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The evaluation of drought indices: Standard Precipitation Index, Standard Precipitation Evapotranspiration Index, and Palmer Drought Severity Index in Cilacap-Central Java

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Abstract. The Cilacap Regency-Central Java, is the largest agricultural area with a high level of drought vulnerability. This study aims to evaluate three indices in quantifying a drought condition in Cilacap Regency and its application in forecasting. The indices that were used in this study are Standard Precipitation Index (SPI), Standard Precipitation Evapotranspiration Index (SPEI), and Palmer Drought Severity Index (PDSI). The comparison between SPI and SPEI shows that there is no significant difference in terms of determining the drought severity. SPEI should be used when there is a temperature difference more than 2°C in 30 years. PDSI may provide more frequency of drought event and a good result in indicating the effects of drought on agricultural productivity. We used Climate Forecast System Version 2 (CFSv2) to predict drought severity by SPI. The result of model prediction shows that there is no significant improvement in accuracy before and after statistical bias correction. The prediction can be done on three months (lead3) before initial planting.

Keywords : SPEI, PDSI, CFSv2, drought.

1. Introduction

Cilacap Regency, located in Central Java, has the highest level of drought hazard [1], due to its high population. The region is also being one of the main rice resources for Indonesian food resilience [2], where its agriculture area covers 30% of the total area. Consequently, the drought hazard may affect the availability of rice production in complying the food needs in Cilacap.

There are various methods that are often used for the drought hazard monitoring, such as Standard Precipitation Index (SPI) [3,4], Standard Precipitation Evapotranspiration Index (SPEI) [5], and the Palmer Drought Severity Index (PDSI) [6,7,8], which can be estimated by long monthly precipitation data. SPI has several advantages. Firstly, SPI is a simple method since it only calculates based on precipitation data. Secondly, the calculation of SPI can be done on the different timescales, as for example one month (SPI-1), 3 months (SPI-3), 6 months (SPI-6), and 12 months (SPI-12) [3]. In 2010, however, there was a study that introduced a new drought index, namely the Standard Precipitation Evapotranspiration Index (SPEI) [5], computing both precipitation and evapotranspiration data. Moreover, there is Palmer Drought Severity Index (PDSI) method [6,7,8] that uses precipitation,



temperature, and available water capacity (AWC) as input data, thus the parameters of water balance can be calculated, such as runoff, recharge, evapotranspiration, and coefficient of soil moisture loss. Therefore, the aim of this study is to evaluate SPI, SPEI, and PDSI as drought indices in Cilacap, henceforth to be used in the drought prediction that uses rainfall prediction data from Climate Forecasting System Version 2 (CFS v2).

2. Methods

Data used in this study are precipitation, temperature, land cover, soil, and rice productivity. Monthly precipitation and temperature data were provided by Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG) from 1982-2012 (31 years). Land cover and soil data were provided by Plantation and Forestry Service of Cilacap Regency, while rice productivity data was provided by Center of Statistic Agency (BPS Cilacap) from 1997-2012 as annual data.

SPI only needs precipitation data and its calculation refers to [3,4]. The calculation uses gamma distribution to attain the cumulative probability of precipitation as in equation (1) and equation (2).

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}\hat{\alpha}\Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}-1} e^{-x/\hat{\beta}} dx \quad (1)$$

$$\text{with } \hat{\alpha} = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right), \hat{\beta} = \frac{\bar{x}}{\hat{\alpha}}, \text{ and } A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \quad (2)$$

The function above is only able to be used for $x > 0$. Thus when $x = 0$ (or no rainfall event), then the cumulative probability will be approached by the comparison between the number of no rainfall events with the number of total data (q).

$$H(x) = q + (1 - q)(G(x)) \quad (3)$$

$H(x)$ is the cumulative probability with the calculation of zero rainfall event. The value of $H(x)$ is then being transformed to the standard normal random variable value with zero average values and variance equals to one. Z is the value of SPI that is determined by the value of cumulative probability with the approximation of [9] as in equation (4) and equation (5) [4].

Z for $0 < H(x) \leq 0.5$ is

$$Z = SPI = - \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right) \quad \text{where } t = \sqrt{\ln \left(\frac{1}{(H(x))^2} \right)} \quad (4)$$

For $0.5 < H(x) \leq 1.0$ is

$$Z = SPI = \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right) \quad \text{where } t = \sqrt{\ln \left(\frac{1}{(1 - H(x))^2} \right)} \quad (5)$$

With the constant values of $c_0 = 2.515517$, $c_1 = 0.0802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$ [4].

The SPEI and SPI calculations are not far different, where the SPEI calculation refers to [5] and both indices characteristics are the same. The basic difference lies in the data and distribution used. The distribution of the three-parameter log logistic is used to standardize the D value to calculate the SPEI as in equation (6). D is the value of precipitation minus by evapotranspiration (P-E). Evapotranspiration is estimated by Thornwaite [5], that has proven the log logistic distribution is good to use and more coherent, especially at very low D values. In addition, no value is found below the origin parameter of this distribution.

$$F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma} \right)^\beta \right]^{-1} \quad (6)$$

Where α , β , and γ are scale, shape, and origin parameters. Then the $F(x)$ value will be transformed to the standard normal random variable value with zero average values and variance equals to one. Z is the value of SPI that is determined by the value of cumulative probability with the approximation of [9] as in equation (7) and (8) [5].

Z for $0 < P \leq 0.5$ is

$$Z = SPEI = \left(W - \frac{c_0 + c_1W + c_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \right) \quad \text{where } W = \sqrt{-2\ln(P)} \quad (7)$$

For $0.5 < P \leq 1.0$ is

$$Z = SPEI = - \left(W - \frac{c_0 + c_1W + c_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \right) \quad \text{where } W = \sqrt{-2\ln(1 - P)} \quad (8)$$

with the constant values of $c_0 = 2.515517$, $c_1 = 0.0802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$, and $P = 1 - F(x)$ [5].

The PDSI calculation refers to [7,8,10]. The Palmer method is started by the calculation of water balance, using precipitation and temperature data. Calculation of soil moisture capacity is attained by dividing the land into two layers and assuming 25 mm of water can be stored in the soil surface layer (Ls). The bottom layer (Lu) has water capacity that depends on the soil characteristics. Potential evapotranspiration (PE) is generally calculated using the Thornthwaite method [5]. Evapotranspiration occurs when PE (Potential Evapotranspiration) > P (Precipitation), where P is monthly precipitation.

As part of the water balance calculation, the Palmer method calculates evapotranspiration (ET), recharge (R), runoff (RO), loss (L), potential recharge (PR), potential loss (PL), and potential runoff (PRO). Here Palmer assumes that runoff will occur if and only if the moisture content in the two soil layers has reached field capacity. From the results of the PE, PR, PL and PRO calculations, the value will be determined using equation (9) from the four climate constants, namely the evapotranspiration coefficient (α), the charging coefficient (β), runoff coefficient (γ), and water loss coefficient (δ) as in equation (9).

$$\alpha_j = \frac{\overline{ET}_j}{\overline{PE}_j}, \quad \beta_j = \frac{\overline{R}_j}{\overline{PR}_j}, \quad \gamma_j = \frac{\overline{RO}_j}{\overline{PRO}_j}, \quad \text{and } \delta_j = \frac{\overline{L}_j}{\overline{PL}_j}, \quad \text{where } j = 1, \dots, 12 \quad (9)$$

Overbar shows the fact that the coefficients are calculated using the monthly average value (j). These coefficients are used to calculate the differences in d for other months between actual precipitation and "CAFEC" (Climatically Appropriate For Existing Conditions) as in equation (10).

$$d = P - \hat{p} = P - \alpha_j PE + \beta_j PR + \gamma_j PRO - \delta_j PL \quad (10)$$

Definition of \hat{p} is analogous to a simple water balance. Moisture anomaly index (Z) is defined as in equation (11)

$$Z = K_j d \quad (11)$$

with K_j is a weighted factor that defined as in equation (12)

$$K_j = \frac{17.67 \overline{K}_j}{\sum_{i=1}^{12} \overline{D}_i \times \overline{K}_i}, \quad \text{where } j = 1, \dots, 12 \quad (12)$$

with $\overline{D_j}$ is the average of the absolute value d for the month j . The purpose of the weighted factor is to manage the decrease of normal precipitation, therefore it can be compared to different areas for different months. Moisture anomaly index (Z) shows the relative decrease of weather, in month and at a specific location, from the average humidity conditions in the related month. Palmer has evaluated Z at two study areas in Iowa and Western Kansas. Then the final equation to calculate the level of drought as in equation (13).

$$X(i) = 0.897X(i - 1) + \frac{Z(i)}{3} \quad (13)$$

with $X(i)$ is the value of PDSI for month i .

However, the values of those indices are quantified in different categories as shown in table 1, thus the categories equalization is needed. The equalized values will be explained in the next section. Rice productivity data was detrended in order to eliminate the data trend and then to find out its relationship with SPI and PDSI.

We also evaluated CFSv2 data performance in predicting the drought with several lead times, by correcting it using statistical downscaling and bias statistical correction toward BMKG station data [11].

Table 1. SPI and PDSI Categories (unequalized) [3] [4].

SPI	Category	PDSI	Category
$\geq 2,00$	<i>Extremely wet</i>	≥ 4.00	<i>Extremely wet</i>
1,50 to 1,99	<i>Very wet</i>	3.00 to 3.99	<i>Very wet</i>
1,00 to 1,49	<i>Moderately wet</i>	2.00 to 2.99	<i>Moderately wet</i>
-0,99 to 0,99	<i>Near normal</i>	1.00 to 1.99	<i>Slightly wet</i>
-1,00 to -1,49	<i>Moderately dry</i>	0.50 to 0.99	<i>Incipient wet spell</i>
-1,50 to -1,99	<i>Severely dry</i>	0.49 to (-0.49)	<i>Near normal</i>
$\leq -2,00$	<i>Extremely dry</i>	-0.50 to (-0.99)	<i>Incipient drought</i>
		-1.00 to (-1.99)	<i>Mild drought</i>
		-2.00 to (-2.99)	<i>Moderate drought</i>
		-3.00 to (-3.99)	<i>Severe drought</i>
		≤ -4.00	<i>Extreme drought</i>

3. Results and Discussion

3.1 SPI and SPEI

Figure 2 denotes three months of the SPI, SPEI, and PDSI from 1982 to 2012. There are no significant differences between SPI and SPEI in quantifying a drought. Both of them show the drought in the same episodes, namely 1982, 1983, 1995, 1997, 2002, 2007, 2008, and 2012. The relationship between SPI and SPEI is expressed in linear equations (14), which shows that both indices have the same classes in quantifying a drought, thus the index categories equalization is not required.

$$SPEI = 0.9426 SPI - 0.0001 \quad (14)$$

However, the two indices differences may be seen in the level of severity. The severity of SPI is worse than SPEI. When SPI reaches the extreme level (index ≤ -2), SPEI only reaches the moderate level. The variance of the P-E value is lower than the rainfall values, thus the results of the SPI and SPEI methods have different variances. In this case, it turns out that SPI has a larger data range than SPEI (see in methods), therefore SPI is able to define drought up to extreme levels. Another case that we can see is in 2008, where SPI and SPEI described the duration of drought for 6 months length. The index

given by SPI has more extreme values for 4 months, while SPEI only able to provide a drought index in the moderate and severe categories.

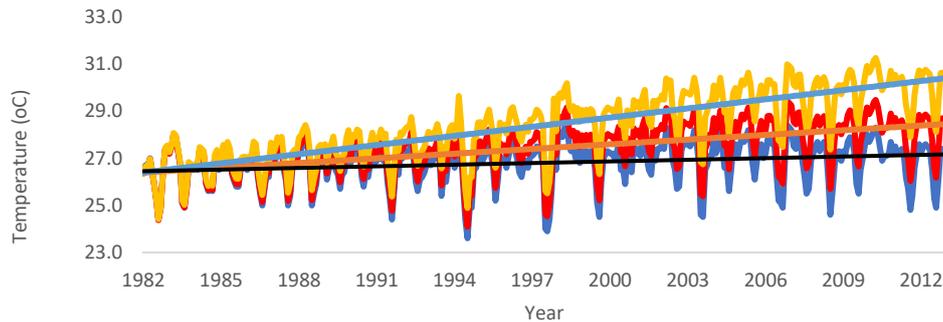


Figure 1. Synthetic data with the temperature increase of 2°C and 4°C, and its real data in 30 years.

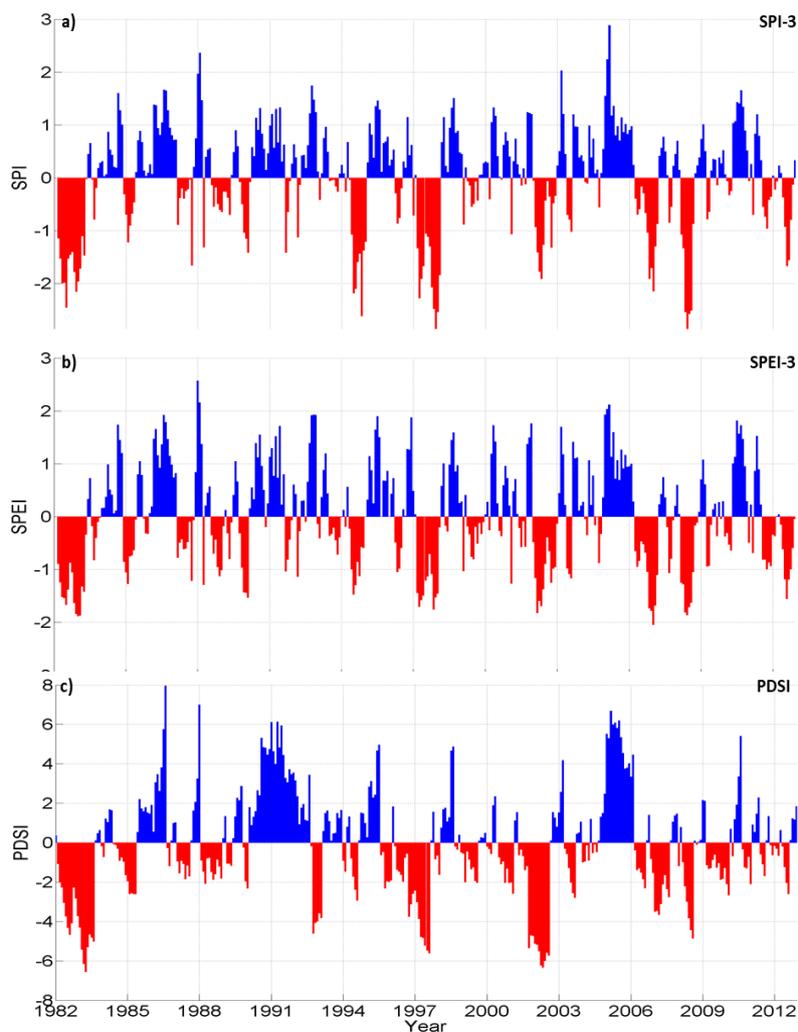


Figure 2. Time series of drought indices, a) Standard Precipitation Index (SPI), b) Standard Precipitation Evapotranspiration Index (SPEI), and c) Palmer Drought Severity Index (PDSI). SPI-3 and SPEI-3 imply the SPI and SPEI that calculate in three months time scale.

It can be concluded that SPEI is able to describe the drought severity in terms of intensity and duration when there is an increase in temperature. Meanwhile, SPI is not able to compute the effects of temperature increase to the drought severity. This certainly makes the use of the SPI method less optimal in drought analysis in the area affected by increasing temperature. However, the temperature in Cilacap Regency has increased about 0.7°C in 30 years, thus there is no significant difference between SPI and SPEI in quantifying a drought. In addition, equation 1 shows that the relationship between SPI and SPEI is $\text{SPEI} \approx \text{SPI}$.

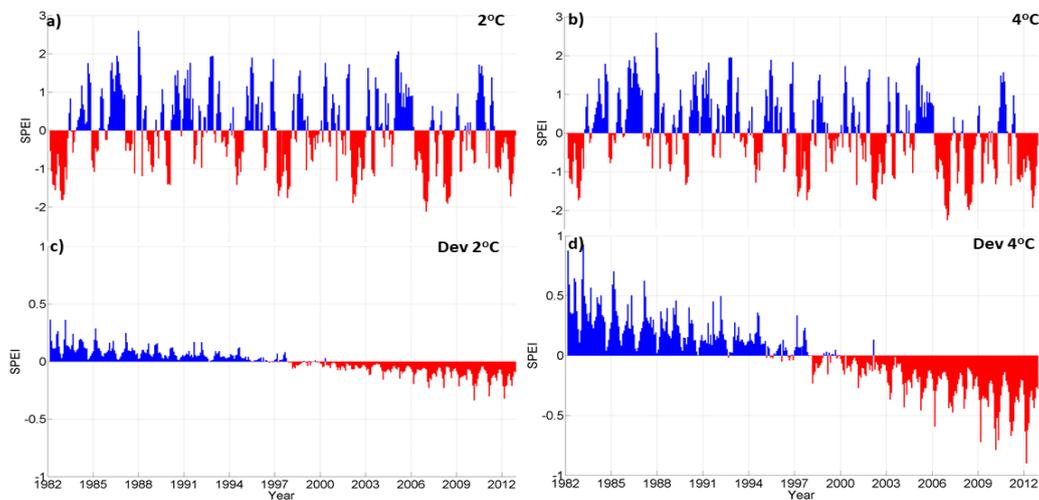


Figure 3. SPEI and the deviation of SPEI, **a)** SPEI with the temperature increase scenario of 2°C , **b)** SPEI with the temperature increase scenario of 4°C , **c)** The deviation of the SPEI 2°C scenario, and **d)** The deviation of the SPEI 4°C scenario towards the original SPEI.

3.2 SPI and PDSI

It can be shown that the drought categories of PDSI are different with SPI and SPEI (figure 2). Consequently, the drought categories equalization between SPI and PDSI is required. Figure 4 shows a relationship between PDSI and SPI that can be expressed in equation (15). The equation can be simplified by $\text{PDSI} \approx 1.4 \text{ SPI}$, thus the SPI and PDSI categories can be equal as shown in table 2.

$$\text{PDSI} = 1.395\text{SPI} - 0.1309 \quad (15)$$

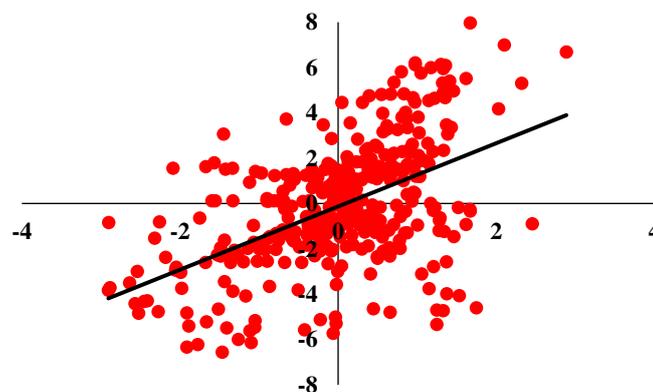


Figure 4. The relationship between Palmer Drought Severity Index (PDSI) and SPI. y -axis is PDSI and x -axis is SPI.

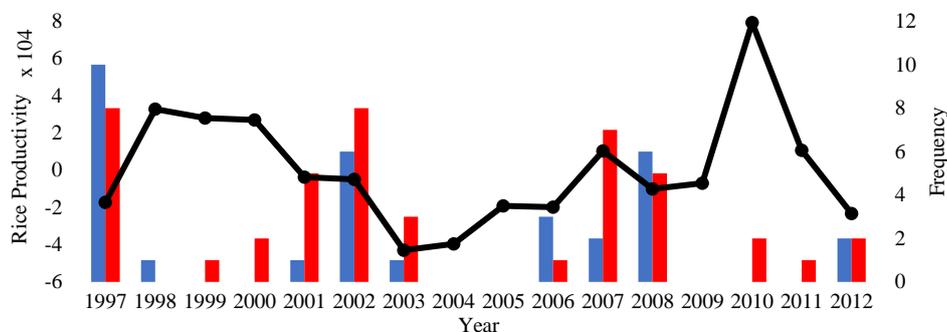
Table 2. SPI and PDSI categories (equalized)

Category	SPI	PDSI
<i>Extremely wet</i>	$\geq 2,00$	$\geq 2,80$
<i>Very wet</i>	1,50 to 1,99	2,10 to 2,79
<i>Moderately wet</i>	1,00 to 1,49	1,40 to 2,09
<i>Near normal</i>	-0,99 to 0,99	-1,39 to 1,39
<i>Moderately dry</i>	-1,00 to -1,49	-1,40 to -2,09
<i>Severely dry</i>	-1,50 to -1,99	-2,10 to -2,79
<i>Extremely dry</i>	$\leq -2,00$	$\leq -2,80$

One of the differences between SPI and PDSI is the frequency of drought event (table 3). In consequence, it can indicate that PDSI is able to quantify more in the drought events frequency rather than SPI. In figure 5, there is low rice productivity when the number of drought events is high. SPI shows the decline in rice productivity rate when there are values of SPI in 1997, 2001, 2002, 2003, 2006, 2008, and 2012. Where the declines that are shown by PDSI are in 1997, 1999, 2000, 2002, 2003, 2006, 2008, 2011, and 2012. In conclusion, both SPI and PDSI are good to illustrate the relationship between rice productivity and drought event. However, in particular case, namely 2007 and 2010, PDSI shows drought events when the rice productivities are high. These are due to the temporal resolution of rice productivity data which is not good enough (it is yearly data) thus there is a need for better data resolution to understand the drought in further studies. However, it still can be concluded that both SPI and PDSI can be useful as drought indices in the agricultural sector.

Table 3. The frequencies of drought events in *extreme*, *severe*, and *moderate* categories for SPI and PDSI.

Category	SPI	PDSI
<i>Extreme Dry</i>	16	49
<i>Severe Dry</i>	15	22
<i>Moderate Dry</i>	28	38
Sum	59	109

**Figure 5.** The frequencies of extreme, severe, and moderate drought occurrences for rice productivity. Blue bars and red bars show SPI and PDSI, respectively. Black line shows detrended rice productivity data.

3.3. Experiment using CFSv2 data to predict the drought with SPI

We chose SPI to predict the drought rather than two other indices, to be used in the experiment with CFSv2 data in this section, due to the simple calculation process (it requires only precipitation data).

Precipitation in SPI uses CFSv2 output as prediction data. Figure 6 shows CFSv2 data before and after being corrected in our experiment. CFSv2 data underestimates (red lines) when it is compared to the observation data (blue lines), thus statistical downscaling and bias correction are applied to CFSv2 output for correction (green lines). Predictions for the next 1 month, 2 months, and 3 months are expressed by lead 1, lead 2, and lead 3, respectively.

SPI-3 was calculated using corrected CFSv2 data (CFSv2-C) and raw CFSv2 (CFSv2-Raw) for each lead, and SPI-3 which was calculated with CFSv2-C and CFSv2-Raw, later called as SPI3-C and SPI3-Raw, respectively. Figure 7 shows SPI3-C and SPI3-Raw boxplot diagrams in 2001-2010. A value below zero is a negative SPI value. There are missing values in SPI3-C and SPI3-Raw, namely in 2004 (for lead 4 and lead 2) and 2008 (for leads 2 and 1). SPI3-C and SPI3-Raw do not have any significant differences. Those are because the SPI calculation process uses normal distribution and depends on historical rainfall data. Thus, CFSv2 data can be used to calculate SPI without data correction process, where in this case is with the statistical bias correction.

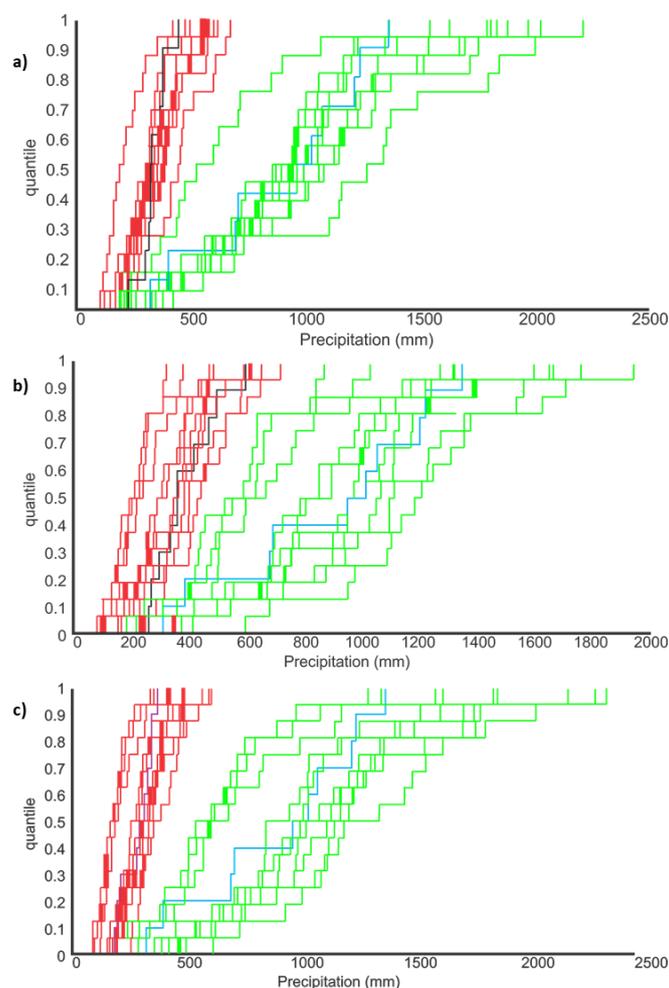


Figure 6. CDF (Cumulative Distribution Function) with bias correction testing period plots, (a) lead3; (b) lead2 and (c) lead1. Red lines and green lines show CFSv2 data before and after correction, respectively. Blue lines show observation data.

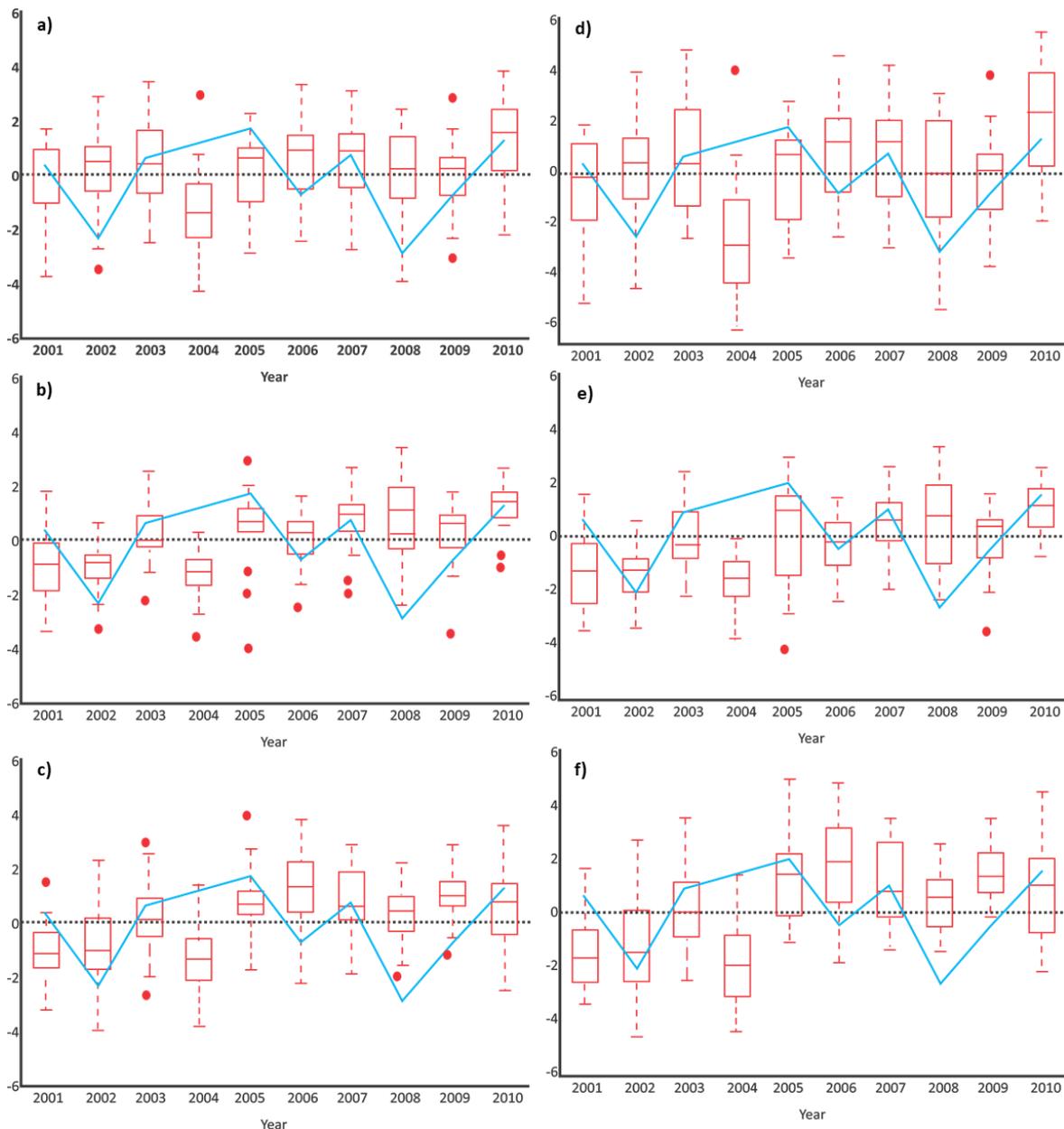


Figure 7. SPI boxplots from CFSv2 data in May, a) SPI-3 Correction lead3, b) SPI-3 Correction lead2, c) SPI-3 Correction lead1, d) SPI-3 Raw lead3, e) SPI-3 Raw lead2, f) SPI-3 Raw lead1.

4. Conclusion

We have evaluated three indices, namely SPI, SPEI, and PDSI in quantifying a drought. Those three indices are able to identify the drought in Cilacap-Central Java. There are no significant different characteristics of SPI and SPEI in quantifying a drought in the present time. The SPEI will significantly different with SPI if there is an extreme change in climatological temperature (e.g. an increase more than 2°C/30 years). SPI and PDSI are both able to identify the drought in the agricultural sector. However, PDSI overestimates when quantifying rice productivity.

We chose SPI to be used for drought prediction because of the ease in data processing. The CFSv2 rainfall model is capable enough to forecast the drought by SPI, in lead3, lead2, and lead1. There are no

significant differences between corrected CFSv2 data and raw CFSv2 data. Thus, the precipitation of CFSv2 does not need to be corrected to calculate SPI.

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