

PREDICTION OF DROUGHT IMPACT ON RICE PADDIES IN WEST JAVA USING ANALOGUE DOWNSCALING METHOD

Prediksi Dampak Kekeringan pada Tanaman Padi Sawah di Jawa Barat Menggunakan Metode Downscaling Analog

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ABSTRACT

Indonesia consistently experiences dry climatic conditions and droughts during El Niño, with significant consequences for rice production. To mitigate the impacts of such droughts, robust, simple and timely rainfall forecast is critically important for predicting drought prior to planting time over rice growing areas in Indonesia. The main objective of this study was to predict drought in rice growing areas using ensemble seasonal prediction. The skill of National Oceanic and Atmospheric Administration's (NOAA's) seasonal prediction model Climate Forecast System version 2 (CFSv2) for predicting rice drought in West Java was investigated in a series of hindcast experiments in 1989-2010. The Constructed Analogue (CA) method was employed to produce downscaled local rainfall prediction with stream function (ψ) and velocity potential (χ) at 850 hPa as predictors and observed rainfall as predictant. We used forty two rain gauges in northern part of West Java in Indramayu, Cirebon, Sumedang and Majalengka Districts. To be able to quantify the uncertainties, a multi-window scheme for predictors was applied to obtain ensemble rainfall prediction. Drought events in dry season planting were predicted by rainfall thresholds. The skill of downscaled rainfall prediction was assessed using Relative Operating Characteristics (ROC) method. Results of the study showed that the skills of the probabilistic seasonal prediction for early detection of rice area drought were found to range from 62% to 82% with an improved lead time of 2-4 months. The lead time of 2-4 months provided sufficient time for practical policy makers, extension workers and farmers to cope with drought by preparing suitable farming practices and equipments.

[**Keywords:** Rice paddy, agronomic drought, probabilistic prediction, statistical downscaling, analogue method]

ABSTRAK

Indonesia secara konsisten mengalami kondisi iklim yang kering dan kekeringan selama kejadian El Niño, yang berdampak

terhadap produksi beras. Untuk mengurangi dampak kekeringan, prediksi curah hujan yang akurat, sederhana, dan diterima tepat waktu sangat diperlukan sebelum waktu tanam terutama di daerah sentra produksi padi di Indonesia. Penelitian ini bertujuan untuk memprediksi kekeringan agronomis di daerah sentra produksi padi menggunakan prediksi musiman ansambel. Kemampuan model prediksi musiman dari National Oceanic and Atmospheric Administration (NOAA)-Climate Forecast System version 2 (CFSv2) untuk memprediksi kekeringan padi di Jawa Barat diteliti menggunakan prediksi hindcast periode 1989-2010. Metode Constructed Analogue (CA) digunakan untuk mendownscale prediksi curah hujan lokal dengan fungsi arus (ψ) dan potensial kecepatan (χ) pada paras 850 hPa sebagai prediktor serta curah hujan observasi sebagai prediktan. Penelitian menggunakan empat puluh dua alat pengukur hujan yang terdapat di bagian utara Provinsi Jawa Barat, yaitu di Kabupaten Indramayu, Cirebon, Sumedang, dan Majalengka. Untuk mengkuantifikasi ketidakpastian, skema multi-jendela diaplikasikan dalam membangun prediksi musiman ansambel. Kekeringan padi pada musim kemarau diprediksi berdasarkan nilai ambang curah hujan. Kemampuan prediksi curah hujan hasil downscaling dinilai menggunakan metode Relative Operating Characteristics (ROC). Hasil penelitian menunjukkan bahwa kemampuan prediksi curah hujan musiman probabilistik dalam mendeteksi dini kekeringan padi berkisar antara 62-82% dengan lead time 2-4 bulan. Dengan lead time 2-4 bulan menyediakan waktu yang memadai bagi pengambil kebijakan, penyuluh pertanian, dan petani untuk menyusun strategi budi daya serta mempersiapkan sarana dan prasarana pertanian yang antisipatif kekeringan.

[**Kata Kunci:** Padi sawah, kekeringan agronomis, prediksi probabilistik, downscaling statistik, metode analog]

INTRODUCTION

Large areas of severe droughts occurred worldwide and caused high economic and social costs. The profound impact of the El Niño-Southern Oscillation (ENSO) on the climate of Indonesia is well-known and

causing drought over much of the country (Nicholls 1981; Harger 1995; Allan 2000). The Indonesian Ministry of Agriculture (MoA) reported that during the El Niño's years, damaged rice areas due to drought covered 350-870 thousand hectares, while during the normal years were 17-340 thousand hectares. Other studies indicated that El Niño occurred in most of rice production areas during the dry seasons (Alimoeso *et al.* 2002; Meinke and Boer 2002). Moreover, West Java Province was found as the most vulnerable province to El Niño's during the first and second dry season planting (DSP1 and DSP2) (Surmaini *et al.* 2014a).

ENSO is a common indicator for the policy maker in managing adaptation strategy to cope with climate extreme events in many countries including Indonesia. Several studies can predict rice production in Indonesia in advance using the ENSO indices (Kirono and Tapper 1999; Naylor *et al.* 2002). In more detail, Falcon *et al.* (2004) concluded that the changes in August Niño 3.4 index are particularly significant on harvested rice area and rice production throughout September-December and January-April trimesters. However, these effects are likely to diminish in May-August trimester, i.e., the peak period of drought in rice areas. Surmaini *et al.* (2014a) found that Niño 3.4 events in March and June are useful for detecting the potential of drought impact on rice during dry season planting. However, it is not effective due to short lead-time (0-2 months). Furthermore, the use of ENSO indices themselves is difficult to be understood by non-expert users such as practical policy makers, extension workers and farmers. Practitioners need indicators fairly easy to be understood and accessible. Rainfall is the most important factor influencing the onset, duration and severity of drought conditions (Lloyd-Hughes and Saunders 2002; Msangi 2004; Sonmez *et al.* 2005). Critical thresholds of rainfall may be used as practical indicator for predicting drought in rice areas (Surmaini *et al.* 2014b).

As ENSO is not effective as indicator of rice area drought, coupled Global Circulation Models (GCMs), which have been known to exhibit reasonable skill in predicting El Niño and related climate signal in 9 month lead time, may serve as better tools for predicting rice area drought. The widely accepted basis of GCM is the downscale of the roughly resolved information to local scale. Downscaling is expected to improve GCM output through enhan-

cement of the spatial resolution. Nowadays, statistical downscaling provides several techniques to use low resolution GCMs on regional or local scale (Zorita and von Storch 1999; Maraun *et al.* 2010). This method links to the large-scale predictions of the GCMs with simultaneous local historical observations of the interest regions. Many authors pointed out the potential benefits from this seasonal (Hansen and Inez 2005; Meinke and Stone 2005) in particular, as well as for regions where the impact of ENSO on the local or regional climate is pronounced (Patt *et al.* 2007).

Predictions of weather and climate associate with high uncertainties. According to Palmer (2006), essentially there are three reasons why forecasts are uncertain: uncertainty in the observations used to define the initial state, uncertainty in the model used to assimilate the observations and to make the forecasts, and uncertainty in external parameters. The level of uncertainty can be conveyed in a quantitative way by using probabilities (Zwiers 1996; Kharin and Zwiers 2001). For model forecasts, the level of uncertainty can be derived from an ensemble of model forecasts (Doblas-Reyes *et al.* 2000; Palmer *et al.* 2004). Owing to their ability to quantify the uncertainty, probabilistic forecasts are of potentially greater value to decision makers than deterministic forecasts (Murphy 1977; Krzysztofowicz 1983).

This study aimed to predict drought of rice production areas in the northern part of West Java using ensemble seasonal prediction. This study is motivated by the need of drought prediction for DSP1 and DSP2. Local areas within this region frequently experience extreme drought especially in dry season. Also, West Java has the largest rice growing areas in Indonesia. Development of accurate seasonal rainfall prediction tools with high spatial resolution is essential for mitigation of impacts.

MATERIALS AND METHODS

Experimental Sites

The study was conducted in the rice growing areas in the northern part of West Java, i.e. in the Districts of Indramayu, Cirebon, Sumedang and Majalengka, which are vulnerable to drought (Surmaini *et al.* 2014a). These districts are located in Citarum watershed.

Data Collection

The observed multi-site rainfall data series of 1982 to 2009 were obtained from the Ministry of Public Work and the Indonesian Geophysics, Climatology and Meteorology Bureau (Fig. 1). MoA reported that damages of rice crops due to drought mostly occur during May to October. For that reason, our investigation focused on DSP1 during March to May, and DSP2 during June to August. These DSPs associate with rice drought during May to July and August to October, respectively.

The data used were the NOAA's-CFSv2 seasonal prediction model as predictor. The meridional (U) and zonal (V) 850 hPa data for the periods of 1982-2009 followed Saha *et al.* (2014) at the <http://nomads.ncdc.noaa.gov/data/cfsr-fri-ts9/wnd850>. The vector fields of U and V 850 hPa data were decomposed into scalar field of rotational stream function (ψ) and divergent velocity potential (χ) components. According to Palmer (1952), ψ and χ are used extensively in meteorology and oceanography. Moreover, ψ and χ are more suitable scalar variables for depicting flow patterns than other variables in low latitudes, where geostrophic balance breaks down as the Coriolis parameter becomes small. These 9-month data were

initiated from every 5 days and run from all four cycles of that day for 0, 6, 12 and 18 UTC, beginning from January 1st of each year, over a 28-year period from 1982 to 2009.

Ensemble Members

Ensemble members comprised of multiple (5-100) runs of numerical weather prediction models representing initial conditions and/or the numerical representation of the atmosphere of two major sources of uncertainty data (Gneiting and Raftery 2005). In this study, ensemble is performed by ψ and χ at 850 hPa in multi-windows monsoon regions and statistics of hindcast run. Multi-windows of the monsoon's regions used in this study consisted of five indices, i.e. (1) the Australian Monsoon Index (AUSMI): 5°S-15°S, 110°E-130°E (Kajikawa *et al.* 2010), (2) the Western North Pacific Monsoon divided into two regions, such as 5°N-15°N, 100°E-130°E and (3) 20°N-30°N, 110°E-140°E (Wang *et al.* 2001), (4) the Webster and Yang Monsoon Index (Webster and Yang 1992) divided into two regions, i.e. EQ-20°N, 75°E-110°E and (5) EQ-20°N, 40°E-75°E (Fig. 2). CFSv2 released 9-month hindcasts initiated from every 5 days and run from all four

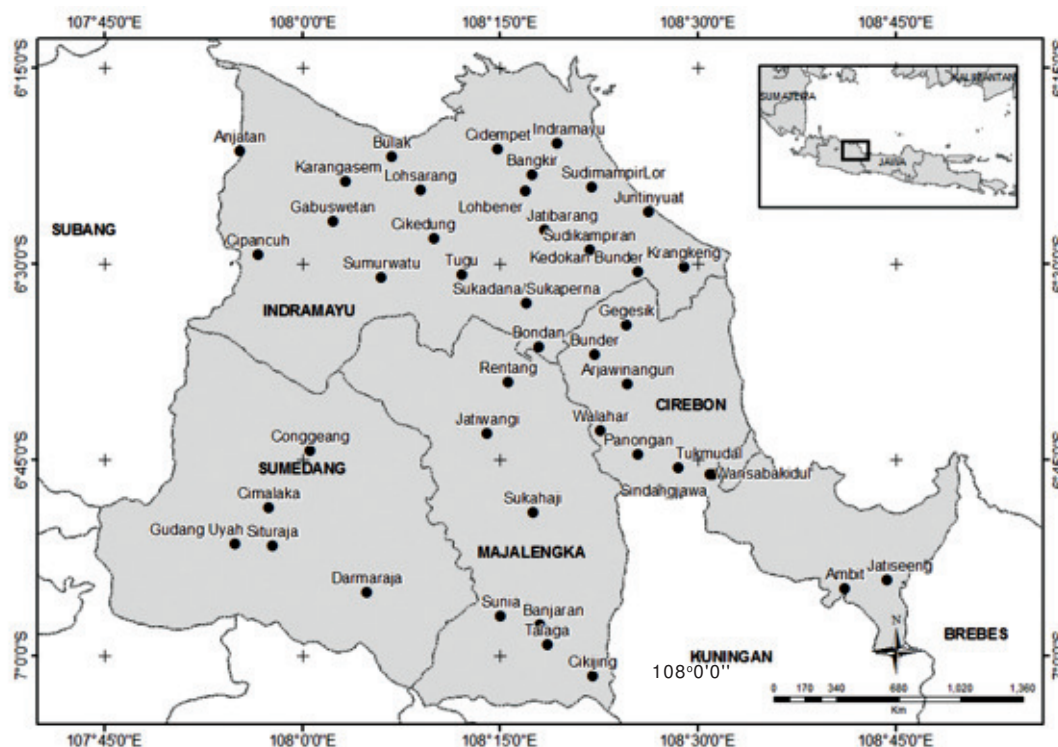


Fig. 1. Locations of forty-two rain gauges of the study area in northern part of West Java as represented by black dots.

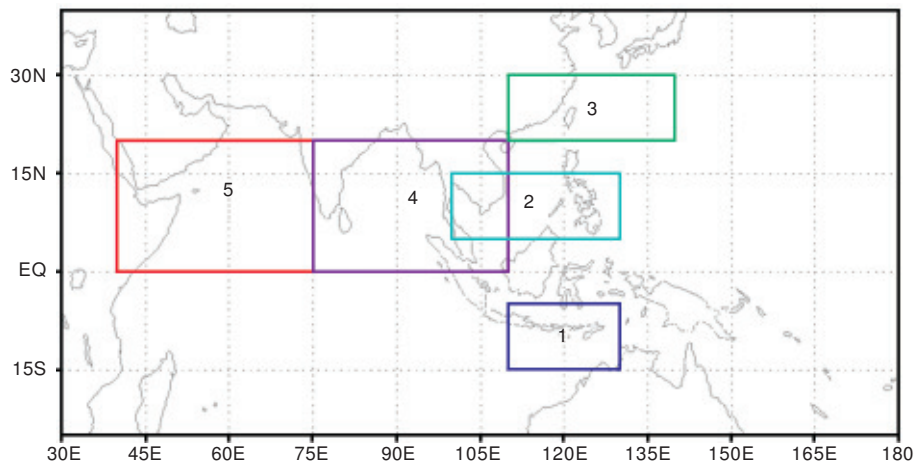


Fig. 2. Multi-windows of monsoon areas used as predictor namely (1) Australian Monsoon Index, (2 and 3) Western North Pacific Monsoon Index, (4 and 5) Webster and Yang Monsoon Index.

cycles of that day, beginning on January 1st of each year, over a 29-year period from 1982 to 2010. We used statistic of hindcast run, i.e. 3th quartile, mean and 1st quartile as members. These components performed 30 members for ensemble. CFSv2 was employed for predicting droughts in the periods of May-June (DSP1) and August-October (DSP2) released in December and March, respectively.

Analogue Downscaling Method

The skill of NOAA's seasonal prediction model CFSv2 for predicting drought on rice areas in northern part of West Java was investigated in a series of hindcast experiments. The Constructed Analogue (CA) method of van Den Dool (1994) and Hidalgo *et al.* (2008) was applied to look for subset analogues in a large scale field (supposed to be reliably predicted by GCMs) and then use the local target field simultaneous to the large scale analog to reconstruct the local rainfall scale field (Zorita and von Storch 1999). Hindcast data of ψ and χ of NOAA's CFSv2 from 1982 to 2000 were used as a library or pool of potential analogues and data from 2001 to 2009 were used to validate the downscaling results. The procedure for using CA for prediction or downscaling can be divided in two parts: diagnosis and prognosis.

The diagnosis step consists of selecting a subset of weather patterns from a large library of historical patterns at low resolution and then determining the multiple linear combination of those patterns that

best match the target pattern. We used 30 subsets to form CA, considering previous researches indicated that 30 subsets had optimal correlation coefficient (Hidalgo *et al.* 2008; Syahputra 2013).

Empirical Orthogonal Function (EOF) was applied to reduce the degree of freedom (d.o.f) on atmospheric circulation fields used as predictors (Zorita and von Storch 1999). Predictor library $F(u)$ and target $F(t)$ were reduced to spatial component (c_k) and temporal component (a_k) as described below:

$$F(u) = \sum_{k=1}^M c_k(u) a_k(u) \quad (1)$$

$$F(t) = \sum_{k=1}^M c_k(t) a_k(t) \quad (2)$$

where M is the number of significant Principal Components (PC).

The PC number was assessed using the scree plot of eigenvalue to determine the appropriate number of components. The component number is taken to be the point at which the remaining eigen values are relatively small and all about the same size ("elbow" in the scree plot).

The prognosis step is the derivation of the high-resolution pattern by applying the linear fit developed from the subset of predictors. In this study we used multiple linear regression method (Fig. 3), which is analogous search member as an independent variable and rainfall observations (R) as dependent variable, to obtain the regression coefficients $\{B_1, B_2, \dots, B_{30}\}$ and a constant C. CA of target rainfall $t(R_{CA(t)})$ then can be calculated by equation as follow

$$R_{CA(t)} = \sum_{n=1}^{30} B_n R_n(t) + C \quad (3)$$

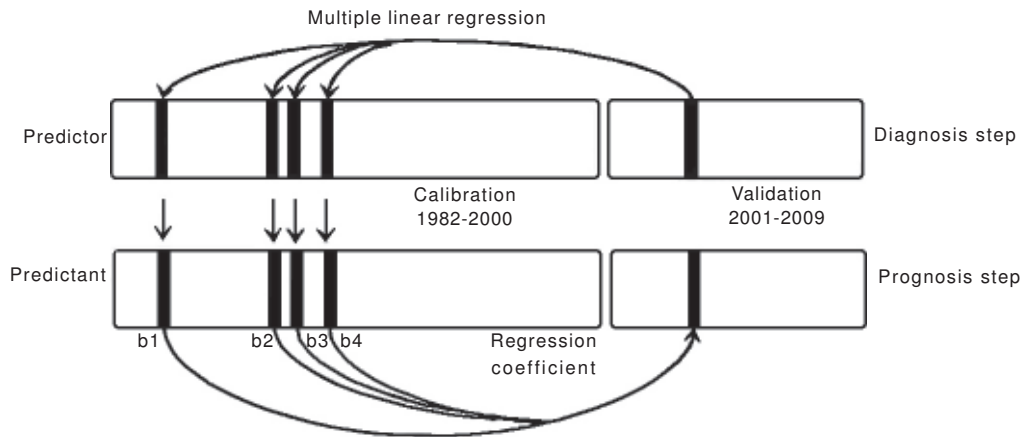


Fig. 3. Constructed Analogue (CA) methods for the validation period of 2001-2009 are searched in the historical records (1982-2000) of the large-scale variable. The local scale values associated to the analogue records found are used to reconstruct the local variable using multiple linear regression.

To be able to quantify the uncertainties, a multi-windows scheme for predictors was applied to obtain ensemble rainfall prediction. Drought events are predicted by rainfall thresholds which values are 20 mm in the first decade (10-day) of March for DSP1 in irrigated rice field and 60 mm in the first decade of June for DSP2 in rainfed rice field (Surmaini *et al.* 2014b).

One of the key aspects of the analogue search is the selection of the similarity measure to select the past analogues (van den Doll 1994). Analogue search was carried out using cosine similarity (Garcia 2006). Cosine similarity is a measure of similarity between two vectors by measuring the cosine of the angle between them. The result is equal to 1 when the angle is 0, and it is less than 1 when the angle is of any other values. Degree of similarity between vectors $\vec{a}(u)$ and $\vec{b}(v)$ is calculated using equation as follows

$$S(u) = \frac{\vec{a}(u) \cdot \vec{b}(v)}{\|\vec{a}(u)\| \|\vec{b}(v)\|} \quad (4)$$

For each target of time t a set of analog predictors in the database and predictant paired were selected based on the similarity value $S(u)$.

Verification of Rice Drought Prediction

The skill of probabilistic prediction of drought on rice field was measured using Relative Operating Characteristic (ROC) curve. ROC curve is a useful method representing the quality of deterministic and probabilistic detection and forecast systems. The

area under the ROC curve characterizes the quality of a forecast system by describing the system’s ability to anticipate correctly the occurrence or non-occurrence of pre-defined ‘events’. In constructing a ROC curve, forecasts are expressed in binary as ‘warnings’ or ‘no warnings’ indicating whether or not the defined event is expected to occur based on contingency table (Harvey *et al.* 1992; Mason and Graham 1999) (Table 1).

The total number of events is given by e , and of nonevents by e' . The total number of warnings is given by w , and of no-warnings by w' . The following outcomes are possible: a hit, if an event occurred and a warning was provided (h is the number of hits); a false alarm, if an event did not occur but a warning was provided (f is the number of false alarms); a miss, if an event occurred but a warning was not provided (m is the number of misses); a correct rejection, if an event did not occur and a warning was not provided (c is the number of correct rejections). The hit and false-alarm rates, respectively, indicate the proportion of events for which a warning was provided correctly, and the proportion of non-events for which a warning was provided incorrectly (Mason and Graham 1999).

Table 1. Contingency table for verification of a binary forecast system.

Observation	Forecast	
	Warning, w	No warning, w'
Event, e	hit, h	miss, m
Non-event, e'	false alarm, f	correct non-event, c

hit rate = $h/(h + m)$ and false-alarm rate = $f/(f + c)$.

RESULTS AND DISCUSSION

Diagnosis Step

The number of PCs determining scree plot of eigenvalue showed that the points tended to level out or approaching zero after PC5. PC1-5 appear to explain more than 95% variance of the predictor. The degree of freedom (d.o.f) reduction of atmospheric circulation is very important in an analogue method. With a high d.o.f and a short period of observations, Lorenz (1969) found an almost similarly small analogue of hemispheric-scale climate patterns. On the other hand, Guzler and Shukla (1984) found improved forecast skill by reducing the d.o.f. using spatial and temporal averaging. Result of analogue search showed that spatial pattern of selected χ and ψ in database had a much closer match with the target time. Figure 4 depicts four of thirty analogues of spatial pattern of χ on 19 July 2001 indicating similar pattern with the target time. Interval time of analogue search has been restricted between 22 days before and after target data as recommended by Hidalgo *et*

al. (2008). They showed that analogues of spatial pattern of χ are much closer to target time.

Prognosis Step

The prognosis step is the derivation of the high-resolution pattern by applying the multiple linear fit developed from the subset of most suitable low resolution predictors. The regression coefficients derived for each low resolution pattern were applied directly to the corresponding high resolution weather patterns for the same days. The result of rainfall downscaling showed that determination coefficient (R^2) between predicted and observed rainfall ranged between 56% and 68% (significant at 0.05 probability level; Fig. 5). In addition, observed rainfall pattern had reasonable representation by downscaled rainfall. However, the prediction was not able to capture the extreme low and high original rainfall values. According to Fernandez and Saenz (2003), the analog models better maintain the non-normality, which are more suitable for assessing GCM

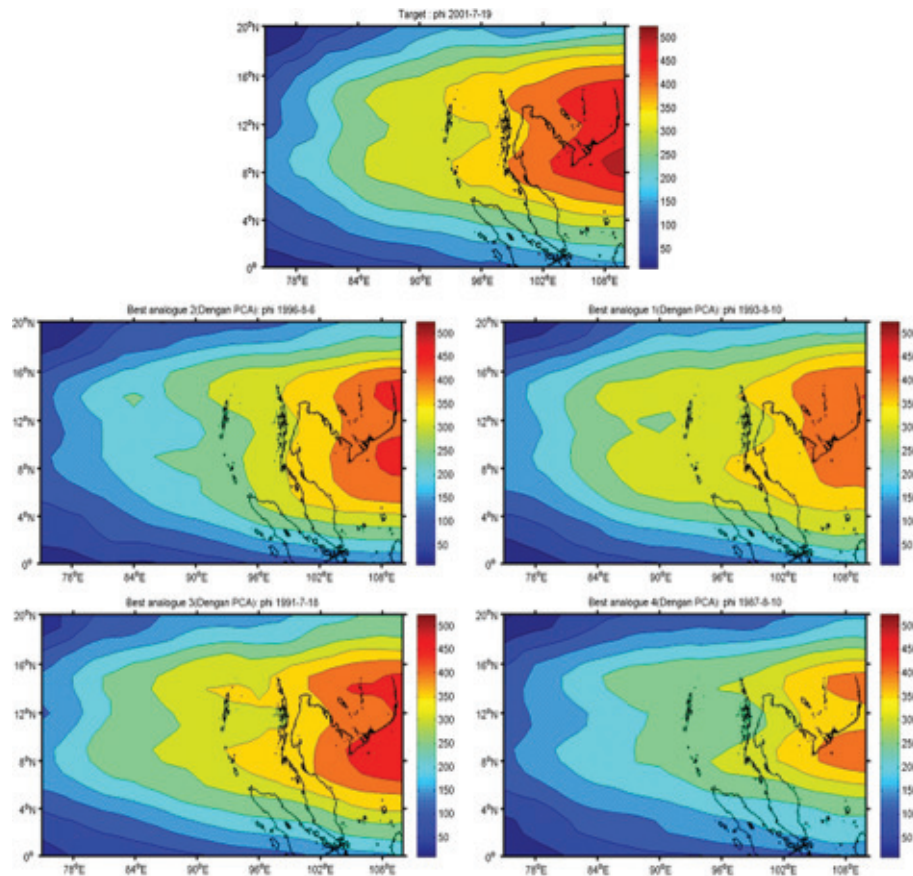


Fig. 4. Spatial pattern of velocity potential or χ (m^2s^{-1}) on 19 July 2001 and four of thirty best analogues.

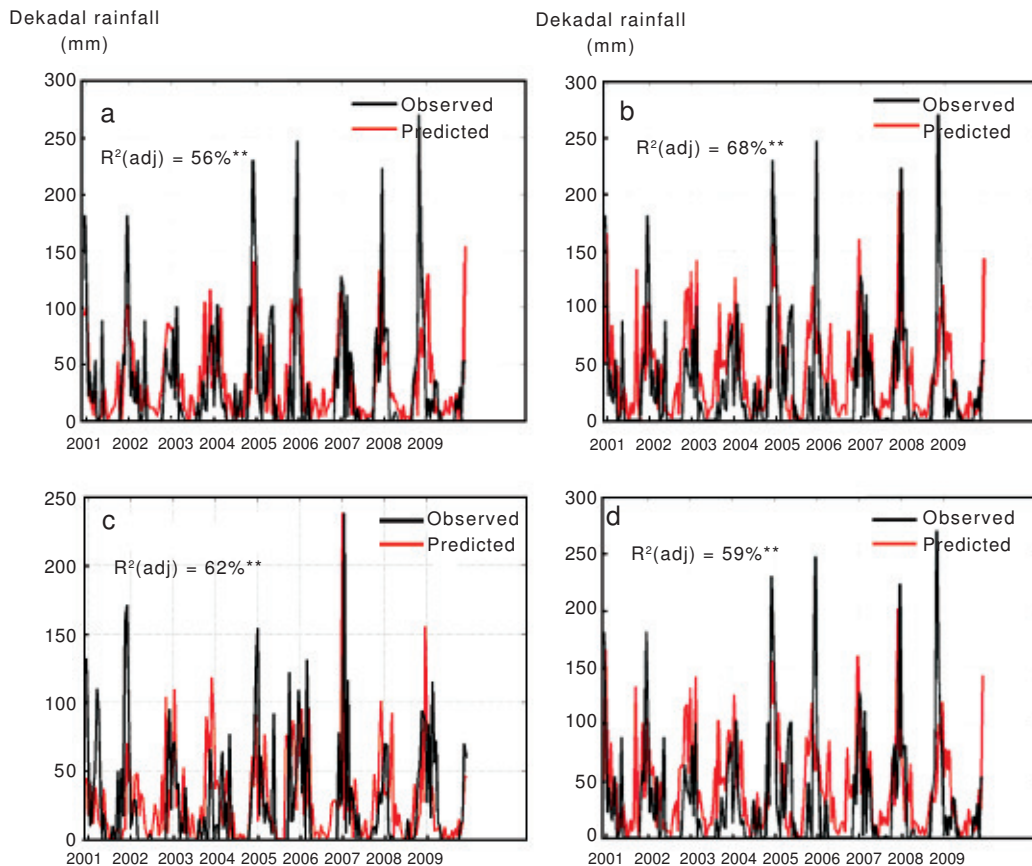


Fig. 5. Plots of observed and predicted first decade rainfalls for April–November period from 2001 to 2009 for four selected rain gauges, namely (a) Cikijing, Majalengka District, (b) Gegesik, Cirebon District, (c) Bugel, Indramayu District, and (d) Darmaraja, Sumedang District. * and ** indicate significant differences at 0.01 and 0.05 probability levels, respectively.

downscaled precipitation, but they do not simulate possible trends leading to extreme smaller or larger values than those observed during the calibration period.

Comparison of all ensembles and the corresponding observed series for the first decade of March and June rainfall showed that rainfall predictions of the first decade of March were relatively better for capturing the variations of observed rainfall (Fig. 6). On the other hand, some of the first decade of observed June rainfall lied in the lower end of the ensemble spread. We also found that the ensembles were not able to reproduce a value closer to zero as illustrated in Figure 6c and 6d. As noted earlier (Buizza *et al.* 2005; Zhu 2005), the perfect ensemble prediction is expected to have a similar ensemble spread for the same lead time. However, most of ensemble spread was un-equally distributed which came from each process of numerical weather prediction system such as observation and data collection, data assimilation, and forecast model.

Verification of Probabilistic Rice Area Drought Prediction

Figure 7 shows ROC curve of rice area drought prediction for DSP1 in rainfed rice fields and DSP2 in irrigated rice fields. The area under ROC curves shows the skill of the probabilistic seasonal prediction for early detection of rice drought of 0.82 and 0.62 for DSP1 and DSP2, respectively. As noted by Mason and Graham (1999), the forecast only has skill when the hit rate exceeds the false-alarm rate. The ROC curve will lie above the 45° line from the origin if the forecast system is skillful and the total area under the curve is greater than 0.5.

For a probabilistic system, the ROC curve illustrates the varying quality of the forecast system at different levels of confidence in the warning (the forecast probability). For examples, for DSP1, on 40% probability, the hit rate was 0.76. This hit rate indicated that 76% of rainfall below 60 mm occurred in the first decade of March. In a forecasting

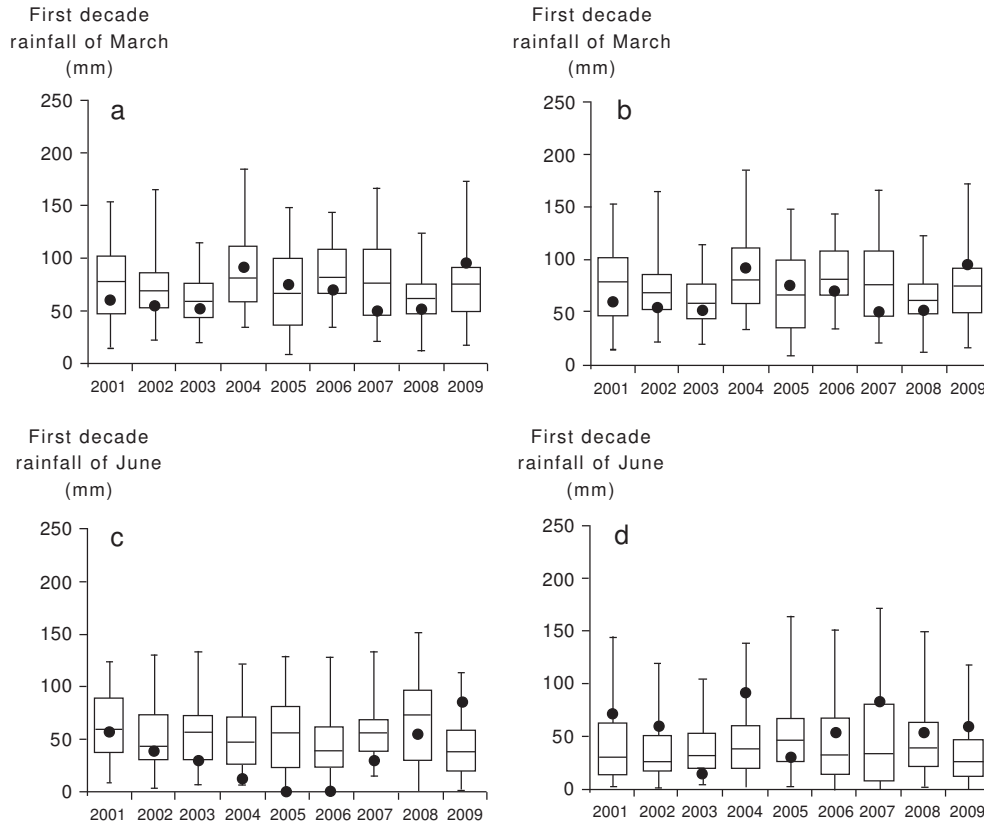


Fig. 6. Box plots of first decade of March rainfall of the ensembles within 2001 and 2009 for four selected rain gauges, (a) Bunder, Cirebon District, (b) Cimalaka, Sumedang District and first decade of June rainfall for (c) Losarang, Indramayu District, and (d) Banjaran, Majalengka District. The observed rainfall is shown as dot plots. The medians of ensemble values are shown as solid line within each box.

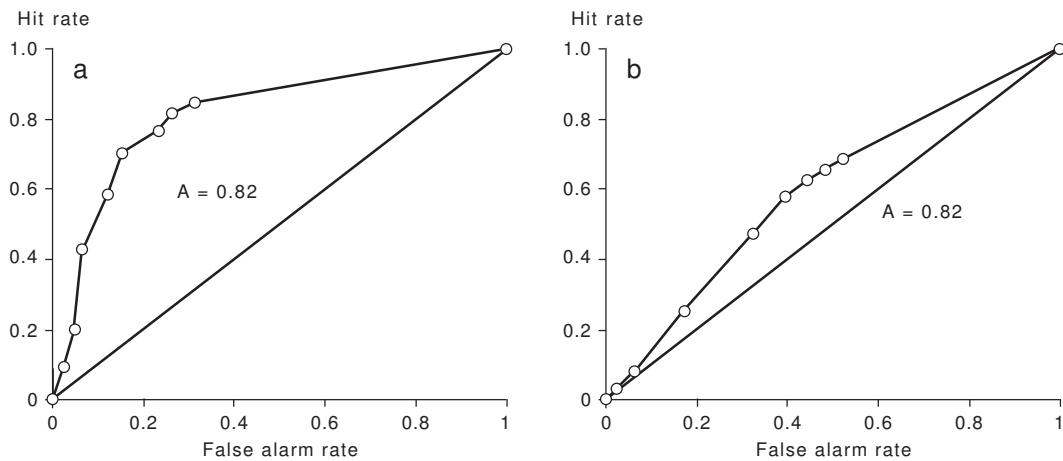


Fig. 7. Hit rates versus false-alarm rates for (a) dry season planting I (DSP1) and (b) DSP2. ROC area is calculated from 30 ensemble members of predicted rainfall of 42 rain gauges for 2001-2006 period.

environment, a hit rate of 0.76 provided an estimate that a warning could be provided for 76% of future first decade of March which is below 60 mm, assuming no change in predictability or forecast performance.

The ROC curve can be used in helping to identify the optimum strategy in any specific application (Harvey *et al.* 1992). For example, it is decided that a warning is to be issued only when there is at least an 80% confidence that an event will occur. Decision

can also be determined using optimal probability, which is defined by Youden index (J). J is a maximum vertical distance or difference between the ROC curve and the diagonal or chance line as noted by Schisterman *et al.* (2005). J is a commonly used measure of overall diagnostic effectiveness of the forecast. In this study, J for DSP1 was 40% and for DSP2 was 30%. This probability indicated that rice drought events can be forewarned when at least 40% of the ensemble members simulate rainfall amounts below 60 mm occur in the first decade of March for DSP1 and 30% members simulating rainfall amount below 20 mm in the first decade of June for DSP2.

This study also showed that the skill of the probabilistic seasonal prediction for early detection of rice drought was found to range from 62% to 82% with an improved lead time of 2-4 months compared to that of using Niño 3.4 index with lead time of 0-2 months. Lead time of 0-2 months would not allow adequate time to predict rice drought impact concerning those plants in the earlier DSP1 (March) and DSP2 (June) as described by Surmaini *et al.* (2014a). Rice drought prediction with lead time of 2-4 months provided sufficient time for policy makers, farmers and extension workers to cope with yield reduction by preparing suitable farming practices and equipments. In practice, this probabilistic drought prediction should be very informative to the forecaster. The forecaster may interpret and recommend to end-user the optimal probability of forecast.

CONCLUSION

The CA method has been employed to produce downscaled local rainfall prediction using GCM with ψ and χ at 850 hPa as predictors. The skills of rice drought on DSP 1 and DSP2 were found to range from 62% to 82%. GCM with 6-9-month lead time in multi-windows monsoon areas may serve as better tools for predicting rice drought compared to ENSO indices with an improved lead time of 2-4 months.

Drought events in rice areas can be forewarned when at least 40% of the ensemble members simulate rainfall amounts below 60 mm in the first decade of March for rainfed rice field in DSP1 and 30% for amount below 20 mm in the first decade of June in irrigated rice field for DSP2. Furthermore, the CA method can be used for downscaling the CGM rainfall prediction in the dry season over areas of Indonesia under the influence of monsoonal rainfall pattern. However, for areas under the influence of local rainfall

pattern, the use of CGM prediction should be evaluated further.

For users such as practical decision makers, extension worker and farmers, result of the study can ultimately be applied for predicting drought in rice production areas, such that any form of insightful anticipation and intervention can be done. The lead time of 2-4 months provides sufficient time for preparing suitable farming practices and supplies of incoming planting season.

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