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Short Communication

El Niño and Indian Ocean influences on Indonesian drought: implications for forecasting rainfall and crop productivity

Rosanne D'Arrigo[a]* and Rob Wilson[a,b]
[a] *Tree-Ring Laboratory, Lamont-Doherty Earth Observatory, Palisades, NY, USA*
[b] *School of Geography and Geosciences, University of St Andrews, St Andrews, FIFE, KY16 9AL, Scotland, UK*

ABSTRACT: Indonesia is impacted by severe droughts that cause major food shortages over much of the country, and have long been linked with El Niño events in the tropical Pacific Ocean. Despite seasonal forecasts based on relatively complex climate models, the 1997–1998 'El Niño of the century' was still followed by huge shortfalls in crop production (e.g. a loss of 3 million tons of rice in Java alone), reflecting the large gap that can exist between these forecasts and their actual utilization in agricultural planning. Alternatively, simple predictive models of rainfall and crop yields for Indonesia and other Indian Ocean rim countries have utilized an index of equatorial Pacific sea surface temperatures (Niño-3.4 SST), and related this index directly to indices of rainfall and crop productivity. However, these latter models have not included climatic information from the Indian Ocean, also implicated as a likely cause of drought in western Indonesia. Here we show that an index of Indian Ocean SSTs, when combined with the previously utilized Niño-3.4 SSTs, provides a significantly more accurate model of Sept-Dec drought (PDSI) over Java, Indonesia, than Niño-3.4 SSTs alone (ar^2 64.5% *vs* 37.9%). Based solely on data for the month of August, this model provides the best tradeoff between model skill and adequate lead time for the Sept-Dec rice planting season. Such simple models can be used to generate readily usable early warning forecasts of drought and crop failure risk in Indonesia, particularly in the western part of the country that is most influenced by Indian Ocean climate variability. Copyright © 2008 Royal Meteorological Society

KEY WORDS ENSO; Indian Ocean dipole; SST; Indonesia; Java; PDSI; drought; rice

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1. Introduction

The profound impact of the El Niño-Southern Oscillation (ENSO) on the climate of Indonesia is well known and results from the tendency for the Indonesian Low to migrate eastward in the tropical Pacific during El Niños, causing drought over much of the country (Nicholls, 1981; Harger, 1995; Allan, 2000). One indication of this relationship is the highly significant correlation between Indonesian rainfall and tropical Pacific sea surface temperatures (SSTs), such as those in the Niño-3.4 region (Allan, 2000). The climate of the Indian Ocean also impacts Indonesia. The Indian Ocean dipole mode (IOD), its index defined as the SST gradient between the eastern and western tropical Indian Ocean, is considered by some (Saji *et al.*, 1999; Webster *et al.*, 1999) to be distinct from ENSO, while others contend that it is intrinsic to ENSO system (e.g. Allan *et al.*, 2001, 2003; Baquero–Bernal *et al.*, 2002). The IOD begins to form in boreal summer and peaks in the subsequent autumn months (Sept–Nov). It has been associated in its positive phase with cold SST anomalies west of Java and Sumatra, and implicated as an additional cause of drought over these regions (Saji *et al.*, 1999; Webster *et al.*, 1999; Saji and Yamagata, 2003).

Seasonal forecasts generated using global climate models (GCMs) and/or relatively complex model compilations have varying levels of skill in the tropics (http://iri.ldeo.columbia.edu/climate/forecast/). Such models generally do not downscale well to regional hydrological conditions of most relevance for agricultural planning (http://iri.columbia.edu/cgi-bin/staff?jqian; re-downscaling and prediction using global and regional climate models such as REGCM3; portal.iri.columbia.edu/.webloc; example of projects related to agricultural planning in Asia), and typically, have only limited coverage over Indonesia (Naylor *et al.*, 2001, 2007; Falcon *et al.*, 2004). Empirically based statistical models (e.g. those based on principal components analysis of tropical Indo–Pacific SSTs – http://www.bom.gov.au/bmrc/clfor/cfstaff/jmb/Seasonal_Forecast_CD/Forecasting_Report.pdf) have also been utilized for Indonesia. The modelling of rainfall and crop production in Indonesia has been limited, however, by the varying seasonality, geography and local climate response to ENSO over this vast, diverse archipelago.

* Correspondence to: Rosanne D'Arrigo, 61 Route 9W, Palisades, NY 10964, USA. E-mail: rdd@ldeo.columbia.edu

Alternative, relatively simple predictive models have been developed based only on Niño SSTs for several Indian Ocean rim countries, including Zimbabwe (Cane *et al*., 1994), Sri Lanka (Zubair, 2002; Zubair *et al*., 2003) and Indonesia (Nicholls, 1981; Naylor *et al*., 2001, 2007; Falcon *et al*., 2004). Such models provide quantitative predictive tools, readily usable for agricultural planning, that complement more complex model simulations. With the exception of one of these cited studies (Zubair *et al*., 2003), which described a significant relationship between the IOD and monsoon rainfall over Sri Lanka, none examined the potential for indices of Indian Ocean climate to improve simple forecasts of rainfall and crop yields. We demonstrate below that a significantly improved model of drought for Java can be generated by combining the previously utilized Niño-3.4 SSTs with an SST index from the Indian Ocean.

2. Data and methods

The climate indices utilized in this paper are illustrated in Figure 1. We use the monthly Niño-3.4 SST index for the equatorial Pacific Ocean based on the Kaplan *et al*. (1998) analysis (5°N–5 °S, 120°–170 °W), and a version of the monthly IOD index [dipole MODE index (DMI), Saji *et al*., 1999] based on Kaplan SSTs (http://www.jamstec.go.jp/frsgc/research/d1/iod/; Indian Ocean Dipole Index homepage), available since 1869. A monthly index of zonal surface wind for the equatorial Indian Ocean (EQWIN) is based on ICOADS data for anomalies averaged over 62°–90 °E, 4°N–4 °S, for 1884–1997 (Worley *et al*., 2005). EQWIN is a sensitive indicator of Indian Ocean climate which has been utilized to improve a simple predictive model of the Indian monsoon based on Niño-3 SST, while the DMI did not show a strong relationship (Gadgil *et al*., 2004; Ihara *et al*., 2007). Rainfall data were obtained from the GPCC Variability Analysis of Surface Climate Observations (Beck *et al*., 2005, Vasclim-0 0.5, 1951–2000) precipitation data set. We use the monthly Palmer drought severity index (PDSI) (Dai *et al*., 2004, 1879–2003), which integrates both surface air temperature and precipitation, and is generally considered a more sensitive, less noisy indicator of drought than rainfall station data. The PDSI data was averaged over the island of Java, Indonesia (5°–10 °S, 105°–115 °E). Finally, we use the area harvested rice data (in ha) averaged over Indonesia (1988–2002, from Badan Pusat Statistik, http://www.bps.go.id/aboutus/; http://www.bps.go.id/index.shtml).

A series of regression models of the PDSI, based on various combinations of the tropical Pacific and Indian Ocean climate indices, were developed. The best model results are presented as the estimated values obtained from regression analyses of the climate variables used as predictors of PDSI. Various calibration and verification statistics (Cook and Kairiukstis, 1990) are used to evaluate the models.

3. Results and discussion

Table I presents the regression model results based on different combinations of the three tropical Pacific and Indian Ocean climate indices (1. Niño-3.4 SSTs, used in previous analyses, 2. the DMI, and 3. the EQWIN index) for the common period 1958–1997 (the most analysed and considered relatively reliable interval – e.g. http://www.int-res.com/articles/cr/17/c017p247.pdf; Janowiak *et al*., 1998). It was previously determined that variables related to rice productivity for Java and elsewhere in Indonesia (particularly area harvested and production) could be best predicted from models that utilized either May–August or August-only Niño-3.4 SSTs to estimate Sept–Dec rainfall (Naylor *et al*., 2001, 2007; Falcon *et al*., 2004). May–August is just prior to the Sept–Dec main planting period, the latter at the onset of the northwest monsoon season (∼Nov–April) in Java. We independently identified Sep–Dec as the most appropriate target season for estimating PDSI in the regression models. Table I shows the variance explained (ar^2 – i.e. variance explained adjusted for degrees of freedom) by various combinations of the three predictors for the 12 months of the concurrent year and selected seasons, and Figure 2 displays the individual and combined monthly models of Sept–Dec Java PDSI.

Of the three individual variables, the DMI (for Sept–Oct) has the strongest overall relationship with Sept–Dec PDSI ($ar^2 = 62.8\%$), considerably improved over using Niño-3.4 SST alone for any month or season (maximum 40.2%; Table I). EQWIN explains a similar

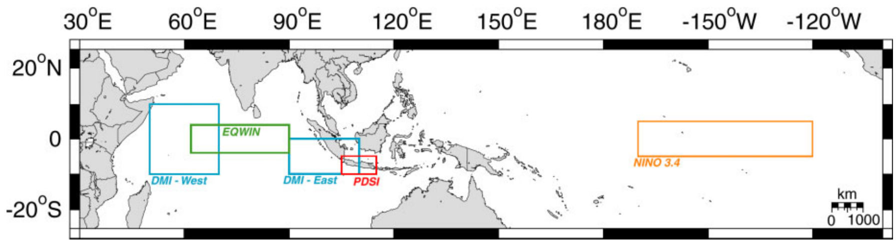

Figure 1. Map showing locations of time series used in this study, including gridcell (red) of Java PDSI (D'Arrigo *et al*., 2006, D'Arrigo *et al*. submitted, *I.J. Climatol*.) and two gridcells of SST (blue boxes) used to define the DMI (Saji *et al*., 1999). The gridcell used to develop the EQWIN index of equatorial zonal winds for the central Indian Ocean (Gadgil *et al*., 2004; Ihara *et al*., 2007) is indicated in green, and the Niño 3.4 SST gridcell in orange. This figure is available in colour online at www.interscience.wiley.com/ijoc

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Table I. Variance explained (ar^2, adjusted for degrees of freedom) for predictive regression models of Sept–Dec Java PDSI for 1958–1997 based on single (Niño-3.4 SST, DMI and EQWIN (EQ)) and multiple climate predictors and monthly and seasonalized models. No models showed positive (robust or strong) results for Jan–March. For certain early months only 1 predictor entered some combined regression models, with these predictors indicated as N (Nino-SST), D (DMI),E (EQWIN) and D, N(DMI and Nino-SST).

	Niño-SST	DMI	EQ	Models NINO+ DMI	NINO+ EQ	DMI+ EQ	DMI + EQ +NINO
Months							
April	0	0	24.4	0	24.4E	24.4E	24.4E
May	18.1	0	0	18.1N	18.1N	0	18.1N
June	33.5	6.5	0	28.5	33.5N	6.5D	28.5D,N
July	33.4	26.3	20.2	49.3	42.9	32.3	47.4
August	37.9	49.8	19.9	**64.5***	44.8	44.4	59.0
September	37.8	61.2	42.7	65.9	62.5	58.6	68.9
October	39.9	61.1	58.6	60.9	60.8	67.5	67.7
November	**40.2**	49.4	33.2	53.9	46.7	49.4	54.2
December	39.7	15.1	5.6	39.5	39.7	16.7	39.5
Seasons							
June–July	35.7	16.9	15.0	40.6	43.5	23.0	39.8
July–August	36.5	40.2	27.6	59.0	48.6	43.3	56.9
July–September	38.5	51.2	42.2	64.3	59.6	53.7	65.1
July–October	39.9	57.9	58.6	65.5	65.2	63.7	70.4
August–September	39.5	57.6	41.5	**66.9**	60.1	55.9	66.9
September–October	40.1	**62.8**	**62.6**	64.6	**65.8**	**68.2**	**71.4**

Highlighted in red are the highest levels of explained variance found for each model version over all months and seasons. In blue (asterisked) is the August NINO + DMI model selected as being the optimal tradeoff between model accuracy and lead time prior to the main planting and subsequent wet season in Java.

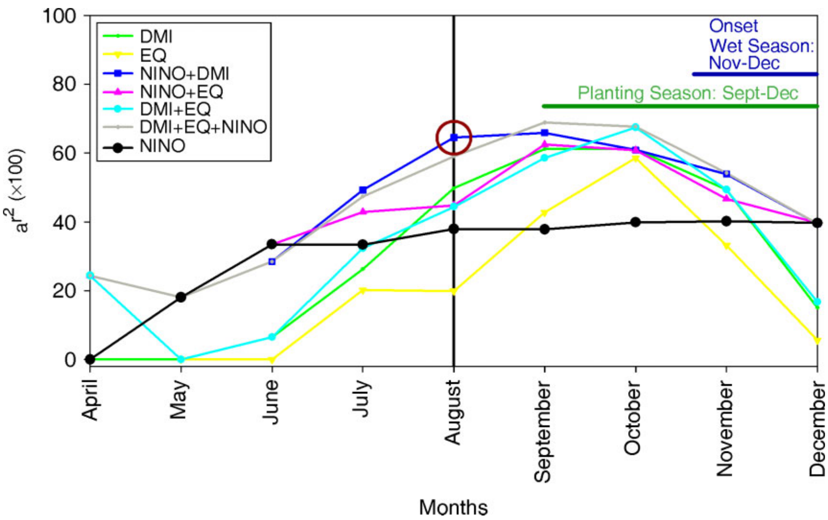

Figure 2. Monthly variance explained for PDSI using individual and combined models for the concurrent year of Sept–Dec growing season for rice in Java (labelled in green), just prior to the onset of the wet season (labelled in blue). Vertical thin black solid line indicates month of August, for which the NINO + DMI model (highlighted by circle) provides the best tradeoff between model skill and predictive lead time. This figure is available in colour online at www.interscience.wiley.com/ijoc

proportion of the PDSI variance (62.6%) for Sept–Oct, although this season is rather late for crop forecasting. Of the combined monthly models, the DMI-EQ-NINO version is the strongest (for Sept, 68.9%), while the best seasonalized model (also the best of all the models) is that based on Sept–Oct DMI-EQ-NINO (71.4%). Although versions using these later months improve the fit, model selection must be a tradeoff between strength of correlation and a reasonable lead time for crop plantings. When both factors are taken into account, the August model of NINO + DMI (Table I, Figure 2) appears to be the optimal compromise (64.5%; 66.2% for 1958–2002). The variance explained by this model is 26.6% higher than that obtained for Niño-3.4 SST alone for August (64.5% *vs*. 37.9%). The ar^2 is only 36.1% for the Niño 3.4 SST model for May–August, another season

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with predictive value for rice production (Naylor *et al.*, 2001, 2007; Falcon *et al.*, 2004). Since the DMI and NINO series are intercorrelated (Allan *et al.*, 2001), their linear combination may inflate the ar^2 value through multicollinear effects. The correlation between the NINO and DMI over 1958–1997 is, however, relatively low at 0.38. The square root of the variance inflation factor for both variables does not exceed the 2.0 critical threshold (Fox, 1997), indicating that the ar^2 value has not been artificially inflated due to multicollinearity between the variables. The Akaike Information Criterion (AIC) (Sakamoto *et al.*, 1986) provides additional information for comparing these models. The AIC takes into account the decline in degrees of freedom that results from including more than one predictive variable: the model with the lower value, if lower by more than 10 points, is considered significantly superior to the other (Sakamoto *et al.*, 1986). The NINO + DMI August model has an AIC value of −38.1 compared to −15.8 for Niño-3.4 SST alone. We therefore conclude that adding the DMI predictor significantly improves the August model based only on Niño-3.4 SSTs. The AIC value for August DMI alone (ar^2 49.8%) is −24.3, indicating that this DMI-only model is still better, although not significantly so, than that based only on Niño-3.4 SST (note, however, that the difference between their AIC values is 8.5, which does approach the 10-point criterion). Finally, the Durbin Watson statistic for the August DMI-NINO model is 1.99 (0.01 level), indicating an absence of autocorrelation in model residuals. The 1958–1997 calibration model is well verified over 1879–1957: the Coefficient of Efficiency is positive (0.21), with highly significant Sign Test (54 correct, 25 incorrect; 0.001), and T-test (4.23; 0.000) results, indicating considerable model skill (Cook and Kairiukstis, 1990).

To be most useful for agricultural planning, climate forecasts must be directly translatable into relevant variables. Figure 3 compares the actual and modelled Sept–Dec Java PDSI based on the August NINO-DMI to the area harvested rice data (in ha) averaged over Indonesia (1988–2002, Badan Pusat Statistik, http://www.bps.go.id/aboutus/).

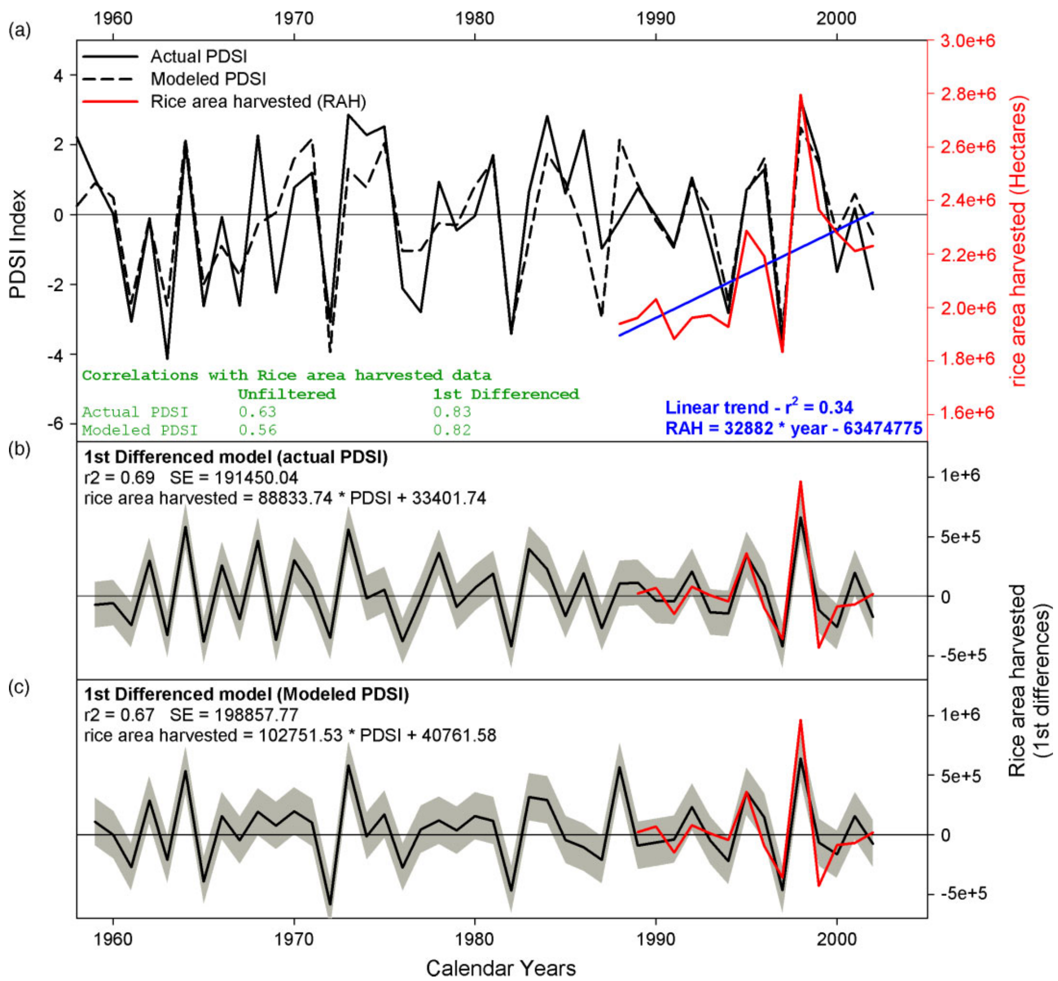

Figure 3. (A): Actual and modelled Sept–Dec PDSI for 1958–2002 (ar^2 66.2%) based on August DMI and Niño-3.4 SST indices. Also shown is rice area harvested data (in hectares, ha) averaged over Indonesia (1988–2002, Badan Pusat Statistik). Its linear trend is highlighted in blue. Correlations between the actual and modelled PDSI and rice area harvested data are shown for unfiltered (A) and 1st differenced versions of the time series; (B) 1st difference regression model results between the actual PDSI data and rice area harvested data; (C) as in B, but using modelled PDSI data. Shading denotes the 1 sigma error envelope derived from the standard error of the calibration model. This figure is available in colour online at www.interscience.wiley.com/ijoc

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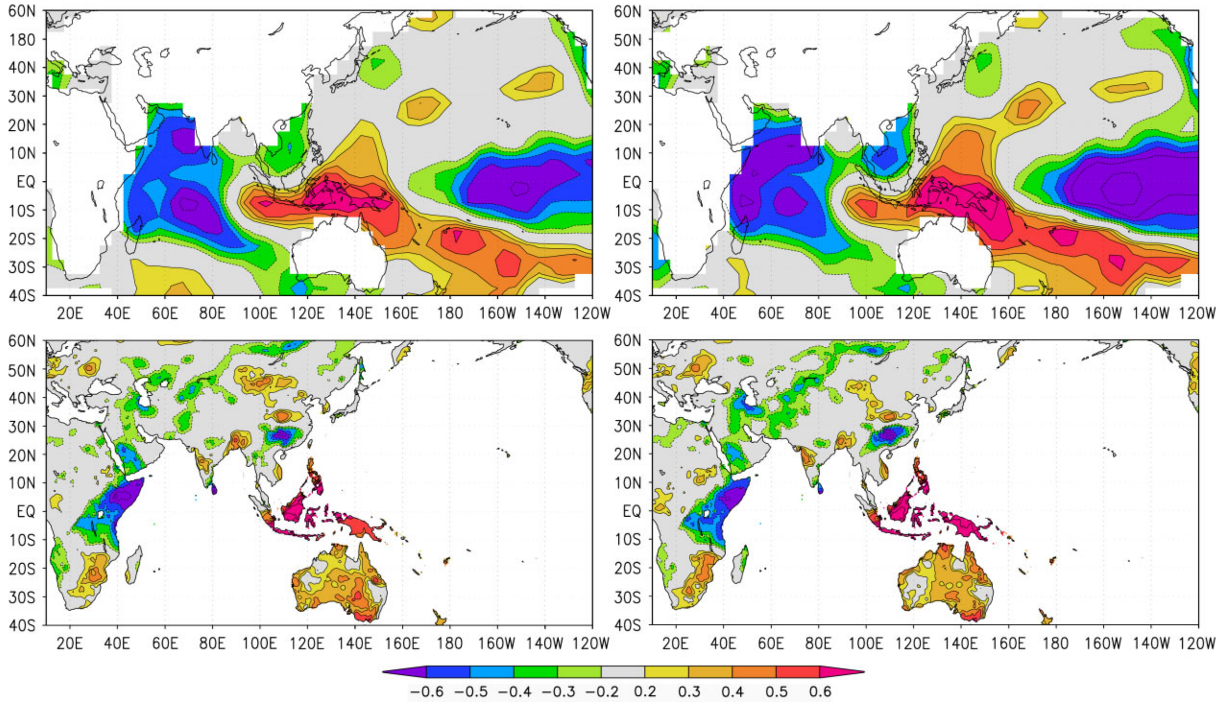

Figure 4. Spatial correlation plots comparing actual (left panels) and modelled (right panels) Sept–Dec PDSI (the latter based on August DMI + NINO model) with Sept–Dec SST fields (Kaplan *et al.*, 1998) (top panels) and rainfall data (Beck *et al.*, 2005) (bottom panels). Figure generated using KNMI Climate Explorer (http://climexp.knmi.nl/). This figure is available in colour online at www.interscience.wiley.com/ijoc

Correlations and regression equations relating the Java PDSI to this rice data are also indicated (Figure 3). These relationships are generally consistent with previous studies showing linkages between rainfall, rice area harvested and other crop data for Java and Indonesia (Naylor *et al.*, 2001, 2007; Falcon *et al.*, 2004). Results are best for first differenced actual and modelled PDSI (Figure 3(B) and(C)), as there is a linear trend in the rice data (Figure 3(A)) that may partly reflect economic factors (Naylor *et al.*, 2001, 2007; Falcon *et al.*, 2004). Economic factors, along with low variability, may also help explain the relatively low agreement in a few years (e.g. 1999–2000). Spatial correlation fields (Figure 4), compare the actual and modelled Sept–Dec Java PDSI with Sept–Dec SST for the Indo–Pacific region and rainfall for land areas surrounding the Indian Ocean rim. These fields illustrate the strong influences of tropical Pacific and Indian Ocean SSTs on drought over Indonesia, and the association of Indonesian drought with large-scale rainfall patterns over the Indian Ocean rim land areas.

4. Conclusions

Our results demonstrate that a simple empirical forecast model of drought for Java using the DMI in combination with Niño-3.4 SSTs presents a significant improvement over one based only on the latter index, the variable previously utilized in such models (Cane *et al.*, 1994; Naylor *et al.*, 2001, 2007; Zubair, 2002; Falcon *et al.*, 2004). This finding has direct relevance for forecasting drought as well as agricultural productivity in Indonesia. Of the various models explored for this study, we find that drought can best be predicted, while also providing a reasonable lead time of one to several months, using both tropical Pacific and Indian Ocean indices for August alone. This lead time may potentially be longer, when taking into consideration that peak planting often does not take place until Oct–Dec, and that the model provides useful information about conditions impacting the second, April–May, planting as well (Naylor *et al.*, 2001, 2007; Falcon *et al.*, 2004). These results are particularly relevant for western Indonesia where the influence of the Indian Ocean on rainfall is the strongest in the archipelago (Haylock and McBride, 2001; Aldrian and Susanto, 2003), and where the bulk of the country's rice crop is grown (Naylor *et al.*, 2001, 2007; Falcon *et al.*, 2004).

Robust, simple and timely forecasts are critically important for predicting drought and agricultural productivity over Java and elsewhere in largely agrarian Indonesia and other drought-prone Indian Ocean rim countries. Although seasonal forecasts are available, this information cannot always be translated directly into readily usable information for planning purposes. Further studies are warranted to better understand potentially complex linkages between Indonesian drought and tropical Indo-Pacific SSTs, as well as the Asian monsoon (Gadgil *et al.*, 2004; Ihara *et al.*, 2007). Another consideration is how droughts may change due to greenhouse warming in the tropics. Mid-Holocene corals from the Mentawai Islands off Sumatra (Abram *et al.*, 2007) suggest that an increase in Asian monsoon intensity, as some climate models have predicted, may intensify Indonesian droughts with

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future greenhouse warming. These and other proxies can yield insight into past Indonesian drought variability (D'Arrigo *et al*. 2006; Abram *et al*., 2007, D'Arrigo *et al*. submitted, *I.J. Climatol*.). Some models and analyses demonstrate or predict drier conditions in Java due to projected climate change (Aldrian *et al*., 2007; Naylor *et al*., 2007; Aldrian and Djamil, in press). These expectations of greater drought and crop failure risk indicate that improved, directly translatable schemes for climate risk management are still urgently needed (Amien *et al*., 1999; Asian Inst. Technology, 2005).

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