An Empirical Method for Forecasting Low Rainfall Using the Southern Oscillation Index (SOI) and Dipole Mode Index (DMI)

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Abstract The study is a seminal investigation on the possibility of using in combination the consistently negative phase of the Southern Oscillation Index (SOI) and the Dipole Mode Index (DMI) of the Indian Ocean to forecast low rainfall. Using precipitation data for 107 Australian districts from 1913 to 1996, the individual influence of the SOI phase and DMI on subsequent seasonal precipitation was examined. From the quantile plots of precipitation exceedance probabilities derived for all districts and for various SOI phases, it was found that a consistently negative SO phase generally preceded a below-median seasonal rainfall in many parts of Australia. This was especially true in eastern Australia, where El Niño Southern Oscillation (ENSO) has a major influence on climate variability. By partitioning the data using the lowest 25% of SOI values, the relationship between DMI and low rainfall was also investigated. Concurrent and lagged relationships between low rainfall and DMI were found to be strong ($r \geq -0.6$) throughout most of Australia especially in autumn and winter. When the consistently negative SOI phase and DMI were used together in one regression model, strong relationships were also observed between DMI and low rainfall over large areas especially during summer and autumn. This was taken as an indication of the potential of this 'combination' model for forecasting low rainfall in many parts of Australia.

Keywords: Probabilistic forecasting; Low rainfall; SOI; Dipole Mode Index (DMI); Data-partitioning

1. INTRODUCTION

The climatic variability of Australia is influenced by at least three ocean-atmospheric phenomena. The El Niño-Southern Oscillation (ENSO) phenomenon in the Pacific Ocean, which is numerically defined by the Southern Oscillation Index (SOI), has been known to cause Australia's interannual climatic variations. Strong relationships between ENSO and precipitation have been documented [Ropelewski and Halpert, 1996; McBride and Nicholls, 1983] and efforts had been directed towards using such relationships for forecasting rainfall. An ENSO-like phenomenon called the Indian Ocean Dipole (IOD) had also been found to influence Australia's climatic regime. Nicholls [1989] and Drosdowsky [1993] documented the effect of IOD, which is defined by the Dipole Mode Index (DMI), on the variability of winter rainfall. The third ocean-atmospheric phenomenon that influences climate variability in Australia is the Antarctic Circumpolar Wave (ACW) in the Southern Ocean, which is characterised by a persistent contemporaneous phase relationship between warm and cool sea surface temperature (SST) anomalies. White [2000] found that ACW was capable of predicting rainfall in some seasons over many locations in Australia.

ENSO's importance as a global phenomenon is unquestionable, but it no longer remains as the only basis for climatic forecasting in Australia. One reason is that ENSO's influence on the Australian climate has its limitations. During late summer and autumn period, when ENSO events tend to decay, the relationships between Australian rainfall and Southern Oscillation (SO) become weak. Its influence over the western third of the continent is also known to be generally low [Drosdowsky and Chambers, 2001]. The other reason is the uncertainty and inconsistency of an

ENSO-based forecast. A good illustration of this is the two El Niño events of 1982-83 and 1997-98. The former produced a devastating drought in Australia while the latter produced slightly below normal rainfall. Some inconsistencies in relationships between precipitation and SOI were also observed in eastern Australia [Cordery, 1999]. Two important droughts occurred in 1919 and 1937 when SOI remained close to its long-term average, and two very low SOI values in 1905 and 1937 corresponded to concurrent precipitation that was either average or above average. These shortcomings of the ENSO led to the ongoing search for other predictors for Australian rainfall.

The discovery of IOD and ACW opened up possibilities for incorporating the effects of ENSO, IOD and ACW in one forecasting model. Drosdowsky and Chambers [2001] developed a statistical scheme for prediction of rainfall in Australia based on IOD and global indices of ENSO, which they found to have better skill than a prediction based on the SOI alone. Australia's Bureau of Meteorology (BOM) now considers both Indian Ocean and Pacific Ocean SST in its three-month Seasonal Climate Outlook rainfall probabilities [BOM, 2001].

This study examines the possibility of using in one forecasting model the continuously negative phase of the SOI and DMI to predict low rainfall in Australia. Described in sections 2 and 3 are the two models that constitute this 'combination' model. Based on the works of Stone et al. [1996] and Cordery [1999], these models demonstrate how the SOI phase and DMI influence Australian rainfall. The intention of presenting these two models in this paper is not only to highlight their applicability to the Australian setting but also to prove that a rainfall-forecasting model that combines their concepts is logical.

2. SOI PHASE METHOD

The SOI Phase Method (SPM), derived from Stone et al.'s concept, is a probabilistic rainfall-forecasting scheme that uses lagged-relationships between the values of the SOI and future rainfall. SPM functions without requiring ENSO predictive ability, as the rainfall exceedance probabilities it provides are based on how previous rainfall events behaved in response to the antecedent SOI phase. Hence, seasonal forecasting can be attempted once the early stages of various SOI phases are underway.

2.1 Data and Procedure

The data used in this study consisted of the monthly district precipitation values for all 107 districts in Australia for the period 1913-1996. Sourced from BOM, these data indicated the mean of the monthly precipitation observed in each district. SOI data, downloaded from the BOM website, included monthly values for the same period. SOI is defined as 10 times the standardised sea level pressure difference between Tahiti and Darwin [Troup, 1965].

SPM was applied using a seasonal interval for forecasting purposes. Winter comprises June-July-August; spring comprises September-October-November; and so on. This study dealt only with the SOI phase during the two months prior to the season, although the method could possibly be used for lagged-relationships of up to six months for long-term forecasting purposes. For this SPM model, SOI values of –5 and +5 were arbitrarily chosen as boundary limits. Using these limiting SOI values, each season of the 84 years was categorised into one of the following SOI phase types: (1) Near Zero (NZ), (2) Consistently Positive (CP), (3) Consistently Negative (CN), (4) Rapid Rise (RR), and (5) Rapid Fall (RF). If the SOI of the two months preceding the season were both greater than 5, then the seasonal SOI phase was CP; CN if both were less than –5. The SOI phase was said to be RF if the first month had SOI greater than 5 while the second month had SOI less or equal to –5 and vice versa.

Of the five possible SOI phases, only NZ, CP and CN came up with a number of occurrences adequate enough to plot the exceedance probability curves. There were very few seasons that satisfied the criteria for the Rapid Rise (RR) and Rapid Fall (RF) phases. The only exception was winter, which had eight RR events. This is a limitation of SPM that can only be overcome by using longer periods of data. Even if 84 years of data were used in this study, 14 more than the 70 years recommended by Stone [1996], the shortfall was still there.

Rainfall response after a NZ phase was found to be very similar to the '84-year' response in most districts; hence, only CP and CN phases were included in the investigation. CP and CN events for each season amounted to about 18% of the 84 available phase events; ranging from 14% for CN phase events in autumn to 21% for CN phase events in summer. Quantile plots of subsequent rainfall associated with CP and CN phases were derived for all 107 districts from the 84-year rainfall data. Variability of rain in a district was attributed to the preceding SOI phase if the CP and CN quantile plots significantly varied from the '84-year' quantile plot. If at least 65% of the rainfall values included within the interquartile range (25-75%) of the quantile plot were greater or less than the '84-year' median rainfall value, then the SOI phase was said to have an influence on seasonal precipitation. If this criterion was not satisfied, then the SOI phase was considered as a poor predictor of future rainfall. For areas where CP and CN phases of SOI have an influence, the quantile plots can be used as a forecasting tool; although, only probabilities of exceeding the long-term median rainfall can be given.

2.2 Results and Discussion

The initial logical assumption of a CN (CP) phase preceding rainfall events likely to fall short of (exceed) the long-term median rainfall was validated in all seasons except autumn. This was particularly evident in spring, when the eastern half of Australia was characterised by above-median rains following a CP phase and below-median rains after a CN phase (see Figure 1). This confirmed the findings of McBride and Nicholls [1983] who used correlation analysis in concluding that the strongest lag correlations occur between SOI and spring rainfall. What was surprising though was the number of districts in southeastern Australia that indicated above-median rainfall following a CN phase during autumn. The occurrence of this phenomenon might be caused by a local variable whose rain-inducing property far outweighs the influence of a CN phase.

Quantile plots for autumn rains in districts 9A, 16 and 14BC during the period 1913-1991 are shown in Figure 2. From such plots, the exceedance probabilities for any particular rainfall amount, corresponding to whether the SOI phase is CN or CP, can be readily obtained. For district 9A, located in southwestern Australia, the probabilities of autumn rain exceeding 200mm are 15% and 45% when preceded by a CN phase and CP phase respectively (see Figure 2a). District 16 displays a different response in autumn, as rainfall is likely to exceed the long-term median when preceded by a CN phase. Figure 2b shows that the CP phase has little influence on rainfall for this district in the following season. Figure 2c illustrates how a RR phase influences subsequent autumn rain for areas located north of Australia.

SPM was then used for districts 9A and 16 to illustrate its forecasting capability for the period 1992-1996. During the period, there were at least two CN events occurring in all seasons and there was one CP event for spring. Table 1 shows the long-term median rainfall, the median exceedance probabilities and the observed rainfall values for each season in the two districts. Observed rainfall values in district 9A corresponded with the median exceedance probabilities, except for some values during autumn and summer. District 16, on the other hand, displayed several inconsistencies, with half of the observed rainfall values not conforming to the median exceedance probabilities.

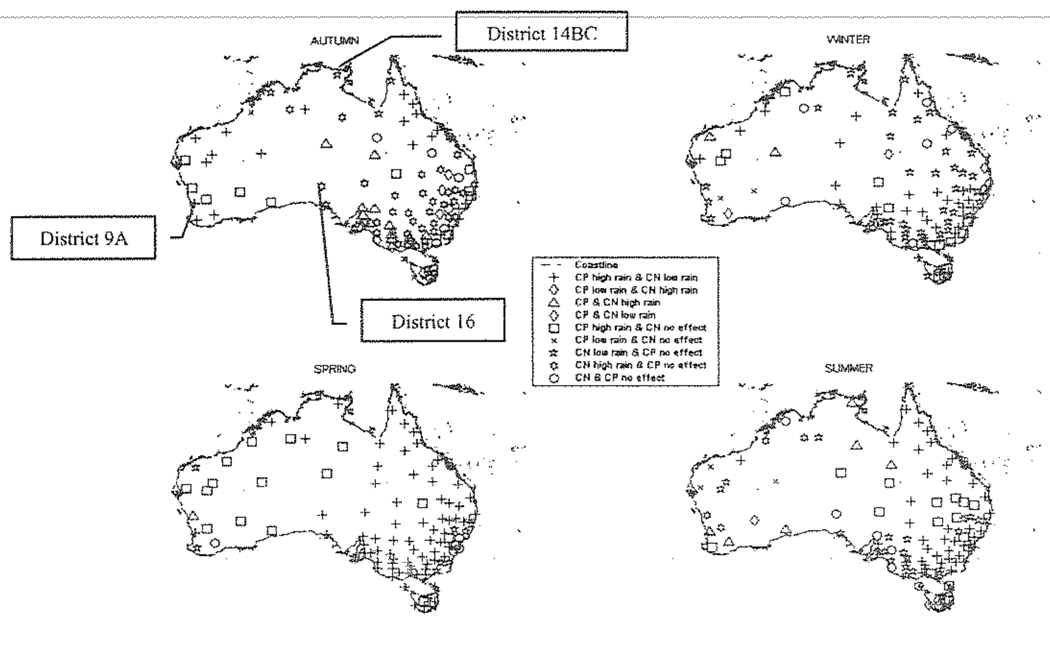
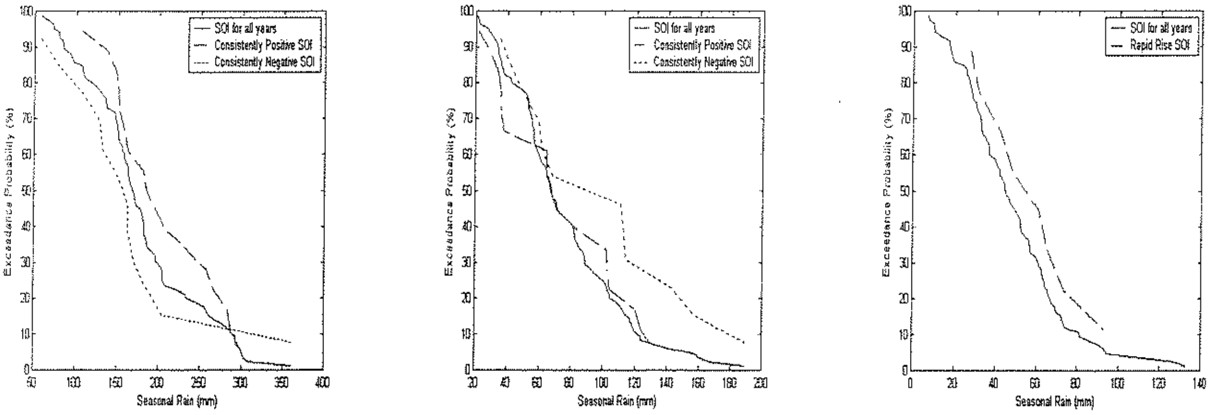


Figure 1. Responses of seasonal rain to antecedent CP and CN phases of SOI.



(a) (b) (c)

Figure 2. Quantile plots for autumn rainfall in districts 9A, 16 and 14BC respectively.

3. DATA PARTITIONING METHOD

The Data Partitioning Method, henceforth to be called DPM, is an empirical method of forecasting rainfall, especially low rainfall events when low SOI values are expected. Derived from the Cordery [1999] model, DPM partitions a multivariate dataset into a manageable size such that the correlation between two variables can be assessed.

For the case of datasets with three variables, Cordery [1999] suggested that in order to examine the influence of two correlated variables on a third variable, one variable could be used as a marker to partition the data. In his work, Cordery [1999] used the lowest 25% of SOI values to partition the Geopotential Height (GpH) and rainfall values prior to regression analysis. What resulted was a conditional model whose regression relation included not two but three variables. DPM was used in this study to identify areas in Australia where DMI can be used as a predictor of low rainfall.

3.1 Data and Procedure

In addition to precipitation and SOI data, monthly GpH values at five locations in Australia were also obtained from BOM from which GpH gradients between locations were derived. A principal component analysis of several GpH gradients across the country revealed the GpH gradient between Perth and Brisbane was a significant dimension of the reduced gradient dataset. Hence, this GpH gradient was used in this study.

The DMI was developed by Saji et al. [1999] to represent SST anomalies in the tropical Indian Ocean. It is defined as the difference of SST anomalies between the tropical western Indian Ocean (50°E-70°E, 10°S-10°N) and the tropical southeast Indian Ocean (90°E-110°E, 10°S-Equator). DMI data from 1958 to 1996 was from http://w3.frontier.esto.or.jp/d1/saji/dmi.index.

DPM was applied to the 39-year precipitation, GpH and DMI datasets for all 107 districts. Correlation analysis in this study was limited to

Table 1. Median seasonal rainfall, median rainfall exceedance probabilities and observed seasonal rainfall for districts 9A and 16 for period 1992-1996.

SEASON	SOI Phase	DISTRICT 9A (southwestern Australia)			DISTRICT 16 (southern Australia)		
		Median Rainfall (mm)	Probability of Exceeding Median Rain	Observed Rainfall (mm)	Median Rainfall (mm)	Probability of Exceeding Median Rain	Observed Rainfall (mm)
Autumn	CN	197	35%	192, 209	36	65%	81, 21
Winter	CN	450	30%	356, 345, 434	48	35%	45, 36, 83
Spring	CN	189	40%	171,125	41	35%	52, 6
	CP	189	55%	223	41	90%	31
Summer	CN	49	53%	33, 29	36	50%	127,30

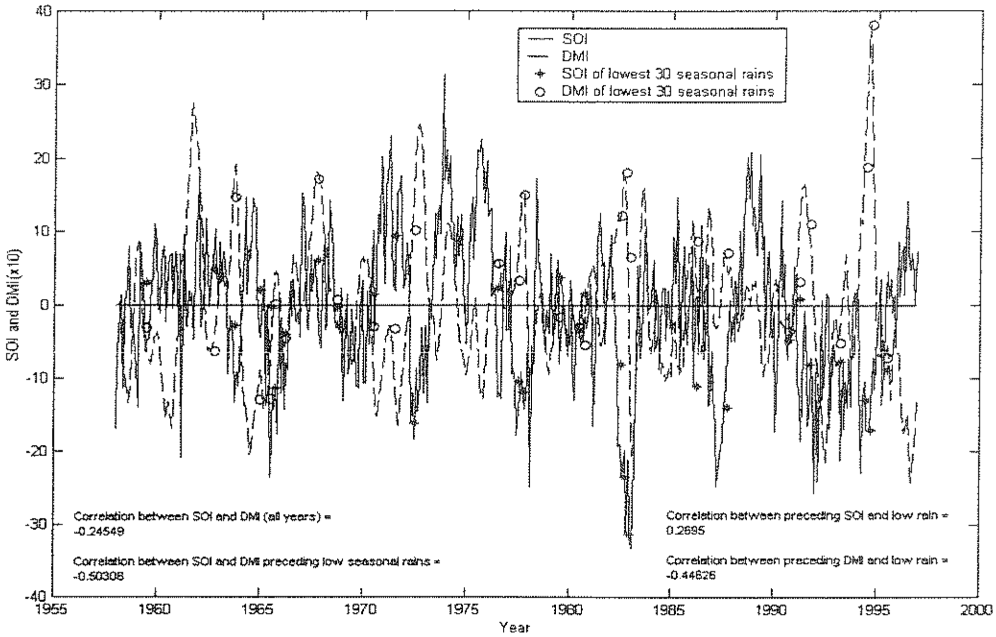


Figure 3. SOI & DMI values preceding the 30 lowest seasonal rainfall in eastern Australiafor the period 1958-1996.

low rainfall events; hence, the dataset was partitioned using the lowest 25% of SOI values. Correlation coefficients for the concurrent, one-month and two-month lagged relationships between rainfall and GpH or DMI were calculated and compared. Districts where there was strong correlation ($|r|\geq 0.6$) between low rainfall and either DMI or GpH were identified.

3.2 Results and Discussion

When the 30 lowest total seasonal rainfall values for eastern Australia were regressed against the preceding monthly DMI and SOI values for the 1958-1996 period, DMI indicated stronger relations with low rain (r=-0.45) than SOI (r=0.27, see Figure 3). Though a significant correlation (r= –0.5) existed between these DMI and SOI values, results of this investigation show that DMI can be an indicator of the occurrence of low rainfall or droughts in Australia.

Regression analysis of concurrent partitioned data revealed that, for winter and autumn seasons, low rain was more strongly correlated with DMI than GpH in western and southeastern Australia. A similar finding was observed by Nicholls [1989] who described this particular rainfall pattern as an effect of the difference in sea temperatures between the Indonesian region and the central Indian Ocean. Neither DMI nor GpH was correlated with low rain in spring and summer. However, for lead times of one and two months, both DMI and GpH showed strong relationships particularly in western, eastern and southern Australia, with DMI taking more spatial coverage. DMI was also strongly correlated with rainfall in spring and summer in southeastern and southwestern Australia.

4. COMBINED SPM AND DPM MODEL

The DPM was used on the 1958-1996 seasonal datasets; however, this time, data partitioning was done using the preceding CN phase of the SOI instead of the lowest 25% SOI values. The mean DMI and mean GpH of the two months preceding the seasons were separately taken as the third variable. Regression analysis between rain and these DMI or GpH mean values was performed to identify which variable had a stronger relationship with low rainfall. DMI was found to have stronger relationships with low rainfall events than GpH in all seasons, except winter, for both concurrent and lagged relationships (see Figure 4). This finding is an indication that a forecasting model that combines the concepts of SPM and DPM while at the same time using SOI and DMI as predictor variables could provide more accurate forecasts of low rainfall events.

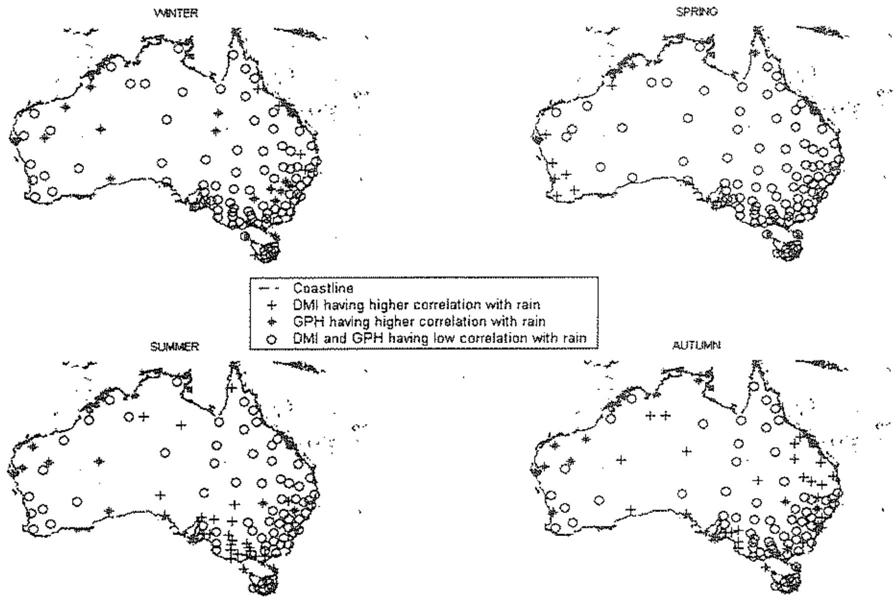


Figure 4. Districts with low rainfall having strong two-month lagged correlation with DMI or GpH using CN SOI phase as the partitioning variable.

5. CONCLUSION

The separate application of the SPM and DPM models on Australian seasonal precipitation data had demonstrated that a continuously negative SOI phase and high DMI values generally precede below-median rainfall. By putting these two models into one and thereby combining the effect of the SOI phase and DMI, the study demonstrated that this 'combination' model has the potential of forecasting more accurately low rainfall in Australia. The applicability of this 'combination' model is particularly promising in many parts of Australia and in all seasons except winter. Further studies are being undertaken to improve the model's forecasting skill, which will be evaluated by means of cross-validation techniques.

6. REFERENCES

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