Persistence of Australian streamflow and its application to seasonal forecasts

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Abstract: High climate variability in Australia leads to even higher variability in streamflow, and therefore difficulties in managing water resources for economic, social and environmental outcomes. Thus there is a need for skilful seasonal forecasting tools with useful lead-times. Forecast tools based on the El Nino/Southern Oscillation (ENSO) such as the Southern Oscillation Index (SOI) and Sea Surface Temperature (SST) are currently used to forecast seasonal rain in Australia, and have similar value for predicting streamflow. This paper evaluates the skill of persistence as a tool for forecasting streamflow on large and small catchments in Australia, and makes some comparisons with the skill of SOI-based forecasts.

Monthly streamflow records for 320 unimpacted Australian gauging stations were assessed using an advanced prototype of the Australian Rainman Streamflow version 4.3 software package. This data set had 302 stations with historical time series data from state water agencies and 18 stations with extended/modelled data for small catchments. The following factors were systematically examined in each region of Australia: (1) duration of the predictor period, (2) lead-time, and (3) duration of the period to be forecast. The statistical significance of persistence as a forecasting tool was assessed via serial correlation, Kruskal-Wallis tests and cross-validated LEPS skill scores. Results were evaluated spatially to compare regional responses across Australia.

This study showed that persistence is a useful predictor of streamflow in all seasons over much of Australia, with lead-times that are longer than that of ENSO-based forecasting tools. The lag relationship between prior and predicted streamflow was strongest with a lead-time of zero. The strongest relationships were in south-eastern Australia during late spring and early summer and in northern Australia during autumn and early winter.

Keywords: *Persistence; Serial correlation; Streamflow; Seasonal forecasts*

1. INTRODUCTION

Australian rainfall is highly variable and related streamflow can display an even greater level of variability. Management of water resources is difficult in this regime and this has consequences for the planning and delivery of environmental, social and economic outcomes. Persistence in streamflow is the relationship between streamflow in one period of time and that in the following period of time. A portion of the incident rainfall in a catchment is temporarily stored and this creates a lag in the subsequent streamflow which is expressed as a persistence or memory of flow conditions within a catchment. Chiew et al. (2000) found that serial correlations or persistence of streamflows in Australia were higher than those found for rainfall, and Simmonds and Hope (1997) established that the persistence of monthly rainfall in the eastern states was largely due to El Niño-Southern Oscillation (ENSO).

Seasonal forecasting of rainfall using indices of ENSO such as the Southern Oscillation Index (SOI) is well established and in common use in Australia (Stone and de Hoedt, 2000) and the method has also been applied to forecasting of streamflow (Chiew et al., 2000). The impact of ENSO on streamflow is up to twice that on rainfall (Clewett et al., 2000), and thus ENSO also has important influences on the characteristics of streamflow.

There is a need to forecast flows with useful lead-times that provides some level of 'skill' to the user. The impacts of the inter-annual variability of streamflow on the management of water resources can be reduced with the use of skilful seasonal forecasts. This includes use of persistence via serial correlation to improve prediction of seasonal flows (Chiew et al., 2000). The analyses in this paper were performed on a larger set of point data time series to improve the geographical coverage. Characteristics of the persistence of streamflow include the duration of the predictor period, the lead-time of the forecast and the duration of the predicted streamflow. This paper investigates the influence of each of these characteristics in providing a useful and skilful forecast. The length of predictor period was investigated by Chiew et al. (2000), although the most effective duration was not identified. This paper presents the results for a number of predictor durations for each season. Chiew et al. (2000) found that the lag-one (referred to as lead-time of zero months in this study) correlation with runoff was significant throughout the year and that there was a large difference in the correlations between lag-one and lag-three (lead-time equals two months). Lead-times of 0, 1, 2, 3 and 4 months are examined methodically in this paper. This study applies measures of statistical significance and skill scoring to probabilities of forecast streamflows, thereby enabling the predictor indices of persistence and average SOI to be compared.

The combination of the characteristics of lead-time, duration of the predictor period and duration of the predictand enables the formulation of useful targeted forecasts. These forecasts can be targeted for tactical and strategic decision-making for management of water resources and agricultural production.

Some comparisons with an SOI based forecast will be presented.

2. DATA AND METHODS

Historical time series of streamflow were sourced from the data set compiled in the Land & Water funded Rainman Streamflow project QPI 39 (Clarkson et al., 2000) and used in the StreamFlow supplement to Australian Rainman (Clarkson et al., 2001). The main data was monthly historical observations for 345 locations throughout Australia sourced from the eight state and territory water agencies across Australia. The mean length of streamflow in these data was 65 years and ranged from 30 to 130 years. Stations in which median streamflow was zero were deleted from the persistence analyses (43 stations). An extended data set was also used for a further 107 stations from all Australian states excepting Queensland and NSW. This data set was derived by rainfall-runoff modelling of small catchments (less than 2000 km^2) using a simplified version of the HYDROLOG model (Chiew et al., 2000, Chiew and McMahon, 1994, Clarkson et al., 2000). The length of record for each station in the extended data set was 98 years (1901-1998). Where historical data was available for a location it was included for analysis in preference to extended or modelled data. This deleted all but 18 of the extended stations. The 320 locations in the analyses are shown in Figure 1.

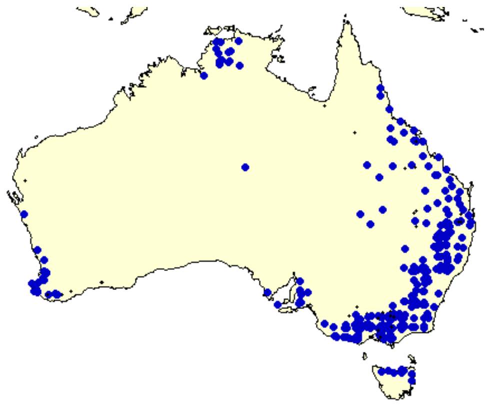

Figure 1. Location of the 320 streamflow stations used in the persistence analyses.

Seasonal forecasts of streamflow at each location using persistence were made by: (a) calculating seasonal streamflow in each year from the historical (or modelled) records of monthly streamflow, (b) classifying these seasonal totals into three groups based upon the terciles of streamflow in the preceding predictor period, and (c) calculating the probability distribution of seasonal streamflow within each group to define the forecast probabilities of seasonal streamflow.

Seasonal forecasts using the SOI were made in a similar way using the method of Clewett et al. (1991) and monthly values of the Troup SOI from the Bureau of Meteorology. The average value of the SOI in the three-month predictor period was used to partition streamflow in the forecast period into three groups as follows: average SOI below –5, –5 to +5, and above +5. The probability distribution of streamflow of each group was used to define the streamflow forecast.

Forecasting skill was assessed in several ways; (1) percentage of stations with statistically significant forecast skill, (2) correlation, and (3) mean skill score as defined below. Statistical significance was calculated using the non-parametric Kruskal-Wallis test (K-W) (Conover, 1971) and Linear Error in Probability Space (LEPS) skill scores (Potts et al., 1996). The K-W test was deemed significant if the probability of a result being not due to chance was >= 0.9.

The K-W test is useful for assessing skewed data that occurs frequently in streamflow and is similar in power to the one-way F test (Conover, 1971). The LEPS method of assessing forecast skill is useful because it enables comparison of observed and predicted probabilities. Cross-validation was used in the LEPS analyses to further reduce forecast errors caused by artificial skill.

The LEPS skill scores were calculated using cross validation and scaled to account for the number of years of data at each location (standardised to 100 years) and the number of classes in the forecast system. This scaling used the method of Clewett et al. (2003, in preparation) and forecasts were defined as significant if the cross validated scaled LEPS skill score was >= 7.6.

Changes in seasonal forecast skill due to persistence were systematically examined with respect to changes in duration of the predictor period, lead-time and forecast period. The duration of the predictor period was examined by adjusting it from one to 12 months. Lead-time (i.e. the time interval between the predictor period and the forecast or predictand period) was adjusted from zero to four months. The length of the forecast period was adjusted from one to 12 months but was kept constant at three months in most analyses for the following seasons: January to March, April to June, July to September, October to December. These seasons were chosen to reflect the geographical differences in rainfall seasons across Australia and to have some relevance to the timing of water management decisions.

Changes in seasonal forecast skill associated with changes in lead-time were also evaluated using the average SOI (three-month predictor period and three-month forecast period) at the same lead-times. These analyses were performed for all 320 Australian data locations (see Figure 1) and then sorted for states and territories to reveal geographical differences. Queensland was split into two regions north and south of the Tropic of Capricorn (Qld[N] and Qld[S]).

All analyses of streamflow data including statistical testing of seasonal forecasts were carried out using an advanced version 4 prototype of the Australian Rainman Streamflow software (Clewett, 2003; Clewett et al., 2003).

3. RESULTS

Effects of predictor period on forecast skill

Streamflow persistence using a duration of one month in the forecasting tool gave the highest skill (% of significant stations) (Table 1).

Increasing the period to two or three months caused only a slight reduction in skill, but beyond three months there was a rapid decline.

Table 1. Effect of length of prior streamflow period on forecasting skill using persistence (lead-time zero).

	Length of prior period (months)						
	1	2	3	6	9	12	
Seas.	% of stations with scaled LEPS >=7.6						Avge
JFM	63	60	53	39	39	40	**49.0**
AMJ	51	49	40	28	32	36	**39.2**
JAS	84	83	84	70	48	38	**67.7**
OND	71	70	65	58	59	45	**61.2**
Avge	**67.1**	**65.7**	**60.4**	**48.5**	**44.3**	**39.5**	

Seasonal and regional influences

Monthly serial correlation was extremely variable and ranged from near zero to 0.98. The mean for all stations over all months was 0.39. Stations with the highest correlations were in southern Australia. For example, the mean of the 12 monthly serial correlations for the Tarago River in Victoria was the highest in Australia and was 0.77. Monthly correlations were generally highest in late winter / spring with the mean correlation for all Australian stations during this period of 0.5. Correlations were generally lowest in autumn with the mean for all stations equal to 0.3. The single month serial correlation across Australia is strongest in July/August (Table 1).

The regional differences in forecasting skill using persistence of flow are presented in Table 2 with values for the four seasons.

Table 2. Regional differences in forecasting skill: Percent stations with scaled LEPS skill score >= 7.6 (Duration of predictor period is one month, lead-time is zero).

	No.S tns	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec	Avge
Qld(N)	21	33	71	76	52	**58.3**
Qld(S)	31	42	58	68	19	**46.8**
NSW	109	59	70	94	85	**77.1**
Vic	97	85	29	78	81	**68.3**
Tas	8	88	38	62	100	**71.9**
SA	12	50	8	92	83	**58.3**
WA	19	47	21	90	47	**51.3**
NT	15	40	67	67	27	**50.0**
ACT	7	86	100	100	100	**96.4**

The lowest percentages were those for southern states in late autumn. Northern Australian locations demonstrated strong persistence relationships for April-June and were weakest in January-March. Percentages of significance were relatively high across Australian regions for the July-September period. New South Wales, ACT and Tasmania have the highest levels of significance. The other measures of forecasting skill were consistent with Table 2 values across geographical regions and seasons (Table 3). The combined criteria of significance in Table 3 yielded lower values than for the percentage of significant LEPS skill scores.

Table 3. Regional differences in forecasting skill: Percent stations with K-W >= 0.9 and correlation >= 0.2. (Duration of predictor period is one month, lead-time is zero).

	Season				
State	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec	Avge
Qld(N)	38	48	33	29	**36.9**
Qld(S)	48	23	32	16	**29.8**
NSW	38	71	95	82	**71.3**
Vic	65	31	83	85	**65.7**
Tas	63	50	75	75	**65.6**
SA	42	8	92	83	**56.3**
WA	37	5	84	63	**47.4**
NT	47	53	67	7	**43.3**
ACT	100	100	100	86	**96.4**

Lead-time and comparison with SOI

The effect of lead-time on several measures of mean annual forecast skill (calculated as the average of the four seasons) and a comparison of forecast skill between persistence and the SOI are shown in Table 4.

Table 4. Comparison of mean annual forecasting skill for persistence (one month predictor period) and average SOI (three month predictor period) at lead-times of zero to four months.

		Lead-time (months)				
Attribute	Tool	0	1	2	3	4
% LEPS *	Pers	67	46	34	23	20
	SOI	41	34	26	27	22
Mean LEPS	Pers	9.8	5.8	3.9	1.8	1.1
	SOI	5.3	4.3	2.8	2.8	1.9
% K-W ^	Pers	82	59	47	n.a.**	n.a.
	SOI	55	47	37	n.a.	n.a.
Mean Corr #	Pers	0.33	0.20	0.18	n.a.	n.a.
	SOI	0.22	0.18	0.15	n.a.	n.a.

* % LEPS is % stations with scaled LEPS >=7.6
Mean LEPS is the mean of scaled LEPS values of locations
^ % K-W is percentage of locations >= 0.90
# Mean corr is the mean correlation of locations
** n.a. = not available

We found the same pattern of significance in all seasons here as we did in Table 1, and therefore the means of the annual forecasting skill values are presented in this table.

The method of cross validated LEPS skill scoring revealed lower percentages of stations with statistically significant forecast skill, than the non-parametric Kruskal-Wallis significance test and was thus a more stringent test.

Table 4 results show that streamflow forecasts based on a one month predictor period have greater forecast skill than the average SOI across almost all measures of forecast skill and lead-times. The exception is in early summer (October to December) when the SOI maintains skill out to a lead-time of three months. The mean LEPS skill score for all stations in October to December season with three months lead-time was 6.9 (51% of stations with statistically significant skill). The percentage of stations that were significant was lower for LEPS than for the K-W test. There is a building of skill from longer to shorter lead-times across all measures of skill testing.

The median seasonal streamflows for the three categories of persistence and average SOI in Table 5 show the relative seasonality and strength of persistence and average SOI as forecast tools. This data shows that seasonal streamflow in Australia is bi-modal with the first peak (January to March) related to the wet-season rainfall of northern Australia, and the second peak (July to August) associated with the winter rains of southern Australia.

Table 5. Median seasonal streamflow (units: ML/1,000) for both predictors (one month predictor period for persistence, three months for average SOI, zero lead-time). (Values are the mean of 320 stations).

		Season			
Forecast tool	Category	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec
Persist.	High	132	33	62	46
	Medium	85	20	42	25
	Low	63	12	23	17
Av SOI	above +5	143	34	53	44
	-5 to +5	78	17	41	26
	below -5	53	18	29	19
Mean	All years	88	19	41	26

Duration of forecast period

The duration of the forecast season of streamflow provides significant skill at three months. A longer season exhibits a marked decrease in skill for most seasons. For example, the percentage stations with significant skill ranged from 75.8% for a three-month season beginning in June, to 35.5% for a season length of 12 months.

4. DISCUSSION

Both persistence and the SOI show considerable capacity for seasonal forecasts and the results in this paper build upon the persistence analyses of Chiew et al. (2000) and the ENSO related streamflow analyses of Clewett et al. (2000). Median streamflow increased by 30 to 80 percent depending on the season when prior streamflow was in the upper tercile, or when the SOI in the previous season was above +5. In contrast, median streamflow decreased by 30 to 40 percent when prior streamflow was in the lower tercile, and by 5 to 40 percent when the average SOI was below –5. These are quite large changes in streamflow and thus valuable from an agricultural management viewpoint. However, in terms of targeting a seasonal forecast to service an agricultural decision it is also important to assess whether the forecast skill is sufficiently reliable and statistically significant, or whether there is just too much variation in the data for the forecasts to be useful.

Table 1 showed that a one month persistence period is sufficient to provide a skilful forecast of subsequent streamflow (with lead-time zero). Lengthening the prior period of persistence does not improve the outcome, but there is negligible penalty up to three months. This relationship is also consistent across the seasons.

The considerable differences in the skill of streamflow forecasts found between regions of Australia may be explained by the time series data being distinctly different between states. Some have extended time series which provides a potential for greater statistical skill. The Northern Territory, South Australia, Queensland, Tasmania and Western Australia have shorter time series. New South Wales including ACT, yielded the largest percentages of significant skill. This data set contains streamflow records from large catchments and rivers. Such rivers would exhibit a strong persistence of flow not directly tied to short-term rainfall throughout the year. This too is the case with northern Queensland which has large coastal rivers. A persistence relationship exists for the drier period of the year, but this relationship deteriorates as the storm season begins in Queensland in late spring / early summer. A lag appears in the system for northern states and territories between large incident rainfall and subsequent river flow. This is represented by the strong peak in the seasonal flow for January to March (Table 5). The strong persistence in winter and spring in southern states, can be linked to the seasonal rainfall 'break'. The persistence of flow for the southern states and locations in the south-west of Western Australia, follows the break in April and May which is the time of peak discharge (Table 5). The usefulness of persistence as a forecasting tool is not restricted to southern states for late winter streamflows, with northern states providing significant skill in summer and autumn months and providing skill in southern states in spring and summer.

Targeted seasonal forecasts can be used most effectively in agricultural management when the forecast system has skill at long lead-times. Forecast skill of both persistence and the SOI was found to increase as lead-time was reduced. The mean percentage of locations with significant LEPS skill scores (Table 4) as well as the mean value of the LEPS score demonstrates the rapid increase in forecast skill across the seasons as lead-time approaches zero months.

Although lead-time zero has highest skill, there is a benefit for decision making in using a longer lead-time. Our results show that although forecast skill is less at a lead-time of one month than lead-time zero, skill is still reasonably high and is therefore useful.

A lead-time of one month has important implications when targeting a forecast to the needs of water planning and tactical cropping decisions. In southern states at the end of winter, a one-month lead-time would provide an amelioration of risk for irrigation scheduling during the drier spring and summer seasons. An assessment of conditions by a manager one month prior to a tactical decision for crop planting or irrigation scheduling can provide an effective forecast. Longer lead-times have an advantage and potentially a combination of persistence and SOI could be used as a predictor. This combined predictor would be useful in the early summer season when average SOI has a higher level of forecast skill. Increased skill at longer lead-times would provide more opportunity for strategic planning to achieve environmental, economic and social outcomes and reduce the associated risk from a more reactive approach.

An appropriate streamflow season duration is linked to its usefulness for a specific targeted planning decision. A longer period may be required for strategic planning of water resources, whereas a shorter one is useful for tactical planning, for example a farming situation. This study found that forecast skill is available for longer season duration, though the skill does decrease dramatically for a 12-month period.

Three months duration provides the largest statistical significance and skill measures.

A comparison between SOI and persistence of flow as predictors of subsequent flow reveals that persistence is stronger across seasons, lead-times and regions, except for long lead-times of three and four months in early summer. This was a consistent result for the three measures of forecast skill that were assessed: correlation, K-W test and LEPS skill score. Forecast methods combining persistence and the SOI warrant further investigation.

5. CONCLUSIONS

Persistence of streamflow is a useful and skilful forecast tool for most parts of Australia with one month of prior persistence flow the superior predictor of subsequent flow.

A forecast lead-time of zero months is best though a lead-time of one month is statistically significant at most sites and provides an opportunity for a strategic response to the forecast.

Persistence is a stronger predictor of streamflow than average SOI for all skill measurements (LEPS skill score, K-W test and mean correlation).

6. ACKNOWLEDGMENTS

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7. REFERENCES

Chiew, F.H.S. and McMahon, T.A. (1994). Application of the daily rainfall-runoff model MODHYDROLOG to twenty-eight Australian catchments. Journal of Hydrology, 153: 383-416.

Chiew, F.H.S., McMahon, T.A., Zhou S.L. and Piechota, T.C. (2000). Streamflow variability, seasonal forecasting and water resources systems. In “Applications of Seasonal Climate Forecasting in Agricultural and Natural Ecosystems – the Australian Experience”. (Eds G.L. Hammer et al.) Kluwer Academic. The Netherlands.

Clarkson, N.M. (ed.), (2000). Rainman Streamflow Project Final Report to LWRRDC. Land and Water Resources Research and Development Corporation, Canberra.

Clarkson, N.M., Clewett, J.F. and Owens, D.T. (2001). StreamFlow: a supplement to Australian Rainman to improve management of climatic impacts on water resources. Queensland Government, Dept of Primary Industries, Toowoomba

Clewett, J.F. (2003). Seasonal climate forecasts and decision support systems for drought prone agriculture: A case study based on the development and application of the Rainman climate analysis software. In “Coping Against El Niño for Stabilising Rainfed Agriculture: Lessons from Asia and the Pacific” (Ed. S. Yokoyama and R.N.Concepcion). United Nations CGPRT Centre, Bogor, Indonesia, Monograph No. 43: 37-55.

Clewett, J.F., Chiew, F.H.S. and Clarkson, N.M. (2000). Seasonal streamflow forecasts to improve management of water resources: 2. Impact of climate variability and ENSO on streamflow and runoff in Australia. Proc. 26th National and 3rd Int. Hydrol. and Water Res. Symp., Inst. Engineers Australia,. pp 637-641.

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

Clewett, J.F., Howden, S.M., McKeon, G.M. and Rose, C.W. (1991). Optimising farm dam irrigation in response to climatic risk. In “Climatic Risk in Crop Production”. (Eds R.C. Muchow and J.A. Bellamy), C.A.B. International. pp. 307-328.

Conover, W.J. (1971). Practical Non-Parametric Statistics. John Wiley and Sons. pp. 256.

Potts, J.M., Folland, C.K., Jolliffe, I.T. and Sexton, D. (1996). Revised “LEPS” scores for assessing climate model simulations and long-range forecasts. Jnl Climate 9: 34-53.

Simmonds, I. and Hope, P. (1997). Persistence Characteristics of Australian Rainfall Anomalies. International Journal of Climatology, 17: 597-613.

Stone, R.C. and de Hoedt, G. (2000). The development and delivery of current seasonal climate forecasting capabilities in Australia. In “Applications of Seasonal Climate Forecasting in Agricultural and Natural Ecosystems - the Australian Experience”. (Eds G.L. Hammer et al.) Kluwer Academic, The Netherlands. pp. 67-76.