Application of Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) satellite data for drought mitigation in Bintan island, Indonesia

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Abstract. The water resources of Bintan Island is limited and dependent on rainfall variability. The exposed location of Bintan small island make this island particularly vulnerable to natural disaster especially drought. The meteorological drought related information is required for the water resources management of Bintan island. This article provides calibration of CHIRPS data. The ground-based rainfall observation data is used for CHIRPS data calibration. The Drought analysis used CHIRPS rainfall data, and ground-based observation data was carried out using the Standardized Precipitation Index (SPI). The results showed that the data set performed well in assessing drought years (1982, 1997, and 2015). The statistical Z test results showed that the CHIRPS data and ground-based observation data were not showing significantly different values. This study concludes that CHIRPS data is valuable for drought monitoring tools in Bintan island, where the ground-based observation rainfall data is very limited.

Keywords: CHIRPS, drought, mitigation, small island, Bintan

1. Introduction

Bintan Island is about 1,173 km² and is classified as a small island with limited water resources [1]. Due to the water resources in this island dependent on rainfall variability, Bintan island is vulnerable to natural disasters, i.e., drought [2]. Generally, small islands tend to experience scarcity of water resources due to the islands’ small size, so water catchment areas are small [3]. Currently, there is an increase in population and economic activities that increase water demand [4,5], so the vulnerability of water resources will increase due to climatic phenomena in the future [3]. The high activity on Bintan Island causes an imbalance between water availability and demands [4,5]. Bintan Island’s water availability continues to decline, while water demand continues to increase [5].

Previous studies suggested that the rainfall anomalies over Indonesia are generally affected by global-scale climate variability, namely ENSO (El-Nino Southern Oscillation) in the Pacific Ocean and IOD (Indian Ocean Dipole) in the Indian Ocean [6–9]. Generally, both phenomena in the Pacific and the Indian Ocean will bring more or less rainfall than normal; when positive (negative) IOD and ENSO have occurred, Indonesia’s rainfall decreases (increases) significantly [9–12]. Reduction in rainfall caused by climate phenomena (ENSO and IOD) will trigger drought. Several previous
research shows that during El-Nino, it will decrease annual and seasonal rainfall throughout Indonesia, including around the equator in the western part of Indonesia, which is the research area [11]. When IOD (+) and El Niño occur simultaneously, the decrease in rainfall is higher than when a single IOD (+) or El Niño event occurs [13–15]. The decrease in rainfall due to climatic phenomena (ElNino/IOD+) will cause drought [9,16]. The drought will be a significant problem for small islands, where the catchment area is small, and the water storage capacity is low. The drought factor will reduce the water resources carrying capacity of the island [3,17,18].

Meteorological drought is the initial trigger of agricultural drought and leads to hydrological drought [19]. Meteorological drought analyses are highly dependent on the monitoring system [20,21]determined by the rainfall data availability, inadequate spatial and temporal scale. Getting along climate records and an adequate number of rainfall observation stations throughout the observation area is one of the main dares in developing countries such as Indonesia, especially in small islands that are very vulnerable to weather and climate change [2,25]. For this reason, rainfall products are derived from satellites on a local and global scale to fill data gaps are needed, especially in developing countries that have data scarcity [23].

The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) is a semi-global rainfall product for monitoring drought and global environmental changes [20,22,23]. The CHIRPS dataset was constructed using long-period precipitation data estimated based on infrared Cold Cloud Duration (CCD) observations [24]. CHIRPS data can quantify the hydrological impact of decreased precipitation and increased air temperature in Africa and southwestern Ethiopia [24]. Compared to other monthly satellite precipitation products, CHIRPS 2.0 showed the highest agreement with gauge observations [23,26,24]. CHIRPS data have a relatively higher spatial resolution (~5 km) and longer periods of records (1982- present) than other rainfall satellite products. Previous studies showed that the CHIRPS satellite dataset has good monitoring of drought in the upper Nile river [25,19]. In this paper, the CHIRPS satellite dataset and rainfall observation data will monitor drought on Bintan Island. Both types of data will be analyzed and evaluated whether the CHIRPS satellite data can be used to monitor drought in small islands. The expected results of the research are to provide drought monitoring information for Bintan island.

2 Methodology

2.1 Study Area

The Bintan Island (Fig. 1) is located between 0° 49’–1° 15.1’ N and between 104° 13.3’– 104° 41.3’E. The island has a strategic geographical location at the junction of the South China Sea, the Malacca Strait, and the Karimata Strait. Bintan is part of one of the economic growth centers for the Republic of Indonesia for the development of Special Economic Zones based on RI Law number 44 of 2007. The area covers about 1,173 km².
Figure 1. The study area, Bintan Island. Color gradation shows elevation and a yellow point shows location of Kijang station

Figure 2. The Observation Station of BMKG and CHIRPS data Position at Bintan Island
2.2 Data and Methods

Kijang station is the only rainfall observation station on Bintan Island provided by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) (Fig. 2). Bintan Island has only one rainfall observation station that is available for analysis and monitoring of drought. This condition is very difficult to carry out drought analysis and monitoring. The drought monitoring system is highly dependent on rainfall data availability at adequate spatial and temporal scales [19,25]. To overcome this challenge, the high-resolution CHIRPS satellite data with a long observation period is a solution [25,26]. We used the CHIRPS rainfall satellite dataset developed by Famine Early Warning System Network (FEWS NET) to enhance this limitation. CHIRPS data is in daily temporal and 0.05° spatial resolutions. CHIRPS data were accessed from https://data.chc.ucsb.edu/products/CHIRPS-2.0/. However, CHIRPS contains errors compared to ground-based rainfall observation due to the indirect rainfall measurement [23]. We corrected the daily CHIRPS dataset to Kijang station observation using the bias correction method [2] which is adopted from Inomata et al. (2012). However, the CHIRPS dataset is better in spatial and temporal resolution than other satellite data sets, i.e., PERSIANN, TARCAT, TRMM, etc. [22,25,27,28].

2.2.1 Standardized Precipitation Index Analysis. Drought potential were analyzed using the Standardized Precipitation Index (SPI). CHIRPS satellite rainfall data were corrected using the statistical bias correction method using i.e quantile-based bias correction [29]. SPI is a normalization index representing the chance of the amount of rainfall observed compared to rainfall at a particular station's geographical location over a long period [20,21,30]. SPI is based on the cumulative probability of rainfall events occurring at the station for at least 30 years. SPI is calculated based on the probability density function (PDF) of the gamma distribution to match the frequency distribution of each station's amount of rainfall. Station rainfall data for 30 years was entered into the Gamma distribution [17]. A negative SPI value indicates a deficit of rainfall, while a positive SPI value indicates a rainfall surplus. Calculation of SPI value Journal of Hydrology: based on total gamma distribution or gamma distribution [17,30,31] is as follows:

\[ G(x) = \int_{0}^{\alpha} (-\beta x + \alpha x) \]  \hspace{1cm} (1)

With: \( \alpha > 0 \) is the form parameter, \( \beta > 0 \) is the scale parameter and \( X > 0 \) is the amount of rainfall (mm). SPI calculations include matching the gamma probability density function to the frequency distribution of the amount of rainfall.

Because the gamma function is undefined for \( x = 0 \), \( x \) becomes:

\[ H(x) = q + (1 - q). G(x) \]  \hspace{1cm} (2)

With: \( q = \) number of rain events = 0 (m) / amount of data (n).

Calculation of \( Z \) or SPI for \( 0 < H(x) \leq 0.5 \) is

\[ Z = SPI = - (t - c_0 + c_1 t + c_2 t^2 / 1 + d_1 + d_2 t^2 + d_3 t^3) \]  \hspace{1cm} (3)

With \( t = \sqrt{\ln (1 / H(x))} \)

Calculation of the SPI value for \( 0.5 < H(x) \leq 1.0 \) is

\[ Z = SPI = (t c_0 + c_1 t + c_2 t^2 / 1 + d_1 + d_2 t^2 + d_3 t^3) \]  \hspace{1cm} (4)

With \( t = \sqrt{\ln (1 / 1 - H(x))} \)

With:
c0 = 2.515517, c1 = 0.802853, c2 = 0.010328, d1 = 1.432788, d2 = 0.189269, d3 = 0.001308

The cumulative probability of \( H(x) \) is then transformed into a standard random variable \( Z \) with an average value of 0 and variation 1. The value obtained by \( z \) is the SPI value. Values in the SPI indicate conditions compared to average rainfall. If the SPI value is positive, it means it shows greater than average rainfall. If the SPI value is negative, it indicates less than average rain. The level of drought or wetness of an area in a certain year can be classified into several categories of SPI drought index values [18].

2.2.2 The Z – test Statistical Analysis. The statistical significance of differences in the accuracy of the classifications was assessed using a McNemar’s test for the independent samples [32,33]. The Z-test was utilized to test whether the two data groups were significantly different or not [34]. The Z-test is generally performed to test the hypothesis whether two SPI indexes generated from CHIRPS data and ground-based observation data provided similar accuracy results. The Z-test is based on the normal standardized test [32] given as:

\[
Z = \frac{(\bar{X}_1 - \bar{X}_2)}{\sqrt{\sigma_x^1 + \sigma_x^2}}
\]  

(5)

Where

- \( X_1 \) is the mean value of sample SPI CHIRPS
- \( X_2 \) is the mean value of sample SPI STASIN
- \( \sigma_x^1 \) is the standard deviation of sample one (SPI CHIRPS) divided by the square root of the number of data points
- \( \sigma_x^2 \) is the standard deviation of sample (SPI STASIN) divided by the square root of the number of data points

Z critical = \[ \sqrt{\sigma_x^1 + \sigma_x^2} \]

In general, in more qualitative terms:

- If the Z-statistic is less than Z critical, the two samples are the same.
- If the Z-statistic is more than Z critical, the two samples are different.

3. Result and Discussion

We used CHIRPS in this study because it has a higher spatial resolution and relatively satisfactory performance in the precipitation estimates than in situ observations over Bintan island. For this reason, we attempt to assess the applicability of CHIRPS for drought monitoring in this section. The number of comparison pairs was 111 for point-based evaluation during the 38 years. The SPI was computed by gauge precipitation and CHIRPS separately at 3, 6- and 12-month scales (Figure 3). The CHIRPS data show drought phenomena due to the El-Nino climate phenomenon year 1982, 1997, 2015/2016 (Fig.3b). Similarly is shown by SPI Kijang observation data (Fig.3a.).
Figure 3a. SPI-3, SPI-6 and SPI-12-time scales for observation data of Kijang Station.

Figure 3b. SPI-3, SPI-6 and SPI-12-time scales for CHIRPS grid data
Figure 3c. Long time-series comparisons of SPI-1, SPI-3 and SPI-6-time scales for observation data of Kijang Station and CHIRPS data.
The result of the calculation of SPI from CHIRPS data and Kijang observation data shows similar pattern between the SPI CHIRPS and SPI Kijang. Based on the Z-test similarity analysis for SPI 3, 6, and 12 (Figure 3c.). The Z-test results in Table 1.

Table 1. Z test SPI 3, 6, and 12 months of two data series (CHIRPS and observation)

|               | SPI CHIRPS | SPI Kijang |
|---------------|------------|------------|
| Mean          | 0.009826896| 0.004929356|
| Known Variance| 1.00370574 | 1.00281436 |
| Observations  | 441        | 441        |
| Hypothesized Mean Difference | 0         |            |
| z             | 0.072606502|
| P(Z≤z) one-tail| 0.471059626|
| z Critical one-tail | 1.644853627|
| P(Z≤z) two-tail| 0.942119253|
| z Critical two-tail | 1.959963985|

|               | SPI CHIRPS | SPI Kijang |
|---------------|------------|------------|
| Mean          | 0.003848785| 0.002488352|
| Known Variance| 1.002734378| 1.002474947|
| Observations  | 438        | 438        |
| Hypothesized Mean Difference | 0         |            |
| z             | 0.020106398|
| P(Z≤z) one-tail| 0.491979248|
| z Critical one-tail | 1.644853627|
| P(Z≤z) two-tail| 0.983958496|
| z Critical two-tail | 1.959963985|

|               | SPI CHIRPS | SPI Kijang |
|---------------|------------|------------|
| Mean          | 0.003672044| 0.003124461|
| Known Variance| 1.002477624| 1.002432205|
| Observations  | 432        | 432        |
| Hypothesized Mean Difference | 0         |            |
| z             | 0.00803794 |
| P(Z≤z) one-tail| 0.49679336 |
| z Critical one-tail | 1.644853627|
| P(Z≤z) two-tail| 0.993586721|
| z Critical two-tail | 1.959963985|
The results of the similarity test of the two group data results can be seen in Table 1. Figure 3a-3c shows that the SPI CHIRPS curve shows a similar pattern to the SPI observation data curve. The Z- test results in Table 1 shows that the two SPI results are similar; there do not differ significantly.

This study has evaluated the performance of CHIRPS data for drought monitoring analysis in small islands. Several previous studies have shown that the CHIRPS data shows a good correlation with the observed rainfall data [19,24] and good performance for capturing extreme rainfall [34]. Also, CHIRPS data has shown satisfactory output as input data in Italy’s streamflow simulations [35]. However, the CHIRPS data has been little done to evaluate the performance and the possibility for application in drought monitoring [21], especially for small islands. Generally, CHIRPS data evaluations are carried out with an area of more than 9000 km² [21,24,26,34]. Our study results show that the CHIRPS data have good performance for drought monitoring (Figure3.a – 3c.) with an area of 1173 km². The results show SPI CHIRPS data and SPI observation data are similar. The SPI analysis results in Figure 3 show that meteorological drought due to climatic phenomena in 1982, 1997, and 2015 caused a long drought in Bintan Island that was identified very well in both SPI CHIRPS and SPI Kijang station at SPI 6, 12 months. The results in Figure 3a – 3c indicate that the CHIRPS data show a good performance to assess meteorological drought to hydrological drought monitoring caused by climate phenomena (El-Nino 1982, 1997, and 2015/2016). The drought intensity values of SPI from CHIRPS data are slightly underestimated. Generally, SPI from Chirps and ground-based observations is in-phase. There are some opposite patterns (e.g., 1992 – 1994). However, the opposite patterns are limited. Z score analysis shows that the CHIRPS dataset could be used as an alternative dataset to monitor drought events.

4. Conclusion

In this study, CHIRPS data was comprehensively evaluated by the gauge (ground-based) observations of Kijang station during 1981–2018. The drought years (1982, 1997, and 2015) could be identified in the CHIRPS data set after the SPI calculation and the SPI calculation of Kijang observation data. The Z-test for the multi-time scale of SPI (3, 6, and 12 months) shows that the SPI form CHIRPS data and SPI form observation data values were not significantly different. However, it generally shows an underestimation of the values of SPI CHIRPS data. Similarly, CHIRPS data underestimated the intensity of drought conditions. The results indicated that the CHIRPS data could be used as an alternative source of information to develop the drought monitoring tools for an early warning in the small island. Overall, this study concludes that CHIRPS is valuable for drought monitoring in Bintan island, where the observation data is very limited.

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