

Observed and blended gauge-satellite precipitation estimates perspective on meteorological drought intensity over South Sulawesi, Indonesia

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Abstract. South Sulawesi province as one of the rice production center for national food security are highly influenced by climate phenomenon that lead to drought condition. This paper quantifies meteorological drought based on Standardized Precipitation Index (SPI) recommended by the World Meteorological Organization (WMO) and Consecutive Dry Days (CDD) as one of the extreme indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI). The indices were calculated by using (i) quality controlled daily and monthly observational precipitation data from 23 weather stations of various record lengths within 1967-2015 periods, and (ii) 0.05° x 0.05° blended gauge-satellite of daily and monthly precipitation estimates of the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) dataset. Meteorological drought intensity represented by Average Duration of Drought Intensity (ADI) from three-monthly SPI (SPI3) show spatial differences characteristic between eastern and western region. Observed and CHIRPS have relatively similar perspective on meteorological drought intensity over South Sulawesi. Relatively high values of ADI and longest CDD observed mainly over south western part of study area.

1. Introduction

Government and policies makers are pay attention about drought, especially when it's occurs during long time period and impact on sensitive sector, such as agriculture that act as thread for food security issue. National food security takes higher priority especially when drought occurred in food production center areas. Drought over Indonesia is commonly associated with warm phase of El Niño Southern Oscillation (ENSO), known as El Niño[1–4].

South Sulawesi as one of the primary national rice production centers also can be affected by El Niño indicated by wider drought coverage area [4,5]. The potential impact of drought due to the weak and moderate El Niño occurrences in Indonesia is such that yields are reduced by about 40 % in average. The most drought- prone areas are located in South Sulawesi for August–October [5].

Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) is a new land-only gridded database of precipitation. It blend three different types of information: global climatologies, satellite estimates and in situ observations. This dataset incorporates monthly precipitation climatology CHP Clim (Climate Hazards Group Precipitation Climatology), quasi-global geostationary thermal infrared satellite observations, Tropical Rainfall Measuring Mission's (TRMM) 3B42 product,

atmospheric model rainfall fields from NOAA CFS (Climate Forecast System), and precipitation observations from various sources, including national or regional Meteorological Services [6]. CHIRPS can be promising to be used as alternative meteorological drought monitoring tools because its showing good performance during evaluation with rainfall observation data [7]

CHIRPS dataset already used to monitor meteorological drought all over the world [8–10] and also applied for seasonal drought forecast in Africa [11]. Nevertheless, evaluation when CHIRPS used as drought monitoring tools in South Sulawesi region are still required. The objectives of this study was to carry out the perspective agreement on meteorological drought intensity monitoring between CHIRPS and observation.

2. Data and Methodology

2.1. Data

This paper quantifies meteorological drought based on Standardized Precipitation Index (SPI) recommended by the World Meteorological Organization (WMO) [12] and Consecutive Dry Days (CDD) as one of the extreme indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) [13]. The SPI and CDD were calculated by using (i) quality controlled daily and monthly observational precipitation data from 23 weather stations of various record lengths within 1971-2015 periods, and (ii) $0.05^\circ \times 0.05^\circ$ blended gauge-satellite of daily and monthly precipitation estimates of the Climate Hazards Group Infra Red Precipitation with Stations (CHIRPS) dataset. This gridded dataset were obtained from Climate Hazards Group/ The Department of Geography, University of California Santa Barbara (<ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/>) for the 35-year period from 1981 – 2015.

Table 1. List of observational station used in this paper from various altitude and type such as rain gauge (Obs Gauge), Agricultural Meteorological station (AgriMet), and BMKG weather station (BMKG). Various precipitation record lengths within 1967-2015 periods and well spatially distributed over South Sulawesi.

Station Name	District	Altitude (m.a.s.l)	Station Type	Data Range	Period (years)	Quality (%)
ANABANUA	Wajo	15	Obs Gauge	1977 - 2015	39	94.87
BATUBASSI	Maros	13	Obs Gauge	1976 - 2015	40	97.92
BATUKAROPA	Bulukumba	81	AgriMet	1967 - 2015	49	99.83
BIRINGROMANG	Makassar	8	BMKG	1972 - 2015	44	96.21
BPPBENGO	Bone	77	Obs Gauge	1971 - 2015	45	99.63
BPPDOPING	Wajo	4	Obs Gauge	1976 - 2015	40	89.38
BPPKGALESONG	Takalar	15	Obs Gauge	1980 - 2015	36	97.69
BPPMALAKAJI	Gowa	750	Obs Gauge	1976 - 2015	40	96.25
BUKITHARAPAN	Pare-pare	80	Obs Gauge	1976 - 2015	40	97.92
ENREKANG	Enrekang	65	Obs Gauge	1976 - 2015	40	90.00
MACOPE	Bone	9	Obs Gauge	1970 - 2015	46	99.82
MENGE	Wajo	38	Obs Gauge	1977 - 2015	39	94.02
PGCAMMING	Bone	132	AgriMet	1983 - 2015	33	95.71
PGTAKALAR	Takalar	15	AgriMet	1983 - 2015	33	90.91
SIWA	Wajo	25	Obs Gauge	1977 - 2015	39	90.38
STAKLIMMAROS	Maros	13	BMKG	1985 - 2015	31	90.86
STAMARPAOTERE	Makassar	2	BMKG	1986 - 2015	30	99.44
STAMETHASANUDDIN	Maros	14	BMKG	1972 - 2015	44	96.78
STAMETMASAMBA	Luwu utara	50	BMKG	1983 - 2015	33	95.71
STAMETPONGTIKU	Tana toraja	829	BMKG	1998 - 2015	18	98.15
STASIUNGEFISKA	Gowa	28	Obs Gauge	1978 - 2015	38	92.11
SUMPANGBINANGAE	Barro	7	Obs Gauge	1977 - 2015	39	98.93
TODOKKONG	Pinrang	18	Obs Gauge	1985 - 2015	31	98.66

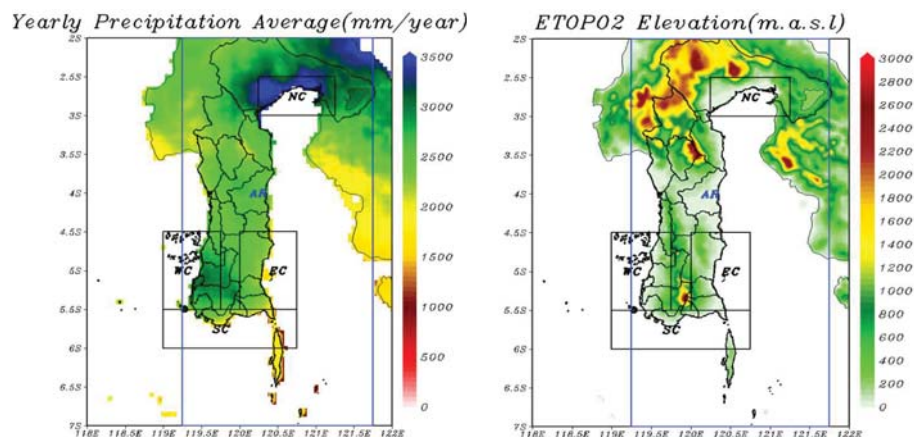


Figure 1. Yearly total precipitation average from monthly CHIRPS dataset (left) and elevation characteristic (right) over study area (meter above sea level/ m. a. s. l) with regional boxes chosen for Western Coast (WC), Southern Coast (SC), Eastern Coast (EC), Northern Coast (NC) and All Region (AR).

2.2. Methodology

Daily precipitation from observation used to calculate maximum number of consecutive days with daily precipitation amount < 1 mm (CDD) [13]. CDD values were also calculated from CHIRPS daily precipitation, for each grid in the study area with a $0.05^\circ \times 0.05^\circ$ horizontal resolution.

SPI was developed in Colorado by McKee et al [14], is based on the probability distribution of precipitation. SPI can be used as valuable estimator of drought severity which requires less input data and efforts than other meteorological drought indices [15]. Furthermore, SPI was reported to be able to identify emerging droughts sooner than Palmer Index [16]. The basis of SPI approach is the calculating probabilities of precipitation for each time scale [14]. SPI values at 3-month time scales (SPI3) were calculated from observation and the CHIRPS monthly precipitation, for each grid in the study area. SPI3 were selected because it represents the typical time scale for precipitation deficits to affect usable water sources and soil moisture important for agriculture [14]. Based on paddy growth period, SPI3 would be able to capture the presence and severity of drought during its growth period [5]. Furthermore, agricultural drought (with soil moisture content as proxy) could be best replicated by SPI on a scale of 2–3 months [17], SPI3 also suggested for seasonal drought studies because the 3 months droughts are having a drastic impact on the agriculture [18].

A drought event onset defined when SPI value are less than -1.0 and terminates when SPI value becomes positive again [14,19]. The positive sum of the SPI for all the months within a drought event is referred as drought magnitude (DM) [14,20]. The average drought intensity (ADI) was calculated based on drought magnitude (DM) divided by number or duration of consecutive months during drought event [14,21,22], using observation and CHIRPS.

Level of agreement between the observed and CHIRPS based meteorological drought assessment for each referred station grid value was conducted using temporal Pearson correlation coefficient (R) [23]. Spatial agreement in CDD and SPI pattern between observations and the CHIRPS is analyzed using pattern correlations. This analysis was widely used previously on several references [23–26].

3. Result and Discussion

3.1. Consecutive Dry Days

Maximum consecutive dry days and correlation coefficient for 35 years period (1981 – 2015) can be seen in Figure 2. South western region experience relatively longer dry spell period compared to eastern and northern region. Observational based CDD value also agreed with gridded data when explain spatial distribution of maximum CDD. Temporal agreement between CDD CHIRPS and

observation were showed by temporal correlation coefficient values $0.3 < R \leq 0.8$ in Figure 2 (right). Furthermore, there are spatial agreement between CHIRPS and observational based maximum consecutive dry days during analysis period could be explained by pattern correlation value ($R = 0.631$).

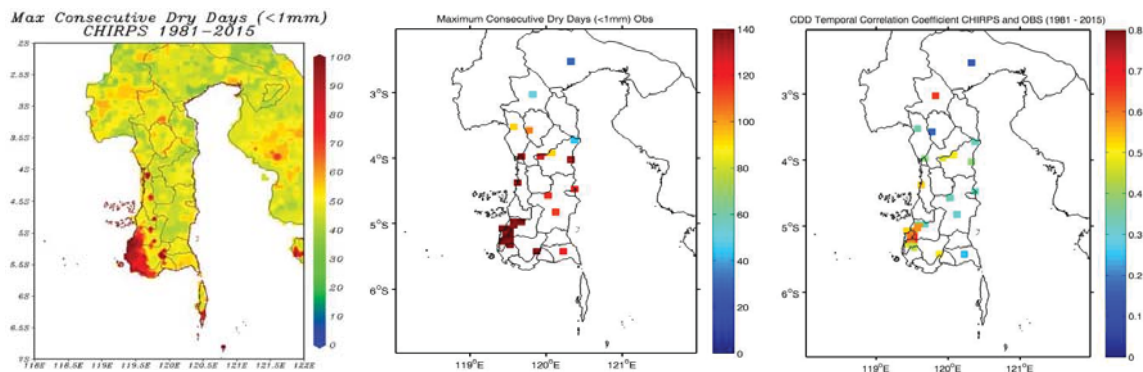


Figure 2. Maximum Consecutive Dry Days (CDD) comparison for each year based on CHIRPS data (left), rain gauge observation (middle) and correlation coefficient between CDD CHIRPS versus observation (right) during 35 years period (1981 – 2015). Longest consecutive number of days with total precipitation amount less than 1 mm/day period and correlation coefficient explained by color bar.

Average consecutive dry days for all time period can be seen in Figure 3. These results are relatively similar with maximum CDD. High pattern correlation value ($R = 0.813$) between CHIRPS and observation average CDD also show spatial agreement of these two dataset. South western region experience relatively longer dry spell period compared to eastern and northern region. Observational based CDD value also agreed with gridded data when explain spatial distribution of average CDD.

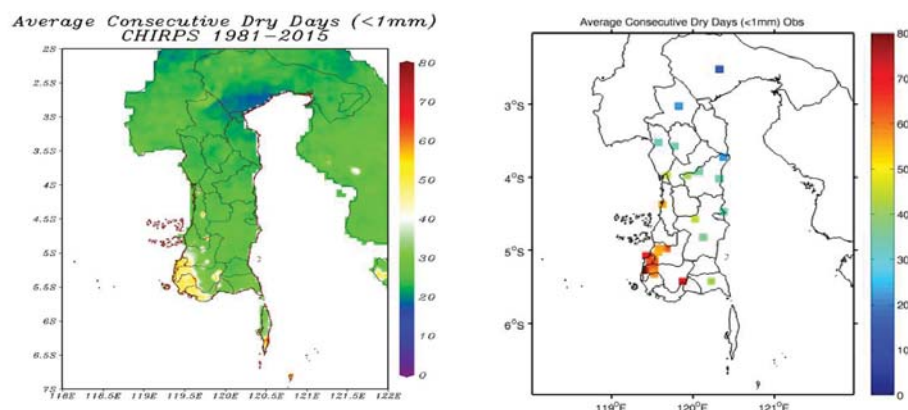


Figure 3. Same as Figure 1 except for Average Consecutive Dry Days (CDD) comparison for each year based on CHIRPS data (left) and rain gauge observation (right).

3.2. Standardized Precipitation Index (SPI)

Average duration of drought intensity (ADI) based on SPI3 for 35 years period (1981 – 2015) can be seen in Figure 4 (left and middle). Temporal agreement between CDD CHIRPS and observation were showed by temporal correlation coefficient values $0.4 < R \leq 0.8$ in Figure 4 (right). Different ADI value between gridded data and observation mainly occurs in south western region. Nevertheless, spatial distribution of ADI based on CHIRPS generally similar with observational based.

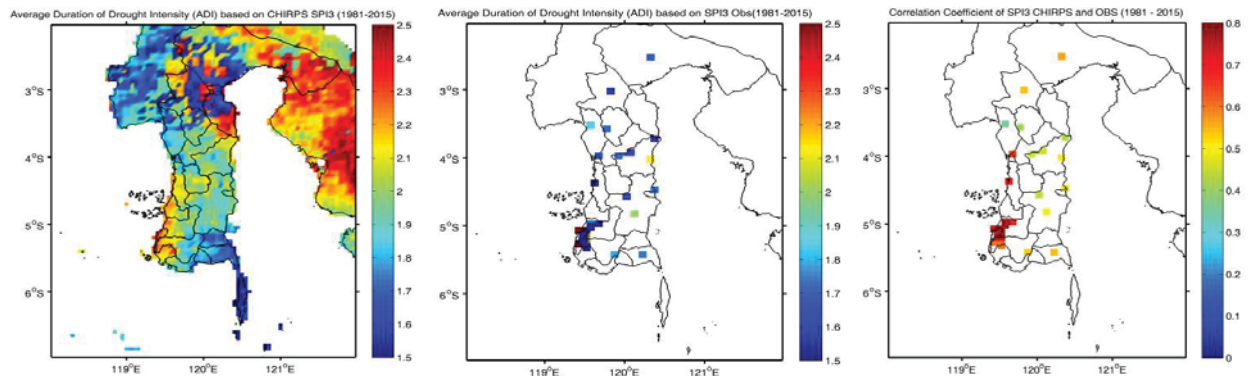


Figure 4. Average drought intensity (ADI) of 3-monthly Standardized Precipitation Index (SPI3) based on CHIRPS data (left), rain gauge observation (middle) and correlation coefficient between SPI3 CHIRPS versus SPI3 observation (right) during 35 years period (1981 – 2015).

Maximum Drought Duration (DD) for all time period can be seen in Figure 5. Different DD value between gridded data and observation generally occurs in all of region. Gridded data slightly over estimate the DD value compare to observation. Nevertheless, spatial distribution of ADI based on CHIRPS generally similar with observational based.

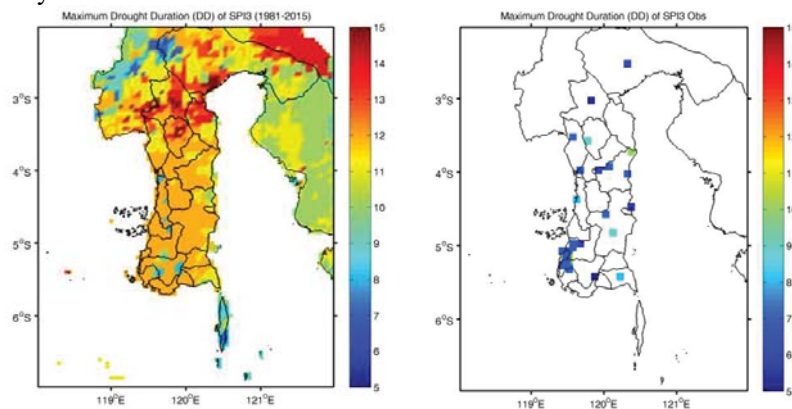


Figure 5. Maximum Drought Duration (DD) of 3-monthly Standardized Precipitation Index (SPI3) based on CHIRPS data (left) and rain gauge observation (right) during 35 years period (1981 – 2015). Longest consecutive number of month with SPI3 values less than -1.0 period explained by color bar.

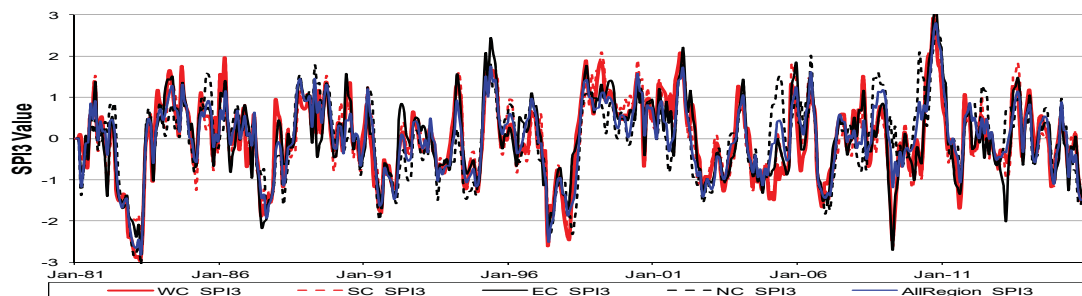


Figure 6. Time series of 3-monthly Standardized Precipitation Index (SPI3) area averaged over five different region i. e. West Coast (WC_SPI3) South Coast (SC_SPI3), East Coast (EC_SPI3), North Coast (NC_SPI3), and All South Sulawesi region (AllRegion_SPI3). More detailed descriptions about region boundary explained in text.

Time series of 3-monthly Standardized Precipitation Index (SPI3) area averaged over five different region i. e. West Coast (WC_SPI3), South Coast (SC_SPI3), East Coast (EC_SPI3), North Coast (NC_SPI3), and All South Sulawesi region (AllRegion_SPI3) can be seen in Figure 6. Strong El Niño impact on SPI3 are clearly shown, especially during 1982/1983 and 1997/1998 (Figure 7). West coast region are highly effected by El Niño compared to another region.

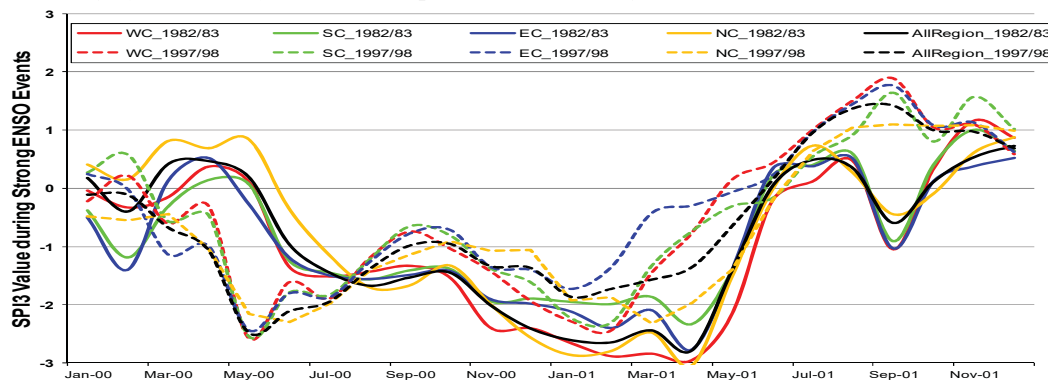


Figure 7. Same as Figure 6, except for two selected strong ENSO event : 1982/1983 (solid lines) and 1997/1998 (dashed lines). Horizontal axis describe ENSO years month (Jan-00 to Dec-00) and following ENSO years (Jan-01 to Dec-01)

4. Conclusion

Observed and blended gauge-satellite precipitation estimates (CHIRPS) have relatively similar perspective on meteorological drought intensity over South Sulawesi. Temporal agreement between CHIRPS and observation meteorological drought were showed by CDD (SPI3) temporal correlation coefficient values $0.3 < R \leq 0.8$ ($0.4 < R \leq 0.8$). Spatial agreement between CHIRPS and observational based maximum consecutive dry days during analysis period also found and could be explained by CDD spatial pattern correlation value ($R = 0.631$). Meteorological drought intensity represented by Average Drought Intensity (ADI) from 3-monthly SPI (SPI3) show spatial differences characteristic between west and east coast South Sulawesi region. Lowest SPI3 value occurred especially during strong El Niño years.

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