Rainfall anomalies assessment during drought episodes of 2015 in Indonesia using CHIRPS Data

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Abstract. Drought is one of the hydrometeorological disasters that have an impact on many sectors in Indonesia. Therefore, it is necessary to study the triggering factors in order to minimize the impact. This research investigates the meteorological drought during El Niño episodes in 2015 compared to normal episodes in 20017 to comprehend the impact on rainfall anomaly in Indonesia. Statistical methods applied to multi temporal CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) data has been applied for this purpose. Results show that the CHIRPS data correlate well with all stations’ observations with the correlation coefficient in the range of 0.7 to 0.86. During drought episodes of 2015, there was an increase in areas affected by drought for extremely dry conditions (100%), severe dry conditions (> 90%), and dry conditions (> 50%). This study is important for understanding the influence of El Niño on drought phenomena in Indonesia.

1. Introduction
Indonesia is one of the countries in the maritime continent that lies between the continents of Asia and Australia and between the Pacific and Indian oceans. The climate variations in the region are linked with the monsoons and the global ocean-atmosphere circulation, modulated by sea surface temperature [1-3]. In general, as a part of the East Asian monsoon and Southeast monsoon, the Indonesian monsoon plays a role in Indonesia's seasonal climate [4,5]. Meanwhile, ENSO contributed more to the occurrence of anomalies conditions, such as extreme rainfall (La Niña), extreme drought (El Niño), seasonal shift, and affect the duration of extreme conditions [6-9]. Anomalies in climate variability can cause hydrometeorological disasters such as drought, which has an impact on environmental, agricultural, social, and economic sectors. The El Nino event in 2015 has resulted in a long duration of agricultural drought, which affected the growth phase of paddy and low rice production in Indonesia with suffered an estimated economic loss of more than 15 billion USD [3,10]. The number of forest fires and burned area reportedly also increased during the El Niño events in 2015 and 1997/1998 [11].

On the other hand, human activities (anthropogenic factors) also contribute to climate change and variability that trigger hydrometeorological disasters, such as floods, drought, and landslides [12,13]. The increase in the average temperature on the earth’s surface as a result of the increase in greenhouse gas emissions (global warming) resulting from the burning of fossil fuels (oil, gas, and coal) apart from burning and deforestation, agricultural and plantation activities have triggered the occurrence of rainfall variability and sea-level rise. This impacts the environmental, health, agriculture, social, economic, coastal, marine, forestry, infrastructure, transportation, tourism, and even human security.
and national resilience sectors [14]. Hence the adaptation and mitigation actions are needed to manage climate change.

CHIRPS (Climate Hazards Group InfraRed Precipitation with Stations) rainfall dataset was developed by the U.S. Geological Survey Earth Resources Observation and Science Center and the University of California, Santa Barbara Climate Hazards Group in order to deliver datasets for early warning objectives. CHIRPS data with a spatial resolution of 0.05° was processed from observational data from various observation stations combined with data on estimated bias-free rainfall that has been produced from 1981 to the present for trend analysis and seasonal drought monitoring [15,16]. This data is a blending of thermal and infrared products and passive microwaves, which are claimed to perform better than infrared products alone, especially in extreme weather conditions [17]. A previous study showed a good correlation between CHIRPS and insitu measurement recorded data by reaching more than 0.9 correlation [18], although an overestimation or underestimation has been noted in some regions that investigated [19,20]. Limited rainfall measurements from insitu measurements can be solved using spatio-temporal and high resolution information obtained from satellite-based rainfall. Related to climate change research and its variability, the limitations of rain gauge stations can be solved using remote sensing technology that allows for extensive and multi-temporal monitoring of the area. The objectives of the study were to assess rainfall anomaly during drought episodes of 2015 in Indonesia using CHIRPS datasets by comparing with normal episodes of 2017.

2. Methods
2.1. Data
CHIRPS rainfall anomaly data was used in this study for the period from December 2014 to February 2016 and from December 2016 to February 2018. The data was a quasi-global using 3 months running mean of rainfall anomaly with gridded 0.05° resolution where obtained from ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_3-monthly_EWX/anomaly/. To validate the data on rainfall variability in Indonesia region, the monthly CHIRPS data (ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_monthly/) also applied. Rainfall daily data from six rain gauges meteorological stations installed by Indonesian Meteorological, Climatological & Geophysical Agency (BMKG) were used for this purpose. Table 1 summarizes the names and the locations of BMKG meteorological stations. The study area covered Indonesian region between 9°N to 11°S and 90°E to 140°E. The comparison CHIRPS and station data is made for a 30 year period (1988–2017), except for code E station, the comparison is for 14 year period (2004-2017). As supporting, the province boundaries data from Geospatial Information Agency is used.

| Code | Station                                 | Latitude | Longitude |
|------|-----------------------------------------|----------|-----------|
| A    | Tangerang Geophysics Station            | -6.1     | 106.38    |
| B    | Kemayoran Meteorological Station        | -6.15    | 106.84    |
| C    | Bandung Geophysical Station             | -6.88    | 107.59    |
| D    | Perak I Meteorological Station          | -7.22    | 112.72    |
| E    | Tanjung Mas Maritime Meteorological Station | -6.94  | 110.41    |
| F    | Stasiun Geofisika Yogyakarta            | -7.82    | 110.3     |

2.2. Methods
This research used descriptive statistical method. The comparisons between CHIRPS and station data was performed by correlation coefficient. Anomalous rainfall was defined as a difference from the base-period average averaged across the country [21]. In short it was called with deviation in climatology. The averaged standard normals for climatology was computed for the following consecutive periods of 30 years, for example, 1 January 1981 to 31 December 2010, 1 January 1991 to 31 December 2020, and so on [22]. Formula for compute rainfall anomalies is stated in equation (1).
where $AP_i$ is the averaged anomaly in the month $i$, $P_i$ is the averaged value of rainfall of the month $i$, and $P(\text{avr})$ is the averaged of the entire dataset. The 3 months running mean of rainfall averaged anomaly then defined as shown in equation (2).

$$AP_{i-1-3} = P_{i-1-3} - P(\text{avr})$$  \quad (2)$$

where $AP_{i-1-3}$ is the averaged anomaly in the month $i_1$ to $i_3$, $P_{i-1-3}$ is the averaged value of rainfall of the month $i_1$ to $i_3$, and $P(\text{avr})$ is the averaged of the entire dataset.

The first stage was validating between CHIRPS data and rainfall data from the rain gauge station using statistical linear correlation method ($r^2$). The second stage was calculating and analysing the rainfall anomaly from January 2015 to December 2015 which represents the rainfall conditions in El Niño event. The same process is repeated for data from January 2017 to December 2017 that represents the rainfall conditions in normal event.

3. Result and Discussion

3.1. Validation

The rainfall daily data six rain gauge station for location with A code to location with F code (as shown in Table 1) is calculated to obtain the monthly rainfall average. The results of linear correlation calculation between CHIRPS data and rainfall data obtained from six different rain gauge station showed the value of the correlation coefficient ($r^2$) is in the range of 0.70 to 0.86. The $r^2$ for location with A to F code are 0.78, 0.85, 0.70, 0.86, 0.78, and 0.84 respectively. Figure 1 to Figure 6 shown the time series comparisons data for location with A to F code.

**Figure 1.** Correlation curve and scatterplot comparisons between CHIRPS data and rainfall data from rain gauge measurement for A code location ($r^2=0.78$).

**Figure 2.** Correlation curve and scatterplot comparisons between CHIRPS data and rainfall data from rain gauge measurement for B code location ($r^2=0.85$).
Figure 3. Correlation curve and scatterplot comparisons between CHIRPS data and rainfall data from rain gauge measurement for C code location ($r^2=0.70$).

Figure 4. Correlation curve and scatterplot comparisons between CHIRPS data and rainfall data from rain gauge measurement for D code location ($r^2=0.86$).

Figure 5. Correlation curve and scatterplot comparisons between CHIRPS data and rainfall data from rain gauge measurement for E code location ($r^2=0.78$).

Figure 6. Correlation curve between CHIRPS data and rainfall data from rain gauge measurement for F code location ($r^2=0.84$).

The comparison with CHIRPS resulted in relatively high correlation, with the highest values over the Perak I Meteorological Station (D code, 0.86) as shown in figure 4 and the lowest values over the Bandung Geophysical Station (C code, 0.70) as shown in figure 3. These results are consistent and also support the previous study [18,19]. The limited availability of field data and the timing of data collection and processing are still major problems that affect the result.
3.2. Rainfall Anomalies
In second stage, the rainfall anomaly from January 2015 to December 2015 which representing the rainfall conditions in El Niño event was calculated and analyzed. By comparing image by image the variability of rainfall during the El Niño event in 2015 to normal episode in 2017, it can be visually analyzed. Furthermore, month by month change detection of rainfall anomalies also detected for further analysis. Figure 7 to figure 19 shown the variation of rainfall anomalies during January 2015 to December 2015 for Indonesia region.

Figure 7. Rainfall anomalies during Dec 2014 – Feb 2015 (left side) compared by rainfall anomalies during Dec 2016 – Feb 2017

Figure 8. Rainfall anomalies during Jan 2015 – Mar 2015 (left side) compared by rainfall anomalies during Jan 2017 – Mar 2017

Figure 9. Rainfall anomalies during Feb 2015 – Apr 2015 (left side) compared by rainfall anomalies during Feb 2017 – Apr 2017

Figure 10. Rainfall anomalies during Mar 2015 – May 2015 (left side) compared by rainfall anomalies during Mar 2017 – May 2017
Figure 11. Rainfall anomalies during Apr 2015 – Jun 2015 (left side) compared by rainfall anomalies during Apr 2017 – Jun 2017

Figure 12. Rainfall anomalies during May 2015 – Jul 2015 (left side) compared by rainfall anomalies during May 2017 – Jul 2017

Figure 13. Rainfall anomalies during Jun 2015 – Aug 2015 (left side) compared by rainfall anomalies during Jun 2017 – Aug 2017

Figure 14. Rainfall anomalies during Jul 2015 – Sep 2015 (left side) compared by rainfall anomalies during Jul 2017 – Sep 2017
Figure 15. Rainfall anomalies during Aug 2015 – Oct 2015 (left side) compared by rainfall anomalies during Aug 2017 – Oct 2017

Figure 16. Rainfall anomalies during Sep 2015 – Nov 2015 (left side) compared by rainfall anomalies during Sep 2017 – Nov 2017

Figure 17. Rainfall anomalies during Oct 2015 – Dec 2015 (left side) compared by rainfall anomalies during Oct 2017 – Dec 2017

Figure 18. Rainfall anomalies during Nov 2015 – Jan 2016 (left side) compared by rainfall anomalies during Nov 2017 – Jan 2018

Figure 19. Rainfall anomalies during Dec 2015 – Feb 2016 (left side) compared by rainfall anomalies during Dec 2017 – Feb 2018
### Table 2. Condition of rainfall anomalies

| Code  | Value     | Condition       |
|-------|-----------|-----------------|
| > 0   | wet       |                 |
| -99 to 0 | dry      |                 |
| -299 to -100 | severe dry |             |
| < -300 | extremely dry |            |

In this stage the image by image comparison was calculate from three months sequentially rainfall anomaly in 2015 to 2017 using equation (2) and then classified into four classess as shown I table 2. The classification of rainfall anomaly was known as Rainfall Anomaly Index (RAI), index that can be used to evaluate extreme rainfall condition as an alternative to the Standardized Precipitation Index [23]. Visually it was clear the differences of drought level between 2015 and 2017.

Further analysis about El Niño effect on area affected by drought in Indonesia region was investigated. Table 3 summarize the differences of dry value for each class during El Niño event in 2015 compared to 2017. It was clear that El Niño had a tremendous impact on the drought disaster in Indonesia in 2015. The number of affected areas for extremely dry class was increased up to 100%. Similarly for the severe dry class increased up more than 90% and for dry class increased more than 50%. In contrast, for area with wet class was decreased for almost 100%.

**Table 3. Rainfall anomaly change during drought and normal year (2015 and 2017)**

| Periods | Δ Rainfall Anomalies (%) | Extremely Dry | Severe Dry | Dry | Wet |
|---------|--------------------------|---------------|------------|-----|-----|
| Jan-Mar | 100.0                    | 85.7          | 6.4        | -30.8 |    |
| Feb-Apr | 99.9                     | 56.7          | 14.1       | -31.2 |    |
| Mar-May | 100.0                    | 90.9          | 37.8       | -69.1 |    |
| Apr-Jun | 99.9                     | 90.9          | 54.5       | -66.1 |    |
| May-Jul | 99.7                     | 86.5          | 48.7       | -95.0 |    |
| Jun-Aug | 99.9                     | 91.5          | -7.3       | -97.1 |    |
| Jul-Sep | 100.0                    | 95.5          | -29.6      | -97.2 |    |
| Aug-Oct | 100.0                    | 77.8          | -38.8      | -98.4 |    |
| Sep-Nov | 100.0                    | -37.7         | -99.0      |    |    |
| Oct-Dec | 100.0                    | -43.1         | -94.6      |    |    |
| Nov-Jan | 99.1                     | -15.8         | -35.8      |    |    |
| Dec-Feb | 95.9                     | 27.5          | -38.0      |    |    |

### 4. Conclusions

Global factors, El Niño, significantly influenced the drought disaster that hit Indonesia in 2015. There was an increase in the area affected by drought for extremely dry conditions up to 100%. Similarly, for severely dry and dry conditions, the percentage of areas affected has also increased more than 90% and 50%, respectively. Further research using longer temporal data is needed to know when El Niño's effect gradually decreases and returns to normal conditions.

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