Use of the dry-spell seasonal forecast in crop management decisions

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Abstract. Climate forecasts have shown the potential for improving the resilience of agriculture to climate change. The usefulness of climate forecasts for applications in agriculture can be enhanced if the forecasts are translated into agricultural outlooks, in which the information is targeted for decision-making. The sequence of dry periods is necessary for successful crop management decisions, especially in dry season planting. This paper investigates how well the Climate Forecast System version 2 (CFSv2) seasonal forecasts predict the dry spell (DS) over the Indonesia region. The seasonal forecasts were downscaled using the constructed analogue method and, in turn, were corrected with TRMM 3B42 rainfall data to match daily precipitation totals. The DS is defined as rainfall less than 5 mm day⁻¹ for ≥10 consecutive days. Accuracy of the DS prediction was assessed using the Brier Score (BS) method for December-January-February (DJF) and June-July-August (JJA) periods. The results demonstrate that the highest accuracy of the DS forecast occurred in JJA in southern part Indonesia with a range of the BS value between 0-0.2 (>80%). The operational DS seasonal forecasts are needed to manage agriculture practices for the upcoming planting season such as the choice of a crop/variety, supplementary irrigation, and crop water requirement.

1. Introduction
Recent advances in climate modelling have resulted in increased rainfall prediction in many parts of the world by using dynamical forecasts or statistical methods [1], with a lead time ranging from a few days to a few months [2-4]. However, seasonal forecasts of weather and climate associate with high uncertainties. The level of uncertainty can be conveyed quantitatively by using probabilities [5,6]. For model forecasts, the level of uncertainty can be derived from an ensemble of forecast model [7]. Owing to their ability to quantify the uncertainty, probabilistic forecasts are of potentially greater value to decision-makers than deterministic forecasts [5,8].

Weather and climate can strongly influence agricultural production in Indonesia, especially in areas where the monsoon rainfall plays a dominant role in crop production. For rice, there are typically three planting periods, a single wet season planting (WSP) followed by two dry season plantings (DSP). DSP are typically exposed to high drought risk, as during this period rainfall decreases significantly [9,10]. Thus, the DSP contributes 30-40% of the farmer’s income [11]. Dry spell information also important during wet season planting, in case of season break/false rain, to avoid drought risks during the growing season.
The dry spells forecast during the growing season could be used for deciding a particular crop or variety in a given location, and in decision making concerning supplementary irrigation and field operations in agriculture [12,13]. The decision on the upcoming planting season would benefit from seasonal forecasts covering the full growing season [13,14]. The seasonal forecast may provide information on the development of the climate up to 6 months, or in some cases even 12 months ahead.

Several seasonal forecast systems have been developed and used [15-17]. The Climate Forecast System version 2 (CFSv2) developed by the National Centre for Environmental Prediction (NCEP) has been widely used for agriculture and most reliable model for seasonal forecasting of global drought onset [18, 19, 20]. The usefulness of climate forecasts for applications in agriculture can be enhanced if the forecasts are translated into agricultural outlooks such as dry spell. The dry spell forecast is necessary for successful crop management decisions especially in DSP. This paper investigates how well CFSv2 seasonal forecasts predict the dry spell (DS) over Indonesia region and how to implement the dry spell forecast in crop management decisions.

2. Materials and methods

2.1. The CFSv2 dataset
The CFSv2 provides daily atmospheric variables at 0.25° gridded resolution from the retrospective forecasts. Seasonal integrations initialized in each calendar month of the year simulate global atmospheric fields out to 9 months into the future. The meridional (U) and zonal (V) wind at 850 hPa data for the periods of 1998-2014 [18] were accessed at the http://nomads.ncdc.noaa.gov/data/cfsv2frlts9/wnd850. 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 28 years from 1982 to 2009. The vector fields of U and V 850 hPa data were decomposed into the scalar field of rotational stream function (ψ) and divergent velocity potential (χ) components.

2.2. Observed dataset
The Tropical Rainfall Measuring Mission (TRMM) 3B42 rainfall product for 17 years period from 1998 to 2014 was used for model validation. These data are derived from a combination of calibrated microwave and infrared precipitation estimates [21, 22]. The TRMM 3B42 rainfall product is available at temporal and spatial resolutions of 3-hourly and 0.25°×0.25° over tropical regions. For the present analysis, the 3-hourly rainfall data from TRMM 3B42 have been aggregated at a daily time step.

2.3. Constructed Analogue Downscaling Method
Hidalgo et al. [23] was applied to look for subset analogues in a large-scale field and then use the local target field simultaneously to the large-scale analogue to reconstruct the local rainfall scale field [24]. Hindcast data of ψ and χ of NOAA’s CFSv2 from 1998 to 2010 were used as a library or pool of potential analogues and data from 2011 to 2014 to validate the downscaling results. The Constructed Analogue (CA) method used for downscaling can be divided into 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 combinations of 30 patterns that best match to the target pattern. The previous research indicated that 30 subsets had optimal correlation coefficient [23]. Thus, the Empirical Orthogonal Function (EOF) was applied to reduce the degree of freedom of ψ and χ [24].

The prognosis step is the derivation of the high-resolution pattern from the subset of predictors (figure 1). In this study, we used a multiple linear regression method, which is a wind vector as an independent variable and rainfall observations as a dependent variable [25]. Wind vector was determined by an analogue search that is carried out using cosine similarity [26]. The regression
coefficients \{B_1, B_2, \ldots, B_{30}\} and a constant C. CA of target rainfall (CH) CA(t)) were calculated by the equation as follows:

\[
CH_{CA}(t) = \sum_{n=1}^{30} B_n CH_n(t) + C
\]  

(1)

**Figure 1.** Overview of the daily rainfall downscaling using the Constructed Analogue method.

2.4. Ensemble

In this study, the ensemble was performed by \(\psi\) and \(\chi\) at 850 hPa in multi-windows monsoon regions and statistics of hindcast run. Multi-windows of the monsoon’s regions used in this study consist of five indices, i.e. (1) the Australian Monsoon Index (AUSMI): 5°S-15°S, 110°E-130°E, (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, (4) the Webster and Yang Monsoon Index divided into two regions, i.e. EQ-20°N, 75°E-110°E and (5) EQ-20°N, 40°E-75°E [25] as detailed in figure 2. The statistic of hindcast run, i.e. 3\textsuperscript{rd} quartile, mean and 1\textsuperscript{st} quartile were used as members. These components performed 30 members for ensemble.

**Figure 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.
2.5. Definition of dry spell
The dry spell was defined as consecutive dry days for ≥10 days. Dry days were defined as rainfall less than 5 mm day\(^{-1}\).

2.6. Dry spell forecast verification
The accuracy of dry spell forecast was estimated using Brier Score (BS) \([27,28]\) as defined by equation as follows:

\[
BS = \frac{1}{n} \sum_{k=1}^{n} (y_k - O_k)^2
\]

where BS is the Brier Score, \(n\) is the number of samples, \(y_k\) is the probability forecast of dry spell, and \(O_k\) is the corresponding observation. The probability forecast for a particular event have any value between 0.0 (0% probability) to 1.0 (100% probability), while the corresponding observation have a value of either 0 (the event did not occur) or 1 (the event did occur). Hence, a BS is essentially the mean squared error of the probability forecasts. BS values range from 0.0 (perfect accuracy) to 1.0 (perfect inaccuracy). Usually, a BS was calculated for the occurred events \((O_k = 1)\) known as Half-BS. In this study, the Full-BS which included non-event samples \((O_k = 0)\) were calculated to obtain more complete information about the accuracy of the forecast.

Hereinafter, the BS were applied to analyse forecast skill for two lead time forecasts, corresponding to 1\(^{st}\) season and 2\(^{nd}\) season leading from every issued month. For example, a forecast issued in May for June-July-August as the 1\(^{st}\) lead forecast and issued in February as the 2\(^{nd}\) lead forecast. For verification, the TRMM 3B42 product was used to derive the observation of the dry spell for the period of 2011-2014.

2.7. The use the dry spell forecast in crop management decisions
The operational dry spell forecast is now available and can be accessed at http://balitklimat.litbang.pertanian.go.id/. The operational dry spell forecast of January and July 2020 were selected as examples of dry spell forecast application in planning crop management decisions.

3. Results and discussion

3.1. Diagnosis and prognostic step
The result of analogue search of \(\chi\) for 19 July 2014 presented that selected spatial patterns within the database had the closest pattern with the target time. Figure 3 details five of thirty analogues of the spatial pattern of \(\chi\) on 19 July 2011. Interval time of analogue search has been limited between 22 days before and after target data as suggested by Hidalgo et al. \([23]\).

The results of rainfall downscaling show that all ensembles were relatively better in capturing the variations of the corresponding observed cumulative monthly rainfall because all observed rainfall lied within the ensemble spread (figure 4b). However, the highest rainfall forecast in March 2014 lied above the ensemble spread (figure 4a). For cumulative daily rainfall, figure 4c depicts that the ensembles were not able to reproduce a value closer to zero. According to Fernández and Sáenz \([29]\), the analogue method was more precise in maintaining the non-normality, which are more suitable for assessing GCM downscaled precipitation. However, its performance was not rigorous in simulating trends leading to extreme events, which have smaller or larger values than those observed during the calibration period. As noted earlier by Buizza et al. \([30]\) and Zhu \([31]\) the perfect ensemble prediction is expected to have a similar ensemble spread for the same lead time. However, most of the ensemble spread was un-equally distributed which came from each process of numerical weather prediction systems such as observation and data collection, data assimilation, and forecast model.
Figure 3. Five of thirty best analogues (BA) of spatial pattern of velocity potential for $\chi$ (m$^2$s$^{-1}$) on 19 July 2011 in Webster and Yang Monsoon area.

Figure 4. Spaghetti graphs of the monthly rainfall (a) cumulative monthly rainfall (b), and cumulative daily rainfall (c) in Bojonegoro District. Monthly Forecasts starting in December 2014 for the following 6 months, daily forecast starting at 0000 UTC, 1 December 2014 for the following 4 months. The light red lines highlight the ensemble rainfall forecast. The black lines indicate the TRMM rainfall observed.

3.2. Skill of dry spell forecast

The verification of dry spell forecast for DJF and JJA is shown in figure 5 and 6, respectively. In general, based on Full-BS values, forecasts for both wet season (DJF) and dry season (JJA) show high accuracies with a range of 0.02 (>80%). Otherwise, the dry spell event forecast in the wet season (figure 5a and 5c) reveals very low accuracy all over Indonesia region with BS range of 0.8-1.0 (<20%). We presume that this is related to the rare occurrence of dry spell events in the wet season during our short verification period (2011-2014).

On the other hand, forecast of the dry spell event on dry season shows promising results especially over Java and southern Sumatera region (figures 6a, 6c), while most northern parts of Indonesia generally show an unsatisfactory result. Again, we suspect this is related to the limited occurrence of the dry spell over the northern part of Indonesia, as supported by Full-BS values (figure 7b, 7d). The figures show that the inclusion of non-event improves the values of BS, hence support our earlier suspicion.
Another interesting finding is that there is no significant difference between the accuracy of the 1st lead and the 2nd lead forecasts. This indicates that the dry spell forecast can be done at least two (i.e. 6-months) instead of one season ahead with slight decrease accuracy.
3.3. Application of the dry spell in crop management decisions

Information on dry spell is required for the upcoming planting season decisions. The occurrence of long dry spell during the growing season, in particular at drought-sensitive stage, should be avoided. Proper planning of agricultural crops and water management requires the knowledge of chances of dry spells during the planting period. In the cropping calendar, the timing of dry spells and rainfall distribution is critical to crop viability and crop production [32,33]. IAHRI has developed dry spell operational forecast since 2018. Examples of operational dry spell probabilistic forecasts are detailed in figure 7. Some of the applications of a dry spell in agricultural planning are outlined below.

![Figure 7](http://balitklimat.litbang.pertanian.go.id/)

**Figure 7.** The operational dry spell probabilistic forecast of Indonesia region for January 2020 and July 2020 (Source: http://balitklimat.litbang.pertanian.go.id/). The dark orange hues indicate high probability to experience dry spell.

![Figure 8](http://balitklimat.litbang.pertanian.go.id/)

**Figure 8.** Sequence of dry spell of forecasts of the Southeast Sulawesi Province in June, July, and August 2020. (Source: http://balitklimat.litbang.pertanian.go.id/). The dark orange hues indicate regions with the highest probability to experience dry spell events.

The seasonal dry spell forecast maps of June, July and August 2020 released in April 2020 were used to specify appropriate farming practices of DSP in Southeast Sulawesi Province (figure 8). This map has 0.25° grid resolution which is fine enough to capture spatial variation in District level. In July,
it is predicted that the 80% dry spell probability will occur in southern part of Southeast Sulawesi namely Baubau, Buton and Muna District. In August, the area is predicted to expand to Bombana and Kolaka districts. This map shows that dry spell is expected to occur more than one month. Hence, the May planting could suffer from low soil moisture as the plant may require more water as it develops. Therefore, some soil and water conservation techniques should be exercised during wetter periods (in April-May and before) to conserve soil moisture in the latter days of the growing season. Alternatively, it is recommended that food crops should be planted in April so that drought in July has not much effect on the crop because at that time the plant is already in ripening phase. Drought-tolerant varieties should be selected and supplementary irrigation should be available if planting is carried out in May and after.

Managing weather conditions is one of the greatest challenges faced by farmers. The challenge is to reach farmers with tailored information about the future weather to support strategic and tactical crop management decisions. Forecasts in agriculture are generally used more by skilled internet users such as researchers, extension workers, policymakers and progressive farmers. For that reason, dissemination target is for those who have skill in internet-based information as trainer of trainer (TOT). Afterwards, the TOT’s will deliver the forecast to farmers in more simple way using the local language.

The high skill of dry spell forecast in this province (see figure 6) may help build evidence on the benefits of seasonal forecast in agricultural decisions. This will ultimately help establish climate services for the agricultural sector. Establish stakeholder-driven processes that allow two-way communication between forecast issuing institutions and farmers’ organizations and extension worker need to be enhanced.

4. Conclusions
The findings conclude that the forecast of the dry spell events on DSP have higher accuracy with a range of 0-02 (>80%) in monsoon area especially over Java and southern Sumatera. However, the forecast generally shows lower accuracy over the northern part of Indonesia due to the limitation of the dry spell occurrence. In addition, the high accuracy of the 1st and the 2nd lead forecasts indicates that the dry spell forecast can be done at least two instead of one season ahead.

The dry spell seasonal forecasts may be suitable used by skilled internet users such as researchers, extension workers, policymakers and progressive farmers, who will deliver the forecast to the farmers. This information will assist farmers to develop better planting arrangement, such as planting time, soil and water management, selection of crop/varieties. Hereinafter, stakeholder-driven processes need to establish to allow two-way communication between forecast issuing institutions and farmers’ organizations and extension worker need to be enhanced.

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