is used for irrigated agriculture.

The Murray Irrigation Area (MIA) is one of the largest irrigation areas in the MDB and is located in the south New South Wales (NSW), just north of the Murray River across NSW–Victoria state border. The Murray Irrigation Limited (MIL) is the only player this part of the extensive and integrated catchment with a bulk water entitlement of 1479 GL of which 1475 GL is under general security entitlements. MIL enjoys the ownership of irrigation supply to the Berriquin, Denimein, Deniboota and Wakool Irrigation Districts and

Tullakool Irrigation Area. The average annual water use (latest five years) of about 853,695 ML in the MIL represents approximately 7.7% of water used for irrigation in the Basin. MIL diverts water from the Murray River at Lake Mulwala via the Mulwala Canal off-take and supplies 2,416 landholdings with a total area of 748,000 ha, as well as town water supplies for eight communities (MIL, 2004).

Figure 1. The Murray River and its tributaries. (Source: Wikipedia.org)

The summer irrigation season in the Murray Valley is from July to April/May of the following year. In New South Wales, the volume of water that irrigators have access to for any water year is based on the seasonal water allocation announcements delivered by the Department of Natural Resources (formerly called department of Infrastructure, Planning and Natural Resources). The seasonal water allocation in the valley is determined by the amount of storage in the two main reservoirs, Hume and Dartmouth dams, the Lake Mulwala and minimum expected inflows from tributaries and upstream watersheds including Snowy Mountains. The two dams; Hume and Dartmouth, have maximum water holding capacities of 3,038 GL and 3,900 GL respectively.

In a given year, depending on storage levels of dams and inflows, the water is allocated according to the following hierarchy:

- environmental water provisions;
- basic rights requirements;
- licensed domestic and stock requirements;
- local water utility requirements;
- water carried forward in water accounts;
- high security and;
- general security.

The amount of water required for environmental flows, mandatory requirements (such as for domestic and stock licences, local water utilities and high security licences) and general security water carried over from the previous year is set aside to ensure that the allocated water will be delivered. In addition, a volume is set aside for conveyance losses inside the irrigation corporations areas (in accordance with their licence) as well as to account for losses in delivery of allocated water. The remaining water is then allocated to general security licence holders which are generally broad acre crops growers. In other words, general security access license holders have the least priority. If general security allocations are below 100%, the system is monitored and if there are improvements in the amount of water available these allocations are progressively increased. In this paper ‘allocation’ refers to the general security water allocation unless otherwise stated and is always expressed on a percentage scale

By virtue of the least priority in the water allocation hierarchy, and the fact that more water allocations will be available as the season proceeds, the general security water users require advance prediction of what the allocation would likely be in the next irrigation season so as to plant their crops accordingly, maximise irrigation efficiency and economic return from available water and avoid potential crop losses by growing less if there is a prediction of low allocations.

3. ANALYSIS FRAMEWORK

The water year in MIA starts in July and ends by the end of June. The intermediate water allocation announcements, especially those made in the months of August (start of irrigation season), October (mid of irrigation season) and February (end of irrigation season) are more critical in relation to taking cropping decisions by the farmers. Therefore, the current study has selected February allocation as the variable to be forecasted (dependent variable). The methodology framework adopted in this study is shown in Figure 2 and is explained in the following sub-sections. Final allocation in Figure 2 refers to the February allocation.

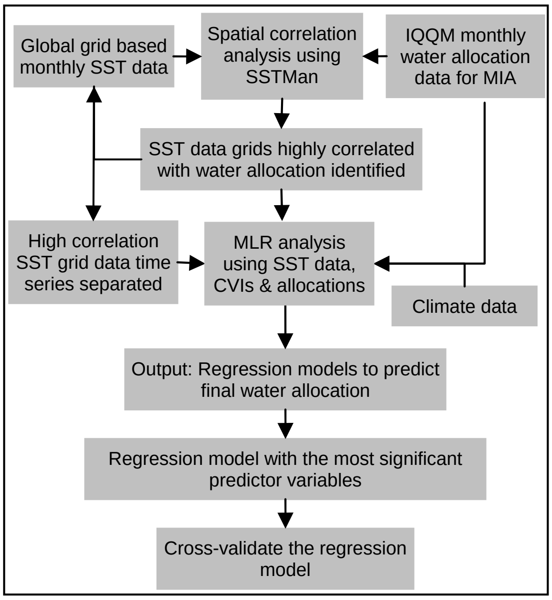

Figure 2. Analysis framework

3.1. High Correlation SST Datasets

Global scale 2° gridded monthly SST data constructed by NOAA scientists (Smith and Reynolds, 2004) is available in public domain. Spatial correlation analysis was conducted between the various combinations of the monthly SST data and the February (following year) water allocations for the period of 1981 to 1995 using SSTman (McIntosh, 2004) software. The aim of trying SST datasets with different lags was to find the best predictor of the February allocation. SSTman plots a map of correlation coefficient ‘r’ for each SST dataset. A high level of correlation (r range from 0.6 to -0.83) between the average Jan – Feb SST at three locations around Australia (Figure 3) and the February allocation was identified with one-year lag time. The lag time looks longer which is due to the fact that SST correlation is sought with allocation instead of the rainfall.

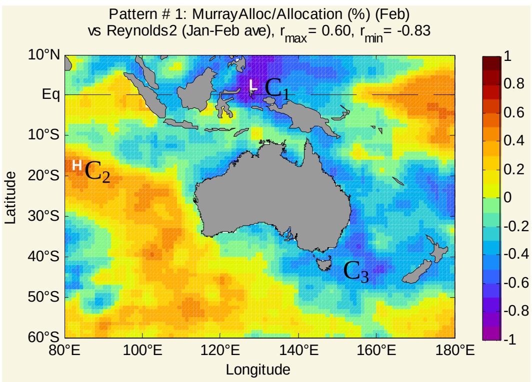

Figure 3. Spatial pattern of correlation coefficient for February water allocation levels versus average Jan - Feb SST

The location of the three highly correlated clusters of SST gridded data (Figure 3); one being in equatorial Pacific, second in the Indian Ocean and third in the Tasmanian Sea confirm the synoptic explanation of rainfall patterns in Australia (Drosdowsky, 1993, Drosdowsky and Chambers, 2001).The three SST datasets were included as predicator variables (Table 1) in the multiple linear regression (MLR) analysis (Section 3.3).

Table 1. Input variables and their data sources

Variable	Data Source
February allocation	IQQM model results
August allocation	IQQM model results
October allocation	IQQM model results
Probability of exceedance of February allocation	Computed
Average Jan – Feb SST at cluster C_1	ERSST from NOAA
Average Jan – Feb SST at cluster C_2	ERSST from NOAA
Average Jan – Feb SST at cluster C_3	ERSST from NOAA
Average Dec – Feb Southern Oscillation Index	Australian Bureau of Meteorology
Average Jan – Mar sea level pressure at Tahiti	Australian Bureau of Meteorology
Average annual SST anomalies within NINO3 region	Climate Analysis Section of Climate and Global Dynamics, FTP site

3.2. Input Data

Based on an extensive review of literature and analyses; nine independent variables that showed some effect on February allocation levels in the MIA were identified. These variables and their data sources are listed in Table 1. The month of August represents the initial water allocation and was chosen to be one of the model inputs while the October allocation was included as an optional input variable. The monthly water allocation data used in this study for MIA was generated by IQQM (Integrated Quantity and Quality Model) simulation for 105 years (1891 – 1995). Using the 105 years August, October and February allocations data, probability of February allocation to exceed an allocation level of 85% was computed for given levels (0 – 100%) of August allocation and October allocation for each year. A logarithmic model (Equation 1) fitted best (R^2 value of 0.72) to the scatter plot of August allocation and the probability of exceedance of February allocation. Similarly a linear model (Equation 2) fitted best (R^2 value of 0.50)) to the scatter plot between October allocation and the exceedance probability of February allocation The probability of exceedance of February allocation was also used as predictor variable in MLR as given in Table 1.

$$P1 = 0.357\ln(X) - 0.606\,, \tag{1}$$

$$P2 = 0.011(Y) + 0.0364\,, \tag{2}$$

Where P1 is the probability of exceedance of February allocation for known August allocation (X) and P2 is the probability of exceedance of February allocation for known October allocation (Y).

3.3. Multiple Linear Regression

To quantify the relationship among more than one independent or predictor variables and a dependent or criterion variable, MLR is one of the widely used statistical approaches. In the MLR technique, for each independent variable a regression coefficient (the average amount the dependent variable increases when the independent variable increases by one unit and other independent variables are held constant) is calculated. Depending on the level of influence (significance tests e.g. F-test and t-test) some of the independent variables are dropped and MLR analysis is revised for the remaining independent variables unless all variables fulfil the statistical significance criteria. The final relationship is expressed in the form of a regression equation/model. MLR analysis has been applied by Ahmad et al. (2003) for long term flow prediction of the Maipo River in Chile. Regression models were developed to forecast February water allocation levels by utilising MLR analysis capabilities of SPSS software. The MLR was performed using backward elimination method of variable removal on the 105 year dataset. Since the August allocation and October allocation become known at points in time, two separate MLR analyses were conducted; one using all of the predictor variables listed in Table 1 except for October allocation and second analysis excluded August allocation. All variables were found statistically significant, except for SST anomalies of NINO3 region in both cases. Hence the MLR analysis produced two regression models. The first regression model (Model 1) forecasts February allocation with lead time of six months and is applicable only if the August allocation is known. The second regression model (Model 2) is applicable if October allocation is known and its forecast lead time is reduced to four months. October allocation was treated as unknown and was not included in the MLR for the Model 1

3.4. Model Assumptions

The development of allocation forecast model is based on the following assumptions:

- The model is trained using long term data and therefore it is assumed that it implicitly accounts for allocation rules and management practices that might have changed over time,
- Since the model is based on the long term dataset, it is capable to adapt itself to the climatic variations.

4. RESULTS AND DISCUSSION

Table 2 presents basic statistics about the two regression models. It must be noted that probability of exceedance calculated from Equations 1 and 2 actually represent value of the risk factor. For example, manipulation of probability to a higher value will force the model to forecast a higher level of February allocation which may not actually happen on ground and hence a higher degree of risk will be involved. Opposite is the true for the lowering of probability value. Figure 4 shows comparison of actual February allocation levels with those forecasted by the two models. Model 1 performs relatively better while predicting very low allocation levels which is a positive point as low allocations are more critical during the drought years. Both models seem conservative at predicting high allocation levels. Overall, accuracy of the both models is good with a maximum value of coefficient of determination (R^2) for Model 1 being 0.74 while that of Model 2 being 0.83; however, the two models have different start times and therefore are not directly comparable. Also the latter has the advantage of using more accurately determined input variable the October allocation.

Table 2. Application criteria and error statistics of the MLR models

Model	Applicability	R^2	#SEE
1	Known August allocation	0.74	11.59
2	Known October allocation	0.83	9.47

#standard error of the estimate

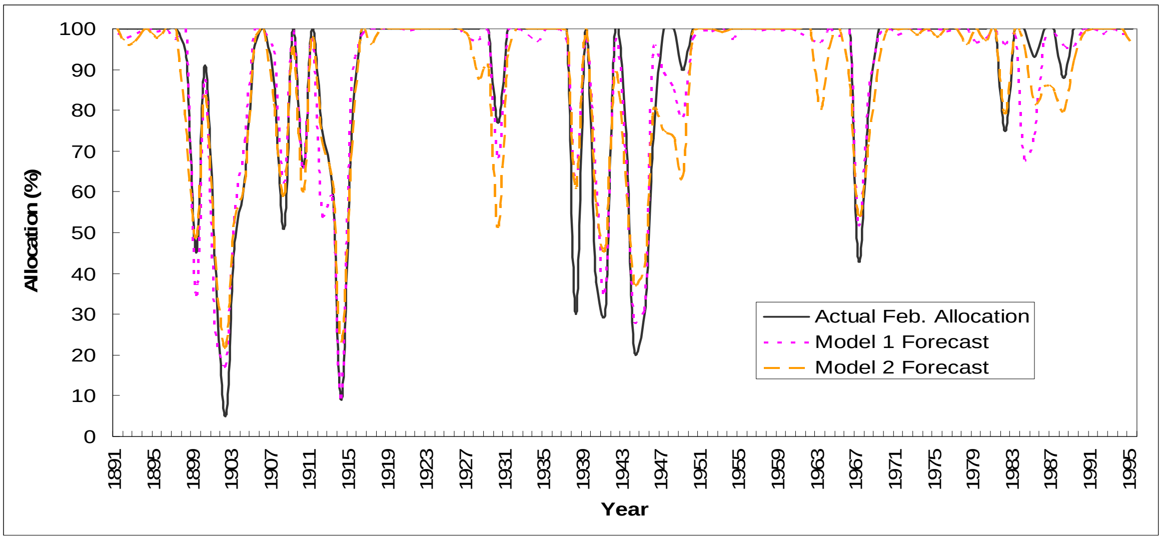

Figure 4. Comparison between actual February allocation levels and the MLR models output

4.1. Validation of Models

The MLR models were developed using 105 years (1891 – 1995) data and each model was cross validated for ten years from 1996/97 to 2005/06. The actual water allocation data for the validation period is downloaded from DNR website (DNR, 2007). Figure 5 and Figure 6 show the comparison of actual and forecasted February allocations as well as their upper and lower 95% confidence limits for Model 1 and Model 2, respectively. The validation R^2 for Model 1 and Model 2 were calculated to be 0.53 and 0.63, respectively, which are slightly lower than the regression R^2 due to different distribution of the error. Forecasts produced by Model 2 are expectedly more accurate than that of Model 1 however; both models were unable to accurately reproduce the 2000/01 high allocations.

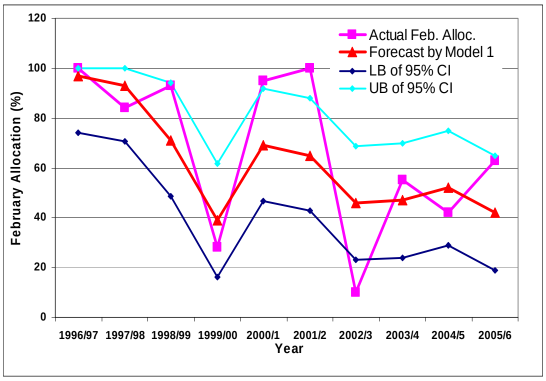

Figure 5. Comparison of actual and predicted February allocations by Model 1

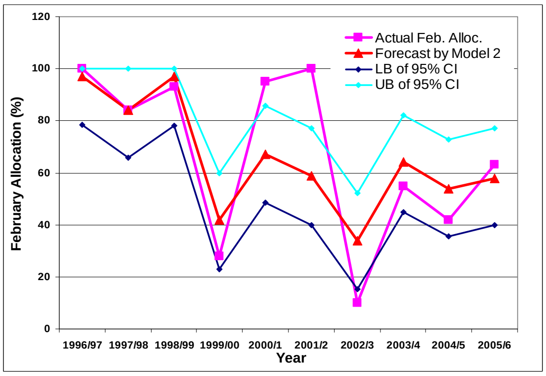

Figure 6. Comparison of actual and predicted February allocations by Model 2

Both of the models underestimated allocations for the years 2001 and 2002. This may be due to borrowing of water from the future years despite exceptionally low rainfalls during the season and not taking into account the emerging drought conditions. Borrowing and subsequent repaying of water from future further distorts the water allocation data and therefore the models become less reliable.

5. CONCLUSION

This study shows that end-of-season allocation can be forecasted by incorporating early announced allocations, SST, climate variability indices and the farmer's risk factor. The following conclusions are drawn from this study:

- Statistical performance indicators R^2 (0.74 – 0.83) and SEE (9.47 – 11.59) computed for the two models suggest reasonable confidence on the model predictions.

- The accuracy of the statistical models is biased by the original data series generated by the IQQM. The forecast process is further complicated by the borrowing of water from the future years and carrying forward from the previous years.
- The value of the risk factor need to be chosen with care while setting model up for allocation forecast. A higher value of risk factor forces model to predict higher allocation thus suggesting to grow more crops but at the same time involve a higher degree of risk of actually not getting that level of allocation.
- Model validation over the last ten years shows reasonably good match between the predicted and the historical data with some discrepancy in forecasting high allocations of the years 2000/01.

6. ACKNOWLEDGEMENT

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