Journal of Computation Physics and Earth Science
ISSN: 2776-2521 (online)
Volume 5, Number 1, April 2025, Page 59 - 66
https://journal.physan.org/index.php/jocpes/index

Rainfall Trend Analysis in Tangerang City Using Linear Regression and Random Forest

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Article Info

Article history:

Received March 6, 2025
Revised March 11, 2025
Accepted March 12, 2025

Keywords:

Rainfall
Linear Regression
Random Forest
Machine Learning

A B S T R A C T

Rainfall is an important element in the hydrological cycle that has a significant impact on the environment and human life, especially in tropical areas such as Tangerang City. This study aims to analyze annual and monthly rainfall trends and compare the performance of Linear Regression and Random Forest methods in predicting daily rainfall. Daily rainfall data from the Soekarno-Hatta Meteorological Station during the period 2019–2024 are used as model input. The results show that Random Forest has superior performance in capturing complex and extreme rainfall fluctuation patterns, with lower Mean Squared Error (MSE) and higher R-squared (R^2) compared to Linear Regression. Linear Regression is only able to predict linear trends simply but is less accurate in handling non-linear variations. This study provides practical contributions to flood risk mitigation, water resource management, and urban infrastructure planning. The development of more accurate prediction models, such as Random Forest, is an important step in supporting climate change adaptation and environmental management in urban areas. Further research is recommended to include additional atmospheric variables and more complex validation techniques to improve prediction accuracy.

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1. INTRODUCTION

Rainfall is a major element in the hydrological cycle that has a significant impact on human life, especially in tropical areas such as Indonesia (Barrera-Animas et al., 2022). Tangerang City, part of the Jabodetabek urban area, faces major challenges due to changes in extreme rainfall patterns exacerbated by rapid urbanization. Data shows that urbanization has reduced water catchment areas by 30% in the last decade, increasing the risk of flooding that causes economic losses of up to billions of rupiah each year, damages infrastructure, and disrupts community activities. Global climate change has worsened the situation, with the intensity of extreme rainfall in Jabodetabek increasing by 20% in the last 10 years (BMKG, 2023).

Similar studies in various regions have shown the success of rainfall prediction methods using machine learning algorithms. In China and South Korea, approaches such as Random Forest, LSTM, and Support Vector Machines (SVM) were able to capture non-linear patterns and seasonal fluctuations with high accuracy (Bhusal et al., 2022). In Indonesia, research using Gradient Boosting showed success in capturing seasonal trends. Although models such as LSTM offer advantages for complex data, Linear Regression remains relevant due to its simplicity and ease of interpretation. However, to capture non-linear patterns and extreme rainfall, Random Forest is superior because it is able to process complex relationships in data with a low risk of overfitting (Sarvani et al., 2021).

This study utilizes the daily rainfall dataset from Soekarno-Hatta Meteorological Station during the period 2019–2024 to analyze rainfall trends in Tangerang City. By comparing the performance of Linear Regression and Random Forest, this study aims to provide practical solutions in flood risk mitigation, water resource management, and urban infrastructure planning. The results of the study are expected to support more adaptive management of climate change and become the basis for developing rainfall prediction models in the future.

2. DATA AND METHOD

This study uses a daily rainfall dataset collected by the Soekarno-Hatta Meteorological Station for the period 2019 to 2024. This dataset includes information on rainfall intensity in millimeters (mm) and observation time. A detailed explanation of the data is as follows:

1.1 Dataset

The dataset used is daily rainfall data collected by the Soekarno-Hatta Meteorological Station from 2019 to 2024. This data includes:

a) Dependent Variable: Daily rainfall (mm).
b) Independent Variable: Time (date in ordinal format).
c) Data Issue: There are values “8888” (data not measured) and “9999” (data not available), which are processed or removed during data preprocessing.

1.2 Data Preprocessing

Data preprocessing is done to ensure the quality and consistency of the dataset before it is used in the analysis. Preprocessing steps include:

a) Removes the values "8888" and "9999" from the dataset.
b) Filling missing values using linear interpolation.
c) Outlier analysis using the Interquartile Range (IQR) method.
d) Transform time into an ordinal format for use as model input.

1.3 Analysis Method

1.3.1 Linear Regression

Linear Regression is used to model the linear relationship between the independent variable (time) and the dependent variable (daily rainfall) (Colombia, 2017). Linear Regression is expected to capture a simple linear relationship between time and rainfall intensity. This model assumes that daily rainfall can be predicted based on time (in ordinal format). The model function for Linear Regression is as follows:

$$\text{Rainfall} = \beta 0 + \beta 1 \;.\; \text{Time}$$

Where:

- $\beta 0$ is the intercept (constant).
- $\beta 1$ is the regression coefficient for the time variable.
- The time is converted into ordinal format, which is the order of dates during the period 2019-2024.

Model evaluation is performed using two main metrics:

- Mean Squared Error (MSE): To measure the model error in predicting rainfall.
- R-squared (R^2): To evaluate how well the model can explain the variation in rainfall data over time.

1.3.2 Random Forest

Random Forest Regressor is used to capture more complex and non-linear patterns in daily rainfall data (Diez-Sierra & del Jesus, 2019). Random Forest can handle interactions between multiple factors and has the ability to correct prediction errors from linear models. The parameters used in this model are:

- Number of decision trees: 100.
- Data distribution: 70% for training and 30% for testing.
- Model evaluation: The model is evaluated using Mean Squared Error (MSE) and R-squared (R^2), which allows us to measure the model error and how well the Random Forest is in predicting rainfall.

By using Random Forest, the model is expected to be able to capture more complex seasonal patterns and extreme rainfall fluctuations that cannot be handled by Linear Regression.

1.4 Model Evaluation and Comparison Process

a) Model Performance Comparison: After both models are trained, the prediction results from Linear Regression and Random Forest will be compared with actual data which aims to measure the effectiveness of each method in predicting rainfall.

b) Evaluation Metrics: Evaluation is done using MSE to measure how well the model predicts rainfall values and R-squared (R^2) to evaluate how well the model explains data variation.

c) Seasonal Trend Analysis: In addition to evaluating prediction errors, analysis will be conducted to see whether the model can capture seasonal trends in rainfall and how the model handles extreme rainfall that occurs throughout the year.

1.5 Data Visualization

After the data is processed and the model is trained, visualization is performed to provide a better understanding of the rainfall distribution and model performance:

a) Annual Rainfall Distribution Graph: To illustrate the distribution of annual rainfall from 2019 to 2024, both based on actual data and prediction results from both models.

b) Average Monthly Rainfall Graph: To see how rainfall varies each month throughout the year and verify whether the model can capture monthly fluctuations well.

c) Prediction vs Actual Data Scatter Graph: To compare model predictions with actual data, and to assess the suitability of the results obtained from Linear Regression and Random Forest.

1.6 Evaluation and Interpretation Results

After the models are trained and evaluated, the prediction results from Linear Regression and Random Forest will be compared with the actual data to see how well each model predicts daily rainfall. This evaluation aims to measure the accuracy of the model on seasonal trends and the model's ability to handle extreme rainfall (Fuladipanah et al., 2024). Based on the evaluation results, a discussion was conducted to identify the advantages and disadvantages of each model in the context of urban planning and water resources management.

a) Strengths and Weaknesses of the Model: In interpreting the results, we will discuss the strengths of Linear Regression in terms of its interpretability and simplicity, as well as the strengths of Random Forest in handling more complex data patterns.

b) Practical Applications: The discussion will also cover how this model can be used in urban planning and water resources management, as well as provide recommendations for future use of the model.

1.7 Discussion Sgnificance

The results of this study contribute to water resource management and flood risk mitigation. By using Linear Regression and Random Forest models, this study can help predict rainfall more accurately, which has implications for:

a) Flood Risk Mitigation: Provides rainfall predictions that can be used for flood mitigation planning and city infrastructure.

b) Infrastructure Planning: Assists in planning infrastructure development that can cope with extreme rainfall.

c) Water Management: Providing further insights for more efficient water management in Tangerang City.

3. RESULTS

3.1 Annual Rainfall Distribution

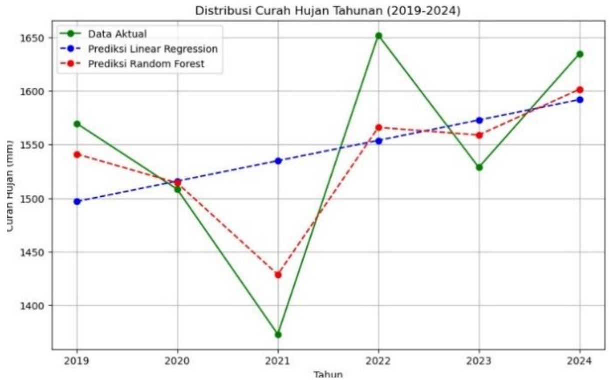

Figure 3.1 Distribution of Rainfall

Figure 3.1 shows the distribution of annual rainfall based on actual data and predictions from the Linear Regression and Random Forest models.

a) Actual data shows rainfall fluctuations between 1400 mm to 1650 mm during 2019–2024. 2021 experienced a significant decrease with the lowest rainfall of around 1380 mm, while 2024 recorded the highest increase in rainfall of around 1650 mm.

b) Linear Regression predictions tend to form a linear line with gradual increases. This model fails to capture the sharp decline in 2021 and shows an overly simplistic trend.

c) Random Forest predictions more accurately follow actual data patterns, including a significant decline in 2021 and a sharp increase in 2024.

Initial Conclusion: Random Forest is better able to capture annual fluctuation patterns than Linear Regression.

3.2 Average Monthly Rainfall

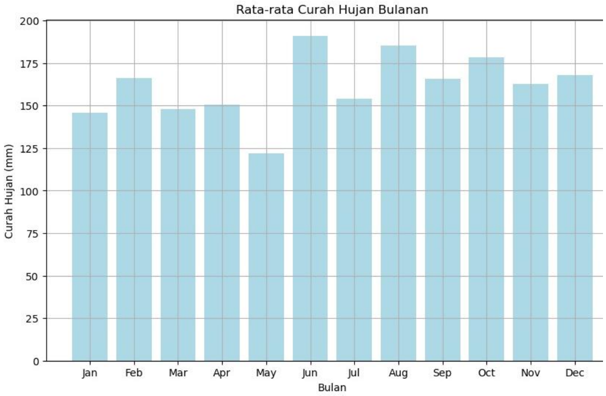

Figure 3.2 Average Monthly Rainfall

Figure 3.2 shows the average monthly rainfall during the study period.

a) Peak rainfall occurs in June (about 190 mm) and August (about 185 mm), showing a pattern of increase during the rainy season.
b) May has the lowest rainfall (around 120 mm), indicating the transition to the dry season.

Observation: The seasonal rainfall pattern follows a tropical trend, with a significant increase in the middle of the year and small fluctuations at the end of the year.

3.3 Scatter Plot Prediction vs Actual Data

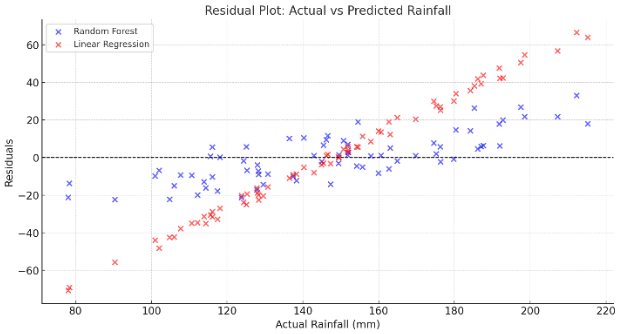

Figure 3.3 Scatter Plot Prediction vs Actual Data

Scatter Plot Interpretation Prediction vs Actual Data:

a) In the residual plot, Linear Regression (marked in red) shows a larger deviation from the zero residual line, especially for extreme rainfall. This indicates that Linear Regression is unable to capture the existing non-linear pattern.
b) Meanwhile, Random Forest (marked in blue) shows residuals closer to zero, indicating better accuracy in capturing actual rainfall values.
c) Residuals in Linear Regression tend to increase with increasing rainfall intensity, while Random Forest is more stable and has a more even error distribution.
d) Significance: This plot confirms the superiority of Random Forest in capturing complex rainfall patterns compared to Linear Regression, especially at extreme rainfall values.

4. DISCUSSION

4.1 Interpretation of Results

Based on the results obtained from this study, it can be concluded that the Random Forest model has a better performance in capturing annual rainfall fluctuation patterns compared to Linear Regression. The annual rainfall distribution graph shows that Random Forest predictions are more accurate and able to follow significant changes in rainfall from year to year, including a sharp decrease in 2021 and a drastic increase in 2024. In contrast, the Linear Regression model tends to produce simpler and more linear predictions, making it less able to represent significant non-linear changes in the data. This is because

Linear Regression assumes a linear relationship between the independent variable (time) and the dependent variable (rainfall), while Random Forest is more flexible in capturing complex patterns and variables that interact non-linearly.

In addition, the average monthly rainfall pattern confirms the existence of a seasonal trend consistent with the tropical climate in Tangerang City. The peak rainfall occurs in the middle of the year, especially in June and August, indicating high rainfall due to the influence of the rainy season. Conversely, May has the lowest rainfall, reflecting the transition to the dry season. This trend is in accordance with the characteristics of a tropical climate influenced by the monsoon, where rainfall tends to increase in certain periods each year. These results prove that both models, Linear Regression and Random Forest, can detect seasonal trends, but Random Forest remains superior in predictive accuracy for more complex variations.

Furthermore, the scatter plot results between predictions and actual data strengthen the superiority of the Random Forest model. The points of the Random Forest prediction results are closer to the ideal line, indicating that this model is able to predict rainfall values better, including extreme rainfall which is usually difficult to predict. In contrast, the Linear Regression prediction points appear more scattered and move away from the ideal line, especially at extreme values. This indicates that Linear Regression tends to have greater deviations when dealing with significant rainfall values or those outside the average pattern. Thus, the results of this study confirm the superiority of Random Forests in capturing non-linear patterns and rainfall fluctuations, which are difficult to handle by simple linear models such as Linear Regression.

4.2 Model Performance Evaluation

In the evaluation of model performance, Linear Regression and Random Forest show different characteristics in predicting daily rainfall. Linear Regression has several advantages, namely its ease of implementation, simple interpretation, and basic ability to provide an overview of rainfall trends. This model is very suitable for cases that have a linear relationship between independent and dependent variables. However, in this study, Linear Regression has significant limitations because it is unable to capture complex non-linear patterns and extreme variations in rainfall data. As a result, the resulting predictions have a higher Mean Squared Error (MSE) and a lower R-squared (R^2) . This confirms that Linear Regression is only suitable for cases with simpler data patterns.

On the other hand, Random Forest proved to be superior in predicting rainfall. Its main advantage lies in its ability to capture complex, non-linear patterns and extreme variations in the data (Mohammed et al., 2020). This makes Random Forest more accurate in predicting rainfall, both at the mean and extreme values. With a lower MSE value and higher R^2 than Linear Regression, Random Forest managed to show better performance overall. However, the disadvantage of Random Forest lies in its complexity. This model requires a longer computation time and is more difficult to interpret than Linear Regression. However, the advantage in accuracy makes Random Forest a more appropriate choice for this study.

The results of this study provide significant contributions in various fields, especially in flood risk mitigation, water resource management, and urban infrastructure planning. With more accurate rainfall predictions, local governments and stakeholders can plan more effective drainage systems to reduce the risk of flooding during the rainy season. Information on peak rainfall can also be used to determine the location and capacity of water storage infrastructure, such as reservoirs and dams, thereby reducing the risk of drought during the dry season.

In addition, information on rainfall trends can support planning for infrastructure development that is more resilient to extreme weather (Ridwan et al., 2021) . By understanding annual and seasonal rainfall patterns, city planners can design roads, buildings, and other public facilities that are able to withstand high rainfall pressures. The results of this study can also be used as a reference for more sustainable water resource management, including irrigation planning for agricultural needs and clean water supply for the community.

4.3 Research Limitations

In this study, there are several limitations that can affect the prediction results and the contribution of the model in understanding rainfall patterns in Tangerang City. These limitations include:

a) Limited Independent Variables

This study only uses time (date in ordinal format) as an independent variable to predict rainfall. This causes the models, both Linear Regression and Random Forest, to only be able to learn temporal patterns (time-based) without considering other atmospheric factors that also affect rainfall.

b) Historical Data Limitations

The dataset used is limited to daily rainfall data from 2019 to 2024, which is relatively short to study long-term trends or rainfall anomaly patterns. A longer observation period can help the model recognize seasonal, annual, or multidecadal trends more accurately and robustly.

c) No Validation with Additional Observation Data
This study only uses one data source, namely from the Soekarno-Hatta Meteorological Station. Model validation with observation data from other weather stations or alternative sources such as satellite data can increase the reliability of the prediction results.

d) Model Performance on Extreme Data
Although Random Forest is better at capturing extreme rainfall fluctuations than Linear Regression, deviations are still seen at some high residual points. This suggests that the model requires improved parameterization or additional methods such as ensemble stacking or deep learning (e.g. LSTM) to improve prediction performance on extreme data.

e) Limitations of Model Validation
The validation technique used is still simple, and this study has not implemented k-fold cross-validation explicitly to ensure the stability of model performance. Cross-validation can minimize bias and improve the generalization ability of the model.

4.4 Discussion Significance

These results have significant practical implications, particularly in supporting urban planning and disaster mitigation. Accurate predictions of rainfall trends can be used to:

a) Flood Risk Mitigation: This information helps the government in planning better drainage infrastructure and building water catchment areas to withstand high rainfall during the rainy season.
b) Water Resources Management: This data can be used to ensure the management of reservoirs and dams during the rainy season so that water can be stored for needs during the dry season.
c) Infrastructure Planning: This predictive information supports the development of disaster-resilient infrastructure in areas prone to the impacts of extreme rainfall.

4.5 Recommendations for Further Research

To overcome the above limitations, several steps for improvement in further research are suggested:

a) Integrating additional atmospheric variables such as temperature, humidity, air pressure, and wind speed to improve model accuracy.
b) Using datasets with longer time spans to understand long-term trends.
c) Validate the model with observation data from various meteorological stations or satellite data for comparison.
d) Using more sophisticated prediction methods, such as Long Short-Term Memory (LSTM) or Gradient Boosting, to capture more complex temporal patterns.
e) Applying k-fold cross-validation to ensure the stability and reliability of model performance.

By addressing these limitations, future research is expected to provide more accurate results and make a more significant contribution to rainfall management and disaster mitigation in urban areas.

5. CONCLUSION

Based on the results of research on the analysis of rainfall trends in Tangerang City using Linear Regression and Random Forest methods, several points can be concluded as follows:

1. Annual Rainfall Distribution

Analysis of the annual rainfall distribution shows significant fluctuations during the period 2019–2024. The year 2021 experienced a drastic decrease with the lowest rainfall, while 2024 recorded the highest increase in rainfall. The Random Forest model managed to capture these fluctuations more accurately than Linear Regression, which tends to produce simpler and more linear predictions.

2. Average Monthly Rainfall Pattern

The seasonal pattern of rainfall shows a trend consistent with the characteristics of the tropical climate in Tangerang City, where the peak rainfall occurs in June and August, while the lowest rainfall is recorded in May. This indicates a significant influence of the rainy season in the middle of the year.

3. Model Performance Comparison
   - Linear Regression has the advantages of simple implementation and easy interpretation but is less able to capture non-linear patterns and extreme rainfall.
   - Random Forest shows superior performance with the ability to capture complex patterns and extreme variations in the data. Model evaluation using Mean Squared Error (MSE) and R-squared (R^2) indicates that Random Forest has lower MSE and higher R^2, making it more accurate in predicting rainfall trends compared to Linear Regression.

- The scatter plot of predictions vs. actual data reinforces the superiority of Random Forest, where predictions are closer to actual values, especially for extreme rainfall values.

4. Research Contribution

This research provides practical contributions to supporting flood risk mitigation, water resources management, and infrastructure planning in Tangerang City. Accurate prediction results can be used as a basis for planning drainage systems, regulating reservoir capacity, and developing infrastructure that is more adaptive to extreme weather.

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