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Exploring Standardized Precipitation Index for predicting drought on rice paddies in Indonesia

E Surmaini[1], E Susanti[1], M R Syahputra[2] and T W Hadi[2]

[1] Indonesia Agency for Agro-climate and Hydrology Research Institute, Jl Tentara Pelajar no 1 Bogor 16111, West Java
[2] Faculty of Earth Sciences and Technology, Bandung Institute of Technology

elzasurmaini@gmail.com

Abstract. Droughts have severe consequences for rice crops in Indonesia, as these occur annually and increase during El Niño phenomena. Accordingly, paddy drought assessment is necessary for developing adaptation strategies for successful crop production. We conducted a detailed assessment of paddy drought-climate indices in Indonesia. This was done by looking at the onset and trends of the Standardized Precipitation Index (SPI) in a three-month time scale (SPI-3) and exploring their relationship with paddy drought-affected areas. The Cartesian quadrant was used to illustrate the combination of SPI-3 onset and trend on the paddy drought affected area. This gave four different drought risk levels: low, moderate, high, and very high. The hit rate (HR) as the proportion of drought occurrences were correctly hindcast and percent of correct (PC) as the total number of correct hindcast divided by the total number of hindcast was used to verify the accuracy of drought effect prediction on paddy rice. The results demonstrate that the highest accuracy of paddy drought predictions occurred in the peak of dry season in July, while the accuracy of drought and non-drought occurrences (PC) was higher in the non-peak months, April through September, excluding July.

Keywords : SPI, drought, paddies, rainfall

1. Introduction

Climate change-induced drought intensification has been one of the great challenges faced by the in many countries [1,2, 3], including that in Indonesia [4, 5]. As the extent of drought is expected to worsen as the atmosphere continues to warm [6, 7], plant growth and crop production may be negatively affected in terms of yield and quality [8, 9].

An agricultural drought occurs when a shortage of soil moisture adversely affects the regional agricultural production due to evapotranspiration losses [10], causing dry weight accumulation loss and shortens life cycle [11]. During vegetative growth, drought could reduce photosynthetic rate and depress grain formation during the flowering stage more than any other stages [12].

The Indonesian Ministry of Agriculture reported that during El Niño years, damaged paddy areas due to drought ranged between 350-870 kha [5], where the damage mostly occurred during Dry Season Planting (DSP) within May through October. Furthermore, it is estimated that a 30-day delay in the onset of rainy season would diminish wet season rice production in West/Central Java and East Java/Bali by about 6.5 and 11.0 %, respectively [13]. The recent prolonged drought in 2015 has caused widespread crop failures that resulted in loss of almost 600 kilotons of paddy production. For this reason, the effects of recurring droughts should be considered in the context of crop production, where incoming drought events could be anticipated with some lead time that gives adequate response time for preparing adaptive

measures. Accordingly, defining the types of drought helps to monitor droughts and to build strategies for the preparation and response to droughts [14, 15, 16].

At present, a drought alert is typically only delivered during the drought period, after it has been detected through monitoring. As drought is a slow onset phenomenon, it is normally only recognized using the monitored indicators once the impacts have started being measured, which is after the onset of the drought itself. This thus leaves little time for the taking of mitigation measures to avoid or alleviate the impacts, consequently, drought management measures should have a strong focus on response [17].

In this study, we used the Standardized Precipitation Index (SPI) to explore paddy drought characteristics. The SPI is a precipitation probability index that was developed to give a representation of abnormal wetness and dryness [18, 19, 20]. SPI is a suitable index to be applied Indonesia, where most of the available data precipitation. However, SPI values by themselves do not completely describes drought characteristics, as drought is not only marked by its intensity, but also by its duration and severity. In attempting to predict drought events, we have defined SPI characteristics using SPI onset and trend. The objective of this study is to explore the correlation between SPI onset/trend of and the paddy drought-affected areas in Indonesia.

2. Data and Method

2.1. Data
The study was conducted using monthly rainfall data from 16 Provinces (Aceh, North Sumatera, South Sumatera, Jambi, Lampung, West Java, Central Java, East Java, DI Yogyakarta, West Nusa Tenggara, East Nusa Tenggara, Central Sulawesi, South Sulawesi, South Kalimantan, Central Kalimantan and East Kalimantan). Monthly rainfall data record from the period of 1989-2015 were collected from the Indonesian Ministry of Public Works, the Indonesian Agency for Meteorology, Climatology and Geophysics, and the Global Precipitation Climatology Centre (GPCC). Monthly data of paddy affected area due to drought from 1989 to 2015 were obtained from the Indonesian Ministry of Agriculture.

2.2. Method

#### 2.2.1. The Standardized Precipitation Index (SPI).
Application of SPI was recommended in the context of meteorological drought monitoring by the World Meteorological Organization (WMO) [21]. The values of SPI are expressed in standard deviations, where positive SPI indicates greater than the median precipitation and negative SPI indicating less than the median precipitation [22] (illustrated in figure 1).
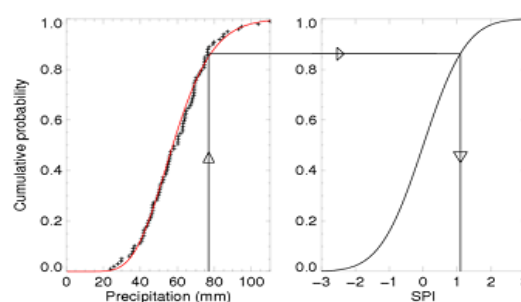
Figure 1. An example of equiprobability transformation from a fitted gamma distribution to the standard normal distribution (After [23]).

2.2.2. The onset and trend of the SPI.
The onset is characterized by the SPI-3 value three months before the drought event. The SPI-3 trend is defined by the linear regression of SPI-3 values after the onset of the drought, up to the actual drought event. For example, paddy drought affected areas in North Aceh District in August 2006 were recorded 13.047 ha (figure 2).
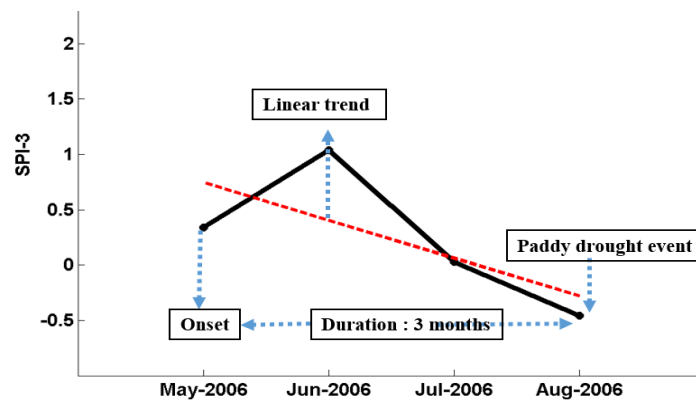
Figure 2. Plot of the onset and SPI trend associated to paddy drought affected areas between May ang August 2006. As illustrated, the onset of SPI-3 was defined three months in advance (May 2006) is 0.45, while the SPI-3 trend from May to August had a gradient of -0.75

### 2.2.3. Determination of paddy drought risk level.

We used Cartesian plane quadrants to explore the correlations between SPI with paddy drought affected area. The four quadrants represent different combinations of SPI onset and trend values (illustrated in figure 3). In order to be understood easily by user, these indices are simplified in forms of paddy drought risk score. The score was calculated as percentage of drought event x probability of paddy drought affected area using cumulative probability (CP) as follow:

$$CP = P(X > x); f(x) = e^{-\lambda x} \tag{1}$$

$$\lambda = \frac{1}{\bar{x}} \tag{2}$$

Where $\bar{x}$: mean and occurrence rate

We then defined a risk score based on the corresponding probability value, defined as the percentage of drought events multiplied by the probability of paddy drought-affected areas. Based on the risk score, we then classified the paddy drought occurrences into four risk levels: low, medium, high, and very high.
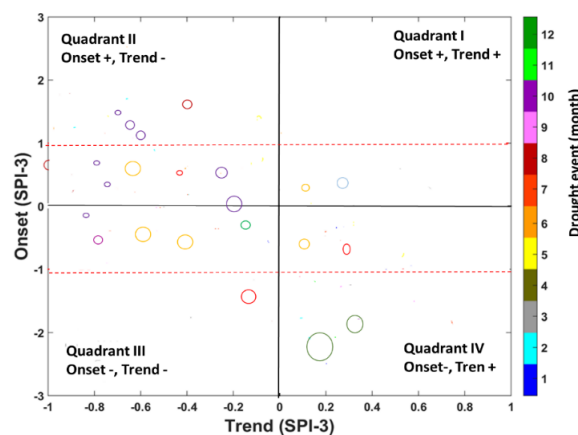
Figure 3. Correlation between the onset of SPI-3 (y-axis) and the trend of SPI-3 (x-axis) and paddy drought affected area. The color of scatter plots indicate time of drought event. The size of circle represent the size of affected area. The red dash lines indicate the range of near-normal SPI-3

2.2.4. Verification of paddy drought prediction.

In order to assess the accuracy of the model's predictive capability on drought occurrence, we used a hindcast on historical SPI onset and trend data as released by IAHRI (http://balitklimat.litbang.pertanian.go.id/) for the period 2011-2015. The accuracy was assessed using a contingency table [5] as illustrated in Table 1.

Table 1. Two-by-two contingency table for verification of a binary forecast system.

Forecast	Observation	
	Yes	No
Yes	Hit (A)	False Alarm (B)
No	Miss (C)	Correct Negative (D)

We then defined the hit rate (HR) as the proportion of occurrences that were correctly forecasted, and the Percent Correct (PC) as the total number of correct forecast (hit + correct negative) divide by total number of forecast. The PC also indicates the accuracy of the forecast. HR and PC are defined as such:

Hit Rate = A/(A+C) x 100%   (3)
Percent of Correct = (A+D)/(A+B+C+D) x 100%   (4)

3. Result and Discussion

3.1. Link between SPI-3 and paddy drought-affected area

Figure 4 shows the relationship between SPI-3 and paddy drought-affected area in Deli Serdang District, North Sumatera Province and Cianjur District, West Java Province. The figure shows that paddy drought events mostly occurred following negative SPI events. This is because soil water content is not reduced directly when rainfall is gradually decreased. According to [23] [24], meteorological drought and agricultural drought generally has lagged in time. For that reason, we conclude that SPI-3 can be used to predict the onset of paddy drought events.
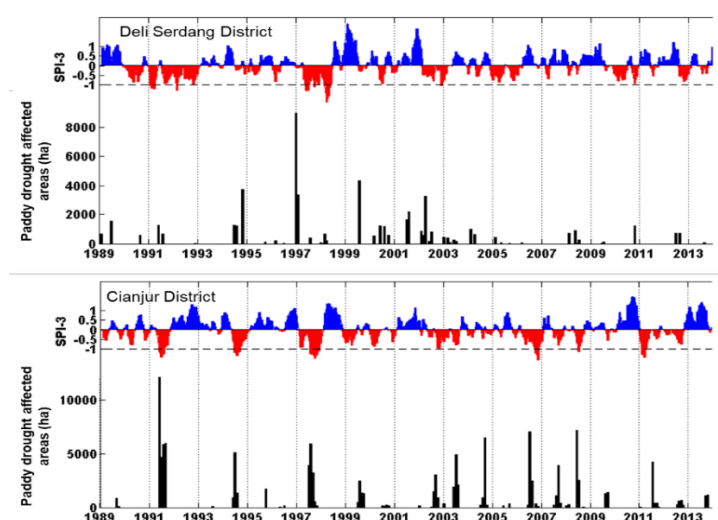
Figure 4. Plots of SPI-3 and paddy drought affected area in Deli Serdang District, North Sumatera Province (top) and Cianjur District, West Java Province (bottom). Bars indicate the paddy drought affected area. The red and blue areas indicates the negative and the positive SPI-3, respectively.

The results of this study also show that the paddy drought can be described properly by SPI within a timescale of three months. This timescale is more effective in showing the condition of groundwater during the growing season. This finding is in agreement with a previous study [25] stating that crops respond to drought after a rainfall deficit of three months. Additionally, it is stated that in general agricultural drought lags behind of meteorological drought by the three months [26].

3.2. Predictive for paddy drought events

Our result in figure 5 illustrates that paddy drought events mostly occur (85% of all occurrences) when the onset of SPI-3 is in the near-normal to wet category (SPI-3 >0), which are then followed by negative SPI trends which indicate drying conditions in the subsequent three months, which leading to high level of drought risk (Quadrant II). Even when the precipitation level and water availability are high enough (SPI-3 > 0) to encourage most farmers to start planting crops at the beginning of the planting season, there is generally no indication of any potential drought occurrence at that point. In particular, in the case of negative SPI-3 trend in the subsequent three months, there is a significant decrease in precipitation levels, causing a severe level of paddy drought occurrence.

Moderate levels of drought risk (SPI-3 values between 0 to -1) indicates near normal condition, is followed by negative trend of SPI results in lower drought risk (Quadrant III). In this case, some farmers would generally avoid planting crops at the beginning of the planting season, or would have already prepared alternative water sources, so that the risk of crop failure is not so dire (medium risk level). Low levels of drought risk (SPI-3 > 1) represent onset conditions that are relatively wet, which are then followed by positive SPI trends, indicating wet conditions in the subsequent three months (Quadrant I). Initial wet conditions, coupled with trends for even wetter conditions, result in low levels of drought risk, given that water is readily available.

Expert judgment was used to define the very high levels of drought risk. For this classification, we chose the SPI-3 value range of -3 < SPI-3 < -1 with subsequent positive or negative SPI-3 trends (Quadrant III and IV). However, lower risk scores were found with higher intensity drought instead, due to the lower number of occurrences of paddy drought (as seen in table 3). This is because for   SPI-3 < -1, there are drier conditions at the beginning of the planting season; hence, discouraging most farmers from planting crops in the first place. Drought events found within quadrants III and IV represent the farmers who speculatively planted paddy despite the dry conditions and subsequently experienced paddy drought due to an inadequate water supply via irrigation. Accordingly, for this risk level, the total number of drought occurrences alone could not fully describe the extent of the drought impact, as some farmers would opt to not plant crops, while others would speculate and decide to plant. Expert judgment was used to determine the very high level of drought risk.
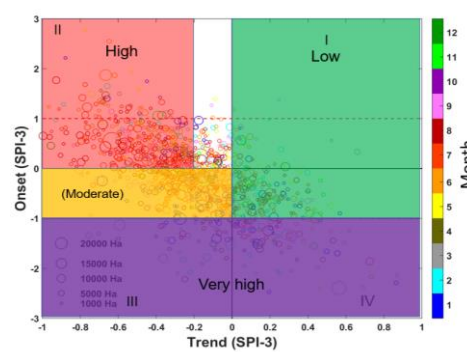
Figure 5. Level of drought risks were classified using quadrant method with the onset of SPI-3 as y-axis and the trend of SPI-3 as x-axis.

Since the paddy drought affected areas are vary greatly in spatial and temporal among districts, thus the minimum drought area was required to be defined. The minimum value was defined using cumulative probability function as described in figure 6. Based on the obtained cumulative probability curve (figure 6), the lower bound paddy drought area value found was approximately 4000 ha.
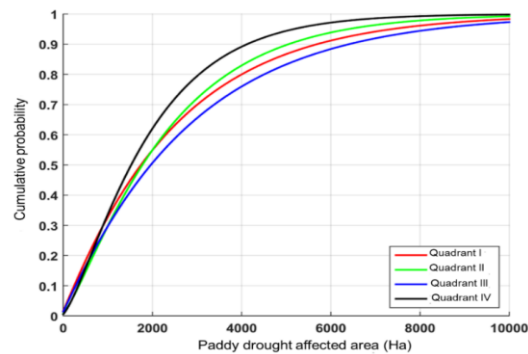
Figure 6. Cumulative probability of paddy drought affected area for quadrant I-IV.

Consequently, there are four level of paddy drought risk, namely low, medium, high, and very high. The higher the score is defined as the higher the risk level as described in table 2. However, for very high level risk we used expert judgement.

Table 2. Criteria used to define drought risk on rice paddies based on the onset and trend of SPI-3.

Level	Criteria	% drought	Probability of paddy affected area > 4000	Score (x10^2)	Level
1	Onset SPI-3 > -1, trend > 0	17.16	17.80	3.05	Low
2	Onset Between 0 to 1, trend < 0	24.94	27.96	6.97	Moderate
3	Onset SPI-3 > 0, trend $\leq$ -0.2	34.65	26.49	9.18	High
4	Onset SPI-3 $\leq$ -1	14.11	16.95	2.39	Very high

*3.3. Accuracy of paddy drought risk prediction*

From the total of 5744 hindcast predictions for period 2011-2015, 123 drought events were correctly predicted (hit rate = 28,4%). In addition, the number of drought events that were correctly predicted (hit) and that of non-drought events (correct negative) in total of 4,214 (PC of 75.5%), as shown in table 3.

Table 3. Contingency tables for the paddy drought prediction for period April–September over Indonesia region for the period 2012-2015.

Forecast	Observation		
	Yes	No	Total
Yes	123	954	1077
No	453	4214	4667
Total	576	5168	5744

Examples of paddy drought prediction maps of August 2014 are presented in figure 7. We can see that: i) drought occurrences were correctly predicted in Sumatra, Java and parts of Sulawesi; and ii) drought non-occurrences were correctly predicted in Papua and parts of Sulawesi; but iii) there were a number of inaccurate predictions in Kalimantan and Nusa Tenggara.
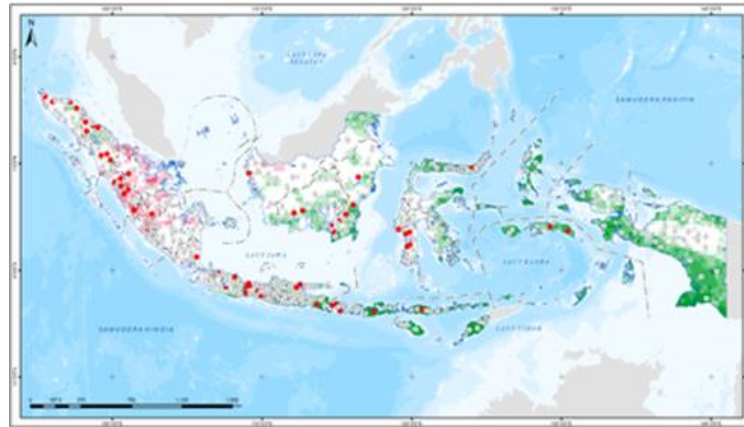
Figure 7. Map of verification of paddy drought events prediction for August 2014. The area with green indicates the area predicted not to experience rice drought. The white circle is an observation data that shows no occurrence of rice drought. The area with pink is an area that is predicted to experience drought, while the red circle is an observation that shows the occurrence of drought.

Verification was conducted for the months April-September, as drought normally occurs during this period. The accuracy of the paddy drought predictions varies significantly from April to September (Table 4). The highest accuracy of drought occurrence prediction (hit rate) is found in the peak dry season (July). However, accuracies during April and September are very low because drought events are rare during this period. Likewise, the accuracy of drought and non-drought occurrences (PC) is higher in other non-peak months (April through September, excluding July), as the number of events that can be predicted correctly is much higher. In fact, the number of drought non-occurrences are higher than that of drought occurrences (correct negative), contributing to higher accuracy. In July, however, the number of correct negatives is low, so that PC is at its lowest due to the smaller number of correct predictions for both drought occurrences and non-occurrences. Overall, the accuracy of the prediction during the peak dry season still needs to be improved.

Table 4. Accuracy of paddy drought prediction using Hit Rate and Percent of Correct method

Target of prediction (Month)	A (Hit)	C (Correct negative)	Hit Rate (%)	Percent of Correct (%)
April	1	1288	3.0	94.2
May	9	990	18.8	85.3
June	31	621	28.2	71.6
July	35	182	56.5	37.1
August	40	386	38.8	61.7
September	7	749	3.2	74.8

Due to climate change severe droughts are expected to become more frequent, increasing the risk of water shortages for agriculture. Future drought outlook may also be possible based on drought indicators

with climate change projections. SPI analysis of the rainfall projection data is needed to identify the indication of future drought. According to Pratiwi et al. [27], the SPI analysis results show that the drought period are predicted to occur more often than in the period 2020-2045 in dry season in Cirebon District, West Java. Such climate information may provide evidence of potential risks to climate shocks in the future which may then essential to determine the appropriate adaptation measures in order to cope with paddy yield loss due to drought.

4. Conclusion

We develop a predictive model of paddy drought risk by investigating the correlation between SPI-3 onset and trend in paddy drought-affected. Cartesian plot diagram was used to four different levels of paddy drought risk: low (the onset SPI-3 > -1 and positive trend), moderate (0 < SPI-3 < 1, negative trend)), high (onset SPI-3 > 0, negative trend), and very high (onset SPI-3 $\leq$ -1). Precise judgment was particularly used to determine the very high level of paddy drought risk due to the low number of events found, given that most farmers would not plant paddy as they anticipated severe droughts.

Based on the verification that was conducted for the months of April-September, when drought normally occurs, the drought events that were correctly predicted (hit rate) is 28.4%. In addition, the number of drought events that were correctly predicted (hit) and that of non-drought events (correct negative) is 75.5%. The highest hit rate was found to occur in July, during peak dry season. The accuracy of drought and non-drought occurrences (PC) is higher in non-peak months, April through September, excluding July.

As the very high level of drought risk could not be properly predicted using SPI-3, we think it is necessary to conduct further studies in order to improve the impact model. One of the ways which the model could be improved is by incorporating paddy crop productivity in the crop simulation mode as this would roughly capture the impact of climate factors on crop growth. Moreover, the projection of SPI and the potential impact on paddy yield due to drought in the future need to be assess.

Acknowledgments

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