EVALUATION OF BIAS CORRECTION METHOD FOR MONTHLY RAINFALL PREDICTION OF ECMWF SEAS5 IN INDONESIA

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ABSTRACT

The seasonal rainfall forecast from ECMWF SEAS5 often suffers from biases that reduce its accuracy, limiting its use in applications like water resource management and agricultural planning. This study evaluates the effectiveness of bias correction methods in enhancing the skill of ECMWF SEAS5 seasonal precipitation forecasts in Indonesia. Observational data from 148 BMKG rain gauges and SEAS5 raw output from 2011 to 2020 are used. Three bias correction methods—linear scaling (LS), empirical distribution quantile mapping (EQM), and gamma distribution quantile mapping (GQM)—are applied to the raw model. Model performance is assessed using scatter plots, root mean square error (RMSE), correlation, and Taylor diagrams. The results show LS consistently outperforms EQM and GQM, reducing RMSE from 128 to 102 and improving correlation from 0.57 to 0.65. Additionally, Brier Score (BS) and Relative Operating Characteristic (ROC) analysis highlight significant improvements in probabilistic predictions, especially in areas with high rainfall variability. These findings indicate LS as a particularly effective approach for bias correction, enhancing accuracy and reliability. This study underscores the potential of applying bias correction methods like LS to improve ECMWF SEAS5 forecasts, supporting better decision-making for climate change adaptation and mitigation in Indonesia.

Keywords: Precipitation, Bias Correction, ECMWF SEAS5, Indonesia

1. Introduction

Accurate seasonal rainfall prediction information is needed for the government and the community to adapt and mitigate climate change's impacts. One of the impacts of climate change is the increase in the frequency and intensity of rainfall, which causes hydro-meteorological disasters such as floods and landslides that harm the community. The National Disaster Management Agency (BNPB) noted that from 2021 to 2023, floods and landslides were the most frequent disasters, with a total of 2,145 floods and 2,350 landslides (BNPB, 2023) [1]. Climate change also impacts national food security; the beginning of the rainy or dry season is increasingly challenging to predict, causing many farmers to experience crop failure. As Yang et al. (2023) observed, the challenges in predicting rainfall seasons due to climate change have significantly increased vulnerability in agricultural sectors worldwide, especially in tropical regions like Indonesia [2].

Therefore, rainfall prediction information must be improved to minimize the impact of hydro-meteorological disasters due to climate change. In Indonesia, the Meteorology Climatology and Geophysics Agency (BMKG) is a government agency responsible for climate information and conducting seasonal predictions using dynamic models derived from the European Center for Medium-Range Weather Forecasts (ECMWF). ECMWF is one of the international institutions running seasonal predictions for operational purposes of climate information with global coverage and a prediction range of up to seven months ahead [3]. Rainfall predictions from ECMWF are made as an Ensemble Prediction System (EPS). However, parameters such as rainfall directly output from the ECMWF EPS, called raw models, have limitations related to the quality of predictions. These models often suffer from biases, especially in tropical regions, which affect forecast accuracy [4].

Qian and Xu (2023) showed that an ensemble mean dynamic model performs worse than statistical methods that use a regression relationship between sea surface temperature and rainfall [5]. This highlights the importance of postprocessing to improve the raw model outputs' skills. The problem of bias in the model can be overcome by making bias corrections, one of the simplest methods being Linear Scaling (LS). Research from Kurnia et al. (2020) comparing two bias correction methods, LS and EQM, shows that the LS method can increase the correlation to 0.4, while EQM showed a lower correlation of only 0.2. The RMSE value in the South Sulawesi region, which has a monsoonal rainfall pattern, also indicates better performance with LS compared to EQM [6].

Furthermore, the GQM bias correction method was evaluated by Reyhan using the ECMWF System 5 (SEAS5) Sub-seasonal to Seasonal (S2S) prediction model in West Sumatra. The results showed that the correction of monthly rainfall using the GQM method was inconsistent at two stations in West Sumatra, with a decrease in correlation in June compared to February [7]. Different results were shown by Muharsyah et al. (2020), who used the GQM method to correct ECMWF SEAS4 monthly rainfall on Java Island; their study found that GQM consistently increased the correlation between ECMWF SEAS4 rainfall and all observation stations on Java Island, from 0.7 to 0.89 [8].

Postprocessing is needed to produce rainfall predictions that have qualified skills, one of which is by performing bias correction. The ECMWF SEAS5 dynamic model's output still requires bias correction to provide better rainfall prediction results [9]. Several bias correction methods, such as empirical distribution quantile mapping, gamma distribution quantile mapping, and linear scaling, still need to be discovered to identify the most suitable method for correcting the SEAS5 raw model in Indonesia.

The objective of this study is to improve the accuracy of monthly rainfall predictions to mitigate the impacts of climate change, such as floods, landslides, and disruptions to food security. It aims to evaluate the limitations of ECMWF SEAS5 raw rainfall prediction models, particularly in tropical regions like Indonesia, where biases often reduce forecast reliability. The study aims to assess the effectiveness of various bias correction methods, including LS, EQM and GQM, in enhancing the skill of rainfall predictions. By comparing these methods, this study intends to identify the most suitable bias correction approach for ECMWF SEAS5 to provide accurate and actionable rainfall forecasts in Indonesia.

2. Methods

The data used in this study is monthly rainfall accumulation. Observation data is taken from 148 BMKG rain gauge in Indonesia, Figure 1. Blank data for each observation station will be filled with the corresponding month's climatology value (1991-2020).

The corrected model data are ensemble seasonal rainfall predictions from the raw output of the SEAS5 model. ECMWF releases SEAS5 predictions for up to seven months, initialized on the first of each month. The SEAS5 system has a horizontal resolution of 36 km. In this study, daily rainfall totals (TP) are used and then accumulated over one and three months. The operational ensemble prediction consists of 51 members, while the re-forecast consists of 25 members.

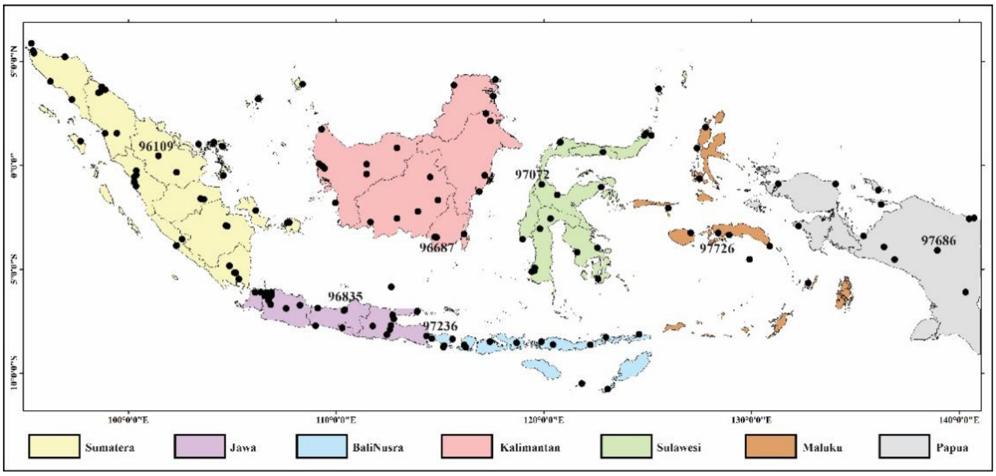

Figure 1. The distribution of rain stations in Indonesia used as a reference to the ECMWF SEAS5 model. The Indonesian region is divided into seven parts, namely Sumatra, Java, BaliNusra, Kalimantan, Sulawesi, Maluku, and Papua, which are distinguished by color.

The bias correction methods used in this study consist of LS, EQM, and GQM. LS is the simplest bias correction approach where monthly correction factors are applied to the rainfall data model [10], shown in Eq. (1).

$$CH_k = CH_m \times \frac{\overline{CH_o}}{\overline{CH_m}} \qquad (1)$$

with:
CH_k = corrected monthly rainfall
CH_m = *ensemble raw* SEAS5 monthly rainfall
$\overline{CH_m}$ = average monthly rainfall SEAS5
$\overline{CH_o}$ = average observed monthly rainfall

The EQM method is based on the empirical cumulative distribution function (fdke) and can be applied to both wet and dry seasons. Both the frequency of rainfall events and their standard deviations can be corrected simultaneously using the EQM method [11] using Eq. (2).

$$CH_k = fdke^{-1}[fdke_m(CH_m)] \qquad (2)$$

with:
CH_k = corrected monthly rainfall
CH_m = *ensemble raw* SEAS5 monthly rainfall
$fdke_m$ = SEAS5 *raw ensemble* empirical cumulative distribution function
$fdke^{-1}$ = *inverse* of $fdke$.

Previous research has shown that the gamma distribution is a suitable distribution function for climatological variables, especially rainfall [12]. The probability distribution function is shown by Eq. (3). (3)

$$F_\gamma(x|\alpha,\beta) = x^{\alpha-1} \times \frac{1}{\beta^\alpha \times \Gamma(\alpha)} e^{-x/\beta}; x \geq 0;\ \alpha,\beta > 0$$

with α and β are the shape and scale parameters, respectively, Γ is the gamma function. The corrected rainfall is then calculated with the cumulative gamma distribution function using Eq. (4).

$$CH_k = F_\gamma^{-1}\left[F_\gamma(CH_m|\alpha_m,\beta_m)|\alpha_o,\beta_o\right] \qquad (4)$$

with:
CH_k = corrected monthly rainfall
CH_m = *ensemble raw* SEAS5 monthly rainfall
F_γ = cumulative gamma distribution function
F_γ^{-1} = *inverse* cumulative gamma distribution function
α_m,β_m = gamma parameter for SEAS5 *raw ensemble*
α_o, β_o = gamma parameter for the observation

In this study, a deterministic rainfall evaluation is conducted which involves comparing model results with observational data to understand how well the model predicts rainfall events. The corrected SEAS5 rainfall will be evaluated based on Scatter plot, RMSE, Correlation, and Taylor Diagram. Probabilistic evaluation is also carried out to provide an overview of how likely an event is to occur, in the study using the Above Normal (AN) criteria for probabilistic evaluation. The evaluation is done by looking at the Brier Score (BS) and Relative Operating Characteristic (ROC) values.

BS is defined as the mean square of the difference between the model's predicted probability and the actual observation [13]. BS is used to measure prediction errors that are dichotomous, e.g. "AN rain occurred" or "AN rain did not occur", the BS value is better if it is close to 0. BS is calculated using Eq. (5).

$$BS = \frac{1}{N}\sum_{n=1}^{N}(f_n - o_n)^2 \qquad (5)$$

with:
N= number of data samples
f_n = probabilistic predicted value for BN or AN event
o_n = observation (value 1 for the event that occurred and 0 for not occurring)

ROC is a measure of the reliability of AN or BN probabilistic predictions or how much the relative change in ROC value is to the climatology value. A prediction system is said to have good reliability if the ROC is positive and close to one [14].

3. Result and Discussion

Figure 2 shows the comparison of monthly rainfall time series between observation data, raw models, and bias correction results (EQM, GQM, LS) from 2011 to 2020. The raw model tends to capture rainfall variability in the Sumatra, Kalimantan, Java, and BaliNusra regions, but in the Sulawesi, Maluku, and Papua regions, the raw model cannot capture rainfall variability. Raw models also have not been able to capture extreme rainfall, as shown in Sumatra (December 2013), Kalimantan (December 2011), and Java (January 2014); this is due to the ECMWF model output, which tends to underestimate the observation [15]. The figure above also shows that the ECMWF model output is quite good at predicting the dry season in Indonesia (June, July, and August) compared to the rainy season (December, January and February).

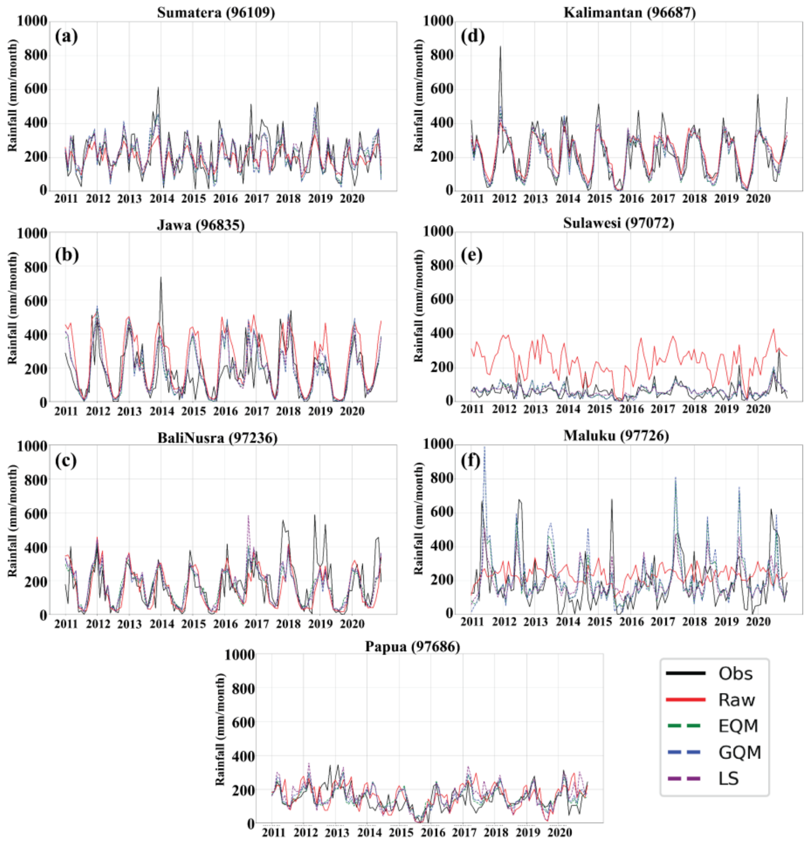

Figure 2. Time series of 2011-2020 monthly rainfall observations, ECMWF SEAS5 raw model and results of the three bias correction methods EQM, GQM, LS in Sumatra (a), Java (b), BaliNusra (c), Kalimantan (d), Sulawesi (e), Maluku (f) and Papua (g).

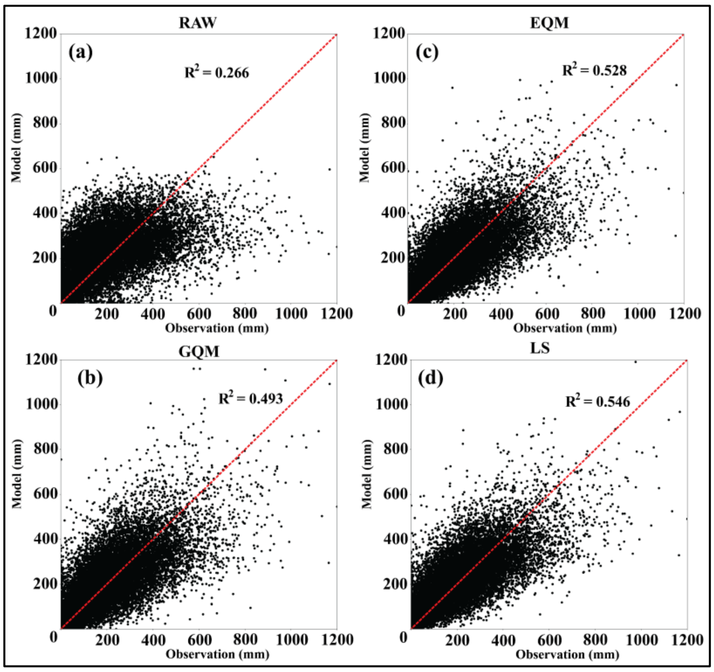

Figure 3. Scatter plot of monthly rainfall between observations and raw models ECMWF SEAS5 (a), GQM (b), EQM (c) and LS (d).

The corrected rainfall from the three methods (EQM, GQM, LS) tends to improve the ECMWF model output, as shown by the variability pattern that adjusts to the observations [16]. This condition is clearly shown in the Sulawesi and Maluku regions, where raw rainfall variability differs significantly from observations. Although corrected rainfall can adjust to the variability of observations, extreme rainfall conditions still cannot be improved.

The scatter plot, which represents all observations across different regions and months, shows a significant clustering of values below the observed rainfall range. From the distribution of raw scatter plot values in Figure 3, it can be concluded that the raw model value is underestimated for the high rainfall category because it does not exceed 700 mm/month, while the observation values range from over 700 mm/month to 1200 mm/month. This discrepancy is indicative of the model's difficulty in capturing extreme rainfall events, which are often more critical in tropical regions like Indonesia. The raw model's R^2 value is quite low at 0.266, meaning that only about 26% of the variance in the observed rainfall can be explained by the raw model. This low R^2 value confirms that the raw model fails to provide reliable predictions, especially for regions with high rainfall variability.

In contrast, the R^2 values of the bias correction results using the LS, EQM, and GQM methods are 0.546, 0.528, and 0.493, respectively, indicating that all three methods increase the R^2 value of the raw model. An increased R^2 value means that the corrected model can better explain some of the variance in observations. This improvement in R^2 suggests that bias correction enhances the model's ability to reflect real-world conditions more accurately. As shown in Figure 2, after the raw model was corrected, the variability between the observed and modelled rainfall became more aligned, demonstrating the efficacy of postprocessing in reducing the raw model's bias.

Of the three correction methods, LS performs the best in representing rainfall in Indonesia when compared to EQM and GQM, as seen in Figure 3d, which shows the highest R^2 value for LS. This indicates that LS is the most effective at addressing the systematic underestimation in the raw model's predictions. Furthermore, LS is a simpler method that only corrects the mean bias by adjusting the raw model's predictions to match the observed average, making it not only effective but also computationally efficient.

The effectiveness of LS in improving model accuracy is consistent with findings from other studies. For instance, Kurnia & Prabowo (2020) found that LS effectively corrected the bias in ECMWF SEAS4 models, improving their predictive skill in tropical areas [6,17]. Similarly, the better performance of LS over EQM and GQM in this study aligns with previous research, which has shown that while EQM and GQM may offer improvements, their application in tropical regions can sometimes lead to inconsistent results. Additionally, other studies, such as Widiastuti & Andriani (2020), have highlighted that Linear Scaling and Quantile Mapping are essential methods for improving the skill of seasonal rainfall models in Southeast Asia, particularly for regions with monsoonal rainfall patterns like Indonesia [18].

In contrast, methods like EQM and GQM, which involve additional parameterization, are better suited for cases where more complex statistical features must be modelled but may suffer in terms of stability and ease of application. Furthermore, Agustina & Fajar (2021) examined the application of bias correction methods on ECMWF's Sub-seasonal to Seasonal (S2S) predictions for Southeast Asia and found that bias correction was crucial in reducing prediction errors in tropical climates [19]. They concluded that empirical methods like Linear Scaling and Quantile Mapping significantly enhanced the model's reliability, reinforcing the importance of such postprocessing steps in generating more accurate seasonal forecasts. Thus, bias correction methods like LS are crucial for improving the performance of seasonal rainfall models in Indonesia, especially for high-rainfall regions, and offer an essential tool for enhancing flood and disaster prediction models.

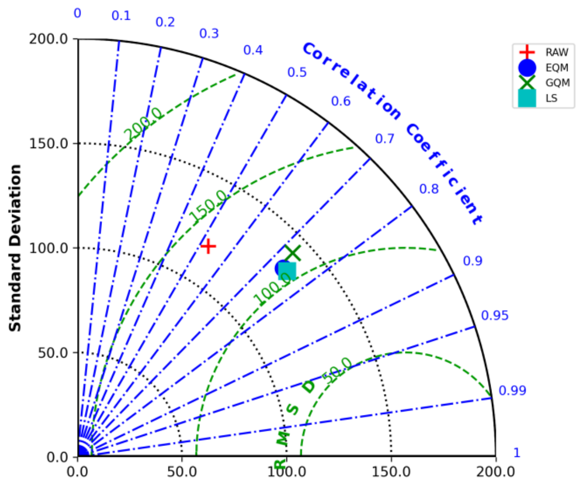

Figure 4. Taylor diagram of RAW, EQM, GQM, and LS.

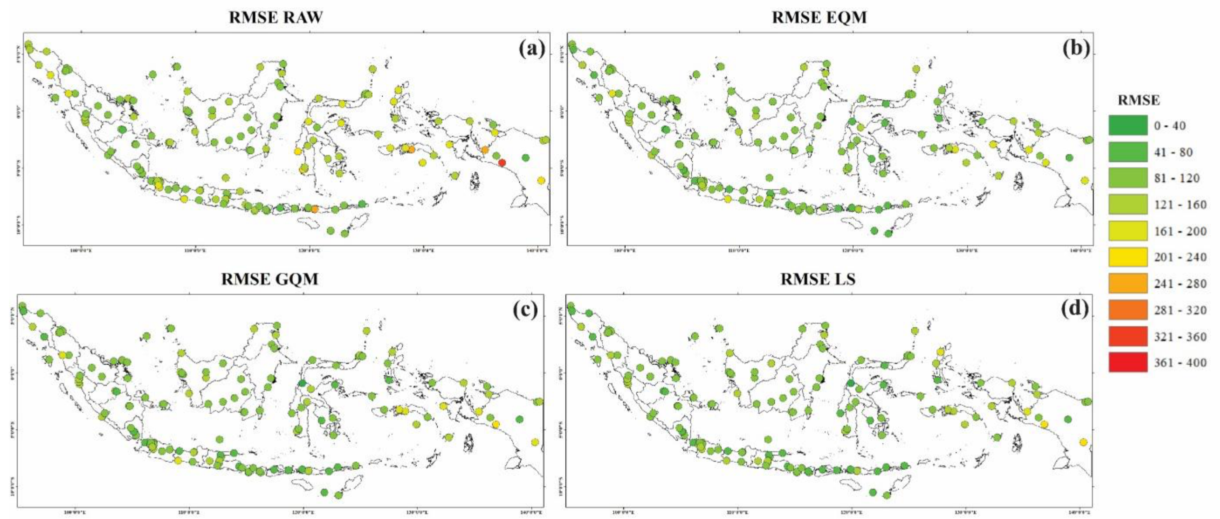

Figure 5. Spatial plots of RMSE between observations and RAW (a), EQM (b), GQM (c), LS (d).

Figure 4 is a Taylor diagram graph used to evaluate the performance of the ECMWF SEAS5 model by comparing the raw model and corrected data (EQM, GQM, LS) to observations. RAW represents the raw ECMWF SEAS5 data, showing that the uncorrected model has a standard deviation value of 115.187, an RMSD of 134.23 and a correlation coefficient of 0.55. The EQM method has better RMSD and correlation than the raw data and GQM method with values of 108 and 0.73, respectively. When comparing the results between RAW, EQM, GQM and LS the best method is LS. The LS method has the lowest RMSD value and the highest correlation to observations with values of 105.9 and 0.74, respectively. Overall, the bias correction methods EQM, GQM, and LS significantly improved the performance of the raw model with the best improvement found in the LS method [20].

Figure 5a illustrates the RMSE for the ECMWF SEAS5 model data across various locations in Indonesia. The results reveal significant spatial variations in RMSE, with some areas, such as Sulawesi and Papua, exhibiting higher RMSE values (marked in orange to red) compared to regions like Sumatra, Kalimantan, Java, and Bali-Nusra, where RMSE values are generally lower (marked in green).

The application of bias correction methods (Figures 5b, 5c, and 5d) shows a significant reduction in RMSE compared to the raw model (RAW). Specifically, Figure 5b (RMSE EQM), 5c (RMSE GQM), and 5d (RMSE LS) demonstrate improvements in RMSE, with more regions transitioning to lower RMSE values (represented by green areas) [21]. Regions with initially high errors, such as Sulawesi and Papua, show notable improvements after applying EQM, GQM, and LS. Among the three methods, LS stands out as the best method for reducing RMSE, producing the lowest errors across high-error regions. The improvements underscore that bias correction methods such as EQM, GQM, and LS significantly reduce prediction errors, particularly in areas prone to high RMSE, such as Sulawesi and Papua.

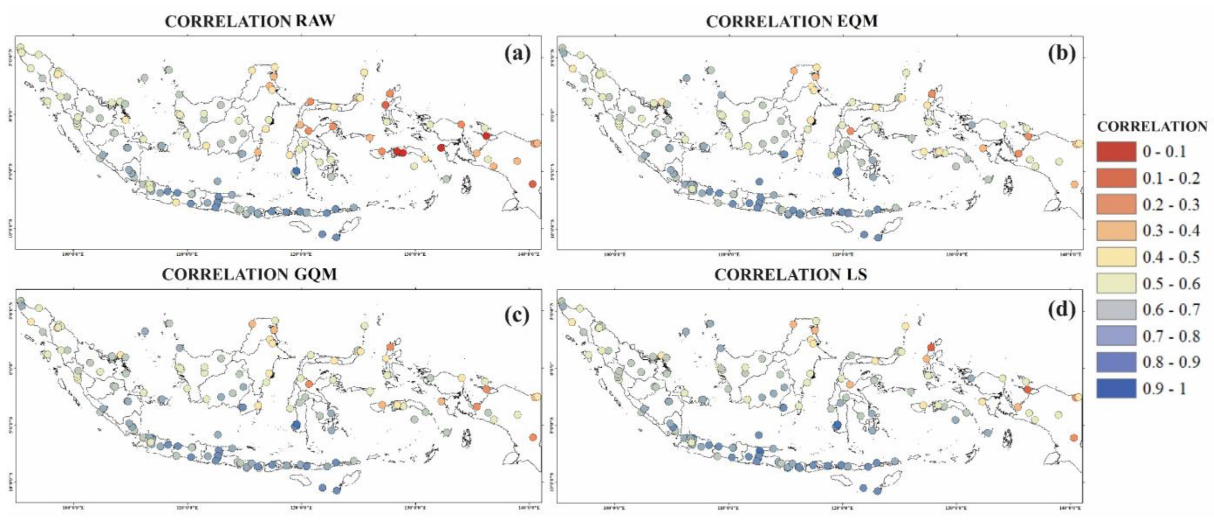

Figure 6. Spatial plots of correlation between observations and RAW (a), EQM (b), GQM (c), LS (d).

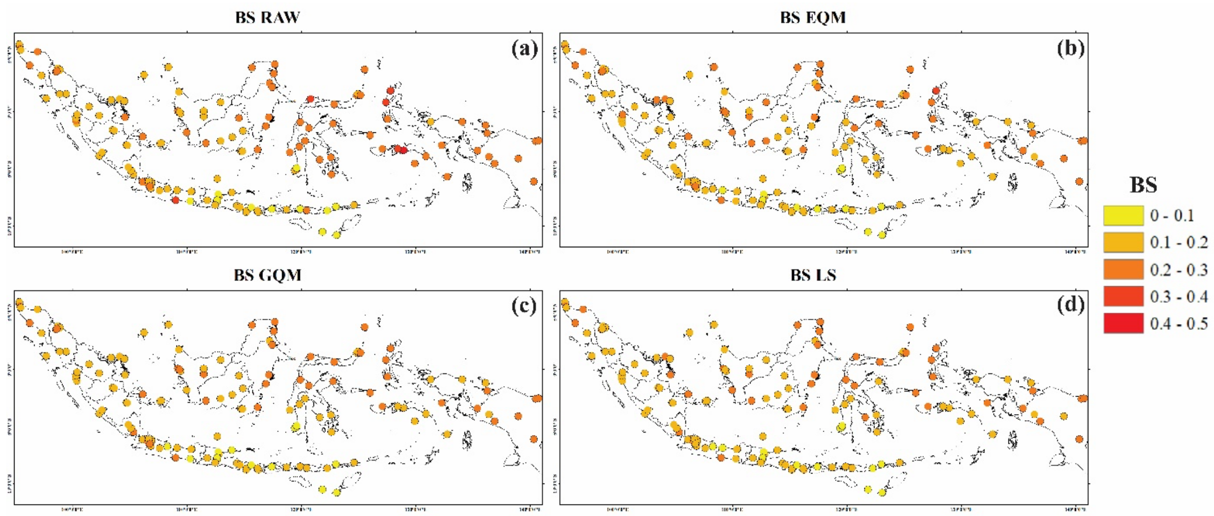

Figure 7. Spatial plots of BS RAW (a), EQM (b), GQM (c), LS (d).

Figure 6a highlights the correlation between RAW and observed (reference) data, revealing substantial spatial variation. High correlations (0.9–1) are observed in some regions (marked in dark blue), whereas lower correlations (0.1–0.2) occur in regions like Papua and Sulawesi (marked in red to orange). Figures 6b, 6c, and 6d (correlation for EQM, GQM, and LS, respectively) demonstrate increased correlation across many regions in Indonesia.

The dominance of blue areas indicates a stronger relationship between predicted and observed rainfall values. Among the methods, the LS method achieves the highest overall correlation, showing the most significant improvements in areas with initially low correlation, such as Papua and Sulawesi. In conclusion, based on the analysis of RMSE and correlation, the best bias correction method is LS. It consistently reduces RMSE and enhances the correlation between predictions and observations across Indonesia, making it the most effective approach for improving the ECMWF SEAS5 model's performance [22][23][24][25].

BS is a predictive performance measure that calculates the average squared error of probabilistic predictions [26]. BS values range from 0 to 1, where lower values indicate better (more accurate) performance. The map on the left (Figures 7a, 7b, 7c, 7d) shows the distribution of BS across different locations in Indonesia. Colour scale yellow to red indicates performance, where yellow (0-0.1) indicates better prediction (low BS), while red (0.4-0.5) indicates less accurate prediction (high BS). Equatorial and local rain-type regions (Sumatera, Kalimantan, Sulawesi, Maluku, Papua) [27] tend to have high BS values, while monsoonal rain type regions (Java, Bali) [28] have low BS values, indicating that the ECMWF SEAS5 model can capture patterns in monsoonal rain type regions compared to Equatorial and Local rain type regions [29]

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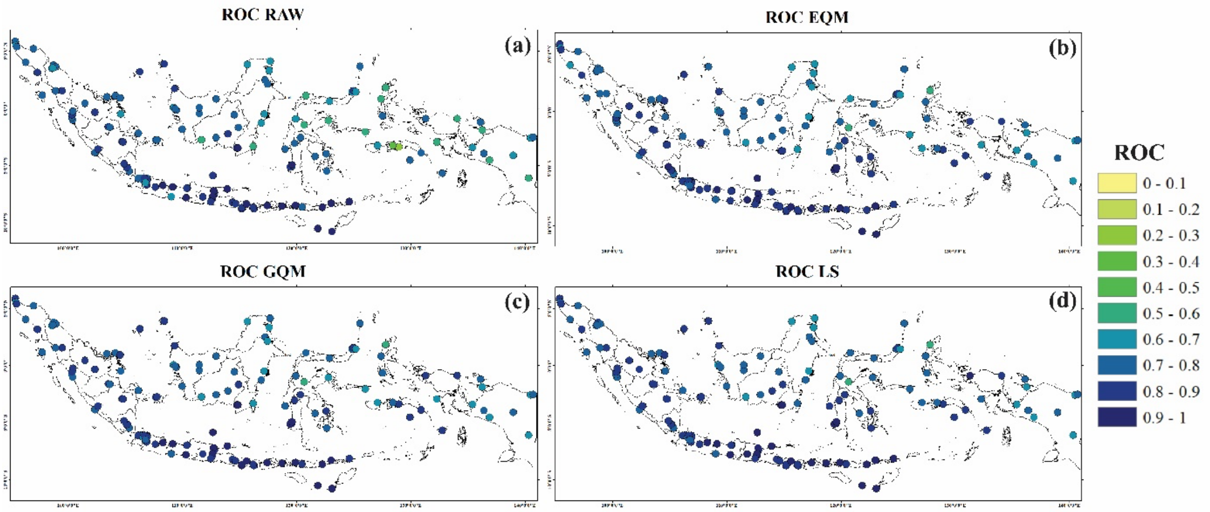

Figure 8. Spatial plots of ROC RAW (a), EQM (b), GQM (c), LS (d).

ROC is a metric that assesses the model's ability to distinguish between two classes (e.g., rain vs. no rain) by looking at the balance between sensitivity and specificity. ROC is measured between 0 and 1, with values close to 1 indicating good prediction. The maps on the right side (Figures 8a, 8b, 8c, 8d) show the distribution of ROC values at the exact location by various methods. The colours are yellow to dark blue, where higher ROC values (dark blue) indicate better performance. High BS RAW and ROC RAW values at some locations indicate poor performance, while ROC RAW shows significant variation across regions. In general, the BS is lower (better) in EQM, GQM, and LS compared to RAW, and the ROC values increase, especially in ROC LS, where there are many locations with high ROC values (dark blue), meaning there is an improvement in prediction performance. Figure 6 shows that bias correction methods such as EQM, GQM, and LS can improve the raw performance of the ECMWF SEAS 5.

LS method consistently outperforms more complex bias correction techniques like EQM and GQM in many scenarios due to its simplicity and robustness. By focusing solely on correcting the mean (and sometimes variance), LS avoids the need for extensive parameterization or assumptions about the underlying statistical distribution, making it less sensitive to small sample sizes and outliers. Unlike EQM and GQM, which aim to address biases across the entire distribution and often struggle with instability in data-sparse regions or extreme values, LS delivers stable outcomes by targeting broad-scale, systematic biases without introducing artifacts. This simplicity also makes LS computationally efficient, a significant advantage when working with large datasets or high-resolution climate models. While LS may not capture higher-order distributional features or extreme events as effectively as EQM or GQM, its ability to provide reliable corrections in cases where biases are predominantly in the mean, or first-order statistics, makes it a robust choice for many applications [30].

4. Conclusion

This study concludes that bias correction is needed to improve the accuracy of seasonal rainfall predictions from the SEAS5 model in Indonesia. LS, EQM and GQM bias correction methods can improve the performance of the ECMWF SEAS5 model in predicting monthly rainfall in Indonesia, especially in the monsoonal region. The bias correction method also improves model performance in probability prediction, with Brier Score (BS) decreasing and ROC. ROC values were higher in areas with monsoonal rainfall patterns. Of the three methods, the LS method had the best performance, with the lowest RMSE and highest correlation with the observed data and BS and ROC values.

Suggestion

This paper analyzes several bias correction methods used for improving precipitation forecasts from the European Center for Medium-Range Weather Forecasts (ECMWF) SEAS5 model in Indonesia, concluding that linear scaling (LS) is the best method overall for correcting the raw model. This is based on the improved R-squared, Root Mean Square Error (RMSE), and correlation coefficients. LS method remains a powerful tool for basic analysis, its limitations highlight the need for more complex methodologies in scenarios involving extreme cases, nonlinearity, or high complexity. Machine learning methods, with their flexibility and robustness, provide valuable alternatives to improve accuracy and insights in such situations.

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