JPPIPA 10(12) (2024)

Jurnal Penelitian Pendidikan IPA

Journal of Research in Science Education

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

Communication Satellite-Based Rainfall Estimation for Flood Mitigation in Papua

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Received: July 06, 2024
Revised: November 21, 2024
Accepted: December 25, 2024
Published: December 31, 2024

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DOI: 10.29303/jppipa.v10i12.8409

Abstract: Papua, an equatorial region in Indonesia, faces unique geographical and natural challenges, including heavy annual rainfall. This heavy rainfall increases flooding risks and impacts infrastructure, the economy, and daily life. Despite the importance of rain gauges for monitoring floods and climate change, Papua's difficult geography and limited transportation infrastructure hinder their installation and maintenance. In this work, we investigate a deep learning one-dimensional convolution neural network (1DCNN) model to estimate rainfall intensity using energy per symbol to noise power density ratio (Es/No) of the signals received from a communication satellite signal coupled with additional data representing satellite daily movement. The findings of this study demonstrate that the performance of the proposed model has a higher accuracy for moderate to heavy rainfall than for light rainfall. The NRMSE values for light rain, moderate rain, and heavy rain are 47.09, 31.78, and 33.58%, respectively. These results show that this method is promising for monitoring heavy rainfall as a flood mitigation effort. However, there is still room to improve the accuracy of the estimation such as using other secondary data that is highly correlated with rain at the satellite transceiver location.

Keywords: Deep learning; One-dimensional convolution neural network; Rainfall prediction

Introduction

Papua is one of the equatorial regions in Indonesia that has unique geographical conditions and significant natural challenges. The geographical conditions rich in mountains and tropical rainforests make this area one of the highest annual rainfall in Indonesia (Aldrian & Susanto, 2003; Hamada et al., 2002). In addition, The diurnal cycle of rainfall across Indonesia is one of the strongest in the tropics (Lin et al., 2000; Sorooshian et al., 2002) and plays a significant role in the global climate (Neale & Slingo, 2003). Heavy rainfall not only increases the risk of flooding but can also impact the infrastructure, economy and daily lives of local residents. For example, the city of Sorong, located in West Papua province, has experienced frequent flooding due to high annual rainfall (Arief et al., 2019).

Rain gauges are one of the key technologies in monitoring and predicting potential floods and climate change (Mujiati et al., 2021; Wang et al., 2008). By increasing the density of the rain gauge network, the ability to predict and provide early warning of potential natural disasters such as flash floods and landslides can be improved. However, the geographical conditions and limited transportation infrastructure in the Papua region provide significant obstacles to the installation and maintenance of rain gauges. The application of the latest technology in weather monitoring, such as remote sensing and satellite technology (Purwanto & Paiman, 2023; Ramadhan et al., 2022), can help overcome these geographical and accessibility constraints.

In the last decade there have been several studies related to rainfall measurement by utilizing satellite signal reception used for data communication and internet access. Satellites with high frequencies ranging

How to Cite:
Mardyansyah, R. Y., Kurniawan, B., Soekirno, S., & Nuryanto, D. E. (2024). Communication Satellite-Based Rainfall Estimation for Flood Mitigation in Papua. *Jurnal Penelitian Pendidikan IPA*, *10*(12), 11326–11335. https://doi.org/10.29303/jppipa.v10i12.8409

from Ku-band to Q/V-band have been studied by several authors (Adirosi et al., 2017; Gharanjik et al., 2018b; Gharanjik et al., 2018a; Rossi et al., 2022; Xu et al., 2017) because in that frequency range, electromagnetic waves correlate linearly with rainfall intensity (Arslan et al., 2018; Upton et al., 2005). In addition, a machine learning technique approach for rainfall estimation by extracting features from the satellite signals has also been previously investigated (Diba et al., 2021; Xian et al., 2020b). However, most of the research on satellite-based rainfall prediction is conducted in subtropical regions with stratiform, evenly distributed rains. Therefore, there is a research challenge for tropical regions where rainfall originates from convective clouds with a narrower coverage than stratiform rainfall (Qian, 2008; Worku et al., 2019; Yamanaka et al., 2018).

In this study, rainfall intensity estimation is carried out by utilizing satellite communication devices that are widely used in the Papua region as data communication infrastructure and internet access. The method used is a deep learning model to estimate rainfall intensity directly from satellite signal reception parameters coupled with two additional parameters as features that have never been used in previous studies. The study was conducted in the city of Sorong to determine the performance of the model to predict rainfall that can lead to flood disasters.

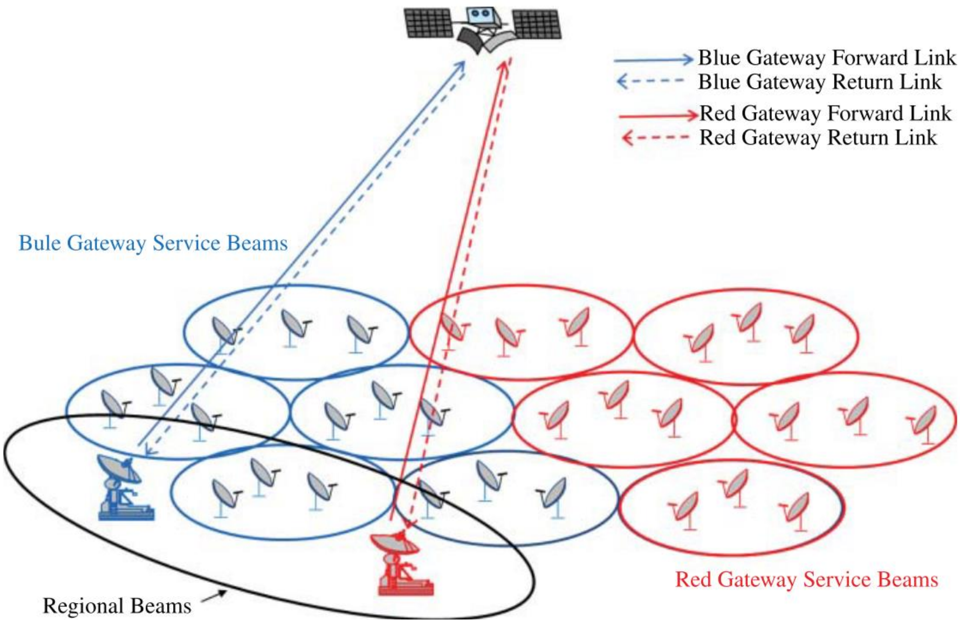


Figure 1. The spot beams-based satellite gateway configuration and servicing (Ippolito, 2017)

Method

The High Throughput Satellite (HTS) system offers two-way communication with electromagnetic wave media using Geostationary satellites orbiting at an altitude of about 36 thousand kilometers above the equator. This communication system connects the satellite gateway (GW) and satellite transceiver (ST) on the user terminal which enables interactive services such as high-speed internet. High data rate capacity is obtained from HTS technology that applies multiple high-capacity spot beams in a region with several GWs as shown in Figure 1. The signal transmission path from GW to ST is called forward link (FWD) while the reverse path is return link (RTN).

In this paper we propose a rainfall estimation approach using energy per symbol to noise power spectral density ratio (Es/No) of the signals emitted by GW and received by ST. The ST receives Ku-band downlink signals from Apstar-5C's 138 east orbital position. The ST then sends the Es/No data back periodically to the network management system server located at GW. The collected Es/No data is then processed based on a model that connects rainfall intensity and signal attenuation to obtain hourly rainfall estimates. The signal attenuation on the FWD path is only affected by the rain that occurs along the path between the satellite and ST. This is because there is an automatic power adjustment mechanism if there is rain on the GW side (Gharanjik et al., 2018b).

Figure 2 shows the correlation between the Es/No signal received by ST and the rain rate (RR) in millimeters per hour (mm/h) highlighted with green color. The Es/No and RR shown are samples of research data at the study site.

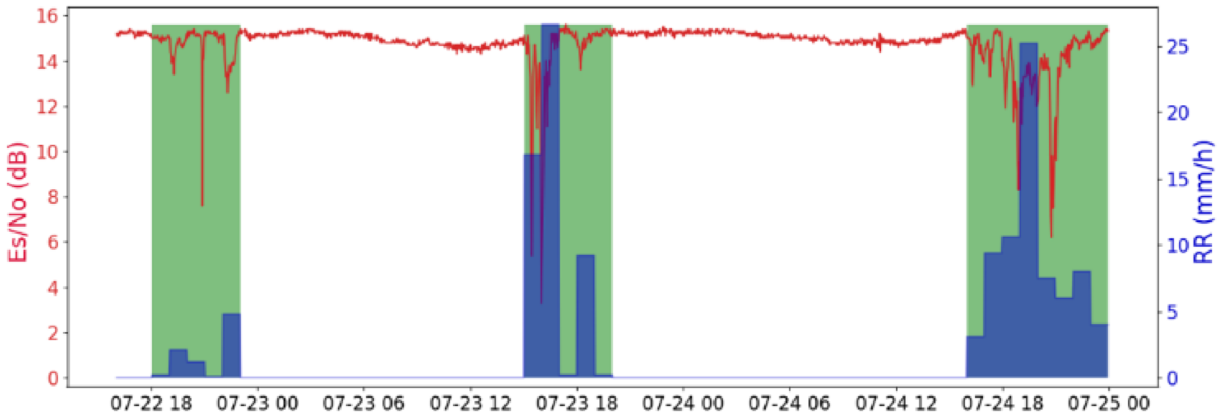


Figure 2. Data sample of the Es/No in decibels (dB) and RR in millimeters per hour (mm/h)

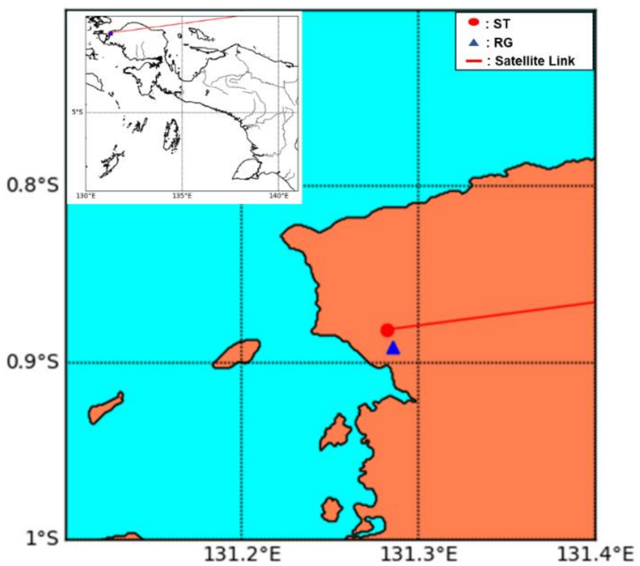


Figure 3. Location of satellite transceiver and rain gauge of the study in Sorong, Papua

The study was conducted in the city of Sorong, Papua where there is an ST from the satellite communication network owned by Telkomsat company. Rainfall intensity data is obtained from the rain gauge (RG) at the Sorong meteorological station which is about 1 km away as shown in Figure 3.

The red line indicates the direction of the link between the ST and the satellite which is in a stationary orbit position at 138^{o} East. The Sorong Meteorological Station is a weather observation facility that is under the ownership of the Meteorological Climatological and Geophysical Agency of Indonesia.

In this work, we use the deep learning one-dimensional convolution neural network (1DCNN) model which is part of deep learning (Kumar et al., 2019). The 1DCNN is a specialized type of CNN used for processing one-dimensional data, like sequences or time series (Allamy & Koerich, 2022; Chen et al., 2021; Chen & Lee, 2021; Kiranyaz et al., 2021; Singh et al., 2021; Yang et al., 2021). Time series data from microwave link and weather radar has also been investigated to estimate rainfall using 1DCNN by previous authors (Mishra et al., 2020; Polz et al., 2020; Zhang et al., 2021). The 1DCNN employs convolutional layers with filters to capture local patterns and features in the input data. In general, it consists of convolutional layer, pooling layer, dense layer and output layer which acts as the prediction output of the model (Islami et al., 2024; Noor et al., 2023). The architecture of 1DCNN is shown in Figure 4 where the output part is the estimated hourly rainfall intensity.

Figure 5 presents the flow chart of the rainfall estimation model which consists of 3 stages: 1. data preprocessing, 2. model construction, and 3. model evaluation. The dataset of input features is 2-minute Es/No data and hourly rain rate output paired for each sample. In this study we propose an additional 2 features in the input of 1DCNN in the form of encoded hour of timestamp for each sample because naturally the signal received by ST has daily fluctuations due to orbital perturbations (Giannetti & Reggiannini, 2021). The expression of the vector features $\mathbf{X}_i$ of the proposed 1DCNN model is shown as follows:

$$\left.\begin{aligned} X_i &= [X_a; X_b] \\ X_a &= [x_1; x_2; \ldots; x_{29}; x_{30}] \\ X_b &= [x_{31}; x_{32}] \\ x_{31} &= \sin(2\pi * h_i/24) \\ x_{32} &= \cos(2\pi * h_i/24) \end{aligned}\right\} \qquad (1)$$

where X_a is the one-hour sample of Es/No data and X_b is the encoded hour of timestamp for each sample.

The first stage in data preprocessing is to use linear interpolation on Es/No data to fill in any gaps caused by the absence of a satellite connection link. The data is then normalized, a process that has been investigated by various authors (Kumah et al., 2020; Polz et al., 2020). Interpolation is restricted to data gaps of up to six minutes. As part of the normalization procedure, the median value determined from the entirety of the prior and subsequent 12-hour data is subtracted for each time step. After interpolation and normalization, the dataset is divided into training and testing sets. The model is trained with datasets ranging from December 2019 to May 2023. For performance evaluation, we employ sample data from June 2023 to February 2024 as data test set. Samples that have data gaps are discarded in the data cleaning process.

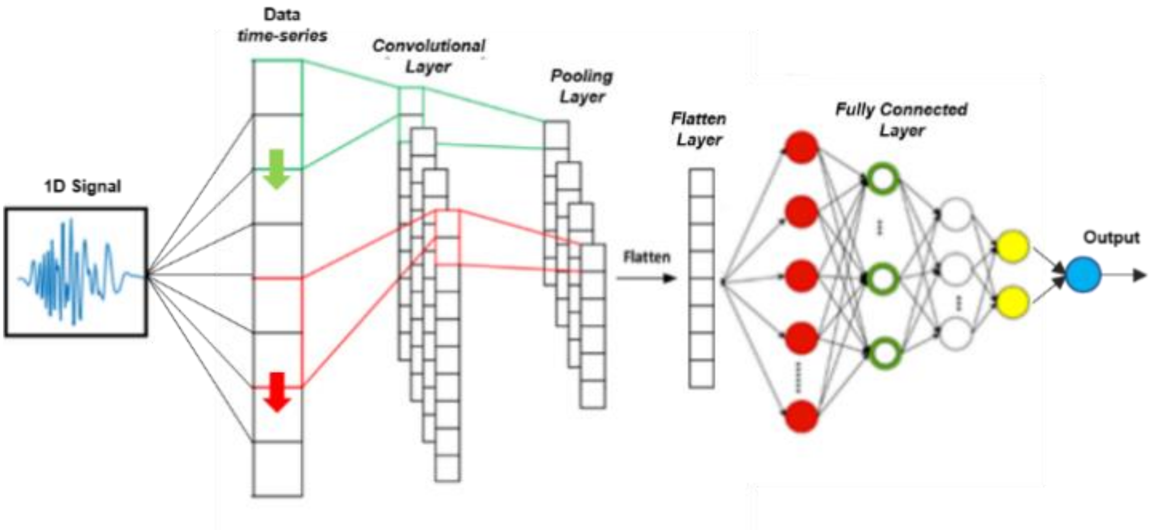


Figure 4. The architecture of 1DCNN

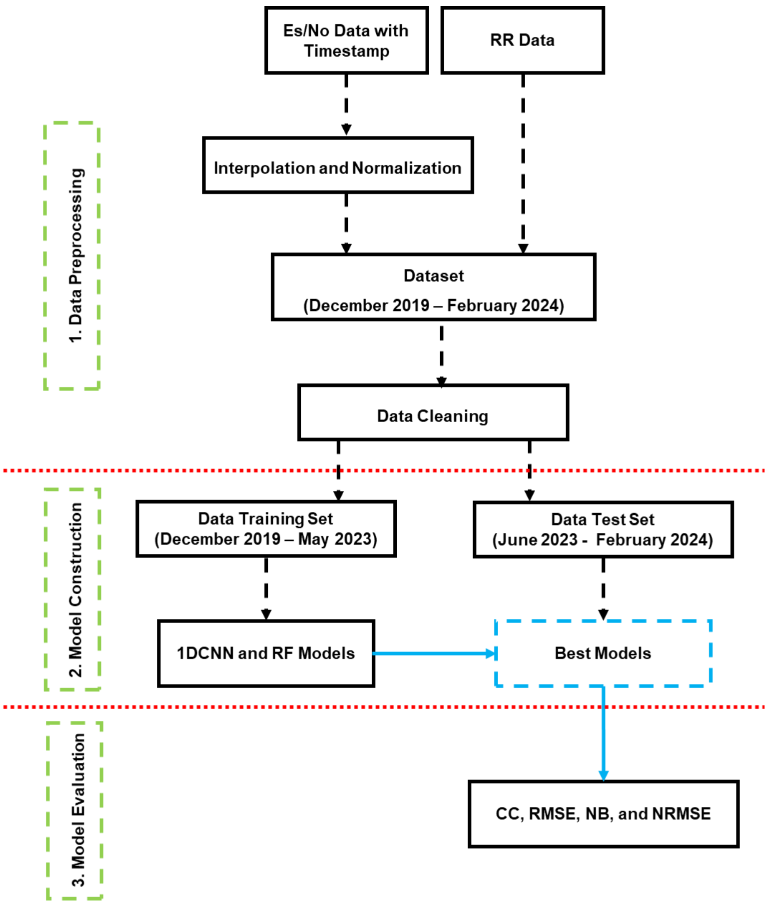


Figure 5. The flow chart of the rainfall estimation model

In the final stage, the performance of the proposed model is tested both as a whole test data and partially based on rainfall categories. The correlation coefficient (CC) and root-mean- square error (RMSE) are chosen as the overall evaluation metrics while for partial evaluation normalized bias (NB) and normalized root-mean- square error (RMSE) are used as follows:

$$CC = \frac{\sum_{i=1}^{n}(P_i - \overline{P})^2(A_i - \overline{A})}{\sqrt{\sum_{i=1}^{n}(P_i - \overline{P})^2}\sqrt{(A_i - \overline{A})^2}} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} * \sum_{i=1}^{n}(P_i - A_i)^2} \quad (3)$$

$$NB = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} A_i} - 1 \quad (4)$$

$$NRMSE = \frac{RMSE}{A_{max} - A_{min}} \quad (5)$$

where A_i is actual value, P_i is the predicted value, n sample size, $\overline{A}$ mean of the n actual values, $\overline{P}$ mean of the n predicted values, A_{max} is the maximum of n actual values and A_{min} is the minimal of n actual values. The NB allows to evaluate the quality of the difference of the two datasets: negative NB values indicate an underestimation of ST with respect to the rain gauge, while positive NB indicate an overestimation of them. Meanwhile, NRMSE is better used for comparison of regression values against datasets with different scales (Moursi et al., 2022).

Result and Discussion

In this section, we evaluate the performance of the proposed model. We use data from October 1, 2019 to February 28, 2023 in training 1DCNN as a regression model to calculate RR. Furthermore, the best model obtained from many trainings was evaluated with test data in the period of March 1, 2023 to February 29, 2024. Figure 6 depicts the comparison of hourly rainfall predicted by ST and measured by rain gauge (actual rain rate). The CC and RMSE for rain rate estimation are 0.83 and 1.491 mm/h, respectively. These results are in line with previous research that evaluated the performance of long-term rainfall estimation (Xian et al., 2020b; Zhao et al., 2021).

These findings indicate that the proposed model is good for measuring rainfall from satellite signals in the Papua region where there are still many valley and mountain areas and experiences high annual average rainfall (Zaini et al., 2023).

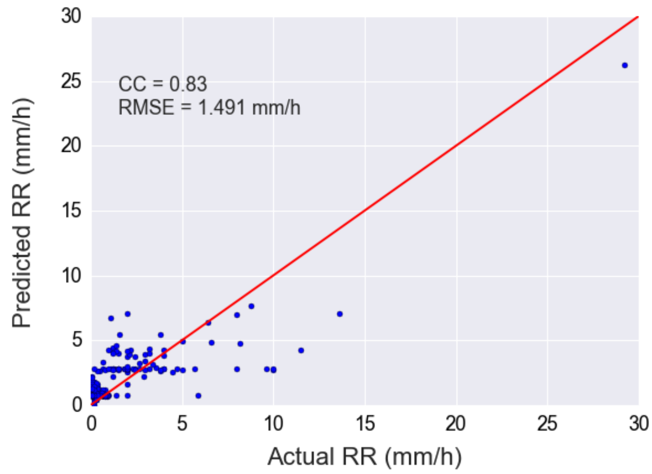


Figure 6. Scatter plot between hourly rainfall predicted by satellite transceiver (y-axis) and rain gauge (x-axis)

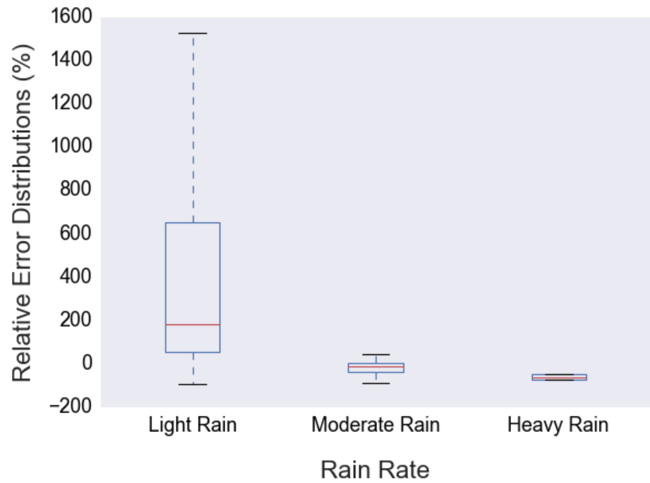
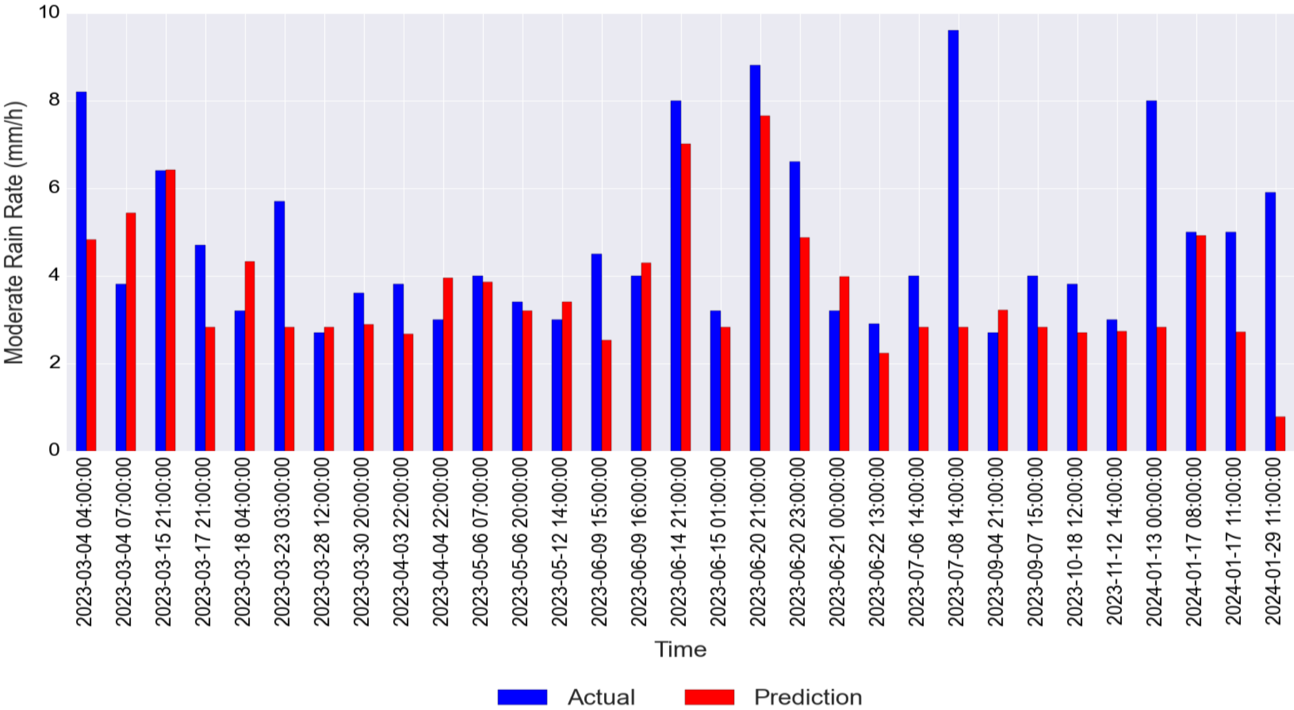
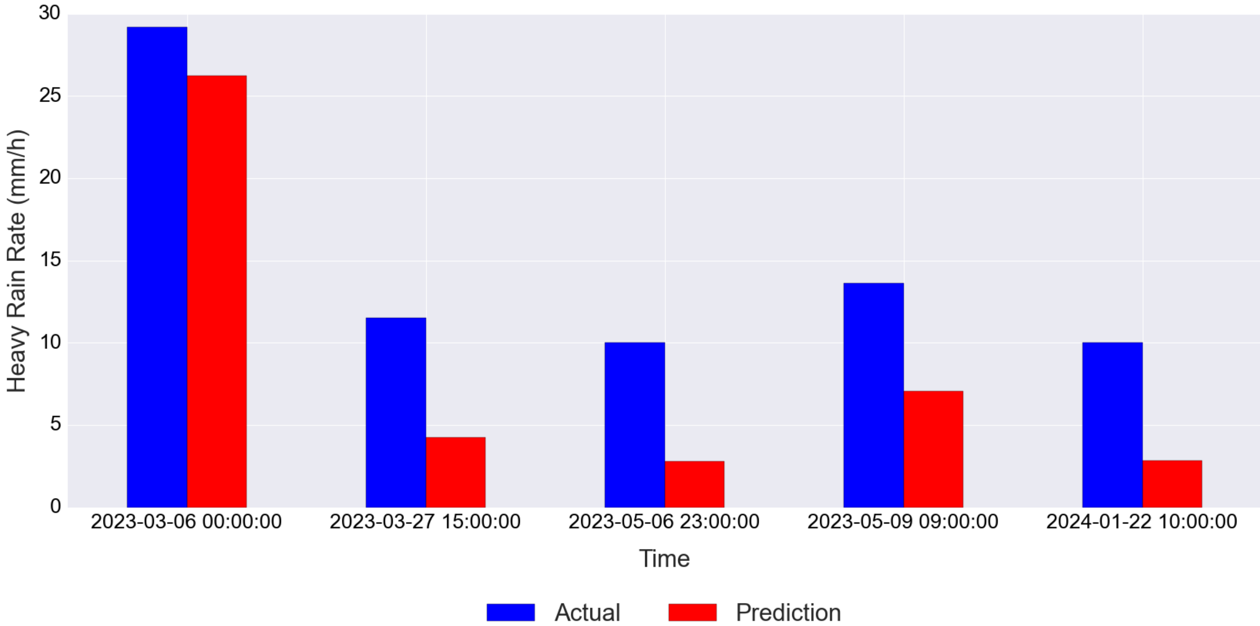


Figure 7. The statistical distribution of the relative percentage error of each rainfall categories

To utilize this measurement technique approach in the prevention of flash floods and landslides caused by significant rainfall, we divide rainfall events into three categories according to the size of the rain intensity. The rain rate categories are divided into light rain (0-2.5 mm/h), moderate rain (2.5-10 mm/h), and heavy rain (10-50 mm/h) (Xian et al., 2020a; Xian et al., 2020b; Zhao et al., 2021). Comparison of model performance in the three categories uses the approach taken by authors in Colli et al. (2019) by means of boxplots ignoring outliers in Figure 7. The boxplot consists of vertical bars that represent the statistical distribution of the quantiles of the relative percentage error. It can be observed that, the proposed model is better at moderate and heavy rain with error medians of –13.03 and – 63.04% compared to light rain of more than 180%. The error distribution at moderate and heavy rain is also better than that at light rain as indicated by the width of the boxes. Above results demonstrate that the proposed model has better accuracy in moderate and heavy rain than light rain.



(a)



(b)

Figure 8. Bar plot of the predicted and actual rain rates in millimeters per hour. (a) Moderate rain. (b) Heavy rain

The performance comparison on the next rain rate category is illustrated in Table I through the values of NB (in %) and NRMSE (in %). Again, the performance of the proposed model is better in moderate and heavy rain than in light rain. The NB (NRMSE) values for moderate rain are –23% (31.78%) and heavy rain are –42% (33.58%). These values compare favorably with light rain of 100.36% (47.09%) which overestimates rain rate characterized by positive NB values. Underestimation in moderate and heavy rain (negative values of NB) is in line with the results of similar recent research (Angeloni et al., 2024). This is also because the rain gauge provides a point measurement, while the attenuation of the satellite signal is affected by rain along its path of a few kilometers. Therefore, additional secondary data that is highly correlative with rain at the ST site is required to improve the accuracy of the estimation (Wardani et al., 2023).

Finally, Figure 8 shows the predicted and actual rain rates. It can be seen that all rainfall both moderate (Figure 8a) and heavy rain (Figure 8b) were detected accurately by the proposed model and there is a relative agreement between predicted and actual values. However, there is still room for improving the performance of the proposed model by conducting research on co-located rain gauge and satellite transceiver. In addition, as an advantage of machine learning is that it can use additional features such as surface meteorological data or satellite remote sensing data to improve the accuracy of the estimation such as research that has been done by previous authors (Kumah et al., 2022; Zhang et al., 2021).

Table 1. Performance of the proposed model for each rainfall categories

Rainfall Categories	NB (%)	NRMSE (%)
Light Rain	1.36	47.09
Moderate Rain	–0.23	31.78
Heavy Rain	–0.42	33.58

Conclusion

Papua, an equatorial region in Indonesia, faces unique geographical and natural challenges, including heavy annual rainfall. This heavy rainfall increases flooding risks and impacts infrastructure, the economy, and daily life. Despite the importance of rain gauges for monitoring floods and climate change, Papua's difficult geography and limited transportation infrastructure hinder their installation and maintenance. As an alternative method of measuring rainfall for regions where the density of rain gauge networks is still low, many studies in estimating rainfall have been conducted using satellite link signals. The proposed model adopts the 1DCNN regression technique from the reception signal of the HTS communication system by adding model features in the form of timestamp data samples. The study was conducted in Sorong city which is prone to flooding due to the high average level of rainfall. Sorong city is located in Papua region where the number of rain gauges per area is relatively less compared to other regions in Indonesia. The performance of the proposed model has a higher accuracy for moderate to heavy rainfall than for light rainfall. These results show that this method is promising for monitoring heavy rainfall as a flood mitigation effort. However, there is still room to improve the accuracy of the estimation such as using other secondary data that is highly correlated with rain at the satellite transceiver location.

Acknowledgments

The research is supported by Badan Riset dan Inovasi Nasional's Degree by Research program. Badan Meteorologi Klimatologi dan Geofisika dan PT. Telkomsat Indonesia are also thanked for supplying the data.

Author Contributions

R.Y.M. and D.E.N. suggested the idea. R.Y.M. performed modelling, data analysis, wrote the paper, revision and proofreading. B.K. and S.S. reviewed the paper. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by Badan Riset dan Inovasi Nasional's Degree by Research program and Badan Meteorologi Klimatologi dan Geofisika and "The APC was funded by Badan Meteorologi Klimatologi dan Geofisika".

Conflicts of Interest

The authors declare no conflict of interest.

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