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Detection of Factors Affecting Rainfall Intensity in Jakarta

Bagus Sumargo[1*], Dian Handayani[1], Alvi Pauziah Lubis[1,2], Irman Firmasyah[2], and Ika Yuni Wulansari[3]

[1]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Negeri Jakarta, Indonesia; email: bagussumargo@unj.ac.id
[2]System Dynamics Centre, IPB University, Bogor, Indonesia
[3]School of Mathematical and Physical Sciences, University of Technology Sydney, Australia

ABSTRAK

Meningkatnya intensitas curah hujan menjadi salah satu masalah terkait iklim yang paling mendesak di banyak bagian dunia. Mendeteksi faktor-faktor yang memengaruhi intensitas curah hujan memerlukan kombinasi teknologi modern, seperti satelit cuaca, sistem radar, dan model atmosfer canggih. Kondisi ekstrem (outlier) sering terjadi. Studi ini bertujuan untuk memodelkan data yang tidak simetris atau mengandung outlier. Penelitian ini mengkaji dan memodelkan regresi kuantil pada intensitas curah hujan harian di Jakarta yang memiliki kejadian curah hujan ekstrem. Hasil dari penelitian diperoleh bahwa nilai ekstrem pada data intensitas curah hujan harian di Jakarta merupakan *outlier* dan asumsi pada pemodelan menggunakan regresi linier tidak terpenuhi sehingga karakteristik dari penduga parameter berdasarkan OLS tidak mempunyai sifat BLUE. Pada pemodelan dengan regresi kuantil menggunakan enam kuantil 0,25; 0,50; 0,75; 0,95; 0,99; dan 0,9999 dengan pertimbangan nilai-nilai kuantil tersebut merepresentasikan seluruh bagian sebaran data termasuk nilai ekstrem, diperoleh bahwa faktor yang memengaruhi intensitas curah hujan di Jakarta berbeda pada setiap kondisi intensitas curah hujan. Model terbaik ditunjukkan oleh kuantil 0,999 dengan nilai koefisien determinasi sebesar 58,21%. Berdasarkan model terbaik diketahui bahwa yang mempengaruhi curah hujan ekstrem adalah suhu maksimum, suhu titik embun, kelembapan udara, kecepatan angin, tekanan udara, dan lama penyinaran. Penelitian ini mengindikasikan bahwa regresi kuantil dapat memberikan wawasan yang lebih rinci tentang bagaimana variabel-variabel tersebut mempengaruhi intensitas curah hujan pada berbagai kondisi curah hujan mulai dari curah hujan rendah sampai dengan curah hujan ekstrem.

Kata kunci: Intensitas Curah Hujan, Kuantil, *Ordinary Least Square*, *Outlier*, Regresi Kuantil, *Robust*.

ABSTRACT

The increased intensity of rainfall is becoming one of the most pressing climate-related issues in many parts of the world. Detecting the factors that affect rainfall intensity requires a combination of modern technologies, such as weather satellites, radar systems, and advanced atmospheric models. Extreme conditions (outliers) often occur. This study aims to model data that is not symmetric or contains outliers. This study examines and models quantile regression on daily rainfall intensity in Jakarta which has extreme rainfall events. The results of the study found that the extreme values in the daily rainfall intensity data in Jakarta are outliers and the assumptions on modeling using linear regression are not satisfied so that the characteristics of the parameter estimator based on OLS do not have BLUE characteristic. In modeling with quantile regression using six quantiles 0.25, 0.50, 0.75, 0.95, 0.99, and 0.9999 with consideration of these quantile values representing all parts of the data distribution including extreme values, it was found that the factors affecting rainfall intensity in Jakarta are different in each rainfall intensity condition. The best model is shown by quantile 0.999 with a coefficient of determination of 58.21%. Based on the best model, it is known that the factors affecting extreme rainfall are maximum temperature, dew point temperature, air humidity, wind speed, air pressure, and length of irradiation. This study indicates that quantile regression can provide a more detailed insight into how these variables affect rainfall intensity in various rainfall conditions ranging from low rainfall to extreme rainfall.

Keywords: Ordinary Least Square, Outliers, Quantile, Quantile Regression, Rainfall, Robust

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1. INTRODUCTION

Rainfall intensity is an important factor influencing various environmental, social, and economic systems. In recent years, several major and current issues related to rainfall intensity have emerged due to climate change, urbanization, and shifting weather patterns. These issues are critical for understanding how rainfall affects society and the environment. Detecting the factors that affect rainfall intensity requires a combination of modern technologies, such as weather satellites, radar systems, and advanced atmospheric models (Martel, J. L., Brissette, F. P., Lucas-Picher, P., Troin, M., & Arsenault, R. 2021). By monitoring atmospheric moisture, temperature, pressure systems, wind patterns, cloud development, and geographic features, meteorologists can more accurately predict when and where intense rainfall will occur. Moreover, the impacts of human activities like urbanization and deforestation are increasingly being incorporated into rainfall intensity models to account for localized changes in weather patterns. Accurate detection is essential for managing the risks associate (D. Dashkhuu, J. P. Kim, J. A. Chun, and W.-S. Lee. 2015).

Extreme daily rainfall intensity often occurs suddenly (outliers). It is interesting to study the creation of detection models for factors that affect rainfall intensity. One measure of data centering that can be used when data contains outliers is quantiles. Quantiles are cut-off points that divide the range of a probability distribution into continuous intervals of equal probability or divide the observations in a sample into equal parts (Mckay, 2019 and Manly, 2000; Chen, C., Zhang, Q., Kashani, M. H., Jun, C., Bateni, S. M., Band, S. S., Dash, S. S., & Chau, K. W. (2022)). Regression analysis that relates quantile values of the response variable to its explanatory variables is called quantile regression analysis. Quantile regression is one of the robust regressions that can provide precise and stable results on data containing outliers (Davino et al., 2014).

Indonesia is one of the tropical countries that has a high level of rainfall. The Meteorology, Climatology and Geophysics Agency (BMKG,2023) said the 2020-2022 "triple-dip" La Nina phenomenon (three consecutive years) poses a threat to many countries in the world, including Indonesia. The phenomenon had previously occurred from 1973-1975 and 1998-2001. This phenomenon will affect weather and climate patterns in Indonesia. One of them causes some parts of Indonesia to experience the rainy season earlier and increase rainfall in Indonesia in general (Aditya, F. et al. 2021; Arsyad, M, et al. 2023; Mondiana, Y. Q. 2021).

Urban areas have the potential for a higher frequency of extreme rainfall events. This is due to the higher air temperature in the city causing the potential formation of convective rain with convective clouds containing a lot of water vapor. Jakarta is the capital city of Indonesia which has a high level of rainfall and is in the lowlands. Extreme rainfall that lasts for a long time will usually cause inundation and then flood in low-lying areas (Nurjani in Nugroho, 2022).

Quantile regression is mostly applied in the field of meteorology to analyze rainfall intensity data that often has extreme values so that the data shape is relatively unsymmetrical. Factors that determine the occurrence of extreme rainfall are very important to know to anticipate the adverse effects of extreme rainfall. One of the most common adverse effects of extreme rainfall is flooding, which can cause various kinds of losses. In addition to flooding problems, extreme rainfall also affects various fields including transportation, telecommunications, and tourism.

There has been quite a lot of research on the application of quantile regression to extreme rainfall data, including Pumo and Noto (2019) using quantile regression to examine the relationship between extreme rainfall and temperature in the Mediterranean dry region, precisely in Sicily (Italy) which produces the best model at quantile 95 ($\tau = 95$). After that in 2021 Pumo and Noto also conducted a study using quantile regression to explore the relationship between dew point temperature and extreme rainfall in the same region and concluded that was coherent with previous observations. Meanwhile, for areas with higher rainfall, Lenderink et al (2011) studied the Hong Kong region where the 99th quantile (τ=99) was found to be the best model (Limantara, Lily Montarcih, et al. 2018).

Rainfall is a form of water vapor precipitation found in the troposphere whose amount is influenced by temperature, air humidity, air pressure, irradiation, and wind speed (Wilson, 1993; Aditya, F. et al. 2021). Research that discusses the factors that influence extreme rainfall includes Modiana et al (2021) predicting extreme rainfall using quantile regression for flood disaster mitigation with five explanatory variables, namely temperature, humidity, sunshine duration, air pressure, and wind speed in Sidoarjo district with the best regression model results at quantile τ=95 (Muyuan Xu, Lelys Bravo de Guenni, José Rafael Córdova. 2024; Limantara, Lily Montarcih, et al. 2018; Cook, L. M., McGinnis, S., & Samaras, C. 2020; Şen, O., & Kahya, E. 2021). Gunadi (2022) conducted research on the classification of daily rainfall using learning vector quantization at the Ngurah Rai observation station, with six parameters namely air temperature, humidity, wind speed, air pressure, cloud cover and length of irradiation Dewi, S. M & Marzuki. (2020).

This study aims to model rainfall intensity in Jakarta using quantile regression to determine the relationship between rainfall and seven explanatory variables that are thought to affect it, namely maximum temperature, minimum temperature, dew point temperature, humidity, wind speed, air pressure, and length of irradiation in the Jakarta area with data obtained from the Seokarno-Hatta meteorological observation station in 2020-2022 to determine the ability of quantile regression on data containing outliers.

2. METHODS

2.1. Data Source

This study uses secondary data on daily rainfall in DKI Jakarta in 2020-2022 from January - December observed from the Seokarno-Hatta meteorological observation station for 1097 days. The data was obtained from the site http://www.ogimet.com, which is a world weather information exchange site. Published data are data used by several world information networks, especially from the National Oceanic and Atmospheric Administration (NOAA) and are license-free to process.

2.2. Analysis Method

The analysis method to achieve the objectives of this research is as follows: (1). Data exploration by conducting descriptive analysis to obtain an overwiew of the data; (2). Detecting outliers with studentized residuals to detect outliers in variable Y, uding leverage values to detect outliers in variable X, and cook's distance to identify outliers that have a large influence on slope coefficient estimate; (3). Modeling the factors affecting daily rainfall using multiple linier regression. The steps used are as follows: (i). Obtain the parameter estimates of the multiple linier regression model $\boldsymbol{\hat{\beta}} = (\boldsymbol{X'X})^{-1}\boldsymbol{X'Y}$; (ii). Interpreting multiple linier regression models; (iii). Measuring the goodness of the model using the coefficient of determination $R^2_{Adj} = 1 - \frac{SS_{Res}/(n-p)}{SS_{Total}/(n-1)}$; (iv). Testing the assumptions of normality, homoscedasticity and non-multicolinearity; (4). Modeling the factors affecting daily rainfall using quantile regression. The steps used are as follows: (i). Obtain the parameter estimates of the quantile regression model $\hat{\beta}(\tau) = \underset{\beta \in \mathbb{R}^p}{min}\{\tau \sum_{i=1;\varepsilon\geq 0}^{n} |\boldsymbol{y} - \boldsymbol{X'\beta}(\tau)| + (1-\tau)\sum_{i=1;\varepsilon\geq 0}^{n} |\boldsymbol{y} - \boldsymbol{X'\beta}(\tau)|\}$; (ii). Testing the significance of the parameters with test statistics: $t = \frac{\widehat{\beta_J}(\tau)}{se(\widehat{\beta_J}(\tau))}$; (iii). Interpreting the quantile regression model; and (iv). Measuring the goodness of the model using the coefficient of determination $R^1(\tau) = 1 - \frac{\hat{V}(\tau)}{\tilde{V}(\tau)}$, $0 < R^1(\tau) < 1$; (5). Determining the best model; (6). Determine the factors that significantly affect daily rainfall in Jakarta based on the best model selected; and (7). Interpretation of analysis result Montgomery, D. C., Peck, E. A., & Vining, G. G. 2012).

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

The significant discrepancy between the mean and median in Table 1 indicates the presence of asymmetry in the data distribution and tends to have a longer tail on the right. In Figure 1, there are outliers in January, April, June, July, August, which tend to be above the third quartile and in February, March, and October tend to be below the first quartile. The presence of outliers will interfere with the data analysis process, especially in estimating model parameters. In the rainfall variable, the first quartile value is 0 mm, the second quartile is 0.1 mm, and the third quartile is 6.1 mm but the maximum value is 150 mm, so for modeling using quantile regression, quantiles 0.25; 0.50; 0.75; 0.95; 0.99; and 0.9999 are used with the consideration that quantiles 0.25 and 0. 50 will represent outliers that tend to be below the first quartile, quantiles 0.75 and 0.95 will represent data in the second quartile, and quantiles 0.99 and 0.999 will represent outliers that tend to be above the third quartile.

Table 1. Variable Descriptive Statistics

Variable	Mean	Median	SD	Minimum	Maxsimum	Q1	Q2	Q3
Y	6,49	0,100	14,2	0	150,2	0	0.1	6.1
X_1	32,04	32,20	1,29	27,6	35,5	31.4	32.2	32.9
X_2	24,63	24,60	0,83	21,5	27,4	24.1	24.6	25.2
X_3	23,44	23,50	0,82	18,8	25,5	23.1	23.5	24
X_4	79,27	79,30	5,46	60,2	95,1	75.7	79.3	83
X_5	8,65	8,100	2,41	3,2	20,8	6.9	8.1	10
X_6	1009,73	1010	1,21	1006,3	1013,2	1008.9	1009.8	1010.6
X_7	5,18	5,300	3,13	0	11,3	2.5	5.3	7.9

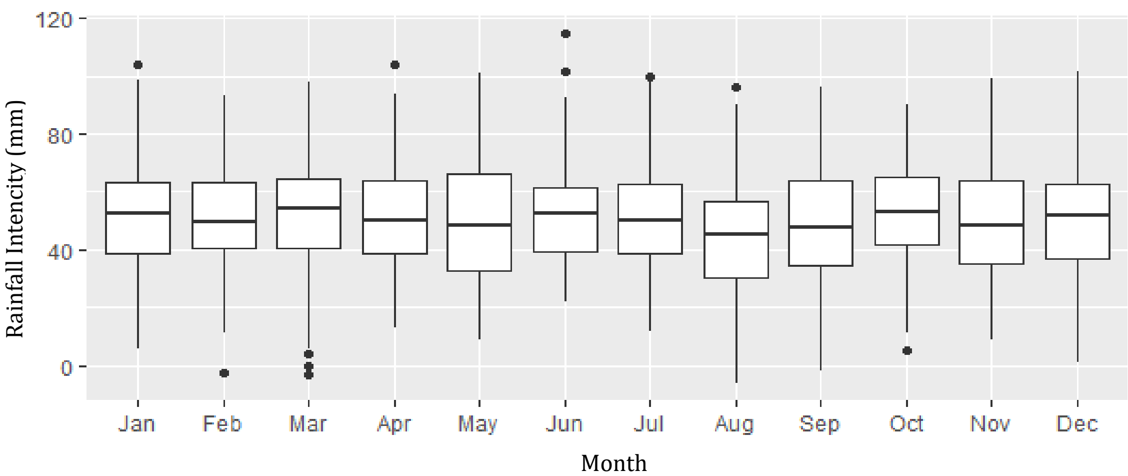


Figure 1. Box Plot of Jakarta Daily Rainfall Intensity 2020-2022

3.2. Outlier Detection

Formal outlier detection in this study is carried out on explanatory variables and response variables. In the explanatory variables, outliers are detected using the leverage value while in the response variables, they are detected using the studentized residual. Observations that affect the estimation of the slope coefficient are seen from the value of cook's distance. The analysis results show that there are observations that are outliers in the response variables and explanatory variables. From the identification of the explanatory variables using the leverage value, 43 days are outliers, from the identification of the response variable there are 46 days including outliers and from the cook's distance value, 51 days are influential observations.

3.3. Multiple Linier Regression

In this study, the multiple linear regression model is used as a comparison for the quantile regression model. Based on the estimation results with the OLS method, the multiple linear regression model is obtained as follows:

$$\hat{y} = 4.98e^{-15} + 0.0515X_1 - 0.1048X_2 - 0.09.56X_3 + 0.5845X_4 + 0.1578X_5 + 0.0493X_6 + 0.0091X_7$$

It is known that using a significant level (α = 5%) there are three variables that significantly affect the intensity of Jakarta's daily rainfall, namely minimum temperature, air humidity and wind speed. The coefficient of determination generated using the OLS method (R_Adj^2) is 0.2587. This shows that the intensity of rainfall in Jakarta can be explained by the multiple regression model by 25.87%, while the remaining 74.13% is explained by other variables outside the model. Multiple linear regression analysis models the relationship between averages to see the value of the response variable for each unit of the explanatory variable. This results in data that is far from the average having large residuals. Therefore, further analysis was conducted to determine the relationship between rainfall and explanatory variables with quantile regression analysis.

Classical Assumption Test

Normality Test: To test the assumption of normality, the Komogorov-Smirnov test is used. The hypotheses underlying this test are:

H_0 : errors are normally distributed

H_1 : errors are not normally distributed

Based on the Kolmogorov-Smirnov test results on the data $D_n = 0.3238 > D_\alpha\ 2.2e^{-16}$ so reject H_0 which means the errors are not normally distributed.

Homoscedasticity Test: The assumption of homogeneity of error variance can be detected by using the statistical value of the Glejser test with the following hypothesis::

H_0 : error variance is homogeneous

H_1 : error variance is not homogeneous

Based on the results of testing the homogeneity of the error variance, it is known that the P-value is $7.859e^{-5}$, this value is smaller than the specified significance level of $\alpha(0.05)$, it can be concluded that the assumption of the homogeneity of the error variance is not met.

Identification of Non-Multicollinearity: The Variance Inflation Factors (VIF) value of each explanatory variable used in this study is as follows:

Table 1. Variance Inflation Factors (VIF)

Variable	VIF
Maximum Temperature (°C) X_1	2.40
Minimum Temperature (°C) X_2	2.38
Dew Point Temperature (°C) X_3	4.33
Air Humidity (%) X_4	6.60
Wind Speed (Km/hour) X_5	1.22
Air Pressure (Hpa) X_6	1.08
Duration of Irradiation (hours) X_7	1.16

Based on Table 2, it is known that the VIF value for each explanatory variable is smaller than 10, meaning that there is no multicollinearity between the explanatory variables.

3.4. Quantile Regression Analysis

In this study, quantile regression analysis is used to obtain a model in each quantile that describes how much influence the explanatory variables have on rainfall intensity in each quantile. The results of the quantile regression model parameter estimation are presented in Table 3.

Based on the results in Table 3, the estimated quantile regression model for each quantile is as follows: Estimated Quantile Regression model for Quantile $\tau = 0,25$ $\hat{Q}_{0,25} = -0.4470 + 0.0027X_1 + 0.0048 - 0.0140X_3 + 0.0282X_4 + 0.0035X_5 + 0.0016X_6 + 0.0001X_7$ Estimated Quantile Regression model for Quantile $\tau = 0,50$ $\hat{Q}_{0,50} = -0.3018 + 0.0288X_1 + 0.0281X_2 - 0.1142X_3 + 0.2567X_4 + 0.0323X_5 + 0.0143X_6 - 0.0041X_7$ Estimated Quantile Regression model for Quantile $\tau = 0,75$ $\hat{Q}_{0,75} = 0.1177 + 0.1157X_1 + 0.0352X_2 - 0.2761X_3 + 0.7038X_4 + 0.0933X_5 + 0.0138X_6 + 0.0069X_7$ Estimated Quantile Regression model for Quantile $\tau = 0,95$ $\hat{Q}_{0,95} = 1.5850 + 0.2122X_1 - 0.1404X_2 - 0.2536X_3 + 1.2463X_4 + 0.2987X_5 + 0.0810X_6 - 0.1105X_7$ Estimated Quantile Regression model for Quantile $\tau = 0,99$ $\hat{Q}_{0,99} = 3.1989 + 0.0883X_1 - 0.0139X_2 - 0.4198X_3 + 1.8088X_4 + 0.7912X_5 - 0.0314X_6 - 0.5738X_7$ Estimated Quantile Regression model for Quantile $\boldsymbol{\tau = 0,999}$ $\hat{Q}_{0,999} = 4.2300 - 0.6918X_1 + 0.0647 - 0.3556X_3 + 1.8262X_4 + 0.6045X_5 - 0.3517X_6 - 0.3796X_7$

Table 3. Quantile Regression Model Parameter Estimation Results

Parameter	Quantile (τ)					
	0,25	0,50	0,75	0,95	0,99	0,999
$\beta_0(\tau)$	-0.4470	-0.3018	0.1177	1.5850	3.1989	4.2300
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\beta_1(\tau)$	0.0027	0.0288	0.1157	0.2122	0.0883	-0.6918
	(0.0129)*	(0.0032)*	(0.0000)*	(0.1481)	(0.5349)	(0.0000)*
$\beta_2(\tau)$	0.0048	0.0281	0.0352	-0.1404	-0.0139	0.0647
	(0.0000)*	(0.0039)*	(0.2049)	(0.3365)	(0.9218)	(0.1903)
$\beta_3(\tau)$	-0.0140	-0.1142	-0.2761	-0.2536	-0.4198	-0.3556
	(0.0000)*	(0.0000)*	(0.0000)*	(0.1981)	(0.0283)*	(0.0000)*
$\beta_4(\tau)$	0.0282	0.2567	0.7038	1.2463	1.8088	1.8262
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*
$\beta_5(\tau)$	0.0035	0.0323	0.0933	0.2987	0.7912	0.6045
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0044)*	(0.0000)*	(0.0000)*
$\beta_6(\tau)$	0.0016	0.0143	0.0138	0.0810	-0.0314	-0.3517
	(0.0283)*	(0.0288)*	(0.4615)	(0.4112)	(0.7426)	(0.0000)*
$\beta_7(\tau)$	0.0001	-0.0041	0.0069	-0.1105	-0.5738	-0.3796
	(0.8998)	(0.5405)	(0.7220)	(0.2789)	(0.0000)*	(0.0000)*

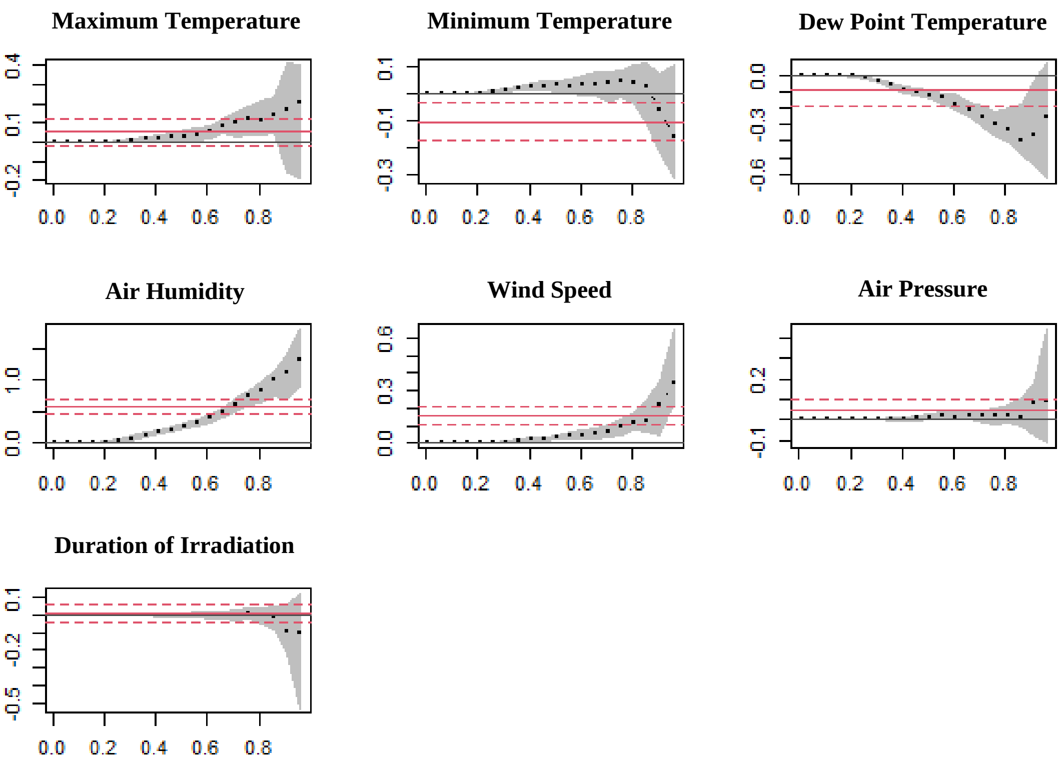


Figure 2. Plot of Quantile Regression Model Coefficients and Multiple Linear Regression Model Coefficients of Rainfall Intensity in Jakarta

Figure 2 shows that the effect of air humidity and wind speed on rainfall intensity looks similar, rainfall intensity will increase significantly as air humidity and wind speed increase as seen from the increase in quantile regression coefficients which are positive and increase as the quantile value increases. However, this increase in rainfall intensity cannot be described by multiple linear regression, because the red and gray confidence intervals do not overlap or only overlap from quantile τ = 0.6 to τ = 0.8, meaning that with the influence of the variables of air humidity and wind speed the estimation of low rainfall intensity by multiple linear regression is estimated to exceed the true value (overestimate) and at high rainfall intensity is estimated to be less than the true value (underestimate). Then in the variables of maximum temperature, minimum temperature, dew point temperature, air pressure and length of irradiation it can also be seen that the red and gray confidence intervals only overlap in a few parts so that when the variable values increase or decrease significantly using multiple linear regression becomes less precise. Therefore, it can be concluded that the effects of maximum temperature, minimum temperature, dew point temperature, air humidity, wind speed, air pressure and duration of irradiation are not constant across the distribution of rainfall intensity but depend on the rainfall intensity (Wati, Trinah and Fatkhuroyan, 2017; Limantara, Lily Montarcih, et al. 2018; Chen, C., Zhang, Q., Kashani, M. H., Jun, C., Bateni, S. M., Band, S. S., Dash, S. S., & Chau, K. W. (2022)).

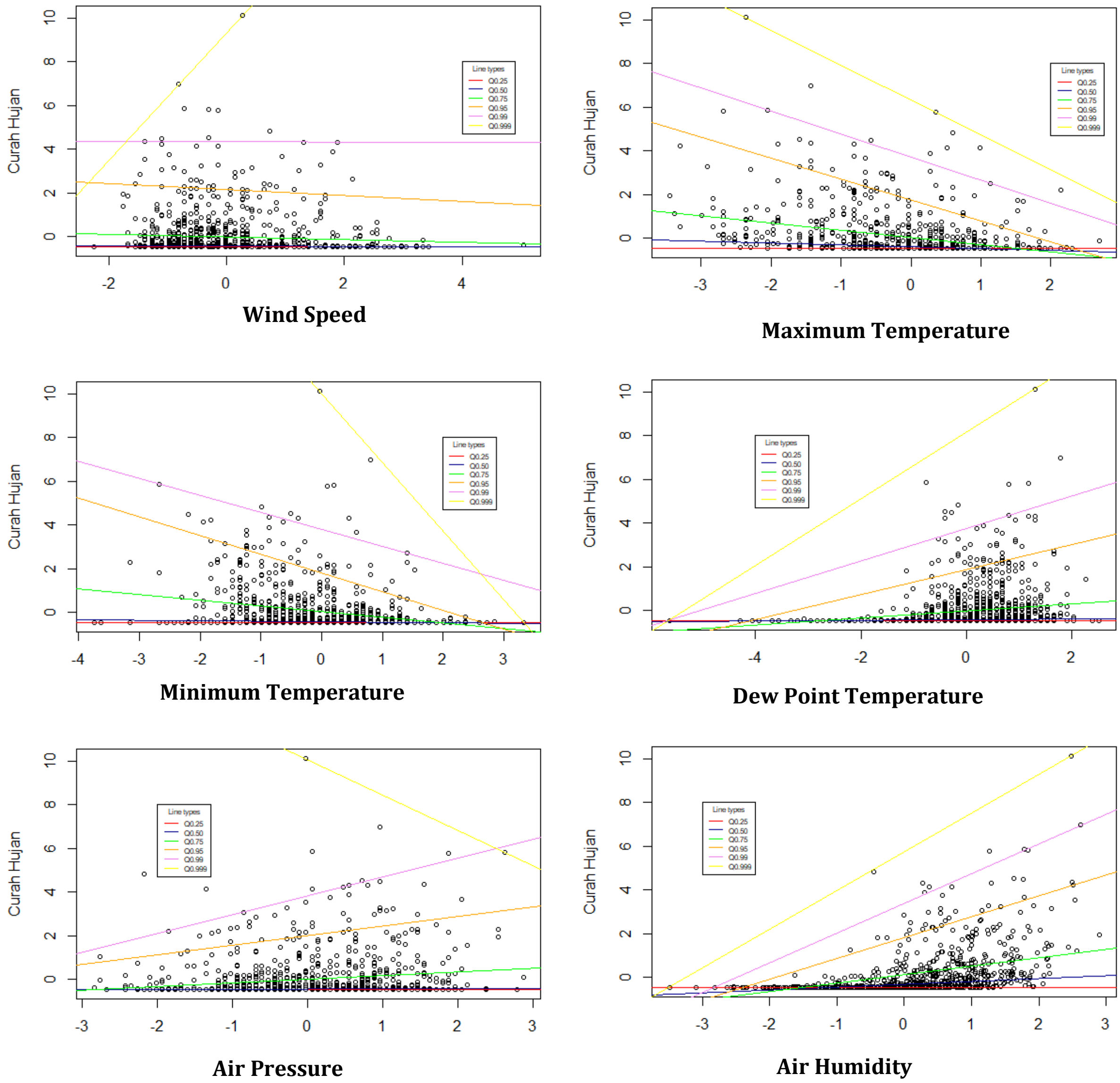
The goodnes of fit of the quantile regression model with the analyzed data can be seen from the coefficient of determination for each quantile presented in Table 4.

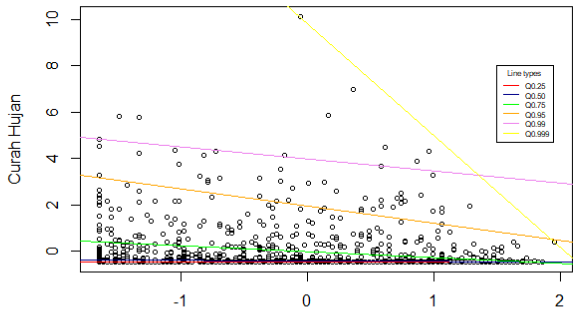
Table 4. $R^1(\tau)$ Value at Each Quantile

Kuantil	0.25	0.50	0.75	0.95	0.99	0.999
$R^1(\tau)$	0.22	7.9	20.03	27.26	33.38	58.21

The coefficient of determination is the amount used to measure the feasibility of the regression model and shows how much of the variability of the response variable is explained by the explanatory variables. The coefficient of determination that is close to 1 indicates that the regression model formed is quite good. Based on Table 4, it can be seen that the highest coefficient of determination is found in the regression model with quantile τ = 0.999 which is 58.21%, meaning that this model can explain the proportion of rainfall intensity diversity in Jakarta by 58.21%. This requires further analysis of the factors that influence rainfall intensity such as the Cloud Type and Development (Cumulonimbus Clouds. Geography and Topography, Storm Types (Cyclones, Monsoons, and Thunderstorms), Ocean-Atmosphere Interactions (El Niño and La Niña), and Human Activities (Urbanization and Deforestation) (Muyuan Xu, Lelys Bravo de Guenni, José Rafael Córdova. 2024).

Based on Table 4, it can be concluded that to model rainfall intensity with explanatory variables that affect it is not enough to use only one model because the shape of the data distribution is not symmetrical and has an inhomogeneous error variance. The τ=0.999 quantile regression model is also a regression model that can model extreme rainfall well. The plot between the response variable and each explanatory variable is presented in Figure 3.





Duration of Irradiation

Figure 3. Quantile Regression Plot

It can be seen from Figure 3 that the maximum temperature and minimum temperature have a negative effect on rainfall intensity in Jakarta, meaning that when the maximum and minimum temperatures are higher, the rainfall intensity is lower. Meanwhile, dew point temperature and air humidity have a positive effect on rainfall intensity, meaning that when dew point temperature and air humidity are higher. The wind speed variable at quantiles $\tau = 0.25; 0.50; 0.75; 0.95; 0.99$ looks flat and does not really affect rainfall intensity but at quantile $\tau = 0.999$ wind speed has a positive effect on rainfall intensity. Air pressure and length of irradiation at quantiles $\tau = 0.25; 0.50; 0.75; 0.95; 0.99$ have a positive relationship with rainfall intensity but at quantile $\tau = 0.999$ air pressure and length of irradiation have a negative effect on rainfall.

In summary, climate change generally leads to more intense and unpredictable rainfall patterns, with heavier rainfall events becoming more frequent in many regions. This is primarily due to warmer temperatures increasing the amount of water vapor in the atmosphere, altering weather patterns, and enhancing storm systems.

4. CONCLUSIONS

From the modeling results, the ability of the quantile regression model is quite good in modeling daily rainfall intensity data in Jakarta containing outliers by obtaining different parameter estimates for each quantile. The magnitude of the influence of each explanatory variable is different in each quantile indicating that quantile regression can provide a more detailed insight into how these variables affect rainfall under various conditions of rainfall intensity including extreme conditions. This approach provides flexibility in handling situations where the influence of explanatory variables on rainfall differs at different intensity levels.

Rainfall intensity is generally lower or tends to be light at a quantile of 0.25 and moderate rainfall at a quantile of 0.50. Almost all explanatory variables have a significant effect on rainfall intensity at both quantiles except for the duration of irradiation. At quantile 0.75, which describes a situation where rainfall intensity is generally higher or tends to be heavy, explanatory variables that have a significant effect on rainfall intensity are maximum temperature, dew point temperature, air humidity, and wind speed. At quantile 0.95, which tends to describe very heavy rainfall, explanatory variables that have a significant effect on rainfall intensity are air humidity and wind speed. At quantile 0.99, which tends to describe extreme rainfall, explanatory variables that have a significant effect on the percentage of rainfall intensity are dew point temperature, air humidity, wind speed, and duration of irradiation. At quantile 0.999, which tends to represent the highest rainfall, all explanatory variables have a significant effect on rainfall intensity except for minimum temperature.

So further research is recommended to consider spatial effects on rainfall by modeling rainfall with spatial quantile regression with more areas.

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