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### RESEARCH ARTICLE

#### BIAS CORRECTION FOR DROUGHT PREDICTION OVER SUMATERA USING ECMWF MODEL

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#### Abstract

Frequently forest fire occurred over Sumatra Island require us to provide seasonal forest fire prediction. With this prediction, hopefully, we can manage and anticipate forest fire which will held. This study utilizes the prediction of seasonal rainfall from the ECMWF model for drought prediction using the SPI drought index. However, before the ECMWF output is used for prediction, the bias is corrected first. The results of this study indicate that with the bias correction the output can produce better predictions. The strong drought event is generally related to the *el-Niño* event. The eastern and southern parts of Sumatra are drier and the chance of getting forest fires is greater in August, September, and October which are drier than other months. This condition occurred due to the monsoonal wind.

#### Introduction:-

Drought is a significant disaster, but the characteristics of drought are different from other natural disasters because they occur slowly, accumulate slowly, so it is very difficult to identify the beginning and end of this natural disasters (Wilhite, 2010). Drought is starting to form from prolonged water shortages because of an area receives rainfall under normal conditions (Ghulam et al., 2007).

Utilization of climate models for drought prediction has begun to be developed by several researchers. Carrão et al. (2018) used a seasonal rainfall prediction from ECMWF combined with observational data to produce a forecast of the SPI drought index for Latin America and see the capabilities of the model with hind cast during the 1981 - 2010 period.

Prediction of drought with wavelet transformation methods and artificial neural networks was developed by Kim and Valdés (2003). Whereas the prediction of drought with artificial neural network models and hybrid stochastic was developed by Mishra et al. (2007). Yuan and Wood (2013) combine drought predictions with ensemble methods from several seasonal prediction models.

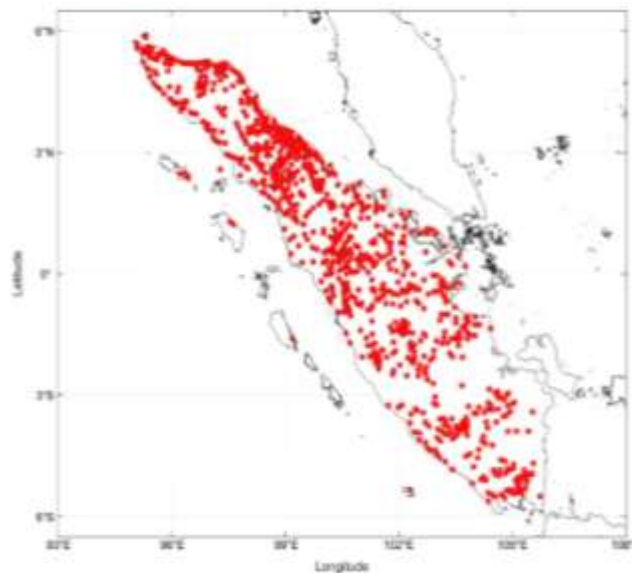
Nijssen et al. (2014) propose that drought predictions are built based on multiple land surface models. Spennemann et al. (2017) tested the ability of soil moisture to determine the level of drought in South America using the Climate Forecast System (CSFv2) model. The results show that SPI and soil moisture anomaly forecasts are very influential both spatially and temporally.

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Drought early warning system in Indonesia needs to be developed and equipped with information on drought predictions that will occur. The ECMWF model is a potential model to be developed because BMKG has collaborated and also utilizes the ECMWF model for various forecasts, both weather forecast and season forecast. Forecasting seasonal drought using the ECMWF S4 Forecast system model has been carried out for the Latin America region (Carrão et al. 2018).

The European Center for Medium Range Weather Forecasts (ECMWF) has been used for operational 31-daily forecasts from 1985 to January 1989 (Palmer et al. 1990). During this time, the forecast score skills of the ECMWF model only reach moderate values for up to 10 days. The model still fails to describe medium-term forecasts or climate predictions (Miyakoda et al. 1986). The forecast capability of the ECMWF model during April 2002 - 2012 and 1995 - 2001 has been re-evaluated by Vitart (2013). He showed that the ability of the ECMWF forecasts to simulate the dynamics of Madden-Julian Oscillation (MJO) has increased since the 2002 period. The consequence of increasing MJO simulation capabilities results in more realistic MJO teleconnection patterns for atmospheric dynamics in the northern and southern hemisphere. Weekly forecasts with the ECMWF model are also getting better. Improvements to horizontal and vertical resolution only have a small impact on the value of the skill score, most changes in the value of the skill score are due to improvements in the physical equation especially for the climate model and the medium-term forecast model. One method of improving the results of the climate model is to use bias correction.



**Fig 1:-** Distribution of rain gauge over Sumatra Island.

## Method:-

### Data and Study Area

The research study area is located on the island of Sumatra geographically located at 6°18' LU - 6°05' LS and 94°08' BT - 108°29' BT. The island of Sumatra is a unique land because there is a mountain range that determines the process of rainfall formation around the range. On the island of Sumatra there are more or less 1,111 rain stations that their data can be used for rainfall research (see Figure 1).

### Bias Correction

Bias correction of ECMWF daily rainfall data make used the method utilized by Piani et al. (2010) can only correct data distribution, it cannot correct the rainfall events. The first step of the method to do the correction is to identify the type of distribution of probability and probability of rainfall from the station and ECMWF, both of which follow the gamma probability distribution with the Probability Density Function (PDF) calculated using the following equation:

$$pdf(x) = \frac{e^{\left(\frac{-x}{b}\right)} x^{a-1}}{\Gamma(a) b^a} \dots \dots \dots (1)$$

Where:

- x = average daily rainfall (mm)
- a = parameter of gamma distribution
- b = gamma distribution scale parameter
- $\Gamma$  = gamma function

The second step is to create a relationship between the transfer function of the gamma Cumulative DistributionFunction (CDF) between the station rainfall data and the ECMWF rainfall data.

$$cdf(x) = \int_0^x \frac{e^{-\frac{x}{\theta}} x^{(k-1)}}{\Gamma(k)\theta^k} dx' + cdf(0) \dots \dots \dots (2)$$

The third step is to determine the transfer function  $y = f(x)$  which can be either a linear or polynomial regression equation to correct ECMWF rainfall data. Simulations conducted by Jadmiko et al. (2017) shows that the regression equation that produces corrected rainfall closest to station rainfall is the 3rd order polynomial regression equation with the intercept value returned at point (0.0) (forcing intercept to zero) with the following form of the equation:

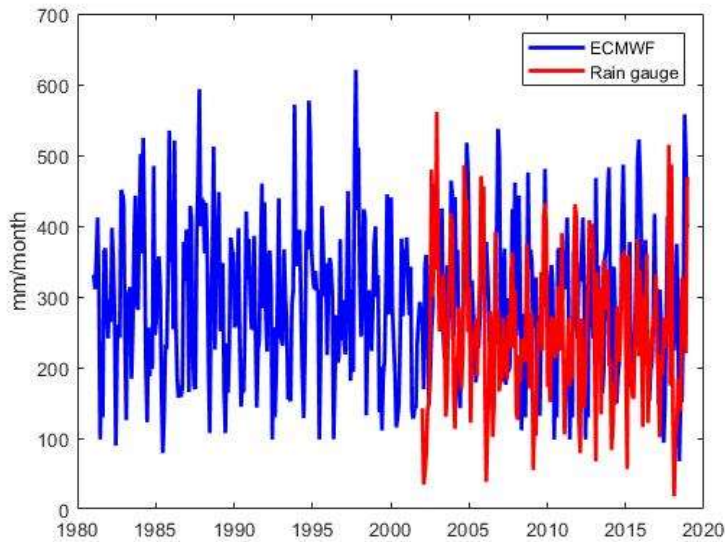
$$y = a_0 + a_1x + a_2x^2 + a_3x^3 + \dots + a_nx^n \dots \dots \dots (3)$$

In this study, the authors will also consider location, lag time in determining the transfer function. After the type of transfer function is determined, the transfer function is used as a correction factor to correct ECMWF data by entering ECMWF data into the transfer function equation so that a corrected ECMWF is obtained.

**Results and Discussion:-**

**Validation Model**

Comparison between ECMWF rainfall (blue) and rainfall observation (red) is shown in Figure 2. The ECMWF model simulation data is longer than the rainfall observation data, where ECMWF data is available starting in 1981 while rainfall observation data appear to be available starting in 1998. The ECMWF model input can be extrapolated from observations of weather parameters in other places so that even if there is no rainfall observation in a place, the ECMWF model can show the rainfall at that location.



**Fig 2:-** Comparison between ECMWF and rain gauge.

The phase of the observational data is almost the same as the phase of the rainfall of the ECMWF. Increase in observed rainfall can be well predicted by ECMWF. The basic difference only lies in the amplitude of the rainfall. In some instances, it appears that the ECMWF rainfall is higher than the observed rainfall.

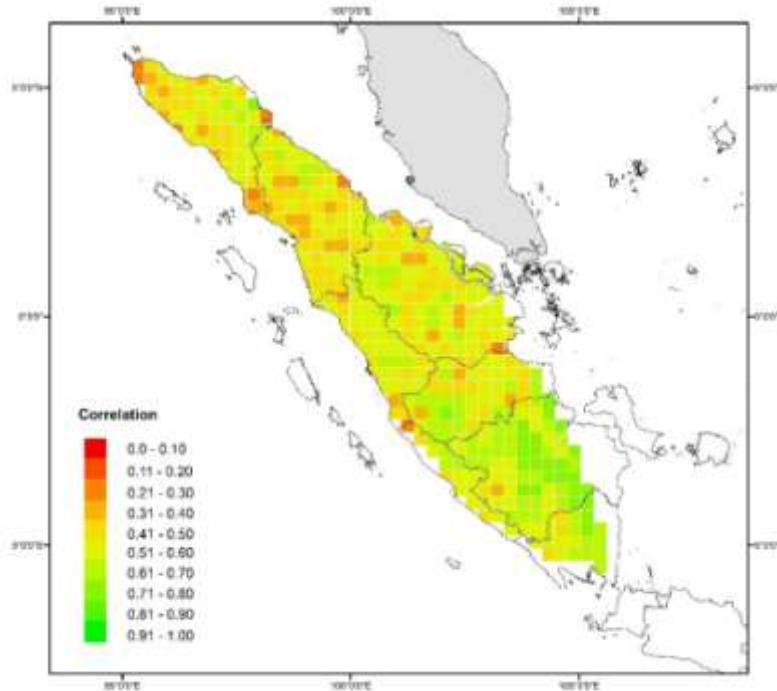


Fig 3:- Spatial correlation ECMWF and rain gauge.

The spatial distribution of the relationship between ECMWF rainfall and observational data is shown in Figure 3. The correlation index in the southern area of Sumatra looks higher than in the northern region. Correlation reaches 0.3 - 0.8 in southern while in the northern it is only 0.2 - 0.4. This difference occurs caused by differences in the factors that form the rainfall in those two regions.

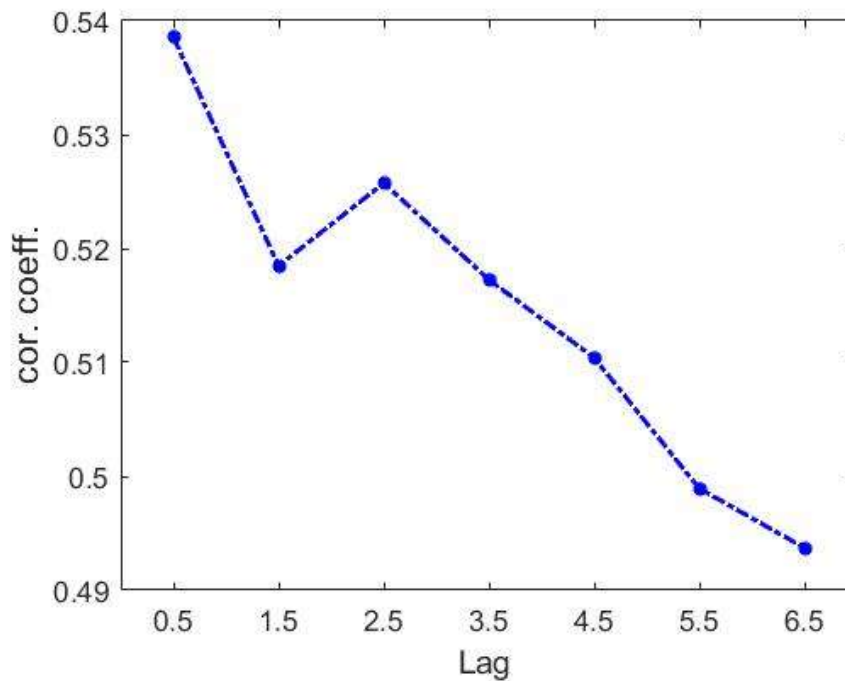
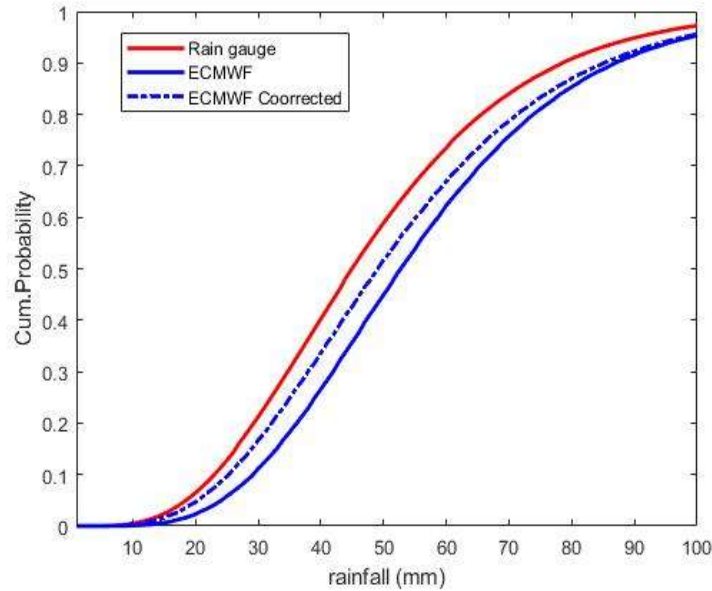


Fig 4:- Correlation lag of between ECMWF and rain gauge.

Monthly correlation lag of ECMWF data with rain gauge data is shown in Figure 4. The results show that lag 0.5 has the best correlation with other lags. Utilization of the latest ECMWF data is needed to obtain the best correlation results.

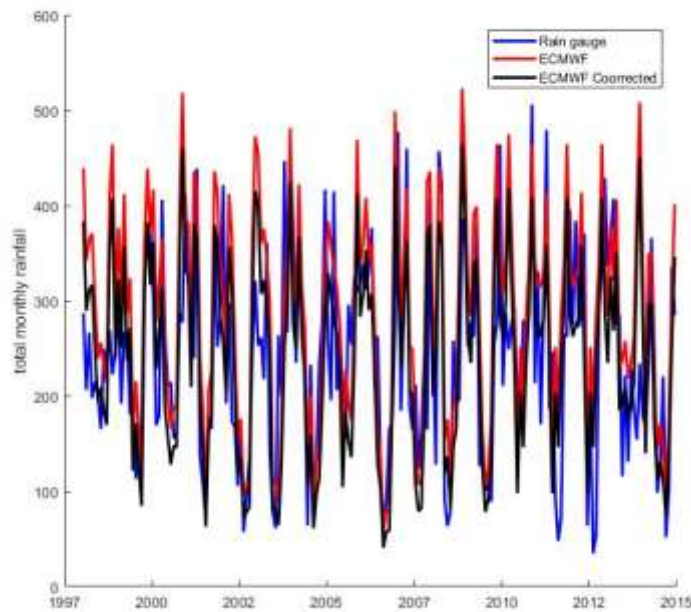
**Bias Correction**

Figure 5 is the cumulative distribution function of the rain gauge, ECMWF, and corrected ECMWF data. It appears that, after the ECMWF data was corrected, the *cdf* graph moved closer to the observational *cdf* graph. This bias correction significantly increases performance of the ECMWF.

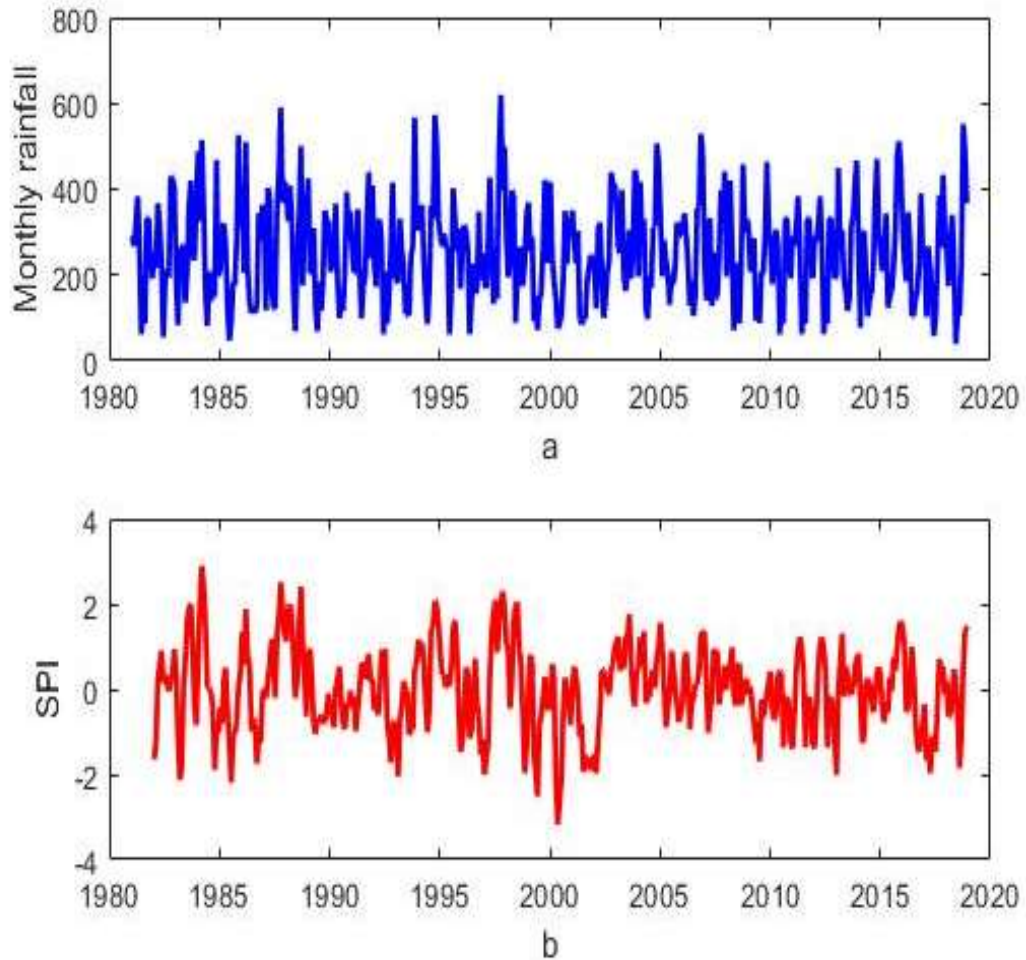


**Fig 5:-** Cumulative distribution function.

Figure 6 shows that the variation in rainfall corrected ECMWF model looks better than the one not corrected. The maximum peak rainfall is slightly lower than the peak rainfall before corrected, overestimate events can be reduced.

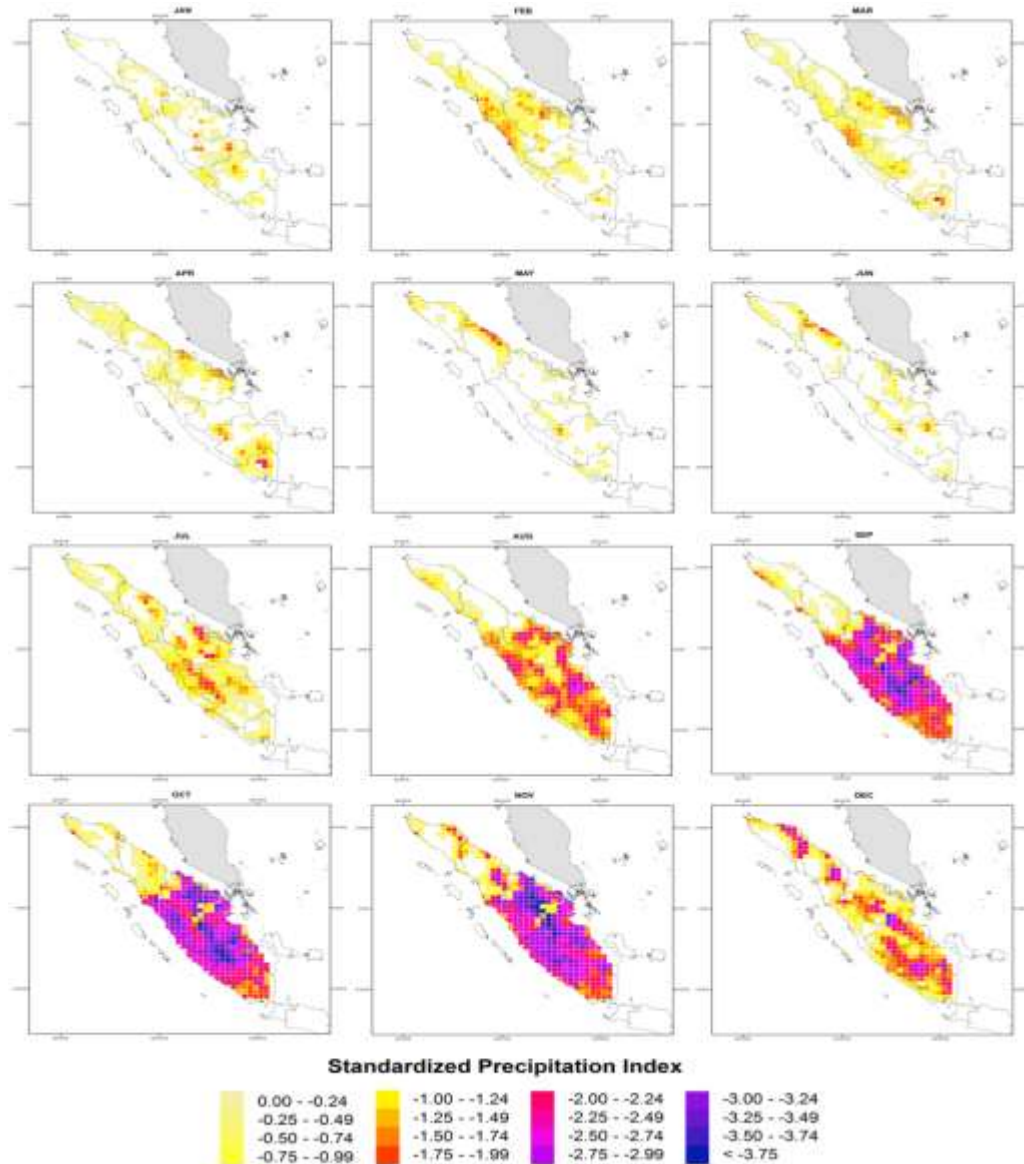


**Fig 6:-** Improvement performance of ECMWF after bias correction processed.

**Standardized Precipitation Index**

**Fig 7:-** Temporal ECMWF corrected (a) and SPI (b).

From Figure 7 it can be seen that the island of Sumatra has a tendency to strong level of meteorological droughts. This can be seen from the fluctuation of the SPI index which only experiences two positive peak values ( $\geq 2$ ) which represent wet to very wet conditions. Meanwhile, the SPI index reached several negative peak values ( $< -2$ ) which indicate very dry conditions, even between 2015 - 2016 the SPI index value reached negative values in several months. In that years a very strong *el-Niño* phenomenon occurred which resulted in a rain deficit in most parts of Indonesia, especially in Sumatra. In that year, there was also a massive forest fire disaster, especially in the island of Sumatra.



**Fig 8:-** Monthly spatial SPI.

Figure 8 is a spatial map of the drought that occurred, the more negative (purple), the stronger the drought. From the picture it appears that the strongest drought occurred in August. This is because along with the emergence of the dry season that usually occurs.

### Conclusions:-

Bias correction can change the performance of ECMWF monthly rainfall prediction for the better. SPI drought index results show that in the Sumatra region it was dry when El-Nino occurred. In general Sumatra is dry in August, September, and October which is attributed with the impact of the change of monsoon winds.

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