was also used as predictor variable in MLR as given in Table 1.

$$P1 = 0.357\ln(X) - 0.606\,, \quad (1)$$

$$P2 = 0.011(Y) + 0.0364\,, \quad (2)$$

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

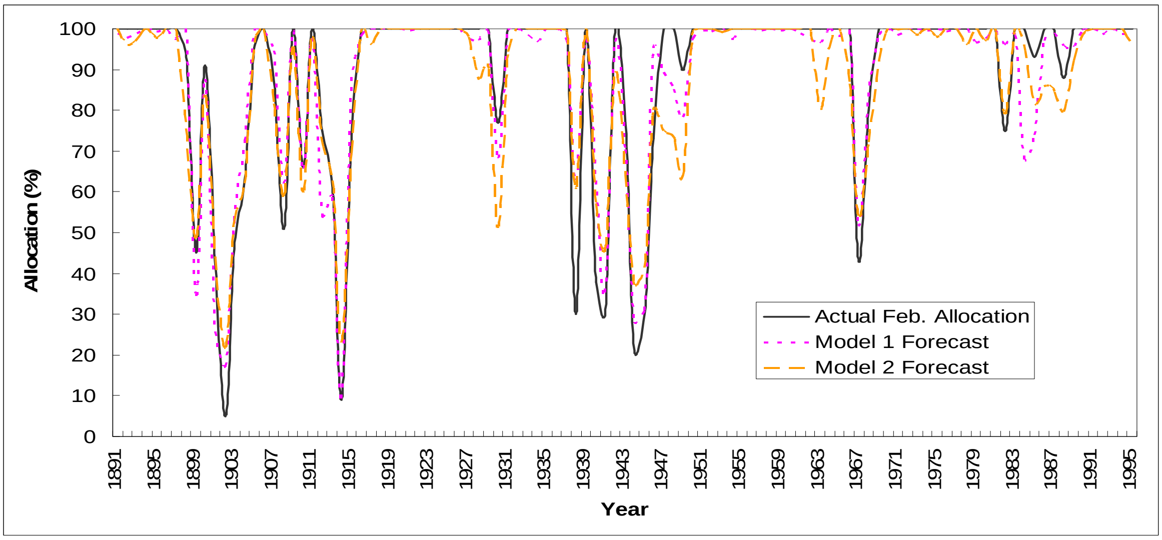

Figure 4. Comparison between actual February allocation levels and the MLR models output

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.

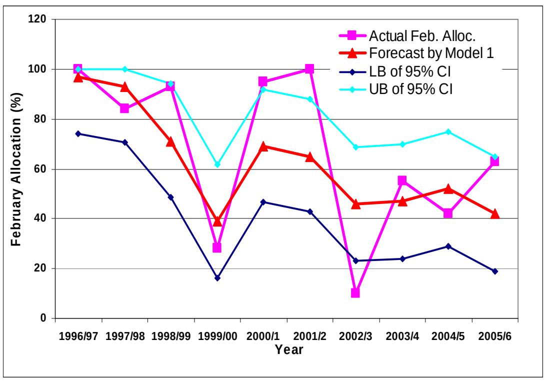

Figure 5. Comparison of actual and predicted February allocations by Model 1

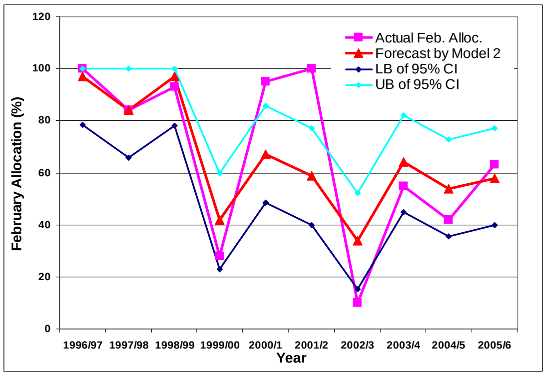

Figure 6. Comparison of actual and predicted February allocations by Model 2

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.

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