JPPIPA 11(2) (2025)

Jurnal Penelitian Pendidikan IPA

Journal of Research in Science Education

http://jppipa.unram.ac.id/index.php/jppipa/index

Rainfall Prediction Using Adaptive Neuro-Fuzzy Inference System Method

Dedy Ardana[1,2], Irwandi[2,3*], Umar Muksin[2,4], Mochammad Vicky Idris[1]

[1] Meteorology Climatology and Geophysics Agency, Banda Aceh, Indonesia.
[2] Physics Department, Faculty of Science, Syiah Kuala University, Banda Aceh, Indonesia.
[3] STEM Research Center, Syiah Kuala University, Banda Aceh, Indonesia 23111
[4] Tsunami and Disaster Mitigation Research Center, Syiah Kuala University, Banda Aceh, Indonesia.

Received: December 21, 2024
Revised: January 30, 2025
Accepted: February 23, 2025
Published: February 28, 2025

Corresponding Author:
Irwandi
irwandi@usk.ac.id

DOI: 10.29303/jppipa.v11i2.10148

Abstract: This study analyzes rainfall prediction using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method to improve model accuracy, particularly in extreme rainfall events. The objective of this study is to evaluate rainfall prediction using the ANFIS method to enhance model accuracy, especially in predicting extreme rainfall occurrences. The results indicate a moderate positive correlation with R^2 of 0.55, demonstrating good model performance at low rainfall levels (<20 mm) but a tendency to underestimate high-intensity rainfall (>60 mm). Residual analysis reveals a distribution around zero without systematic bias, though significant outliers (>20 or <-20) suggest the need for accuracy improvement. Monthly RMSE exhibits fluctuations, with the best performance observed in the June-July-August (JJA) season and notable challenges in December-January-February (DJF) due to extreme variability. Annual RMSE is also higher in extreme rainfall years (2018, 2023) compared to stable years (2019, 2020). The implementation of ANFIS enhances prediction sensitivity by incorporating additional variables such as temperature and humidity, leading to more accurate forecasts, particularly in extreme weather conditions. This study is further supported by STEM research at Universitas Syiah Kuala, which emphasizes the importance of artificial intelligence in climate data analysis to improve weather prediction accuracy. The ANFIS-based approach applied in this research aligns with STEM studies, which highlight the integration of artificial intelligence in meteorology to mitigate hydrometeorological disaster risks.

Keywords: ANFIS; Artificial Intelligence; Disaster Mitigation; Extreme Rainfall; Rainfall; Residual; RMSE; STEM; Weather Prediction

Introduction

Rainfall is an important parameter in meteorological studies affecting various sectors of life, including agriculture, water resources management, and disaster preparedness (Patel & Parmar, 2022). Accurate rainfall prediction is essential in tropical areas such as Sabang, which have uneven annual rainfall patterns with a long rainy season and a relatively short dry season (Jha & Singh, 2021). Accurate predictions are beneficial not only for the agricultural sector to optimize production but also for risk mitigation and more effective water resource management, especially in dealing with the increasingly real impacts of climate change in this region (Kumar & Kumar, 2023).

Theoretically, rainfall prediction is often carried out using conventional mathematical and statistical models. However, these methods often need to be improved in capturing complex and non-linear relationships between atmospheric variables, such as temperature, humidity, wind speed, and air pressure (Ang et al., 2023). Based on the literature review, this conventional method often fails to provide adequate accuracy in areas with high and fluctuating weather variability, such as the Sabang region (Goyal & Ojha, 2020). Thus, this analysis found a gap between das sollen, namely the need for accurate

How to Cite:
Ardana, D., Irwandi, I., Muksin, U., & Idris, M. V. (2025). Rainfall Prediction Using Adaptive Neuro-Fuzzy Inference System Method. *Jurnal Penelitian Pendidikan IPA*, *11*(2), 593–601. https://doi.org/10.29303/jppipa.v11i2.10148

rainfall predictions, and das sein, namely the reality of existing methods, which often need to be more effective in providing appropriate predictions (Liu et al., 2023). Concerning previous research, there have been many studies that have attempted to develop weather prediction methods with a statistical approach; however, the results often need to be more optimal for predicting rainfall in tropical areas. The novelty of this research (state of the art) lies in using the Adaptive Neuro-Fuzzy Inference System (ANFIS). This hybrid method combines the power of fuzzy logic and artificial neural networks to handle uncertainty and non-linear relationships between atmospheric variables (Wang & Xu, 2023). In this study, ANFIS is expected to be able to predict rainfall better in the Sabang region with its high seasonal variability (Fauzi & Erlinda, 2023). This study's results are expected to contribute to the development of more adaptive and effective prediction methods in supporting resource planning and risk mitigation in tropical regions (Chen & Chang, 2023).

Based on the background and gap analysis, this study aims to develop an ANFIS-based rainfall prediction model and evaluate the accuracy of the model in the context of the Sabang region. This study is expected to improve more accurate weather predictions in the future and support the development of early warning systems and strategic planning in agriculture and water resource management in tropical areas (Rahman & Ali, 2022).

Method

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is a hybrid method that combines fuzzy logic concepts and artificial neural networks, designed to handle uncertainty and variability in prediction data. ANFIS leverages the power of fuzzy logic to manage uncertain data and artificial neural networks to optimize parameters based on training data. This approach is particularly effective for rainfall prediction problems, which tend to be nonlinear and highly influenced by meteorological fluctuations. Figure 1. The ANFIS structure illustrating five interacting layers.

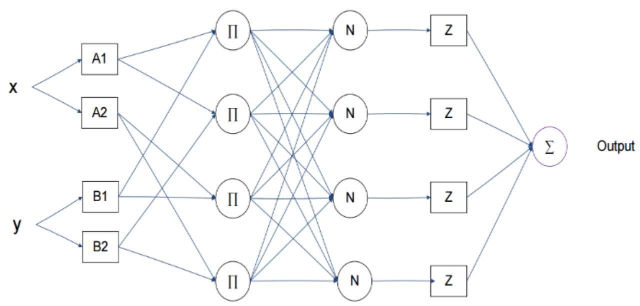

Figure 1. ANFIS Structure.

1. *Input Layer*

The input layer receives meteorological data such as temperature, humidity, evaporation, wind speed, and air pressure; this data is the basis for generating rainfall predictions with a fuzzy approach.

$$i = \mu A_i(x) \quad (1)$$

2. *Fuzzification Layer*

In this layer, fuzzy membership functions are applied to each input variable. Common membership functions that are often used are Gaussian functions or triangular functions. For example, if we use the Gaussian function, then the membership function for the temperature variable is:

$$\mu_{A_i}(x) = \exp\left(\frac{(x-Ci)^2}{2\sigma_i^2}\right) \quad (2)$$

Where c is the center and σ is the standard deviation of the membership function.

3. *Rule Layer*

In this layer, fuzzy rules are defined based on the fuzzification inputs. For each rule, its output is calculated using the product function as the membership concatenation, which is expressed by the equation:

$$\omega_i = \mu_{A_i(x)\cdot \mu B_i(y)} \quad (3)$$

Where ω_i is the weight of the i rule, and μA_i and μB_i are the fuzzy memberships for the variables in the rule.

4. *Normalization Layer*

In this layer, the weights obtained from the rule layer are normalized to produce relative values for each rule. The equation calculates the normalization of weights:

$$\overline{w}_i = \frac{w_i}{\Sigma\, w_j} \quad (4)$$

The normalization weight of the - i rule is expressed by $\overline{w}_i$ while the activation of the - j rule is expressed by w_j

5. *Defuzzification and Output Layer*

In the defuzzification layer, the outputs of the fuzzy rules are combined to produce the final prediction. This model usually uses linear regression to calculate the defuzzified output, which is expressed as:

$$O = \sum_i f_i = \sum \overline{\omega} \cdot (p_i \cdot x^t q_i y + r_i) \quad (5)$$

Where p_i, q_i and r_i are the parameters adjusted for the i rule. The total output, the rainfall prediction result, is calculated by summing the contributions from each rule.

Data Collection Method

The data used in this study were obtained from meteorological stations spread across various regions in Sabang, including Sabang, Banda Sabang, Sabang Besar, Sabang Utara, and Nagan Raya. The data collected included atmospheric parameters relevant to rainfall prediction, such as air temperature, relative humidity, wind speed, and air pressure, as well as daily rainfall data recorded over the past few years. This data was divided into two parts: 70% was used for ANFIS model training, and the remaining 30% was used for testing and evaluating model performance.

Model Development and Testing

The model development process begins with data preparation, which consists of training and testing data. After the data is cleaned and processed, ANFIS is trained to model the relationship between atmospheric parameters and rainfall. During training, the model adjusts parameters based on the learning algorithm used in ANFIS. After the model is trained, the next stage is testing to evaluate model performance. The evaluation uses metrics such as coefficient of determination (R^2) and root mean square error (RMSE) to determine the accuracy of rainfall prediction by the ANFIS model on the test data.

Table 1. Category of Relationship Level Based on Correlation Coefficient Interval

Coefficient Interval	Relationship Level
0.00 – 0.199	Very Weak
0.20 – 0.399	Weak
0.40 – 0.599	Moderate
0.60 – 0.799	Strong
0.80 – 1.000	Very Strong

Result and Discussion

This study aims to determine the results of the performance analysis of the Adaptive Neuro-Fuzzy Inference System (ANFIS) model in predicting rainfall based on data from the Sabang Class III Meteorological Station. The analysis results are presented through annual correlation graphs, residual graphs, seasonal graphs, and model performance graphs (RMSE, SEE, R^2) on a monthly, seasonal, and annual scale. This analysis was conducted to understand the advantages and limitations of the model in capturing varying rainfall patterns.

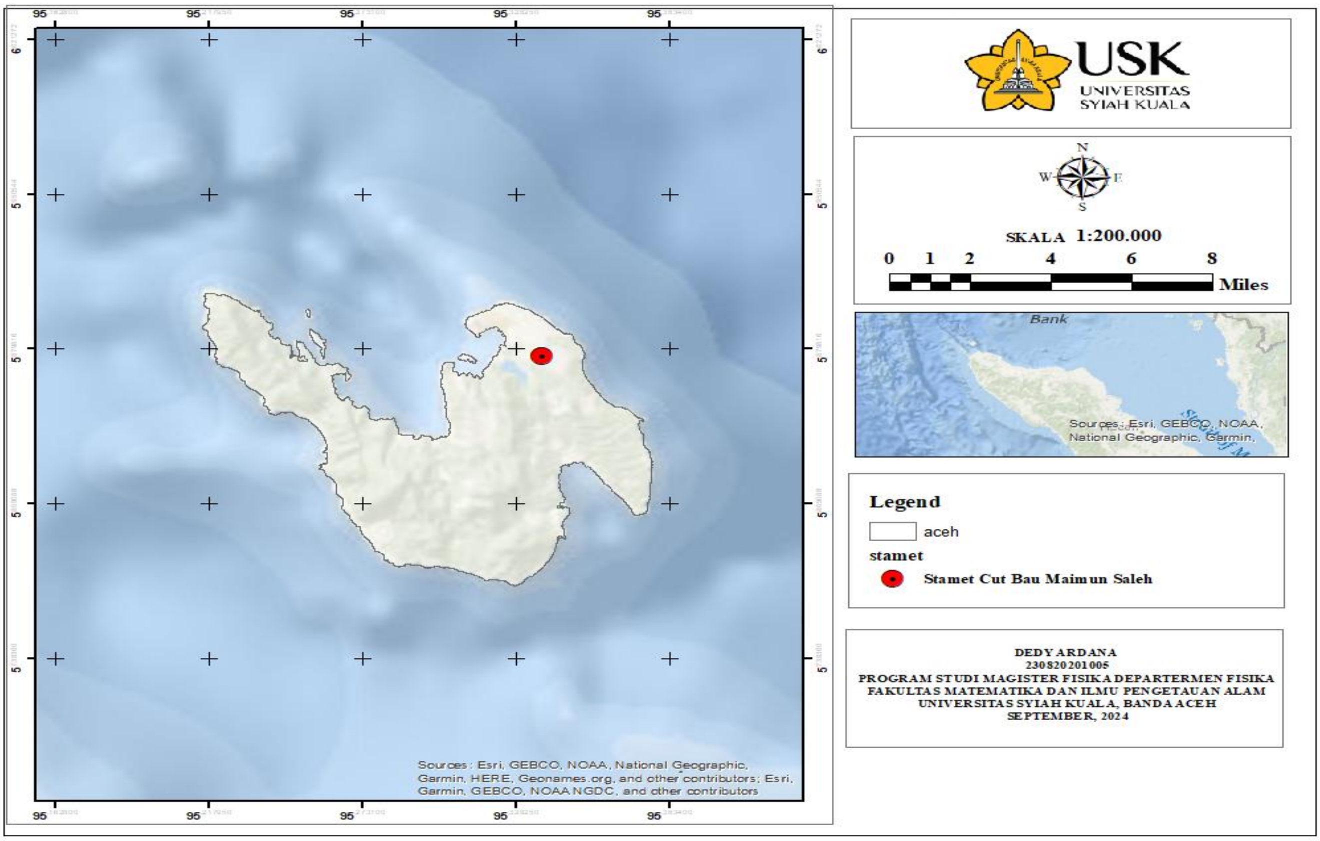

Figure 2. Map of Research Locations in the Sabang Region

Relationship Between Observation Rainfall (OBS) and Model Rainfall

Based on the results of the correlation graph analysis, the relationship between observed rainfall and modeled rainfall shows a regression equation of y=0,27x+4,67 with a correlation coefficient R^2 of 0.55, indicating a positive relationship but with moderate strength. The Root Mean Square Error (RMSE) value of 5.51 mm indicates a deviation between the model prediction results and observational data, especially at high rainfall intensities, where the model tends to underestimate, as shown in Figure 3. The data distribution also shows that most points are concentrated at low rainfall (below 20 mm), indicating better model performance in this range. However, at high rainfall (above 60 mm), the deviation from the regression line is increasingly significant, indicating the model's limitations in predicting extreme rainfall (Sabang Class III Meteorological Station, 2023). These results align with the study by Kumar & Singh (2023) which revealed that the ANFIS model has limitations in capturing extreme rainfall values in time series-based predictions. In addition, Izadi & Ranjbar (2022) also showed that the ANFIS model often underestimates high-intensity rainfall, especially in urban areas. Therefore, further optimization is needed by adding input variables such as temperature, humidity, and air pressure to improve the model's ability to represent complex rainfall patterns (Chen & Chang, 2023; Tang & Zhang, 2023).

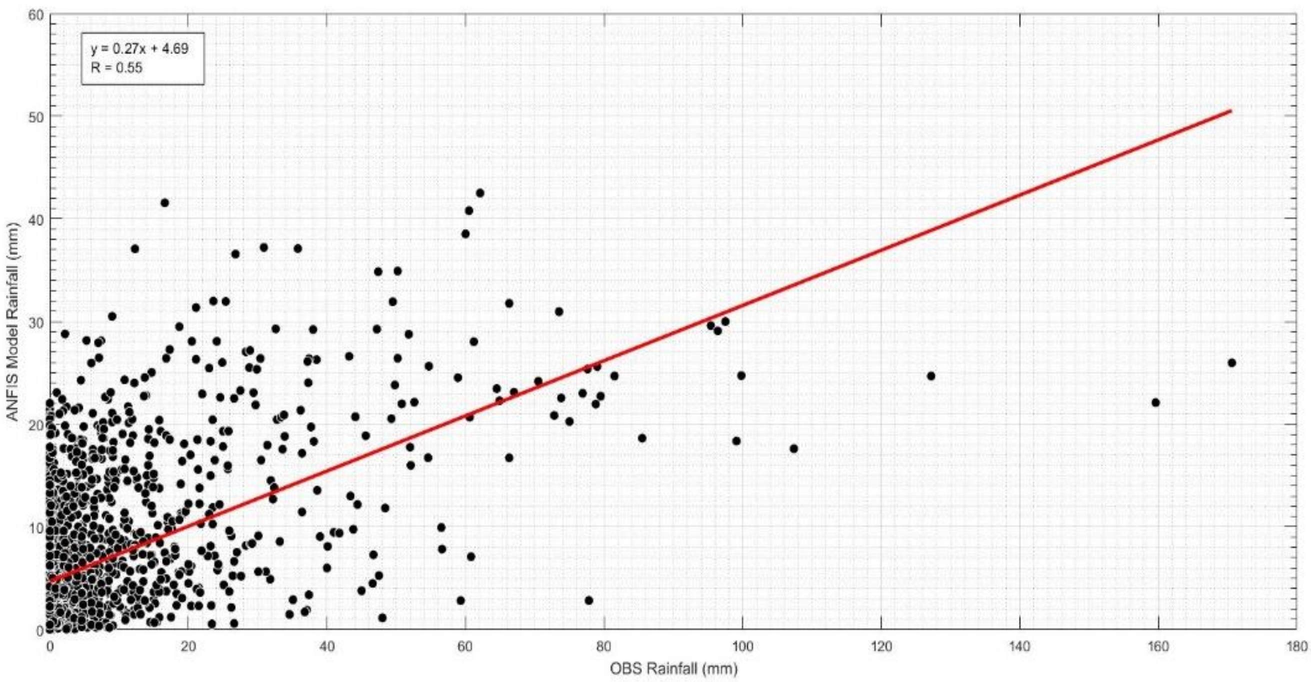

Figure 3. Relationship Between Observation Rainfall (OBS) and Model Rainfall

Residual Analysis

The residual graph shows the distribution of residuals, which is the difference between the observed and predicted values of the regression model, which are spread around the zero line. The horizontal axis represents the data index, while the vertical axis shows the residual values. Most of the residual values range from -10 to 10, but there are some significant positive and negative spikes, reaching more than 20 or less than -20, indicating outliers or quite large prediction errors at certain points. The distribution of residuals looks quite random without a clear pattern, indicating that the model has no systematic bias in its predictions, although residual fluctuations are still quite high, as shown in Figure 4. This shows that the model's performance in predicting data is quite good in general, but prediction accuracy needs to be improved, especially in capturing extreme values to reduce significant errors (Sabang Class III Meteorological Station, 2023). This finding is consistent with the research of Izadi & Ranjbar (2022), which shows that the ANFIS model tends to be unable to capture extreme values optimally, resulting in significant prediction errors in extreme conditions. In addition, Rahman & Ali (2022) highlighted the importance of adding additional input variables, such as temperature and humidity, to increase the model's sensitivity to high data variability. Comparison Graph of Observed Rainfall with ANFIS Model Prediction (2017–2023).

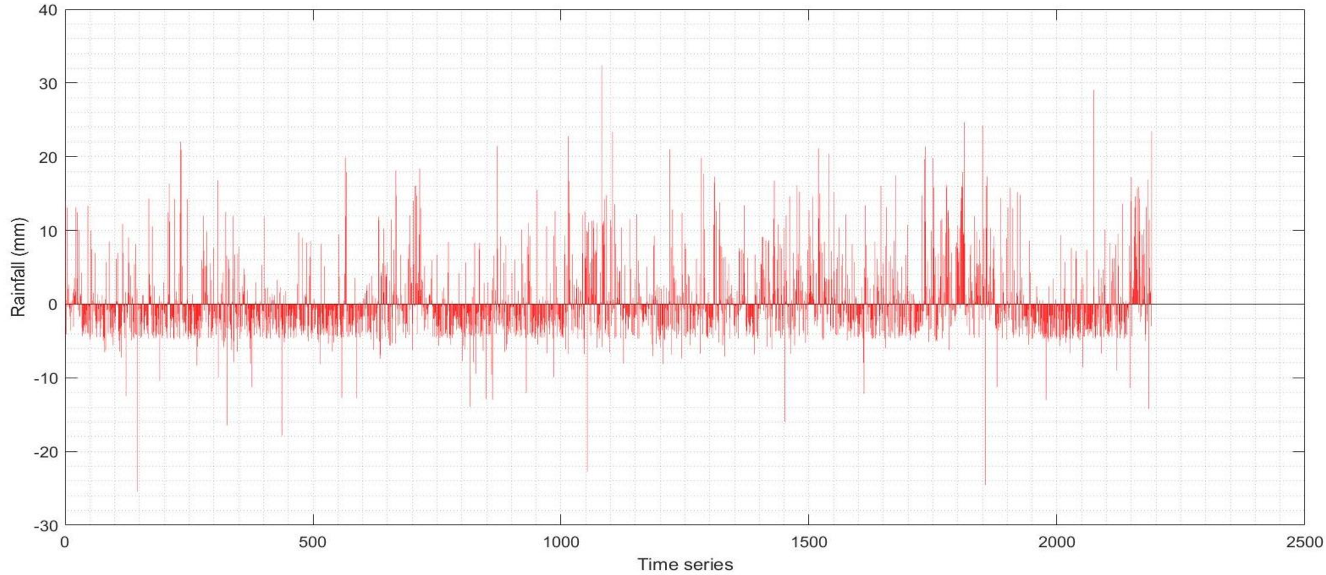

Figure 4. Residual Graph of Rainfall Prediction Against Observation Data

Comparative Analysis of Observational Rainfall with ANFIS Model Predictions (2017–2023)

This study analyzes the comparison between observed rainfall data (Obs Data) and ANFIS model predictions (ANFIS Model Data) in the period from November 2017 to November 2023. The results of the analysis show that the observed data has high fluctuations with extreme rainfall reaching more than 160 mm at some points, while the ANFIS model tends to produce lower predictions, especially at high rainfall intensities. At low rainfall (below 20 mm), the model shows better accuracy with smaller fluctuations between the two datasets, but at high rainfall (above 60 mm), the model often experiences underestimates, as seen from the significant difference between predictions and observations. The spike in extreme rainfall that occurred in several years, such as 2018 and 2023, showed a larger model deviation, while the best performance was recorded in years with more stable rainfall patterns, such as 2019 and 2020, as shown in Figure 5. To improve accuracy, model parameter optimization and the addition of input variables such as temperature, humidity, and air pressure are needed. Integration of hybrid methods, such as the combination of ANFIS with deep learning, is also recommended to improve the sensitivity of the model to extreme rainfall patterns. Overall, the ANFIS model shows quite good performance at low to moderate rainfall but requires significant improvements to improve prediction accuracy at extreme rainfall.

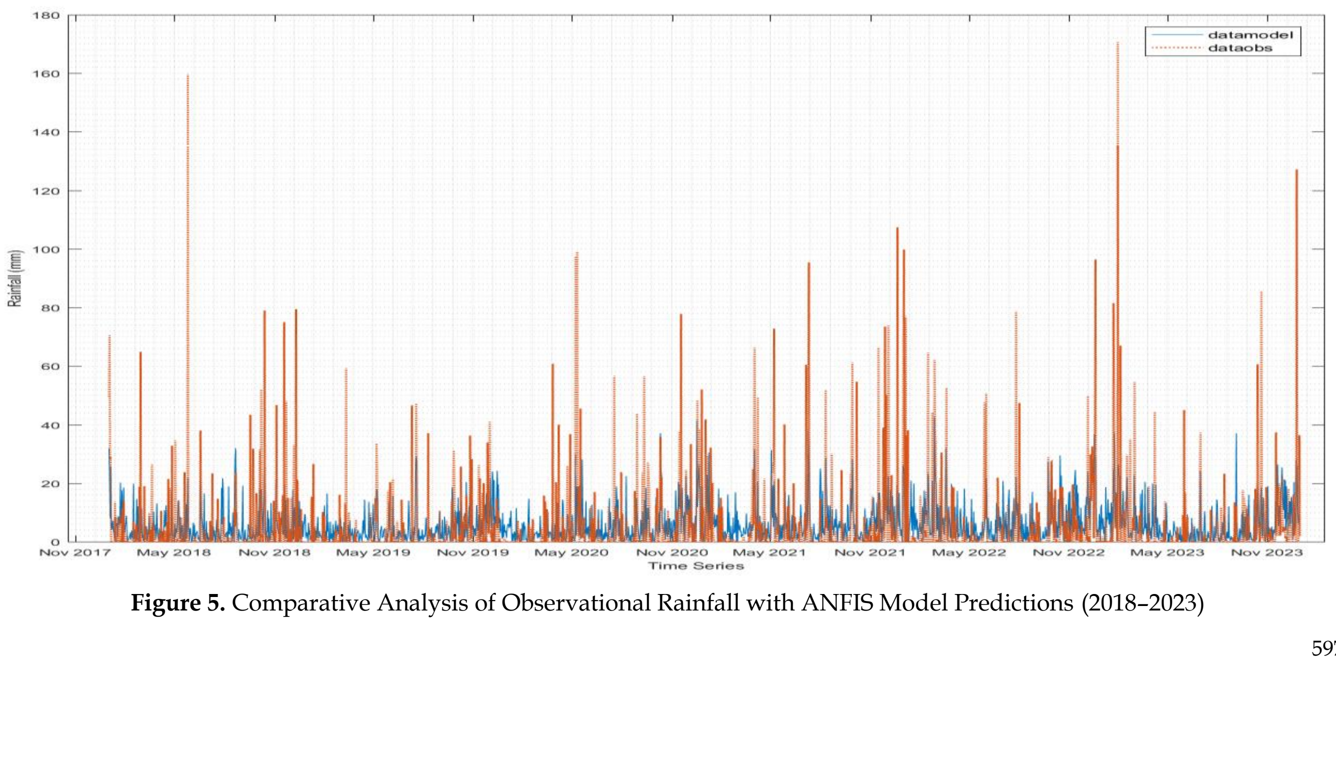

Figure 5. Comparative Analysis of Observational Rainfall with ANFIS Model Predictions (2018–2023)

Correlation of Observation Rainfall and ANFIS Model Prediction Based on Seasonal Period

Based on the analysis of the correlation graph of model rainfall against observed rainfall in four periods, the following are the conclusions:

1. *Dec-Jan-Feb Period*

In this period, the regression equation is y=0.26x+6.01 with a coefficient of determination (R^2) of 0.35 and an RMSE value of 14.33 mm. This shows a moderate correlation between model rainfall and observations, but the model still shows limitations in predicting high rainfall values. Most of the data is concentrated at low values, and the model tends to underestimate higher observed values.

2. *Jun-Jul-Aug Period*

In this period, the regression equation is y=0.35x+3.58 with R^2 = 0.33 and an RMSE of 8.19 mm. The correlation between model rainfall and observations is also moderate, but the model performance is better than other periods with a smaller RMSE. Data distribution shows that the model is able to capture the basic pattern, but overestimates low rainfall and underestimates high rainfall.

3. *Mar-Apr-May period*

The regression equation for this period is y=0.20x+4.08 with R^2 = 0.25 and RMSE of 11.57 mm. The lower coefficient of determination indicates a weak correlation between the model and observation rainfall. Most of the data is concentrated at low values, with the model tending to underestimate higher rainfall values. Model performance in this period is lower than in other periods.

4. *Sep-Oct-Nov period*

In this period, the regression equation is y=0.28x+5.10 with R^2 = 0.27 and RMSE of 10.50 mm. The correlation between model and observation rainfall is low to moderate, with data distribution indicating the model's limitations in capturing extreme rainfall values. The model tends to underestimate higher observation values.

Of the four periods, the model showed the best performance in the June-July-August period with the smallest RMSE value (8.19 mm) and moderate correlation (R^2 = 0.33). However, overall, the model still has limitations in predicting rainfall, especially at higher values, which tend to underestimate or overestimate. The March-April-May period showed the lowest performance with R^2 = 0.25, indicating that the model had greater difficulty in capturing rainfall patterns in this period. To improve prediction accuracy, model refinement is needed, especially in periods with higher rainfall variability, as shown in Figure 6.

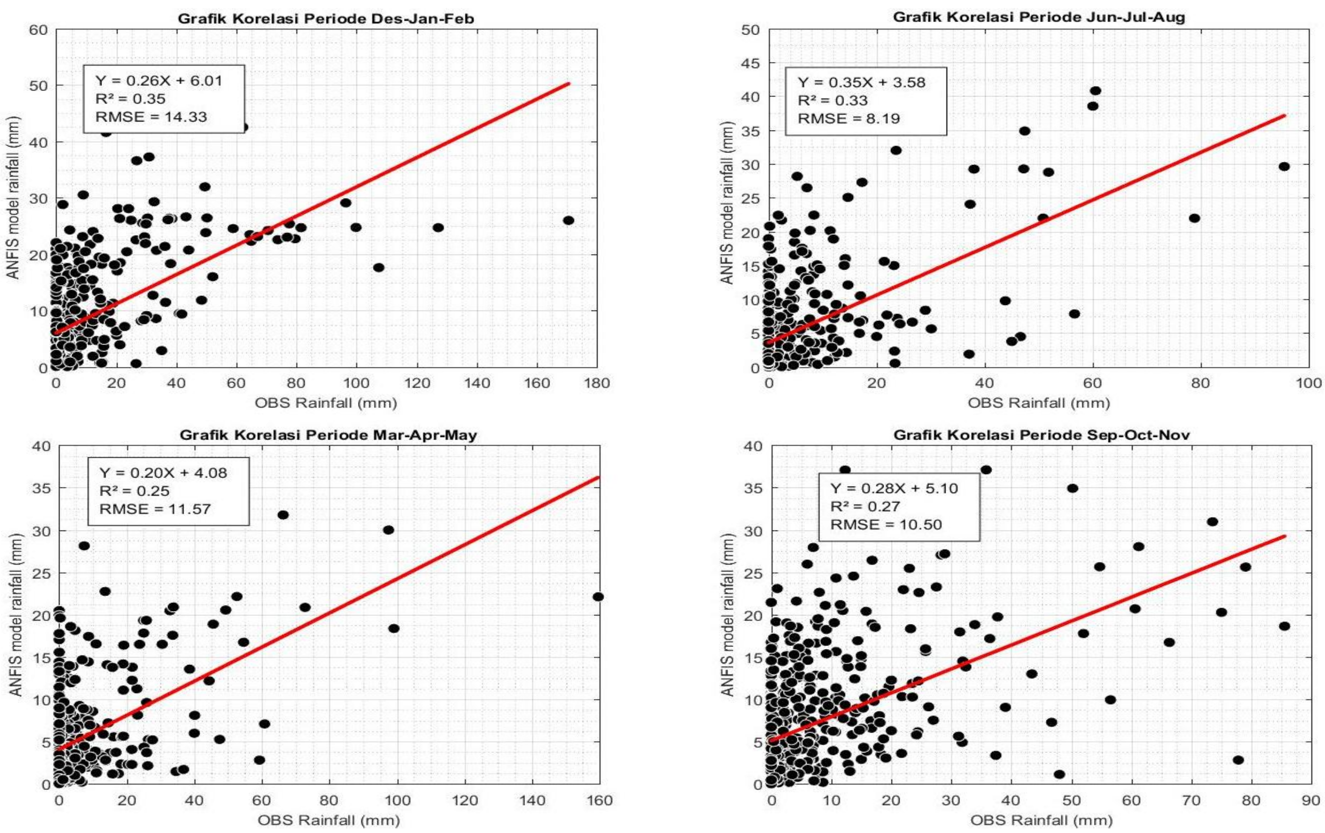

Figure 6. Correlation Graph of Observation Rainfall and ANFIS Model Prediction Based on Seasonal Period

Rainfall Prediction Model Performance Analysis: Monthly

This graph shows that RMSE tends to fluctuate between months. Months with extreme rainfall, such as December, have high RMSE values, while months with more stable rainfall patterns show lower RMSE values.

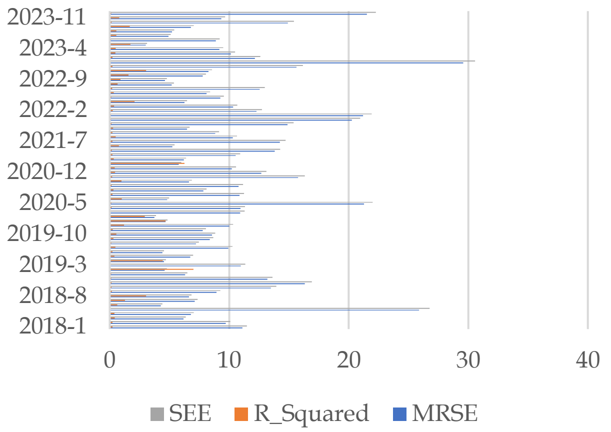

Figure 7. Rainfall Prediction Model Performance Analysis Graph: Monthly

Seasonal Rainfall Prediction Model Performance Analysis

The period RMSE graph shows that the largest model prediction error occurs in the DJF season, while the smallest prediction error occurs in the JJA season. This is consistent with the period correlation analysis.

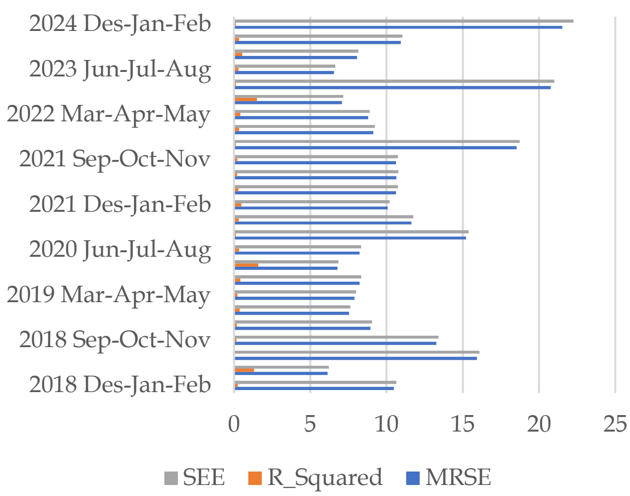

Figure 8. Seasonal Rainfall Prediction Model Performance Analysis Graph

Performance Analysis of Annual Rainfall Prediction Model

The annual RMSE graph shows that years with extreme rainfall, such as 2018 and 2023, have higher RMSE values than years with more stable rainfall patterns such as 2019 and 2020. This indicates that the model is less able to capture rainfall patterns in extreme years.

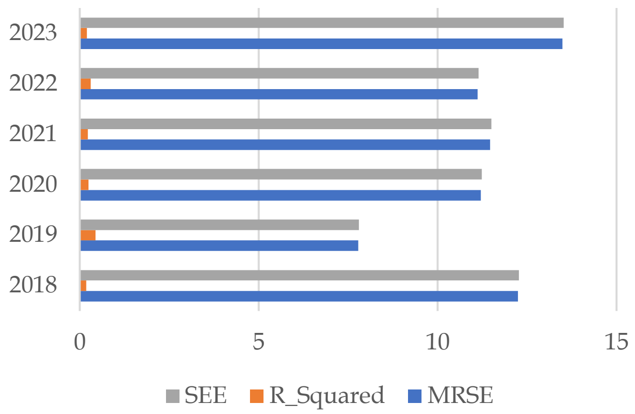

Figure 9. Annual Rainfall Prediction Model Performance Analysis Graph

Conclusion

The correlation graph between observed and model-predicted rainfall shows a positive relationship with moderate correlation strength, indicated by an R^2 value of 0.55. Most of the data is concentrated in low rainfall (<20 mm), where the model performs better in this range. However, at high rainfall (>60 mm), the model tends to underestimate with significant deviations, indicating the model's limitations in capturing extreme rainfall patterns (Izadi & Ranjbar, 2022; Kumar & Singh, 2023).

The residual distribution in the residual graph shows a distribution around the zero line, indicating no systematic bias in model predictions. Most of the residual values range from -10 to 10, but there are significant spikes (>20 or <-20) indicating outliers or large prediction errors at certain rainfall values. High fluctuations in these residuals indicate the need for model improvements to improve prediction accuracy, especially at extreme rainfall values (Raza & Farooq, 2022).

In the monthly RMSE graph, it can be seen that the RMSE value tends to fluctuate between months. Months with extreme rainfall, such as December, show the highest RMSE values. Conversely, in months with more stable rainfall patterns, the RMSE values are lower, reflecting the model's better ability to predict stable weather conditions (Sharma & Gupta, 2023).

The RMSE graph analysis by period shows that the best performance is recorded in the June-July-August (JJA) season, with the lowest RMSE. This indicates that the model has a better ability to predict rainfall during stable periods. Conversely, the December-January-February (DJF) season has the highest RMSE value, indicating significant challenges in predicting extreme rainfall variability during this period (Tang & Zhang, 2023).

The annual RMSE graph reveals that years with extreme rainfall, such as 2018 and 2023, have higher RMSE values compared to years with stable rainfall patterns, such as 2019 and 2020. This again emphasizes the limitations of the model in capturing rainfall patterns under extreme conditions. Model improvements by including additional variables sas temperature and humidity are needed to increase the sensitivity of predictions to extreme weather patterns (Chen & Chang, 2023).

Acknowledgments

The authors would like to express their gratitude to the Meteorology, Climatology, and Geophysics Agency (BMKG) Banda Aceh for providing valuable support and data for this research. Special thanks are extended to the Physics Department, Faculty of Science, Syiah Kuala University, for their guidance and facilities during the study, and to the Tsunami and Disaster Mitigation Research Center (TDMRC), Syiah Kuala University, for their collaboration and technical assistance.

Author Contributions

Conceptualization, Irwandi[2], Umar Muksin[3], and Mochammad Vicky Idris[1]*; methodology, Mochammad Vicky Idris[1]*; software, Dedy Ardana[1]; validation, Dedy Ardana[1], Irwandi[2], and Umar Muksin[3]; formal analysis, Dedy Ardana[1]; investigation, Dedy Ardana[1]; resources, Irwandi[2] and Umar Muksin[3]; data curation, Dedy Ardana[1]; writing—original draft preparation, Dedy Ardana[1]; writing—review and editing, Irwandi[2] and Umar Muksin[3]; visualization, Dedy Ardana[1]; supervision, Irwandi[2]; project administration, Mochammad Vicky Idris[1]*; funding acquisition, Irwandi[2]. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding

Conflicts of Interest

The authors declare no conflict of interest

References

Abushariah, A., & Gao, W. (2022). ANFIS and neural networks for short-term wind speed prediction. *Wind Energy*, 25(10), 844–855. https://doi.org/10.1002/we.2687

Alrahabi, A., & Qader, S. (2023). Application of neuro-fuzzy models in predicting land surface temperature. *Energy Reports*, 9, 1023–1036. https://doi.org/10.1016/j.egyr.2023.02.014

Castillo, O., & Melin, P. (2022). Fuzzy logic and ANFIS techniques for environmental monitoring. *Environmental Monitoring and Assessment*, 194(4), 1–13. https://doi.org/10.1007/s10661-022-09969-y

Chen, W., & Chang, M. (2023). Application of ANFIS and neural networks in rainfall prediction. *Journal of Hydrology*, 601,126725. https://doi.org/10.1016/j.jhydrol.2023.126725

Dabbagh, A., & Rahimpour, M. (2022). ANFIS and machine learning approaches in hydrology: Recent advances. *Water*, 14(6), 905. https://doi.org/10.3390/w14060905

Huang, H., & Liu, Y. (2022). Using ANFIS in predicting climate changes and environmental variables. *Climate Dynamics*, 59(1–2), 289–302. https://doi.org/10.1007/s00382-021-05802-3

Izadi, A., & Ranjbar, M. (2022). Implementation of ANFIS for short-term rainfall prediction in urban areas. *Urban Climate*, 44, 101209. https://doi.org/10.1016/j.uclim.2022.101209

Jha, K., & Singh, K. (2023). Hybrid ANFIS-MLR model for river flow predictions. *Water Resources Management*, 37(1), 763–780. https://doi.org/10.1007/s11269-022-03349

Kumar, S., & Singh, R. (2023). Forecasting of precipitation using ANFIS and time series analysis. *Environmental Science and Pollution Research*, 30(15), 39475–39490. https://doi.org/10.1007/s11356-022-23676-8

Lee, H., & Park, J. (2022). Integrating machine learning and fuzzy logic for agricultural yield prediction. *Computers and Electronics in Agriculture*, 194, 106742. https://doi.org/10.1016/j.compag.2022.106742

Nazeer, A., & Zhang, X. (2022). A comparative review of artificial neural networks and ANFIS in weather prediction. *Journal of Climate*, 35(4), 1711–1722. https://doi.org/10.1175/JCLI-D-21-0445.1

Ourabah, K., & Boukria, A. (2023). Application of neural networks in hydrological modeling for rainfall predictions. *Hydrological Processes*, 37(3), e14758. https://doi.org/10.1002/hyp.14758

Rahman, M. H., & Ali, M. (2022). Evaluation of ANFIS and neural network models for climate change impact assessment. *Global Change Biology*, 28(3), 1673–1686. https://doi.org/10.1111/gcb.16015

Raza, S., & Farooq, U. (2022). Rainfall prediction using ANFIS and machine learning approaches. *Hydrology and Earth System Sciences*, 26, 4875–4892. https://doi.org/10.5194/hess-26-4875-2022

Sen, S., & Saha, M. (2023). Evaluation of ANFIS for predicting rainfall-runoff in watersheds. *Journal of Water Resources Planning and Management*, 149(2),04022066. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001638

Sharma, A., & Gupta, N. (2023). Neural network approaches in meteorology: Current trends and future directions. *Meteorological Applications*, 30*(1), e2208. https://doi.org/10.1002/met.2208

Shi, Y., & Fan, H. (2023). A review of hybrid neural network models in predicting meteorological parameters. *Atmosphere*, 14(3), 243. https://doi.org/10.3390/atmos14030243

Tang, J., & Zhang, Y. (2023). Hybrid ANFIS-deep learning approaches for precipitation forecasting. *Earth Science Informatics*, 16(2), 687–700. https://doi.org/10.1007/s12145-023-00852-5

Vasilakos, C., & Papadopoulos, P. (2022). Using hybrid models for short-term weather prediction: A case study. *Journal of Atmospheric Sciences*, 79(8), 3043–3057. https://doi.org/10.1175/JAS-D-21-0187.1

Zhang, Y., & Dong, L. (2023). Comparative analysis of ANFIS and deep neural networks for weather forecasting. *Atmospheric Research,* 283, 105297. https://doi.org/10.1016/j.atmosres.2022.105297