Multi Model Calibration of Rainfall Forecasts in East Nusa Tenggara Using Ensemble Model Output Statistics

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Abstract. The current weather changes uncertainly, marked by significant rise in surface temperatures and reduced rainfall in the tropics. The impact of this uncertainty often leads to a misprediction which may causes lack of anticipation for the upcoming extreme weather events. Statistical approach is required to reduce the error prediction. In 2015, Indonesia experienced the drought-related threat induced by the impact of El Nino storms in the Asia Pacific region. It affected the agricultural sector where almost 21 thousand hectares of agricultural land along Java, Bali and Nusa Tenggara were experiencing drought. This research calibrates ensemble forecasts to take into account the uncertainty and reduce the bias. The calibration of ensemble forecast is carried out by Ensemble Model Output Statistics (EMOS), which is applied to rainfall forecast in East Nusa Tenggara. The results show that calibration using EMOS is capable to produce a reliable forecasts, in which the optimum forecast is obtained by training window of 24 months.

1. Introduction
Indonesia is a tropical country which is known as Maritime Continent due to its unique geographical location i.e. located between two oceans and two continents. As a tropical country, Indonesia has small temperature variation, but large enough in rainfall variations. This condition lead to a frequent rainfall events in Indonesia [1]. The rainfall in Indonesian territory is dominated by the influence of several phenomena such as the Asian-Australian Monsoon system, El-Nino, North-South atmospheric circulation (Hadley), East-West atmospheric circulation (Walker) and a lot of local wind systems. Disturbance to one of these circulatory systems will affect weather and climate in Indonesia [2]. The amount of rainfall can be used as a benchmark in determining the wet or dryness of a region. Furthermore, the rainfall intensity in a particular region and period can be converted into a Standardized Precipitation Index (SPI). This unit is a common indicator of flood and drought disaster monitoring [3]. Indonesia is still facing a considerable challange to generate reliable rainfall forecast. This leads to a lack of anticipatory action in the prevention of natural disasters such as major floods and droughts [4].

The National Disaster Management Agency report through [5] stated that Indonesia has experienced drought-related threat induced by the impact of El Nino storms in the Asia Pacific region. The report revealed that drought impacts were most visible in eight provinces in Indonesia, where the drought has caused a water crisis along the island. The impact of this water crisis has also affected the agricultural sector where almost 21 thousand hectares of agricultural land along the islands of Java, Bali and Nusa Tenggara. Hence, development of reliable rainfall forecasting methods in Indonesia is
required, one of which is in East Nusa Tenggara which was also experienced significant drought impact due to rainfall forecast misprediction.

Furthermore, there has been a lot of researches on ensemble forecast. The ensemble technique itself is a forecasting technique that combines several output models, resulting on probabilistic forecast. The idea of ensemble forecast is to reduce model uncertainties derived from certain factors such as model specifications, natural rules, initial conditions, and so on [6]. Application of ensemble forecast in Indonesia can be seen in Kuswanto [6] as well as Kuswanto and Sari [7]. The forecast generated from ensemble forecasting has been proven to be more reliable than using deterministic techniques [7]. One of the post-processing methods in generating reliable ensemble forecasting is Ensemble Model Output Statistics (EMOS), which estimates the parameters using Maximum Likelihood Estimation (MLE) based on multiple linear model [8]. This study aims to calibrate the ensemble forecasts to generate reliable rainfall forecast in East Nusa Tenggara as the basis of predicting drought events.

2. Literature Review

2.1. Goodness of Fit Test
To identify whether the ensemble forecast has been well enough to predict an observation, it is necessary to evaluate the goodness of the model used. In this research, the evaluation of ensemble model is assessed by rank histogram. The evaluation itself can be reviewed by looking at the pattern of forecast model distribution. The procedure to develop rank histogram is by sequencing n ensemble members from the lowest to the highest and then determining the location of the actual observations on ensemble members [9]. A good rank histogram has uniform bins for all members, in which each ensemble member has the same frequency [10].

2.2. Ensemble Model Output Statistics (EMOS)
Ensemble Model Output Statistics (EMOS) was firstly introduced by [11], where this method is the development of the Output Statistics Model method developed by [12]. The post-processing procedure using EMOS is done by converting the standard ensemble model with discrete probability into an ensemble model with interval probability in a Probability Density Function (pdf) form. If \( f = (f_1, f_2, ..., f_K)^T \) is vector from total amount of K ensemble model, thus the prediction model of EMOS can be written as follows.

\[
p(y|f_k) \sim g(\alpha, \sigma)
\]

where \( g(\alpha, \sigma) \) is a density function with each is a shape \( \alpha \) and scale \( \sigma \), \( f_k \) is the forecast from k-th ensemble member, and \( y \) is the prediction. This method usually uses single parametric distribution [14]. The number of parameters correspond to the number of ensemble member. Thus, the pdf component can be written in equation as follows.

\[
p(y|f_1, ..., f_K) = g(y|\alpha + b_1 f_1 + ... + b_k f_k, c + d S^2)
\]

where \( f = (f_1, ..., f_K) \) states ensembles forecast which obtained from different K model, \( y \) is calibrated ensemble forecast, \( a \) and \( b \) is the regression parameters, \( c+d \) is the parameter of distribution, and \( S^2 \) is the variance of the ensemble forecasting data [13].

2.3. Continuous Ranked Probability Score (CRPS)
Ensemble calibration generates interval prediction in a pdf form. This condition resulted the evaluation cannot be done through MSE or MAPE. Hence, evaluation of the calibration is done by using CRPS. Continuous Rank Probability Score relates to the rank probability that compares the distribution of forecasting with observations that are both represented in Cumulative Distribution Function (cdf). The formula of CRPS can be written as follow [14].

\[
CRPS = \frac{1}{n} \sum_{i=1}^{n} \int_{x_{i-1}}^{x_i} \left( F_i^f(x) - F_i^0(x) \right)^2 \, dx
\]
where \( F_i^f(x) \) is cdf from forecast at \( i \)-th period, \( F_i^o(x) \) is cdf from observation at \( i \)-th period, and \( n^f \) is the number of forecast. The result of a CRPS is a value by which the forecast is said to be reliable if the resulting CRPS value is very small or close to zero. The CRPS illustration can be seen in Figure 1 [14]. Figure 1(b) shows a CDF, where the area between the forecast and observation is represented by a rectangle formed by two functions. Among the advantages of CRPS are easy to interpret, sensitive to all tested parameter values [15].

![Figure 1](image-url)  
Figure 1. (a) Probability Density Function and (b) Cumulative Distributive Function for an Observation in CRPS.

3. Research Methodology

The data is drawn from the official website of the North-American Multi Model Ensemble (NMME) and the European Center for Medium-Range Weather Forecast (ECMW). The data consists of monthly rainfall forecast results and observed total rainfall on the surface. The grids are limited only to the coordinates of East Nusa Tenggara with resolution of 1° x 1°. Both datasets have the same time periods starting from 2011 to 2016. There are five ensemble members which are analyzed as follows: Evaluating the forecast model in NMME dataset against real time observation in ECMWF dataset using rank histogram, calibrating the forecast models in NMME dataset with pre-process result data using Ensemble Model Output Statistics (EMOS) approach, evaluating the model’s reliability using Continuous Rank Probability Score (CRPS). The calibration process using EMOS will be examined for four types window time (m) i.e. \( m = 6, m = 12, m = 18 \), and \( m = 24 \).

The calibration is carried out by the following steps:

- Starts a regression between forecast as predictor with the observation (dependent variable) through \( Y = a + b_1X_1 + \cdots + b_5X_5 \) using data as much as \( m \)-period before the calibrated period. In this step, the value of \( a, b_1, b_2, b_3, b_4, b_5 \) can be obtained respectively.

- After all parameters are already obtained, then the calibrated forecast can be obtained as:

\[
p(y|f_1, f_2, f_3, f_4) = g(y|a + b_1f_1 + b_2f_2 + b_3f_3 + b_4f_4, c + dS^2)
\]

- Prediction interval can be obtained through \( \mu_y \pm Z_{\alpha/2} \sigma_y \), where \( y \) is calibrated ensemble forecast, \( Z_{\alpha/2} \) from normal standard distribution with level of significant \( \alpha \), \( a, b_1, b_2, b_3, b_4, b_5 \) and \( \sigma^2_y = c + dS^2 \).

4. Results and Discussion

4.1. Data Characteristics and Evaluation of Rainfall Forecast Model

The data showed that the largest rainfall occurred in January 2013 with the intensity of 12.71 mm/day which was observed in northwest region of Flores islands, along the coast of Labuan Bajo (Region A). This location is also known as location with the highest rainfall along the period 2011 to 2016, with the average rainfall of 4.46 mm/day. Meanwhile, the smallest rainfall during the period happened in

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northern coastal area of Timor Island (Region B). Furthermore, it was noted that the wettest period occurred in January 2013, where the average rainfall for the entire East Nusa Tenggara Province in that period was 10.52 mm/day. Then, the driest period occurred in September 2014, where the average rainfall for the entire East Nusa Tenggara Province in that period was 0.15 mm/day. In this research, the evaluation of forecast model is conducted for two lead-times i.e. 1 month ahead and 4 months ahead. The model evaluation is carried out based the rank histogram, which is used to determine the dispersion of ensemble forecast as shown in Figure 2. According to [13], a good rank histogram criterion has a uniformly bins, showing that each ensemble member has the same frequency. Based on Figure 2(a), it appears that rank histogram in lead time 1-month shows a decreasing trend pattern or in other words, the forecast ensemble has a positive bias. Meanwhile in Figure 2(b), the rank histogram in lead time 4-months shows a U shape indicating an underdispersive forecast.

4.2. Model Calibration Using Ensemble Model Output Statistics (EMOS) Approach
It has been shown that both 1-month and 4-months forecasts are still not reliable. Hence, post-processing method is required to generate more reliable forecast results. The idea of Ensemble Model Output Statistics (EMOS) is to reduce the bias and adjusts the variance. The result of calibration is an interval estimate obtained from a predictive distribution. In this research, there are total five ensemble members and hence, \( k = 5 \). There are four window trainings are examined. The first calibration is performed at lead time 1-months. In accordance with the previously explained procedure, the first step is to determine the value of parameters \( a, b_1, b_2, b_3, b_4, b_5, c, \) and \( d \) in order to obtain \( \mu \) and \( \sigma^2 \) values. In this paper, the illustration of parameter estimation is given for coordinates 8° South and 118° as an example. Table 1 shows the parameter of EMOS along within mean and standard deviation values in period November 2016 for the lead time 1-month. Based on Table 1, it is known that the best calibration forecast for the lead time 1-month is obtained by using \( m = 18 \) as the value of \( \mu \)-calibrated in \( m = 18 \) is the closest to observation, although the forecasting results is not the narrowest prediction interval. Table 2 presents the parameters for the lead time 4-months. Based on Table 2, the 4-months lead forecast is obtained by using \( m = 18 \), which has the narrowest prediction interval compared to the other training window. Prediction interval in \( m = 6 \) has the narrower bound, however it does not capture the observation value at all. Hence, we can conclude that window time \( m = 18 \) is the best choice. Furthermore, the comparison between ensemble forecasts is done by CRPS in order to know which training window gives better forecasting result (accuracy and density). The evaluation is done by performing the CRPS. According to Table 3, it is known that all forecast models in each lead time and each coordinate nearly all has the best calibration when it comes to window training of 24. Hence, \( m = 24 \) is the most suitable window training in this calibration.
Table 1. EMOS Parameters in Period November 2016 at 8° South and 118° East (Lead-1)

| Parameter | Training Window |
|-----------|-----------------|
|           | $m=6$ | $m=12$ | $m=18$ | $m=24$ |
| $a$       | -0.283 | -0.514 | -0.168 | -0.292 |
| $b_1$     | 0.520  | 0.281  | 0.427  | 0.370  |
| $b_2$     | $3.02 \times 10^{-10}$ | $2.30 \times 10^{-12}$ | $2.77 \times 10^{-14}$ | 0.059 |
| $b_3$     | $3.98 \times 10^{-8}$ | 0.057 | $1.26 \times 10^{-14}$ | $6.79 \times 10^{-17}$ |
| $b_4$     | $1.74 \times 10^{-10}$ | 0.148 | $1.73 \times 10^{-15}$ | 0.123 |
| $b_5$     | 0.149  | 0.247  | 0.253  | 0.234  |
| $\mu$     | 4.24   | 4.25   | 4.11   | 4.51   |
| $c$       | $3.41 \times 10^{-13}$ | 1.160 | 0.034  | 0.644  |
| $d$       | 0.125  | 1.96$ \times 10^{-13}$ | 0.171  | 0.115  |
| $\sigma$  | 1.13   | 1.16   | 1.58   | 1.68   |
| lower bound | 6.46  | 6.53   | 7.21   | 7.80   |
| upper bound | 2.02  | 1.98   | 1.01   | 1.21   |

Observation Value **2.6054**

Table 2. EMOS Parameters in Period November 2016 at 8° South and 118° East (Lead-4)

| Parameter | Training Window |
|-----------|-----------------|
|           | $m=6$ | $m=12$ | $m=18$ | $m=24$ |
| $a$       | -3.602 | 2.147  | 1.046  | 1.805  |
| $b_1$     | 0.228  | 0.341  | 0.410  | 0.425  |
| $b_2$     | $1.58 \times 10^{-9}$ | $5.39 \times 10^{-12}$ | $2.16 \times 10^{-14}$ | $9.38 \times 10^{-12}$ |
| $b_3$     | 0.643  | $4.20 \times 10^{-13}$ | $4.43 \times 10^{-13}$ | $3.22 \times 10^{-11}$ |
| $b_4$     | 0.013  | $4.57 \times 10^{-18}$ | $3.93 \times 10^{-15}$ | $3.90 \times 10^{-18}$ |
| $b_5$     | $2.88 \times 10^{-10}$ | $2.16 \times 10^{-15}$ | $2.71 \times 10^{-14}$ | $1.35 \times 10^{-14}$ |
| $\mu$     | 6.20   | 5.41   | 4.98   | 5.88   |
| $c$       | $2.68 \times 10^{-11}$ | 4.010  | 3.730  | 8.522  |
| $d$       | $5.84 \times 10^{-4}$ | $1.78 \times 10^{-11}$ | $3.59 \times 10^{-13}$ | $1.96 \times 10^{-10}$ |
| $\sigma$  | $4.18 \times 10^{-3}$ | 4.10   | 3.73   | 8.52   |
| lower bound | 6.20  | 1.34   | 12.3   | 22.6   |
| upper bound | 6.19  | 0      | 0      | 0      |

Observation Value **2.6054**

Table 3. CRPS mean value for Calibrated Forecast Using EMOS for Each Training Window ($m$)

| Coordinate | Lead Time 1-Month | Lead Time 4-Month |
|------------|-------------------|-------------------|
|            | $m=6$ | $m=12$ | $m=18$ | $m=24$ | $m=6$ | $m=12$ | $m=18$ | $m=24$ |
| 8° S - 118°E | 1.887878 | 1.118296 | 1.077187 | **1.057363** |
| 9° S - 118°E | 2.001702 | 1.030065 | 0.9807156 | **0.9154443** |
| 10° S - 118°E | 1.931947 | 1.260596 | 1.125387 | **1.019102** |
| 11° S - 125°E | 1.679966 | 1.016685 | **0.9281474** | 0.9513983 |
| 12° S - 125°E | 1.829949 | 1.099655 | 1.028454 | **1.023468** |

Coordinate | Lead Time 4-Month
5. Conclusion
This study demonstrated the possibility of applying post-processing method for ensemble forecast using Ensemble Model Output Statistics (EMOS). The calibration results using EMOS give optimum results at window training of 24 in both lead times indicated by the small CRPS values. The calibration process using EMOS also proved its ability to correct the bias and narrow the prediction interval leading to a more reliable forecast.

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