Role of monsoon interannual variability on the climate model prediction of seasonal rainfall over Indonesia

Suaydhi*
Centre for Atmospheric Science and Technology (PSTA), National Institute of Aeronautics and Space (LAPAN)
Jl. dr. Junjunan 133, Bandung, Indonesia 40173

*suaydhi@lapan.go.id

Abstract. Hindcast produced by a model used in a numerical model-based seasonal prediction system is an essential part of the operational seasonal prediction system. This paper is aimed at evaluating the performance of POAMA and CFSv2 models in predicting the interannual variability of seasonal rainfall over Indonesia. The data used in this research are obtained from POAMA m24 model and CFSv2 model. A seasonal empirical orthogonal function analysis is used for examining the year-to-year variation of seasonal rainfall. The results reveal the influence of ENSO on seasonal rainfall over Indonesia. These results are well simulated by both models, although there is a decrease in the accuracy of the models for longer lead-time. The areal average may suggest that POAMA m24 model with a resolution of T24 has better accuracy for longer lead time, but CFSv2 with a resolution of T126 is superior in simulating the spatial pattern of rainfall over Indonesia.

1. Introduction
The seasonal prediction has important meteorological and societal impacts. Decision makers in the agricultural sector, water management sector and disaster reduction agency are very much in need of sub-seasonal to seasonal forecasts. They need to devise management strategies for several months or a year ahead [1]. The start or the onset of a season (dry/rainy) and its length vary from year to year [2]. There are many factors that influence the seasonal onset and length in Indonesia. Chang and Wang [3] show that the Indonesian rainfall is greatly influenced by monsoon and complex terrain. El Nino Southern Oscillation (ENSO) is also a major modulator of the Indonesian rainfall [4–6]. Indian Ocean Dipole Mode (IODM) and Madden-Julian Oscillation (MJO) also play a significant role in the Indonesian rainfall variability [7–9]. All of these phenomena make the prediction of rainfall over Indonesia a huge challenge.

The seasonal predictions of rainfall can be generated using statistical and dynamical methods. The statistical method relies heavily on historical rainfall records. The dynamical method uses a numerical model of physical laws of the atmospheric and ocean dynamics, known as General Circulation Model (GCM). The dynamical methods rely heavily on the future state of the sea surface temperatures (SSTs), especially the SST of the tropical Pacific Ocean. Besides SST, GCM also requires initial condition from the current atmospheric state. The dynamical method gives better seasonal prediction than the statistical method because dynamical models have the ability to handle various linear and non-linear interactions and also have the potential resilience against climate change. Van Oldenborgh et al. [10] show that
dynamical models produce better forecast for the start and amplitude of El Nino and La Nina during boreal spring and summer than the corresponding statistical models.

The ability of dynamical models in producing seasonal forecasts have improved significantly since the development of data assimilation system in the 1990s. There are several global seasonal forecast systems, for examples NCEP CFSv2 (National Center for Environmental Prediction Climate Forecast System version 2; [11]), ENSEMBLES [12] from ECMWF (European Centre for Medium-Range Weather Forecast), and POAMA (Predictive Ocean Atmosphere Model for Australia; [13]). Those systems have been developed through intensive research to improve the seasonal forecast skill of numerical models (e.g. [14], [15], [16]). The predictability of the Indonesian rainfall has also been extensively researched (e.g. [4], [17], [18]).

The seasonal forecast systems are developed to gain knowledge of the state of the atmosphere a few months in advance. However, the accuracy of weather and climate predictions usually deteriorates with time due to the model error [19]. This paper attempts to investigate the effect of lead-time on the performance of a forecasting model based on the seasonal prediction of POAMA. A comparison with the performance of CFSv2 seasonal predictions is also described. POAMA is a state of the art operational seasonal prediction covering the climate of the whole world. The first operational version of POAMA (POAMA-1) was established in 2002. In 2007, it was replaced by POAMA-1.5b. The current operating system is the multimodel version POAMA-2.4, operated at the end of 2011 [20]. It has been shown by [20] that POAMA-2.4 is skillful in forecasting seasons over the island nations in the tropical South Pacific. Suaydhi [21] has assessed the performance of POAMA-2.4 in predicting the monthly rainfall over the Indonesian region from the climatological aspect. This paper attempts to elaborate on those results further by assessing the effects of the large-scale circulation patterns in different lead-times.

2. Model, data, and methods

POAMA-2.4 is a coupled ocean-atmosphere model consisting of the Bureau of Meteorology Research Centre unified Atmospheric Model version 3.0 (BAM3.0) for the atmosphere and the Australian Community Ocean Model version 2 (ACOM2) for the ocean. The atmospheric model is a spectral transform model with a horizontal resolution of T47 (~250 km) and 17 vertical levels. The main physics used in BAM3.0 are the Lacis and Hansen scheme [22] for the shortwave radiation, a modified Fels-Schwarzkopf scheme [23] for the longwave radiation, and the Tiedtke mass flux scheme [24] for the cumulus parameterization. The recent POAMA model is initialized by a new Atmosphere Land Initialisation (ALI) scheme [25]. The ocean model component of POAMA is Australian Community Ocean Model (ACOM) version 2, which has a horizontal resolution of 2° in the zonal direction and a variable resolution in the meridional direction (0.5° at the equator increasing to 1.5° at the poles). The ACOM2 has 25 vertical levels with levels between 185 m and the surface [26]. The ocean model is initialized by the POAMA Ensemble Ocean Data Assimilation System (PEODAS) based on an ensemble Kalman filter [27].

Unlike its predecessors, POAMA-2.4 has three slightly different configurations, each with a set of 11 members. The three model variants are identified as POAMA-2.4a, POAMA-2.4b, and POAMA-2.4c. A flux correction is applied in model POAMA-2.4b to reduce the climatological bias in the coupled model, but not in the other two models. In this approach, the shortwave radiation, total heat flux, and wind stress are adjusted to be closer to the observed datasets [28]. A new shallow convection scheme for the cumulus parameterization is implemented in POAMA-2.4a and POAMA-2.4b, but not in POAMA-2.4c [20]. The use of three slightly different model versions has the purpose of sampling uncertainty due to model error and improving forecast reliability. Every run of the 33-member ensemble of the POAMA prediction system is initialized at 1, 11, and 21 of the month. The first date is for 0-month lead, with the initial conditions of the 11th and the 21st of the month used as the ensemble member for the next month. The CFSv2 prediction system has been described by [18]. The two hindcast datasets have a common 29-year period of 1982–2010 with 9-month and 10-month integrations for POAMA.
and CFSv2, respectively. The POAMA ensemble has 33 members and CFSv2 ensemble consists of 24 members.

For verification of the model results, the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP; [29]) dataset is used in this analysis. The observational 850 hPa wind fields are obtained from Interim Reanalysis of ECMWF (ERA Interim; [30]), and the observational SST data are from the improved Extended Reconstructed SST Version 5 (ERSST V5) data [31]. To examine the relationship of rainfall with ENSO, the Nino-3.4 index data are used and obtained from the NCAR-UCAR Climate Data Guide [32]. The Nino-3.4 index is defined by the 5-month running mean of SST over the area of $5^\circ S – 5^\circ N, 120^\circ W – 170^\circ W$.

The definition of seasons used in this study is June-July-August (JJA) as the dry season, September-October-November (SON) as the transition from dry to rainy season, December-January-February (DJF) as the rainy season, and March-April-May (MAM) as the transition from rainy to dry season. That sequence of seasons is adopted here as the “monsoon year” [33], i.e. it spans from JJA of Year 0 or JJA(0) to MAM of the following year (Year 1) or MAM(1). The sequence of JJA(0), SON(0), DJF(0/1), and MAM(1) is treated as yearly block. This sequence is repeated forward in time to obtain a seasonally evolving pattern. A covariance matrix is constructed for each yearly block before applying the EOF (Empirical Orthogonal Function) decomposition. This is called a Season-reliant EOF (SEOF) analysis, which was introduced by [34]. They show that SEOF method is able to distinguish modes of seasonally-evolving variability. In their analysis of the Indo-Pacific SST anomalies, Wang and An [34] obtain two statistically significant leading modes which is produced by the conventional EOF analysis. The two leading modes are low frequency (LF) and Quasi-Biennial (QB) modes.

In this study, the SEOF analysis is applied to both observed and hindcast seasonal precipitation anomalies. The domain of this study is focused on the Indonesian region from $95^\circ E$ to $145^\circ E$, and from $15^\circ S$ to $10^\circ N$.

3. Seasonal rainfall and its relationship with large-scale circulation patterns

Figure 1 shows the climatologies of seasonal rainfall over the Maritime Continent. It shows that most of the Indonesian region experience rainy season during DJF and dry season during JJA. The northern part of Sumatra has the wettest season during SON, while Maluku, the northern part of Sulawesi and the western part of Papua have the driest season during this period. It means that northern part of Sumatra enters the rainy season earlier than other areas of Indonesia, which is in agreement with that found by [2].

The seasonal peaks and troughs of rainfall from the hindcast simulations are shown in figure 2. The POAMA hindcast (top panel of figure 2) show the wettest season occurring in SON extended from northern part of Sumatra to western part of Kalimantan. The SON rainy season is also simulated on some parts of Papua. The seasonal trough of rainfall from the POAMA retrospective prediction is in good agreement with that of the observation, except on the east coast of Sumatra where it has driest period during DJF. The CFSv2 hindcast (bottom panel) spatial pattern of seasonal peak resembles the observation. However, the dry season over Indonesia is simulated a season too early for the south-eastern part of Indonesia. The first impression of these climatological results from two different models is that POAMA performs slightly better in simulating the season trough than CFSv2 model, but the seasonal peak of rainfall is better reproduced by CFSv2 than POAMA model.

To measure the interannual variability of the Indonesian rainfall, an index is constructed by using monthly rainfall averaged over the domain outlined by red boxes in figure 3 for rainy and dry seasons, respectively. These indices are then correlated to Nino-3.4 index. The correlation is shown in figure 3, along with the regression of horizontal wind at 850 hPa level against the rainfall indices. During the rainy season (top panel), the SST over the Indian Ocean and the central-eastern tropical Pacific is negatively correlated with the rainfall over Indonesia, but the SST over the eastern Maritime Continent is positively correlated. This positive correlation is extended to the western North and South Pacific. The low-level horizontal wind converges towards Indonesia from the Indian and Pacific Oceans. This
convergence indicates strengthened Walker Circulation which results in enhanced rainfall over the Indonesian region.

**Figure 1.** Observed seasonal peak (left) and through (right) of rainfall over Indonesia.

**Figure 2.** Model seasonal peak (left) and through (right) of rainfall over Indonesia for POAMA (top) and CFSv2 (bottom).

Local convection may play a role in supplying rainfall source over the eastern Indonesian region during JJA as shown by a fairly strong positive correlation of the local SST and the rainfall index [figure 3(b)]. It might be the reason why there is a rainfall peak during JJA around southern Maluku (35). The positive correlation is also seen on the SST over the western South Pacific. The negative correlation is only shown by SST over the central-eastern tropical Pacific. This suggests the negative influence of ENSO on the Indonesian region, especially during dry season.
Figure 3. Patterns of correlation (shading) between SST and the Indonesian rainfall indices and regression of 850-hPa winds (m/s, vectors) against the Indonesian rainfall indices for observations in DJF (top) and JJA (bottom). Values of correlation coefficients exceeding 95% confidence level are shaded. The domain of the study is outlined in red boxes.

Figure 4. Similar to figure 3, except for POAMA hindcast.
The patterns of correlation of SST with and the regression of low level horizontal wind against the rainfall indices from POAMA hindcast with 0-month lead time are shown in figure 4. The large scale SST anomalies of negative-positive-negative patterns from POAMA hindcast results during DJF [figure 4(a)] show a good agreement with the observation [figure 3(a)], except the model is missing the negative correlation feature over the southern part of Indonesia. The 850 hPa wind patterns from the model generally have similar orientation, but too strong in magnitude, compared with the observation. The observed SST correlation and wind regression patterns for DJF are well reproduced by CFSv2 (see figure 11(a) of [18]).

For JJA, POAMA is also able to simulate the observed large-scale SST correlation patterns [figure 4(b)]. In contrast to DJF patterns where the model misses the significant local SST correlation, the local SST correlation patterns are stronger and more extensive during JJA compared with the observation. The strong positive correlation of SST to the west of Papua might lead to the seasonal peak of rainfall during JJA seen in figure 2(a) above. The observed JJA wind patterns are well reproduced by POAMA. CFSv2 model is also able to realistically simulate the observed SST correlation with and wind regression against the rainfall patterns over the tropics during JJA (18).

4. Assessment of the major modes of model forecast as function of lead times

To evaluate the skill of the model ability to forecast the rainfall several months ahead, the results of POAMA and CFSv2 hindcast are compared with the CMAP datasets. The SEOF analysis has been applied to both the observed and simulated datasets. The percentage variance of the first seven eigenvalues of the SEOF of the seasonal rainfall over Indonesia is shown in figure 5. The red bars in that figure show the unit standard deviation of the sampling errors associated with each eigenvalue’s percentage variance. Larger sampling errors indicate more statistically distinguishable modes (North et al., 1982). The first two observed and simulated modes can be considered distinguishable from the rest of the SEOF modes according to the rule of North et al. (1982). The fractional variances from the two statistically distinguished leading modes produced by SEOF analysis of CMAP rainfall seasonal anomalies (1983–2009) account for 40.82% and 10.80%, respectively. Figure 5 shows that the fractional variances of CFSv2 first two leading modes are considerably closer to those of the observed datasets than the POAMA counterparts. It means that CFSv2 0-month lead seasonal hindcast produces a more realistic fractional variance for the first two SEOF modes (52.39% and 11.26%) than POAMA counterparts (59.44% and 15.08%).

The time series of the first and second mode principal component (PC) of the SEOF analysis is shown in figure 6. The first mode of the PC resembles the interannual variation of SST anomalies over the central tropical Pacific. It indicates that this mode is closely related to ENSO. The 1-month lead of POAMA seasonal rainfall prediction shows a very good agreement with the observation with a correlation coefficient of 0.91. A similarly high correlation is also shown by the corresponding CFSv2 prediction with a correlation coefficient of 0.89. The second mode of the SEOF analysis also shows high correlation coefficients between the observed and the 0-month lead model predictions, i.e. 0.66 and 0.69 for POAMA and CFSv2, respectively.

A lead-lag correlation is carried out between the seasonal NINO3.4 anomalies and the two PCs to examine the relationship of these two PCs with ENSO (figure 7). Very high positive correlation coefficients that exceed 0.8 between Nino3.4 SST anomaly and the first mode of the PCs of the three datasets are found for Year 0. According to (Rasmussen and Carpenter, 1982), El Nino reaches mature stage around November and December each year. This is indicated by the first SEOF mode as shown in figure 7(a). Unlike the results of Wang et al. (2008), the second mode of the SEOF shown in figure 7(b) here does not seem to have any real physical interpretation. Subsequent analysis, therefore, will solely discuss the results of the first mode of the SEOF.

The high temporal correlation shown in figure 6(a) does not necessarily lead to a realistic spatial pattern. Figure 8 shows the comparison between the observed first leading mode of the monsoon interannual variability of seasonal rainfall with the 1-month lead time of the model hindcast. It can be seen that the CFSv2 model prediction replicates the observed first mode of spatial pattern better than
the POAMA model. The seasonal rainfall anomaly pattern correlation coefficient is above 0.6 for CFSv2 and below 0.5 for POAMA. The former reproduces the very high pattern correlation during JJA(0), SON(0), and MAM(1). Meanwhile the latter poorly simulate the observed MAM spatial pattern.

The POAMA and CFSv2 retrospective predictions covered a 9-month and 10-month predictions, respectively. It is, therefore, possible to examine the forecast skill with lead times up to 8 months. The variations of hindcast correlation coefficients with lead time for the two models are shown in figure 9. The temporal correlation coefficients between POAMA and the observed PC time series are always higher than those of CFSv2. The POAMA temporal correlation coefficients remain above 0.8 from 0.94 at 0-month lead to 0.84 at the 8-month lead, while those of CFSv2 drop from 0.92 at 0-month lead to 0.69 at the 8-month lead. Conversely, CFSv2 shows better spatial correlation with the observation than POAMA does (right panel). The pattern correlation coefficients for CFSv2 decrease from 0.73 at 0-month lead to 0.59 at the 8-month lead with a slight dip at the 4-month lead (correlation coefficient of 0.62). Those of POAMA drop from 0.50 at 0-month lead to 0.46 at the 8-month lead with a minimum at the middle, correlation coefficients of 0.39 at the 4, 5 and 6-month lead.

![Figure 5](image_url). Percentage variance (%) explained by the first seven SEOF modes of seasonal rainfall anomalies obtained from CMAP (a), POAMA (b), and CFSv2. The red bars represents one standard deviation of the sampling errors.
Figure 6. Principal components of the first (a) and the second (b) SEOF modes of seasonal rainfall anomaly obtained from CMAP observation (solid blue line), POAMA hindcast (green dashed line), and CFSv2 hindcast (red dotted line), respectively. The numbers within the parenthesis in the figure legend indicate temporal correlation coefficients between the observed and hindcast principal component.

Figure 7. (a) Lead-lag correlation coefficients of Nino3.4 SST index with reference to the first SEOF principal component, and (b) with reference to the second SEOF principal component.
Figure 8. Spatial patterns of the first SEOF eigenvector of seasonal rainfall anomalies obtained from CMAP, POAMA and CFSv2 predictions. The numbers in brackets indicate pattern correlation coefficients, between observation and the corresponding prediction.

Figure 9. Performance of model results against forecast lead time for the seasonal prediction of the first SEOF mode over Indonesia for POAMA (blue) and CFSv2 (red).
5. Conclusion
Neither the seasonal peak nor trough occurs during MAM (figure 1). Because during this period there is a great variation of the state of oceans and atmosphere with time [18]. The rainfall over the Indonesian region is closely related to SST in both the tropical Pacific and the Indian Ocean during DJF and to SST in the tropical Pacific Ocean during JJA. Both POAMA and CFSv2 models can reproduce that feature.

The seasonal EOF (SEOF) analysis is a powerful tool to identify major modes of the year-to-year variability of a climate variable. The first leading mode of the SEOF shows the influence of ENSO on the monsoon interannual variability. POAMA which has coarse horizontal resolution at 2.5 degrees performs better than CFSv2 which has a resolution of 1 degree in the temporal correlation with the observation. However, the higher resolution model has the upper hand in the pattern correlation coefficients.

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