Everingham, Y.L., Clarke, A.J., and Van Gorder, S. (2008) *Long lead rainfall forecasts for the Australian sugar industry*. International Journal of Climatology, 28 (1). pp. 111-117.

http://dx.doi.org/10.1002/joc.1513

Long Lead Rainfall Forecasts for the Australian Sugar Industry

Y.L. Everingham[a,*], A.J. Clarke[b], S. Van Gorder[b]

[a]*School of Mathematical and Physical Sciences, James Cook University, Townsville, Queensland, 4814, Australia.*

[b]*Department of Oceanography, The Florida State University, Tallahassee, Florida, USA*

ABSTRACT

Rainfall variability is a crucial element that impinges on the success of sugarcane growing regions around the world. As the scientific community and industry personnel gain more experience at working participatively, the ability of long range rainfall forecasts to reduce the risk and uncertainty associated with decisions impacted by rainfall variability has become increasingly recognized. Some important decisions, however, require knowing the chance of rain at early lead-times that span the austral autumn period. These types of decisions remain largely unassisted by climate forecasting technologies owing to the boreal spring (austral autumn) persistence barrier. Taking the Australian sugar industry as a case study example, this paper explores the capability of a long-lead statistical ENSO prediction model to reduce the risk associated with decisions that must be made before autumn and are effected by rainfall anomalies post-autumn. Results across all regions considered in this study indicated a higher risk of obtaining an above-median rainfall index when the statistical model predicted La Niña type conditions to emerge post spring. For selected regions this risk was reduced

[*] Correspondence Author:
Yvette L. Everingham, School of Mathematical and Physical Sciences, James Cook University, University Road, Townsville, Queensland 4811, Australia
E-mail address: yvette.everingham@jcu.edu.au
Phone: +61-7-47815067 *Fax:* +61-7-4781 5800

when the model predicted El Niño type conditions for the same period. In addition, the model would have provided an earlier indication of the likelihood of disruption due to wet harvest conditions in a year that devastated the Australian sugar industry. This benchmark study has highlighted the potential of an ENSO prediction model to aid industry decisions that have previously been made in isolation of probabilistic knowledge about future rainfall conditions.

KEY WORDS: ENSO, agriculture, boreal spring, austral autumn, barrier, rainfall

1. **INTRODUCTION**

Rainfall variability impacts agricultural industries in both developed and developing countries across the globe. The generation of probabilistic knowledge about the future state of the climate and the integration of this information into a decision making framework provides opportunities for industries to prepare for climate variability. The El Niño Southern Oscillation phenomenon (ENSO) is a major contributor to the climate variability that is experienced around the world (Trenberth and Caron, 2000). Consequently, substantial research efforts have focused on accurately predicting ENSO type indicators.

A major difficulty in predicting ENSO variability is its lack of persistence across autumn (the autumn barrier). Consider, for example, the often used El Niño monthly index NINO3.4, defined as the departure of the sea surface temperature (SST) from the seasonal cycle for the central-east equatorial Pacific from 5°S-5°N, 170°W-120°W. Like other major ENSO indices, NINO3.4 is highly persistent across the austral spring , but is not persistent across the autumn period. For example, the correlation of the July time series with the following

January time series is 0.85 but the correlation of the January time series with the following July is only 0.03. If forecasting capability across the autumn barrier could reach a level acceptable to industry, and be integrated with key decision making activities, then opportunities exist for agricultural industries to enhance long term forward planning activities previously impeded by the autumn barrier.

The success of an Australian sugarcane cropping season depends on rainfall and the ability to forecast it. In Australia most sugarcane is grown in a narrow strip along the east coast between the latitudes of 15^{o}S to 30^{o}S. Here seasonal rainfall patterns are dominated by ENSO. Everingham *et al*. (2001, 2002a, 2002b, 2003) have investigated the capability of the five phase southern oscillation index climate forecasting system (Stone *et al*., 1996) to improve forward planning across the farming, harvesting, milling and marketing sectors of the industry value chain. ENSO also effects sugarcane growing regions in other countries as well. In South Africa, Singels and Bezuidenhout (1999) found that smaller sugarcane crops were more likely when the SOI phase (Stone *et al*., 1996) in November was consistently negative owing to the reduced chance of rain over the growing season. Warm ENSO events are associated with reduced rainy seasons in Trinidad during the development of the event, and increased rainfall in May to July following the event peak (Pulwarty and Eischeid, 2001). The latter increase in rainfall has been linked to a reduction in crop size the following harvest. Hansen *et al*. (1997) also found a link between ENSO of the year preceding the harvest and sugarcane yields in Florida. Higher yields were more likely to follow La Niña events. Collectively, there exists several examples of how seasonal rainfall forecasts can reduce the risk associated with irrigation, weed control, planting, harvesting and marketing decisions. However, it has been more difficult to reduce the risk of decisions which depend on knowing how rainfall anomalies change across autumn because of the autumn persistence barrier.

There are several crucial decisions that must be finalised by March and are severely effected by climate conditions during September to November. Harvesting sugarcane in Australia is a major operation that traditionally commences around June in each year and under ideal circumstances is completed before the onset of the December-March rainy season. The first half of the harvest season (June - August) tends to be relatively dry for most regions with precipitation levels increasing during the second half of the harvest season (September - November). Having knowledge about the risk of rain later in the harvest season (eg September - November) early in the year (eg January - March) would offer enormous scope for enhancing forward planning activities for several key industry sectors. Marketers who forward sell Australia's sugar early in the year to customers around the world might heed a more conservative forward selling strategy and make more flexible shipping arrangements if disruptions to harvest scheduling due to wet weather were more likely in a particular season. Similarly, millers could supply marketers with improved initial projections of weekly mill production if they knew that the harvest season ahead were likely to be wetter or drier. Mills that crush the harvested cane need to have maintenance completed well before the start of the harvest season. An indication of wetter than average conditions during September - November would urge mill managers together with harvest operators to consider starting the harvest season earlier than traditional start dates. This would reduce the risk of the harvest extending into the monsoon season and would be especially worthwhile to consider when a large crop is expected. Thus, an early indication of the chance of rain in September - November would provide sufficient lead-time for mill managers to arrange labour schedules to ensure completion of necessary mill maintenance and allow harvest operators to plan for an earlier start to the harvest. In addition, a wet end of harvest forecast would suggest that flood prone paddocks be harvested earlier in the season and this scheduling could be planned with longer lead times as discussed in Everingham *et al*., (2001). Knowledge of a drier harvest season would also be helpful to industry. Less rainfall interruptions would call for stringent ship scheduling and given that sugar content often increases later in the harvest season, consideration could be given to delaying the start of the harvest season. To reduce the impacts of low soil moisture levels, drier paddocks could be targeted for harvesting earlier. Clearly, there are many advantages to industry if long lead rainfall forecasts that span the austral autumn barrier could be utilised.

Owing to ENSO, rainfall conditions during the second half of the Australian sugarcane harvest season can be linked to the NINO3.4 index defined earlier. Higher than average SSTs in the NINO3.4 region during the harvest season favours drier periods along the sugar strip in eastern Australia (El Niño). Conversely, lower NINO3.4 indices would increase the risk of rain disruptions (La Niña). Although the strength of the relationship between the NINO3.4 index and rainfall varies with region and time of year, an advanced indication of the NINO3.4 index would offer increased utility in forward planning activities for the industry.

Many models (eg Goddard *et al*., 2001; McGuffie *et al*., 2001; Mason and Mimmack, 2002) predict NINO3.4 and related indices. These models vary in complexity, accuracy and the degree to which they are affected by the autumn barrier. A simple statistical model derived by Clarke and Van Gorder (2003), reported cross-validated correlations that exceeded 0.70 for the September, October and November mean NINO3.4 index when predictions were made given model input data (see equation 1) at the end of January, February and March, respectively. Owing to the simplicity of this model and its ability to forecast across the autumn barrier, it will be used to determine if the risk of wetter or drier conditions during the later half of the harvest season (September-November) can be assessed between January and the end of March.

A recent study by Ruiz *et al*. (2006) found that the statistical ENSO prediction method of Ruiz *et al*. (2005) produced encouraging skill scores (Potts *et al*., 1996) for seasonal rainfall patterns in eight large-scale climate regions of Australia for selected lead-times ranging from three to eighteen months depending on the region and season. This is encouraging because for the period relevant to this investigation, the cross-validated correlations produced by the Clarke and Van Gorder (2003) model, which we will use, compared favourably with the correlative measures produced by the Ruiz *et al*. (2005) model. On the other hand, the Ruiz *et al*. (2006) results are for regions of very large scale, and it is not immediately clear how well an ENSO rainfall prediction scheme will perform in the much smaller sugarcane growing regions of the Australian sugar industry. Our calculations will test the performance of rainfall predictions in the small individual sugarcane growing regions. This will allow industry managers from different regions to understand the capability of the long lead forecasting technology specific to their region and thus facilitate the integration of the technology into their respective decision framework.

The specific objective of the paper is to determine if the risk of wetter or drier conditions during the later half of the harvest season can be predicted early in the year using the method of Clarke and Van Gorder (2003). Following a description of the rainfall data, we will summarize the statistical ENSO prediction model (Clarke and Van Gorder, 2003) and show how this model was used to predict the probability of rain events during September to November early in the year. The Monte-Carlo procedure used to evaluate the computed probabilities is then described and this is followed by a discussion of the results and some concluding remarks.

2. DATA AND METHODS

2.1 Rainfall Indices

To avoid doing multiple tests for nearby highly correlated rainfall weather station locations, a regional rainfall index for each of the seven major sugar sugarcane growing areas spanning 2100 km of Australian coastline was computed. The regions from north to south are referred to as Cairns (CNS), Mourilyan (MLN), Lucinda (LUC), Townsville (TVL), Mackay (MCK), Bundaberg (BUN) and north eastern New South Wales (NSW). Rainfall data for each region were obtained from the nearest high quality official weather station to each of several mills in each region (see Figure 1). A September to November (SON) rainfall index for each region was computed based on the yearly records of total SON rainfall for each weather station in the region. As described in Jones and Everingham (2005), a principal component analysis (Johnson and Wichern, 2002) yielded a leading principal component which was used as the regional rainfall index. The leading principal component is a weighted linear combination of the anomalised SON rainfall totals from each mill rainfall station, where the weights are chosen to maximise the variability of the new linear transformed variable. The range of the new index is dependent on the range of the SON rainfall anomalies. A large amount of variability was explained by the first principal component from each region - CNS,

87.3%; MLN, 91.1%, LUC 97.3%; TVL 93.2%, MCK 92.9%; BUN 94.0%; NSW, 88.8%. As displayed in Figure 2, positive correlations exist between neighboring rainfall indices especially for the more northern regions such as Cairns, Mourilyan and Lucinda. The correlations do however weaken for southern regions and regions that are more spatially disconnected.

2.2 Statistical ENSO Prediction Model

The Clarke and Van Gorder (2003) model uses the predictor

$$S(t) = a\mathrm{NINO3.4}(t) + b\tau(t) + c\bar{h}(t) \qquad (1)$$

to predict NINO3.4(t+Δt) for various lead times Δt. In (1), $\tau(t)$ is an Indo-Pacific equatorial zonal wind anomaly index and $\bar{h}(t)$ describes the anomalous depth of the 20°C isotherm averaged across the equatorial Pacific (5°S-5°N). Each of these indices, by itself, can foreshadow NINO3.4 across the autumn barrier. For example, January or February or March values of each of these indices are correlated with NINO3.4 in either September, October or November later that year with a correlation of at least 0.6. Since also NINO3.4 is strongly persistent from the southern hemisphere spring, we expect that the linear combination in (1) should be an excellent El Niño predictor throughout the year. Note that the coefficients *a*, *b* and *c* depend on calendar month because of the phase-locking of ENSO to the calendar year. The coefficients *a*, *b* and *c* are determined by a least squares fit for each calendar month and each lead time Δt. Since these coefficients pertain to calendar months, NINO3.4(t), $\tau(t)$ and $\bar{h}(t)$ are timeseries of monthly means. Cross-validated calculations by Clarke and Van Gorder indicated that $S(t)$ is an excellent ENSO predictor. At the suggestion of a referee, we have included Figure 3, which suggests that the Clarke and Van Gorder model performs as well or better than other prediction models.

In our case predictions of the September to November NINO3.4 index were made using data from the preceding January, February and March. Owing to the time the model was originally constructed, predictions were made for the years 1981-2001 in cross-validated mode and operationally from 2002-2004. Predicting NINO3.4 indices alone, however, is not useful. These indices must be related to variables that directly impact the sugar industry. In this paper the predicted NINO3.4 index will be used to compute the probability of an above-median rainfall index.

2.3 Computing the Probability of Above-Median Rainfall Index

The phase of predicted SON NINO3.4 was defined to be *cool* if the predicted SON NINO3.4 was less than –0.5°C, *neutral* if the predicted SON NINO3.4 was between –0.5°C and +0.5°C (inclusively), and *warm* if the predicted SON NINO3.4 was greater than +0.5°C. Predictions were made from data up till the end of January (j = 1 in Table I), February (j = 2 in Table I) and March (j = 3 in Table I). For a given prediction month (January, February or March) and a given region, years of the same predicted NINO3.4 phase were pooled. The number years within this pool that had a rainfall index above the median was divided by the pool sample size to calculate a probability of obtaining an above-median rainfall index. For example, Figure 4 shows there were six years (1983, 1984, 1988, 1998, 1999, 2000) when the February predicted SON NINO3.4 phase was cool. In five of these years (all except 1984) the observed rainfall index values for Mourilyan (see Table I) exceeded the median rainfall index. Thus, the MLN, j=2, cool entry in Table II is 5/6.

2.4 Measuring the Significance of the Probability of Above-Median Rainfall Index

A Monte Carlo procedure (Good, 1997) was used to compute the approximate significance level of the probability of obtaining an above-median rainfall index. This procedure closely follows that described in Everingham *et al*. (2003), the only difference being Everingham *et al.* (2003) describe the procedure for a five phase climate forecasting system, whereas the example here has three phases. Briefly, the Monte Carlo procedure involves randomly permuting the NINO3.4 phases one thousand times whilst holding the rainfall index constant. This has the effect of simulating 1000 random forecasts. The probability of exceeding the median of the rainfall index is computed for each permutation. The proportion of probabilities generated from the randomised data that are, as extreme or more extreme than the observed (actual) probability represents the significance level.

More specifically, consider computing a significance level for the example shown in Figure 4. A random forecast was obtained by randomly assigning six years from the 24 possible years (1981-2004) to be cool predictions of SON NINO3.4 from the end of February. Six random years were chosen so that the pool size was the same as that for the model predictions. The number of years in the random pool that exceeded the median rainfall index was then divided by the pool size (6) to obtain a random chance of exceeding the median rainfall index. We repeated this process to obtain 1000 random predictions and found that only 60 times out of 1000 did the random probability equal or exceed 5/6, i.e., the significance level of the probability of an above median rainfall index is 60/1000=0.06. The smaller the significance level, the less likely the model probability of 5/6 could have been obtained by chance. Smaller significance levels (e.g. less than 0.10) suggest that industry may like to reconsider their traditional approach to planning for the coming season as the probability of obtaining an above-median rainfall index will either be significantly higher or lower than normal.

The above calculation of a significance level can be repeated for all months when predictions were made, for all phases predicted and for all regions (see Table II). Significance levels are only approximate, since the estimation process used a finite number (1000) of random samples in each case.

3. RESULTS AND DISCUSSION

Table I shows in January, February and March of 1998 the model predicted that the then current El Niño would switch to La Niña in SON. The associated unanticipated heavy rains in SON of 1998 in Australia's sugar growing regions devastated the Australian sugar industry (Antony *et al*., 2002). An accurate model prediction at that time would have been extremely helpful, especially if industry were advised and took appropriate action. Whilst 1998 is an iconic example for the Australian sugar industry, model credibility derived from a range of years needs to be considered. Table II, derived from all model predictions, shows the probability of an above-median regional rainfall index following each predicted phase from the end of January, February and March, and the corresponding significance level. Table II suggests that when a cool phase is predicted at the end of February there is a higher risk of rain during the later half of the harvest season. This trend is reflected across all regions.

When Equation 1 predicts a warm phase in January then Mourilyan, Lucinda, Townsville and Bundaberg experience a reduced chance of a wetter than average end of harvest season. With the exception of Mourilyan, this effect is less evident for other prediction dates and regions.

4. CONCLUDING REMARKS

This paper has explored the potential of a statistical ENSO prediction model that can overcome the autumn persistence barrier to improve decision making capability for the Australian sugar industry. The main challenge was to provide a useful forecast before the end of March for rainfall in various sugarcane growing regions from September to November. The forecast is needed by the end of March because many industry decisions need to be made by that time. Because of the model's ability to predict El Niño across the autumn period, and the strong association of SON rainfall with El Niño in Australia's sugar producing regions, useful long-range rainfall forecasts can be made. When the model predicted a cool SON NINO3.4 index, the chance of above median rainfall was higher than normal across all sugarcane growing regions. For predictions of warm SON NINO3.4 index, the SON rainfall signal is less distinct. The prediction of a warm SON NINO3.4 index from January favoured below median rainfall for Mourilyan, Lucinda, Townsville and Bundaberg. These findings offer sugar industry decision makers an additional piece of information that previously has not been available to assist industry minimize the risk of climate impacts at the end of harvest. Whilst future research efforts should seek to identify if the size as well as the sign of the rainfall anomaly index can be predicted, this research has provided a starting point for researchers and industry to explore the potential benefits of the long-lead modeling approach. Similar investigations, both in Australia and in other parts of the world can be done for industries that would benefit from long-lead forecasting ability across the southern hemisphere autumn.

ACKNOWLEDGEMENTS

This research has been funded by the Australian Government through the Sugar Research and Development Corporation.

REFERENCES

Antony G, Everingham YL, Smith DM. 2002. Financial benefits from using climate forecasting - a case study. *Proceedings of the 24th Australian Society of Sugarcane Technologists Conference* **24**:153-159.

Barnston AG, Ropelewski CF. 1992. Prediction of ENSO episodes using canonical correlation analysis. *Journal of Climate* **5**:1316-1345.

Clarke AJ, Van Gorder S. 2003. Improving El Niño prediction using a space-time integration of Indo-Pacific winds and equatorial Pacific upper ocean heat content. *Geophysical Research Letters* **30**:521-524.

Everingham YL, Muchow RC, Stone RC. 2001. An assessment of the 5 phase SOI climate forecasting system to improve harvest management decisions. *Proceedings of the 23rd Australian Society of Sugarcane Technologists Conference* **23**:44-50.

Everingham YL, Muchow RC, Stone RC, Inman-Bamber NG, Singels A, Bezuidenhout CN. 2002a. Enhanced risk management and decision-making capability across the sugar industry value chain based on seasonal climate forecasts. *Agricultural Systems* **74**:459-477.

Everingham YL, Inman-Bamber NG, Smith DM. 2002b. Seasonal climate forecasts to enhance decision making capability across the sugar industry value chain. *Proceedings of the 24th Australian Society of Sugarcane Technologists Conference* **24**:67-74.

Everingham YL, Muchow RC, Stone RC, Coomans DH. 2003. Enhancing sugarcane yield forecasting capability using SOI phases: a case study for north eastern Australia. *International Journal of Climatology* **23**:1195-1210.

Goddard L, Mason SJ, Zebiak SE, Ropelewksi CF, Basher R, Cane MA. 2001. Current approaches to seasonal-to-interannual climate predictions. *International Journal of Climatology* **21**:1111-1152.

Good PI. 1997. *Permutation Tests: a Practical Guide to Resampling Methods for Testing Hypotheses* (3rd edn). Springer-Verlag New York Inc: New York.

Hansen JW, Irmak A, and Jones JW. 1997. El Niño-Southern Oscillation influences on Florida crop yields. *Soil and Crop Science Society of Florida Proceedings* **57**:12-16.

Johnson RA, Wichern DW. 2002. *Applied Multivariate Statistical Analysis* (5th edn.) Prentice Hall.

Jones K, Everingham YL. 2005. Can ENSO combined with Low-Frequency SST signals enhance or suppress rainfall in Australian sugar-growing regions? *Proceedings of the International Congress on Modelling and Simulation* 1660-1666.

Knaff JA, Landsea CW. 1997. An El Nino - Southern Oscillation climatology and persistence (CLIPER) forecasting scheme. *Weather Forecasting*. **12**:633-652.

Mason SJ, Mimmack GM. 2002. Comparison of some statistical methods in probabilistic forecasting of ENSO. *Journal of Climate*, **15**: 8-29.

McGuffie K, Hendersen-Sellers A. 2001. Forty years of numerical climate modelling, *International Journal of Climatology* **21**:1067-1109.

Penland C, Magorian T. 1993. Prediction of Niño 3 sea surface temperatures using linear inverse modelling. *Journal of Climate*. 6:1067-1076.

Penland C, Sardeshmukh PD. 1995. The optimal growth of tropical sea surface temperature anomalies. *Journal of Climate* **8**:1999-2024.

Pulwarty RS, Eischeid J. 2001. The impact of El Niño-Southern Oscillation events on rainfall and sugar production in Trinidad. *Proceedings of the 27th West Indies Sugar Technologists Conferencei* **27**:1-11.

Potts JM, Folland CK, Jolliffe IT, Sexton D. 1996. Revised “LEPS” scores for assessing climate model simulations and long range forecasts. *Journal of Climate* **9**:34-53.

Ruiz JE, Cordery I, Sharma A. 2006. Impact of the mid-Pacific Ocean thermocline on the prediction of Australian rainfall. *Journal of Hydrology* **317**:104-122.

Ruiz, JE, Cordery I, Sharma A. 2005. Integrating ocean subsurface temperatures in statistical ENSO forecasts. *Journal of Climate* **18**:3571-3584.

Singels A, Bezuidenhout CN. 1999. The relationship between ENSO and rainfall and yield in the South African sugar industry. *South African Journal of Plant and Soil* **16**:96-101.

Stone RC, Hammer G, Marcussen T. 1996. Prediction of global rainfall probabilities using phases of the Southern Oscillation Index. *Nature* **384**:252-255.

Trenberth KE, Caron JM. 2000. The southern oscillation revisited: sea level pressures, surface temperatures and precipitation. *Journal of Climate*. **13**:4358-4365.

van den Dool HM. 1994a. Searching for analogues, how long must we wait? *Tellus*. **46A**:314-324.

van den Dool HM. 1994a. Constructed analogue prediction of the east central tropical Pacific SST through Fall 1995. *Experimental Long - Lead Forecast Bulletin*. **3**:22-23.

Xue Y, Leetmaa A, Ji M. 2000. ENSO prediction with Markov models. The impact of sea level. *Journal of Climate*. 13:849-871.

List of Figure Captions

Figure 1. Seven groups of raw sugar mills in Australia. Seven rainfall indices for each group were forecast for September to November during January to March. The triangles denote the location of the sugar mills.

Figure 2. Scatterplots demonstrating the relationship between the seven regional rainfall indices. For example the first row shows the CNS regional rainfall anomaly index (mm) on each y-axis plotted against the regional rainfall indices (mm) for MLN, LUC, TVL, MCK, BUN and NSW, along the respective x-axes.

Figure 3. Correlation performance as a function of forecast lead for predicting the El Niño index NINO3.4; open circles, dashed line, the Canonical Correlation Analysis model of Barnston and Ropelewski (1992) for the period 1957-1990; open circles, dotted line, the Linear Inverse Model of Penland and Magorian (1993) and Penland and Sardeshmukh (1995) for the period 1970-1993; open circles, solid line the Constructed Analogue (CA) model of van den Dool (1994a, 1994b) for the period 1981-2001; open triangles, solid line the CA model for the period 1955-2001; open circles dash-dotted line the Markov model of Xue et al. (2000) for the period 1980-1995; closed circles, dashed line the climatology and persistence (CLIPER) model of Knaff and Landsea (1997) for the period January 1993 to November 2006; closed circles, solid line the Clarke and Van Gorder model using Equation (1) for the period 1981-2001. All correlation results are cross-verified hindcasts except for the Knaff and Landsea (1997) CLIPER model for which the correlation results are from operational forecasts.

Figure 4. Graphical display demonstrating how the Mourilyan (MLN) regional rainfall index varied across years and between cool, neutral and warm phases predicted in February. The median rainfall index is approximately zero.

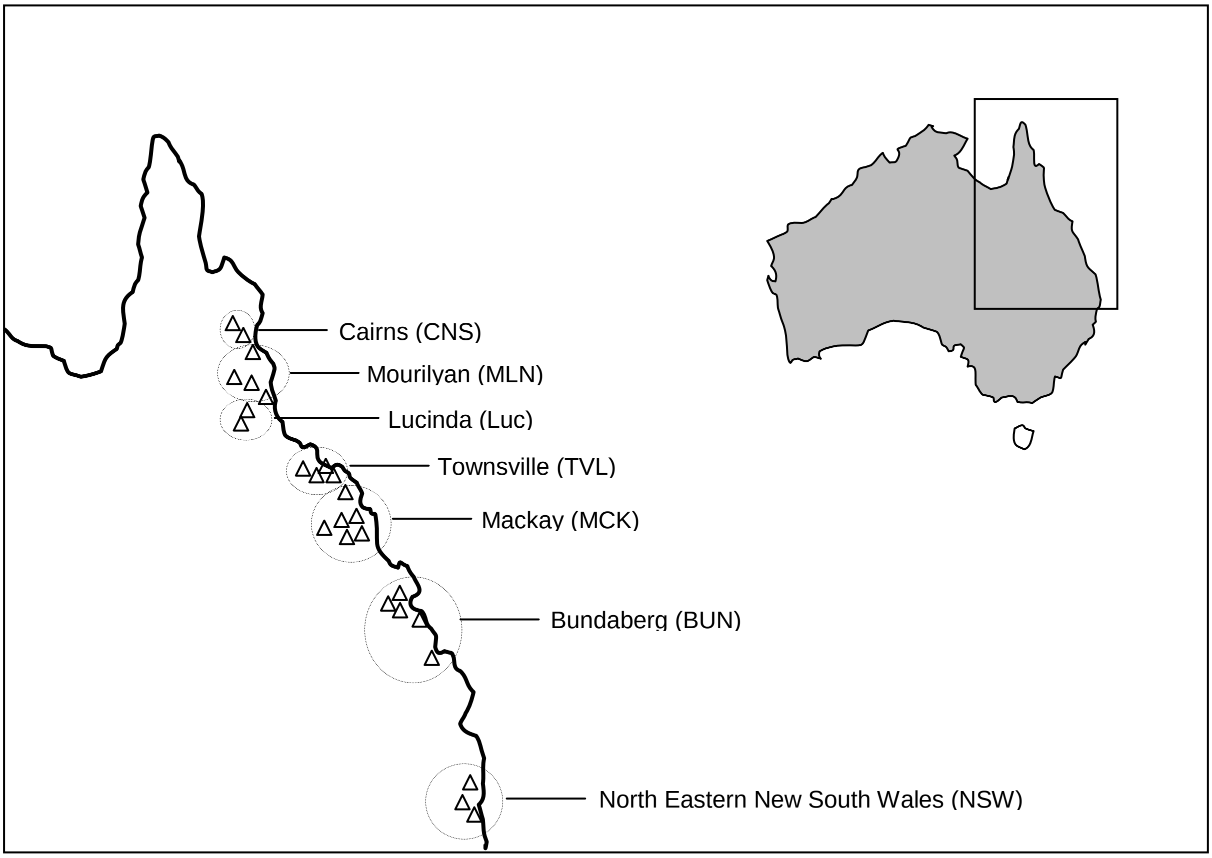

Figure 1. Seven groups of raw sugar mills in Australia. Seven rainfall indices for each group were forecast for September to November during January to March. The triangles denote the location of the sugar mills.

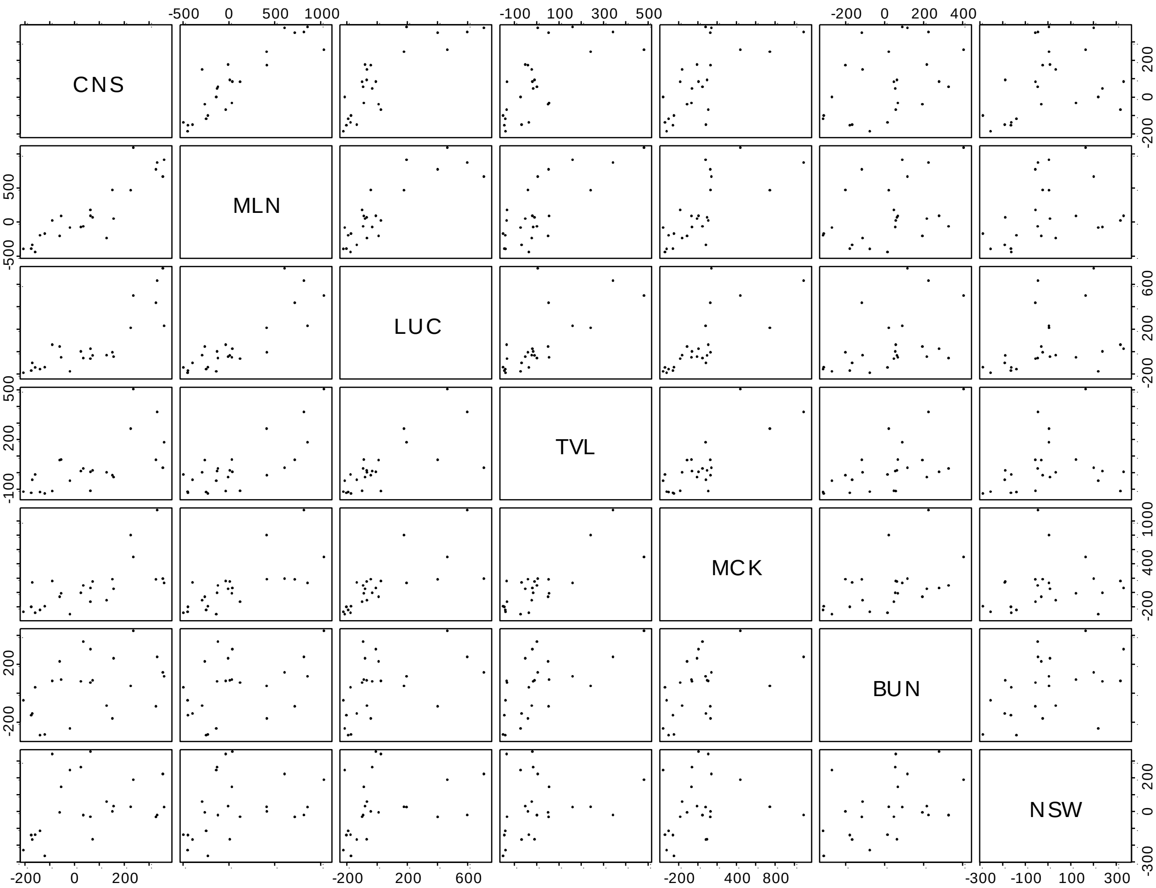

Figure 2. Scatterplots demonstrating the relationship between the seven regional rainfall indices. For example the first row shows the CNS regional rainfall anomaly index (mm) on each y-axis plotted against the regional rainfall indices (mm) for MLN, LUC, TVL, MCK, BUN and NSW, along the respective x-axes.

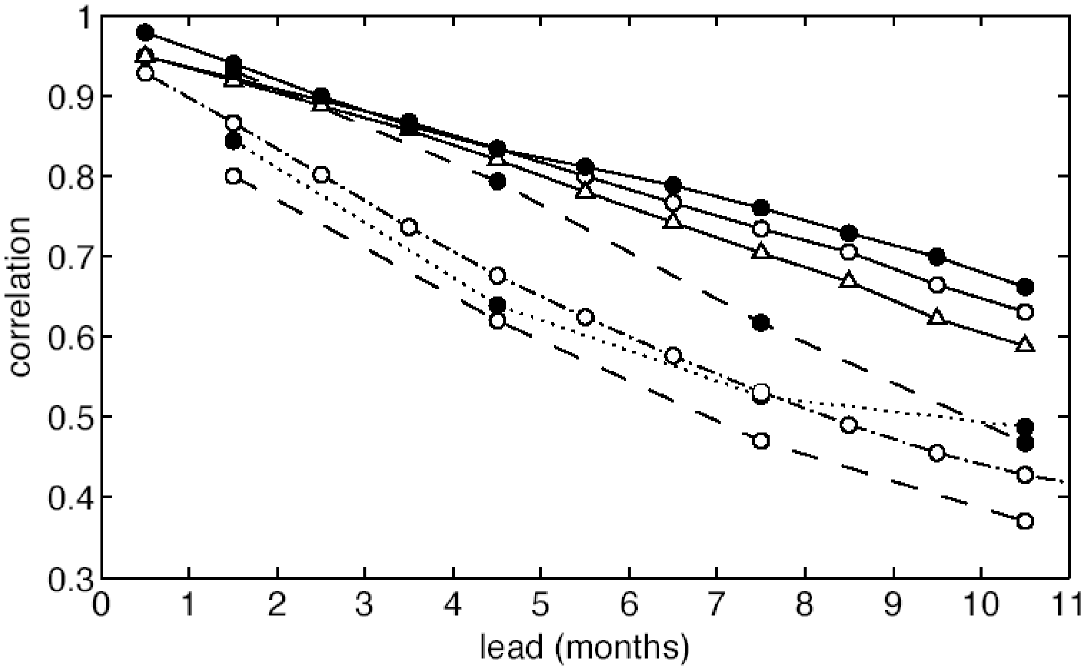

Figure 3. Correlation performance as a function of forecast lead for predicting the El Niño index NINO3.4; open circles, dashed line, the Canonical Correlation Analysis model of Barnston and Ropelewski (1992) for the period 1957-1990; open circles, dotted line, the Linear Inverse Model of Penland and Magorian (1993) and Penland and Sardeshmukh (1995) for the period 1970-1993; open circles, solid line the Constructed Analogue (CA) model of van den Dool (1994a, 1994b) for the period 1981-2001; open triangles, solid line the CA model for the period 1955-2001; open circles dash-dotted line the Markov model of Xue et al. (2000) for the period 1980-1995; closed circles, dashed line the climatology and persistence (CLIPER) model of Knaff and Landsea (1997) for the period January 1993 to November 2006; closed circles, solid line the Clarke and Van Gorder model using Equation (1) for the period 1981-2001. All correlation results are cross-verified hindcasts except for the Knaff and Landsea (1997) CLIPER model for which the correlation results are from operational forecasts.

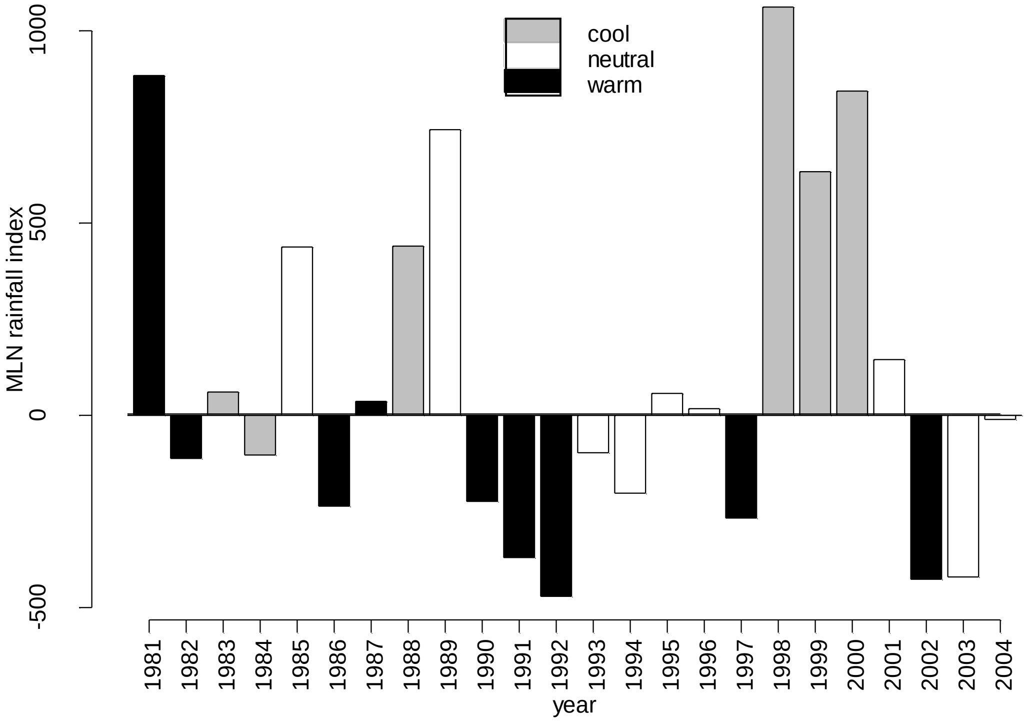

Fig. 4. Graphical display demonstrating how the Mourilyan (MLN) regional rainfall index varied across years and between cool, neutral and warm phases predicted in February. The median rainfall index is approximately zero.

Table I. The predicted NINO 3.4 phase made in January, February and March using Equation 1 and the Mourilyan rainfall index.

	ENSO phase			Rainfall Index (mm)
Year	Jan (j=1)	Feb (j=2)	Mar (j=3)	MLN
1981	neutral	warm	warm	883.6
1982	warm	warm	warm	-112.4
1983	cool	cool	cool	60.5
1984	cool	cool	cool	-103.4
1985	neutral	neutral	neutral	437.7
1986	neutral	warm	neutral	-236.4
1987	warm	warm	warm	36.1
1988	cool	cool	neutral	440.0
1989	neutral	neutral	neutral	742.8
1990	warm	warm	warm	-224.1
1991	warm	warm	warm	-370.1
1992	warm	warm	neutral	-471.0
1993	neutral	neutral	warm	-97.2
1994	neutral	neutral	neutral	-202.4
1995	cool	neutral	neutral	57.1
1996	neutral	neutral	neutral	17.2
1997	warm	warm	warm	-267.0
1998	cool	cool	cool	1061.3
1999	cool	cool	cool	633.4
2000	cool	cool	cool	842.8
2001	neutral	neutral	neutral	144.8
2002	warm	warm	warm	-426.6
2003	neutral	neutral	neutral	-420.7
2004	neutral	neutral	neutral	-10.6

Table II. The probability of exceeding the median September-November rainfall index for a given September-November NINO3.4 phase predicted at the end of January (*j*=1), February (*j*=2) and March (*j*=3), for different regions. Taking Cairns (CNS) as an example, given data till the end of January (*j* = 1), there were 7 years when a 'cool' SON NINO3.4 phase was predicted and in 5 of those years the observed SON rainfall exceeded the median. This leads to an entry 5/7 and a probability of 0.71 in the probability part of the table. The corresponding significant levels for probabilities of exceedence have also been tabulated. Significant levels less than 0.10 are in bold type.

Region	Prediction Month	Fraction of years exceeding the median rainfall index			Probability of above median rainfall index			Significance level		
	j	**cool**	**neutral**	**warm**	**cool**	**neutral**	**warm**	**cool**	**neutral**	**warm**
CNS	1	5 / 7	5 / 10	2 / 7	0.71	0.50	0.29	0.17	0.68	0.20
	2	5 / 6	4 / 9	3 / 9	0.83	0.44	0.33	**0.08**	0.82	0.21
	3	4 / 5	5 / 11	3 / 8	0.80	0.45	0.38	0.15	0.79	0.31
MLN	1	6 / 7	5 / 10	1 / 7	0.86	0.50	0.14	**0.04**	0.66	**0.03**
	2	5 / 6	5 / 9	2 / 9	0.83	0.56	0.22	**0.06**	0.50	**0.03**
	3	4 / 5	6 / 11	2 / 8	0.80	0.55	0.25	0.16	0.48	**0.09**
LUC	1	6 / 7	5 / 10	1 / 7	0.86	0.50	0.14	**0.03**	0.67	**0.04**
	2	6 / 6	3 / 9	3 / 9	1.00	0.33	0.33	**0.01**	0.96	0.20
	3	5 / 5	5 / 11	2 / 8	1.00	0.45	0.25	**0.02**	0.80	0.10
TVL	1	6 / 7	5 / 10	1 / 7	0.86	0.50	0.14	**0.03**	0.66	**0.04**
	2	5 / 6	4 / 9	3 / 9	0.83	0.44	0.33	**0.08**	0.79	0.21
	3	5 / 5	4 / 11	3 / 8	1.00	0.36	0.38	**0.02**	0.95	0.33
MCK	1	5 / 7	5 / 10	2 / 7	0.71	0.50	0.29	0.17	0.68	0.20
	2	5 / 6	4 / 9	3 / 9	0.83	0.44	0.33	**0.08**	0.80	0.22
	3	4 / 5	4 / 11	4 / 8	0.80	0.36	0.50	0.16	0.95	0.67
BUN	1	6 / 7	5 / 10	1 / 7	0.86	0.50	0.14	**0.03**	0.68	**0.04**
	2	5 / 6	4 / 9	3 / 9	0.83	0.44	0.33	**0.07**	0.82	0.21
	3	5 / 5	4 / 11	3 / 8	1.00	0.36	0.38	**0.02**	0.95	0.31
NSW	1	6 / 7	4 / 10	2 / 7	0.86	0.40	0.29	**0.04**	0.90	0.20
	2	5 / 6	4 / 9	3 / 9	0.83	0.44	0.33	**0.07**	0.80	0.20
	3	4 / 5	5 / 11	3 / 8	0.80	0.45	0.38	0.15	0.80	0.34