# NOTES AND CORRESPONDENCE

# Spatial Coherence and Predictability of Indonesian Wet Season Rainfall

MALCOLM HAYLOCK AND JOHN MCBRIDE

*Bureau of Meteorology Research Centre, Melbourne, Australia*

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ABSTRACT

Rainfall from 63 stations across Indonesia is examined for the period 1950–98 to determine the spatial coherence of wet season anomalies. An example of almost unrelated anomalies at two neighboring stations is presented. Principal component analysis is used to quantify the spatial coherence across the entire region. The significant components show high loadings over only a small region, suggesting that rainfall in only this small region varies coherently on an interannual timescale. Correlation with the Southern Oscillation index (SOI) shows that rainfall over only this same region is being largely governed by the El Niño–Southern Oscillation (ENSO) phenomenon. In contrast, a similar analysis for the transition season (Sep–Nov) rainfall shows coherence across almost the entire region and a similarly large area of high correlation with the SOI. Results for all seasons are summarized with the use of an all-Indonesian rainfall index constructed from an averaged percentile ranking of seasonal rainfall from each station across the region. At the times of the year when a large (small) percentage of the variance of rainfall is described by the lowest-order principal components, there is a large (small) correlation between the SOI and the all-Indonesian rainfall index. The implication is that wet season rainfall in Indonesia is inherently unpredictable.

## 1. Introduction

There have been several recent studies examining connections between observed rainfall and a number of large-scale climate signals (e.g., Wang et al. 2000; Drosdowsky 1993; Montecinos et al. 2000; Makarau and Jury 1997; Nicholls 1981). The aim of these studies has generally been to develop, where possible, methods for long-range forecasting. Studies have looked for predictors based on correlation with raw station data (e.g., Montecinos et al. 2000; Nicholls 1981), area averages (e.g., Makarau and Jury 1997), or principal components of station rainfall (e.g., Drosdowsky 1993).

These forecasting methods generally rely on searching for only a few large-scale predictors to account for changes in rainfall across large areas. It is our hypothesis that inherent in such schemes is the assumption that a large proportion of the variation of rainfall is spatially coherent. It is not possible for two (or more) stations to have uncorrelated interannual rainfall for a particular season, yet share the same predictors.

This paper examines the predictability of seasonal rainfall during the wet season (or ''Musim Hujan'') over the Maritime Continent region of Indonesia. As discussed by Nicholls (1981), Hastenrath (1987), and McBride (1999, Chapter 3A), seasonal forecasting in Indonesia has a long history, extending back to Braak (1919). The basis of forecasting in the region has been the persistence of the Southern Oscillation, one simple index of which is the pressure at Darwin, Australia (Nicholls 1981; McBride and Nicholls 1983). Beginning with the early colonial work of Braak (1919) and Berlage (1927, 1934) and continuing through to the major works of the modern era (Nicholls 1981; Hastenrath 1987), exploration into seasonal forecasting was based on the simple concept of lag relationships between Darwin pressure and seasonal rainfall.

The meteorology of Indonesia has been described by Sukanto (1969), Hackert and Hastenrath (1986), and McBride (1999, Chapter 3A). Straddling the equator, much of the region has rain throughout the year. However, for most of the region the major wet season coincides with the Southern Hemisphere summer monsoon (McBride 1983; Murakami and Sumi 1982), with the peak rainfall occurring during the southern summer months of December–February (DJF). Despite this, seasonal forecasting in the region has focused on the early wet season, or ''transition season'' months of September–November (SON); see, for example, Nicholls (1981) and Hastenrath (1987). This focus is due simply

*Corresponding author address:* Mr. Malcolm Haylock, Bureau of Meteorology Research Centre, GPO Box 1289K, Melbourne, Victoria 3001, Australia.
E-mail: m.haylock@bom.gov.au

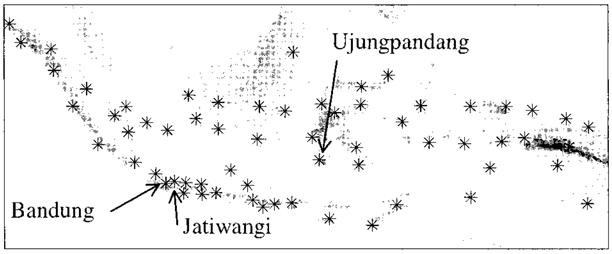


FIG. 1. Location of 63 stations. Three stations mentioned in the text are shown. Shading indicates orography.

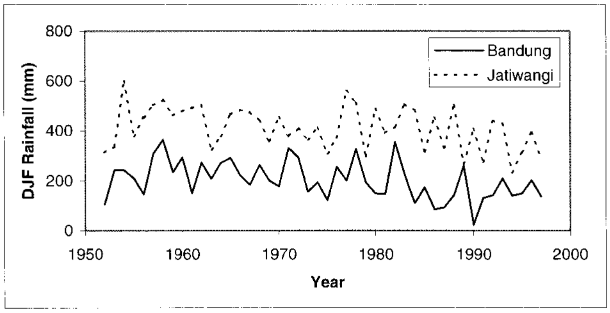


FIG. 2. DJF rainfall at Bandung and Jatiwangi.

to the pragmatic reason that the lag correlations between indices of the Southern Oscillation and rainfall are large for SON rainfall and small for DJF rainfall (Hastenrath 1987; Kirono et al. 1999).

The current paper examines the reasons for this change of predictability following the framework espoused in the above opening paragraphs. Specifically, the relationship between observed rainfall and a large-scale climate signal (viz., the Southern Oscillation) depends on anomalies in the rainfall having a large-scale coherence. As will be shown, rainfall anomalies across Indonesia during the peak of the wet season (DJF) have low coherence, and therefore are hypothesized to be inherently unpredictable.

The following section describes the dataset used. In section 3 coherence of rainfall anomalies in the two seasons of SON and DJF is examined through both correlation analysis and through the use of principal component analysis. The consistency between anomaly coherence and association with the Southern Oscillation is demonstrated in section 4. Section 5 discusses the implications of the results and speculates on the relationship between this definition of predictability and other frameworks that appear in the literature. The final concluding section summarizes the results.

## 2. Data

Figure 1 shows the location of 63 rainfall stations for which monthly rainfall were compiled by D. G. C. Kirono (2000, personal communication). This set is an extension of the 33 stations used by Kirono et al. (1999). Several sources were used: data up to 1988 from the Badan Meteorologi dan Geofisika (BMG) publication ''Rain Observations in Indonesia''; data to 1991 from the BMG publication ''Climate Data in Indonesia''; and more recent data for BMG stations from the BMG database.

In selecting stations from an initial set of over 3000, Kirono et al. (1999) gave priority to meteorological stations that were generally of higher quality and with trained observers. Stations were also selected with recent data to enable possible future updates. Since many of the stations had data in a number of sources, any differences between the sources were reconciled and the longest record compiled. Stations with much missing data were not included. All stations selected have less than 10% of months missing for their period of record and no stations have more than 1 yr when the entire year is missing.

Next, stations were subjected to a statistical test of Buishand (1982) to check for artificial jumps, outliers, and trends in the monthly series. This method examines the cumulative deviation of the series from the mean, tested against critical values derived from randomly generated samples. The test assumes a normally distributed series, a condition that was examined using a Kolmogorov–Smirnov test on the monthly and seasonal series. Stations failing the Buishand test were not included in the final set. More common statistical methods, such as those discussed in Peterson et al. (1998), were not applied due to the lack of a good station network with overlapping data in neighboring stations.

Finally, the series of the monthly anomalies of each station was visually examined for obvious inhomogeneities that were not indicated by the statistical tests.

The final set of 63 stations (Fig. 1) provides even spatial coverage over the Indonesian region. While some of the stations only have data since 1960, most have almost complete records from 1950 to 1998.

## 3. Coherence of rainfall anomalies

### a. Local coherence

As an example of low spatial coherence of DJF rainfall, consider the two stations Bandung and Jatiwangi, the locations of which are shown in Fig. 1. A plot of the DJF rainfall for these two stations (Fig. 2) illustrates the low correlation between the stations. Much of the correlation of 0.30 ($p < 0.05$) is due to the declining trend in both the series. Removing this trend gives a correlation of 0.18 ($p > 0.10$).

The lack of coherent variation between the DJF rainfall at these two stations suggests that it is likely that local effects are dominating the rainfall in the wet season. Any large-scale changes are perhaps masked by stronger local effects.

While the two stations are close (less than 100 km apart), the surrounding areas are very different topographically. The eastern station, Jatiwangi, is located on

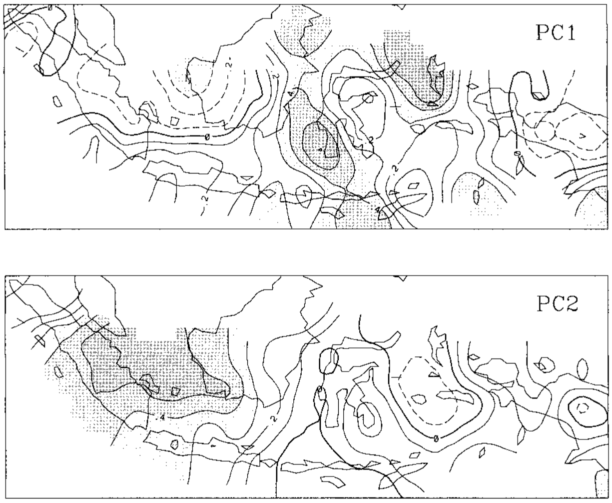


FIG. 3. Spatial pattern of loadings of the first two unrotated principal components of DJF rainfall. Contour interval is 0.1, the zero contour is bold, negative contours are dashed, and areas above +0.3 and below −0.3 are shaded.

the northern coastal plain of Java at an elevation of 50 m. The western station, Bandung, is at an elevation of 791 m and has mountains to the north and south. Therefore, the varied topography in the area (and the island generally) could be contributing to the low coherence of rainfall variation between the two stations.

Performing the same analysis for SON gives a much higher correlation of 0.61 ($p < 0.01$) between the two stations with or without the trend removed. Therefore, the low correlation in DJF is not just a result of the differing topography in the region, but is also due to the less coherent nature of the rainfall during these months.

### *b. Regional coherence*

To examine how coherently the DJF rainfall of all the stations are varying, a principal component analysis was carried out. An analysis based on the correlation matrix was used to focus on coherent variation rather than the covariance matrix, which is weighted toward stations with higher variability. A scree plot of the eigenvalues for this analysis (not shown) indicates that the first two components form a degenerate pair (North et al. 1982) and are the only significant components. The proportion of total variance explained by the first two eigenvectors is 11.1% and 10.5%.

The spatial patterns of loadings of the first two principal components are shown in Fig. 3. Both patterns have high loadings in a small region only; the first pattern in a horseshoe-shaped pattern around the island of Sulawesi; and the second pattern over an area extending from southern Sumatra to western Borneo. A pattern containing high loadings in only a small area is termed ''simple structure'' and means that rotation of the components changes the patterns only very slightly. A varimax rotation of two components yielded the first two eigenvectors appearing almost identical to the unrotated patterns, with variance explained 11.0% and 10.5%. Since we are primarily interested in regionwide variation, and the rotated results are similar to the unrotated results, we will consider only the unrotated results.

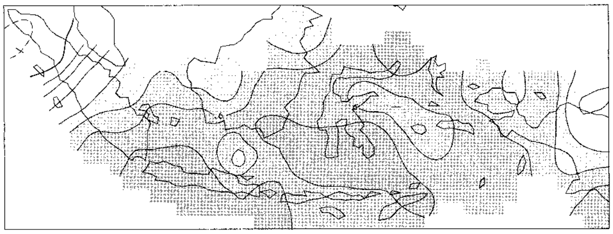

FIG. 4. Spatial pattern of loadings of the first unrotated principal component of SON rainfall. Contour interval is 0.1, the zero contour is bold, negative contours are dashed, and areas above +0.3 and below −0.3 are shaded.

The fact that there is no high-variance principal component (rotated or unrotated) or any significant component with high loadings over a large part of the region implies there is only limited coherence in the DJF rainfall. Therefore, no single predictor [e.g., Southern Oscillation index (SOI) or a single SST principal component] seems likely to explain a high proportion of rainfall variation over the entire region.

The first two components together explain only 21% of the total variance, but both contain high loadings over small areas. Therefore, the variance explained for each pattern over the entire area might be small, but the variance explained for the region with high loadings is probably high. The DJF rainfall at the station Ujungpandang (Fig. 1), which is located in the region with high loadings, has a correlation of 0.72 ($p < 0.01$) with the score series for the first component. Therefore, the first component accounts for almost 52% of the variance at this station.

The fact that there is no high-variance component with high loadings over a large part of the region implies there is no *instantaneous* large-scale coherence. This is because all correlations are calculated with zero lag. There is a possibility that some areas may lag others, but with annual data this would be unexpected.

The low spatial coherence does not hold in other seasons. Figure 4 shows the first unrotated principal component for SON rainfall. This is the only significant component, determined by examining the scree plot of eigenvalues. Note that the loadings are high over almost the entire region, showing that much of the variation is coherent. This component accounts for 38% of the total variance. All other components in this season account for less than 8% each.

There is a possibility that a skewed rainfall distribution could bias any correlation calculations toward wet years. Two alternative approaches were examined to account for this: first, a cube-root transform was used

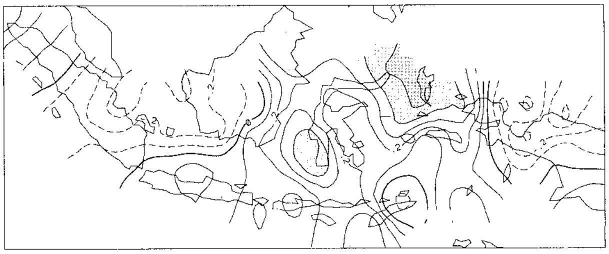

FIG. 5. Correlation between DJF rainfall and DJF SOI. Contour interval is 0.1, the zero contour is bold, negative contours are dashed, and areas above +0.3 and below −0.3 are shaded.

to reduce the skewness before calculating the correlation matrix in the principal component analysis (Stidd 1953); and second, a Spearman rank correlation coefficient was used instead of the Pearson coefficient. Neither approach had any major impact on the results. In both cases, the first two principal components appeared very similar to the previous results.

## 4. Relationship with ENSO

The score series for the components in DJF and SON were correlated with the SOI to determine if variations in seasonal rainfall in the areas with high factor loadings were related to the El Niño–Southern Oscillation (ENSO) phenomenon. In DJF, the first two components (Fig. 3) have correlations of 0.76 ($p < 0.01$) and −0.28 ($p < 0.10$) with the SOI. The SON first component has a correlation of 0.79 ($p < 0.01$) with the SOI. Therefore, in DJF and SON, the area of the first component with high loadings shows rainfall that is to a large part being governed by ENSO. In SON this includes a large part of the region, while in DJF it includes a much smaller area in the north of the region.

These results are reflected in the correlations between the SOI and the station rainfall. Figure 5 shows the correlation between the DJF rainfall and the DJF SOI. The area of strong positive correlation in the north corresponds to the area of high loading in the first principal component. The area of moderately strong negative correlations to the west of this region corresponds to the area of high loading in the second principal component. Since the second component is not as well correlated with the SOI, the correlations are not as strong in this region. In SON the correlations between the station rainfall and the SOI (not shown) are high across most of the region.

We can further examine the relationship between rainfall and ENSO by considering an all-Indonesian rainfall index. For each station we converted the seasonal rainfall total into a rank percentile (0%–100%) for that season. By averaging across all stations for each year, we constructed an annual time series of the index for each season. The index is in the range 0 to 100 and weights each station equally, independently of the stations' mean or variance of rainfall.

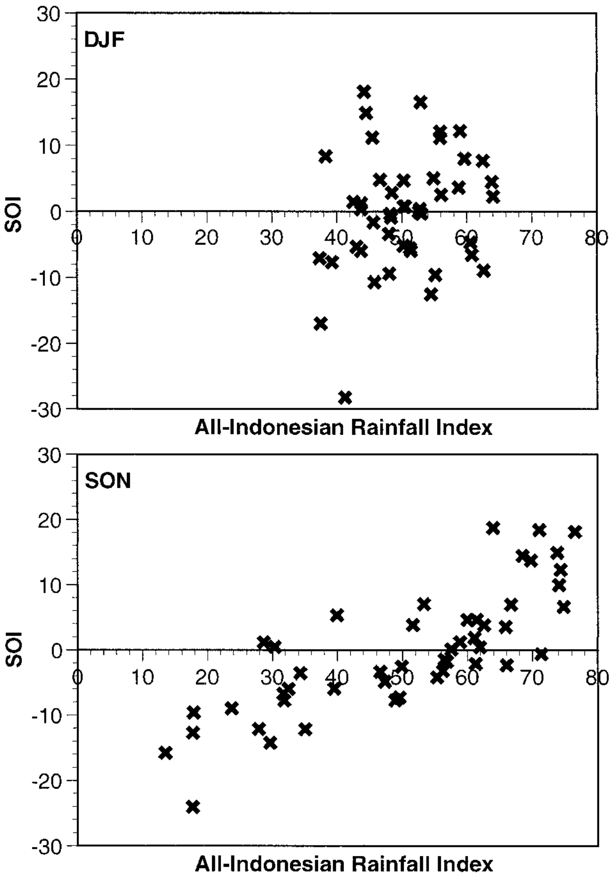


FIG. 6. Scatterplot of all-Indonesian rainfall index and SOI for DJF and SON.

Figure 6 shows this series plotted against the SOI for each year. The much higher correlation between the rainfall index and the SOI for SON is evident in this plot. The correlation for SON is 0.81 ($p < 0.01$), while for DJF it is 0.23 ($p < 0.20$).

Figure 6 also illustrates the reduced spatial coherence in DJF. The range of values along the $x$ axis is an indication of how coherent the rainfall is. For a low stationwide average there needs to be more stations with low rainfall for a particular year. The increased range for SON compared with DJF shows that coherence is higher for SON.

The correlation between the all-Indonesian rainfall index and the SOI was investigated for the other two seasons March–May (MAM) and June–August (JJA). Figure 7 shows the correlation of the index for all four seasons. The correlation is lowest in DJF and MAM and higher for the other two seasons.

Figure 7 also shows the percent of total variance that is explained by the significant principal components for each season. In this figure, the variance has been proportioned into the number of significant components for that season as determined from the scree plot of eigenvalues. The proportion of variance (and therefore the

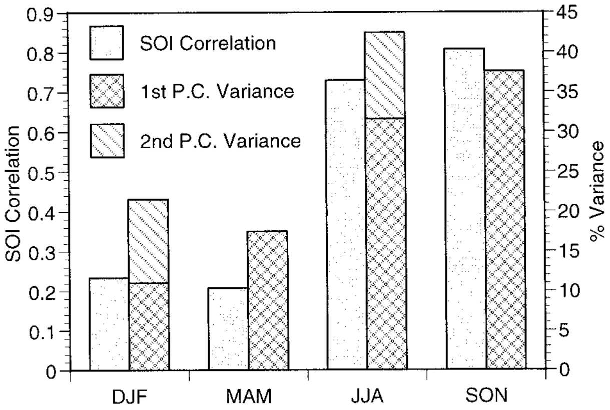


FIG. 7. Correlation between all-Indonesian rainfall index and SOI, and percent of variance explained by significant principal components for each season.

regional coherence) is highest in JJA and SON. This is the time of year when the correlation between the all-Indonesian rainfall index and the SOI is highest. Therefore, at the times of year when ENSO has a stronger influence on the rainfall, the rainfall is more spatially coherent.

## 5. Discussion

To our knowledge the direct association proposed here between predictability and large-scale coherence has not been noted before. There is, however, an extensive literature on seasonal predictability at low latitudes. Most of the early development was based on analysis of time series data at a particular station, with the potentially predictable component of the signal being quantified in terms of the component of the variance in the interannual range compared with the variance associated with weather systems on the timescale of days (Leith 1975, appendix 2.2; Madden 1976; Madden and Shea 1978; Shukla and Gutzler 1983). An important step in the understanding of predictability was made by Charney and Shukla (1981). They demonstrated that at low latitudes a large part of the variability is associated with the variations of the boundary conditions to the atmosphere, specifically quantities such as sea surface temperature, albedo, and soil moisture. According to the Charney–Shukla framework, the variance associated with the slowly evolving boundary conditions represents the predictable component of the signal as distinct from the chaotic component associated with internal flow instabilities. This concept has led to the development of various frameworks to determine the component of the signal governed by boundary dynamics as distinct from internal dynamics, both being measured through analysis of multisample ensemble integrations of general circulation models (Shukla 1998; Rowell 1998; Frederiksen et al. 1999).

We have not yet explored the relationship between the predictability concept of the current paper and the framework developed in the above literature. The simple association, however, is that the slowly evolving boundary dynamics is inherently large scale in nature. The flow instabilities associated with the chaotic aspect of the flow are usually assumed to stem from sub-synoptic-scale fluctuations (Charney and Shukla 1981), whereas the slower dynamics is assumed to evolve on scales at least as large as the deformation radius. Consistent with this, for interannual rainfall variations in a region to be predictable, they must be associated with the evolving boundary condition, which means they must be coherent in space.

As shown in Fig. 7, the most potentially predictable rainfall in Indonesia is during the dry season (JJA) and the least predictable is the wet season (DJF). The lack of spatial coherence in the wet season may simply be a function of low-latitude convective dynamics, whereby the organization of the flow lies mainly in the nonbalanced flow regime at scales smaller than the deformation radius, as described by Ooyama (1982). In the specific case of the Indonesian wet season, the dominance of mesoscale and submesoscale effects will be amplified by the geography, which includes a mixture of sea, islands, and high mountains. However, this raises the question, Is the lack of control by the Southern Oscillation caused by the fact that these mesoscale effects dominate or, alternatively, does the domination by the mesoscale occur because there is little control by the Southern Oscillation? There is no way of satisfactorily answering this question given the evidence just presented. The fact that during DJF the amplitude of the first principal component is still very highly correlated with the SOI implies that ENSO is still active in the north of the region where this component has high loadings. However, a much more vigorous study would be needed to determine if the dynamics of ENSO are still present in the rest of the region but are being dominated by mesoscale convective dynamics.

## 6. Conclusions

Coherence of seasonal rainfall anomalies has been examined for 63 stations across Indonesia for the period 1950–98. During the peak of the wet season (DJF), the coherence is small with, for example, rainfall being almost unrelated at two neighboring stations separated by less than 100 km.

The coherence across the region was quantified with principle component analysis. For the wet season DJF, the low-order components have high loadings over only small areas of the country, which means that it is only these regions that have coherence in interannual rainfall variation. Consistent with this, these same regions have rainfall variations correlating highly with the Southern Oscillation index at that time of year.

In contrast, the dominant principal component for the transition season SON has high loadings over most of the Maritime Continent; and again consistent with this, rainfall over most of the region correlates highly with the SOI.

The conclusion in this paper is that the lack of large-scale coherence in the DJF rainfall anomalies means rainfall at that time of year is inherently unpredictable. To verify this we have used a simple all-Indonesian rainfall index constructed from an averaged percentile ranking of seasonal rainfall from each station across the region. At the times of the year when a large (small) percentage of the variance of rainfall is described by the lowest-order principal components, there is a large (small) correlation between the SOI and the all-Indonesian rainfall index.

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