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Disaster Risk Analysis and Modeling for Strategic Decision Making in DKI Jakarta

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Abstract— DKI Jakarta as an important national center, faces significant challenges in disaster risk management. This research aims to develop a model that can predict and reduce the impact of disasters in Jakarta, thereby making an important contribution to strengthening the city's resilience and the safety of its residents. This research uses an empirical quantitative approach, with main data from the Central Statistics Agency (BPS) and the National Disaster Management Agency (BNPB). The main focus is on correlation analysis and multiple linear regression analysis to explore the relationship between various variables such as infrastructure vulnerability, population density, and disaster frequency, as well as their combined impact on disaster risk. The research results show that Total Casualties, Inflation, Gini Index, and Number of Affected Villages are significantly correlated with disaster risk. Regression analysis reveals that Total Casualties have the most dominant influence. Economic stability and a localized approach to risk management were also found to be important factors. This research confirms that disaster risk management in Jakarta requires a comprehensive and integrated approach. Total Casualties as the dominant variable emphasizes the need for effective disaster response strategies. Meanwhile, economic and social factors such as inflation and the Gini Index also play a key role in determining vulnerability to disasters. A segmented approach based on the Number of Affected Villages is important for an efficient mitigation strategy.

Keywords— DKI Jakarta, Economy, Gini Index, Inflation, Disaster Risk, Total Casualties

I. INTRODUCTION

DKI Jakarta Province, as the capital city of Indonesia, not only acts as the center of government administration, but also as the heart of the country's economic, social and cultural activities. As the largest metropolitan city in Indonesia, Jakarta is a magnet that attracts various elements of society from all over the country, which contributes to its extraordinary population density (Tarigan and Mahera 2020). This growing population, along with developments in city infrastructure, poses various unique challenges, especially in disaster risk management and mitigation (Dwirahmadi et al. 2023). From a geographical perspective, DKI Jakarta has a very strategic location, located on the northwest coast of Java Island (Cao et al. 2023). However, this position also places it in an area that is vulnerable to natural disasters such as floods and earthquakes. Flooding is a disaster that often occurs, especially due to inadequate city drainage systems and rising sea levels. Meanwhile, the risk of earthquakes cannot be ignored, considering that Indonesia is located on the Pacific "Ring of Fire", which makes it one of the most geologically active regions in the world.

Apart from natural disasters, Jakarta also faces the threat of non-natural disasters, such as fires, infrastructure failure and pollution. Fires often occur in densely populated residential areas and industrial areas, while infrastructure damage often occurs due to inadequate maintenance and pressure from rapid population growth (Hidayat, Hasyemi, and Saputra 2020). Air and water pollution is also a serious problem, impacting not only public health but also the overall quality of life. This condition is exacerbated by the fact that the existing infrastructure and disaster management system in Jakarta is still not fully capable of handling the impact of the disaster. Early warning systems, for example, still need to be improved, as do evacuation and emergency response capacities. These limitations not only pose risks to life and property, but also have the potential to disrupt the economic and social stability of the city (Dwirahmadi et al. 2019).

In this context, the importance of conducting in-depth analysis and disaster risk modeling becomes very crucial. This research aims to fill the knowledge gap in terms of disaster risk management in Jakarta, by developing a model that can predict and reduce the impact of disasters that may occur. Through comprehensive analysis, it is hoped that effective mitigation and response strategies can be produced, which will not only be able to reduce the impact of disasters but also strengthen the city's resilience to future threats. This is not only important for the safety and well-being of Jakarta's residents, but also for the city's continued function as an important national center. This research is very important considering that Jakarta routinely faces various disasters that have a significant impact on the city's social and economic life (Rahayu et al. 2020). Comprehensive research will provide valuable insights for policy makers in formulating more effective disaster mitigation and response strategies. Apart from that, this research can also be an important contribution to the field of disaster risk management studies, especially in urban contexts in developing countries. It is hoped that the research results can become a reference for other cities in Indonesia which also face similar disaster risks, so that overall it can increase national resilience to disasters.

II. RESEARCH METODS

This research is a quantitative study that adopts an empirical approach to analyze disaster risk in DKI Jakarta. The main data was obtained through the data approximation method from two key sources, namely the Central Statistics Agency (BPS) and the National Disaster Management Agency (BNPB). Information from BPS will provide data related to demographics, economic conditions and infrastructure, which are essential in understanding the context and vulnerability of cities to various disasters (Firdausi, Lestari, and Ismiyati 2021). Meanwhile, data from BNPB will be used to identify the type and frequency of disasters, as well as the impacts they cause (Jülich 2015).

Apart from data collection, this research also emphasizes the use of correlation analysis and multiple linear regression analysis. Correlation analysis will be used to determine the relationship between various variables, such as infrastructure vulnerability, population density, and disaster frequency. The aim is to identify factors that have a significant relationship with disaster events. After that, multiple linear regression analysis will be applied to understand how the combination of these variables together influences disaster risk. Through this regression model, this research aims to predict the impact of disasters more accurately, based on various risk factors that have been identified (Priscannanda and Hindersah 2022). The application of these two analytical methods will enrich understanding of the dynamics of disaster risk in Jakarta, enabling this research to produce recommendations that are not only based on observations, but also on strong statistical analysis. The results are expected to provide reliable insights for strategic decision making in disaster risk management in DKI Jakarta.

III. RESULT AND DISCUSSION

3.1. Data Description

The main dependent variable in this research is Disaster Risk (Y). This variable is a representation of the level of disaster risk in DKI Jakarta, which includes various aspects such as the frequency of disaster events, the scale of damage caused, as well as the duration and capacity for post-disaster recovery (Yan et al. 2023). Measuring Disaster Risk is important to understand the magnitude of the threat faced by Jakarta, both from natural and non-natural disasters, and is the main focus of this research analysis. Next, the first variable to focus on is the Inflation Rate (X1). The inflation rate in Jakarta is considered an important indicator that influences disaster risk (Fauzia, Lestari, and Wardani 2022). Inflation not only reflects the economic conditions of cities but also affects the capacity of government and society in allocating resources for disaster mitigation and response efforts. When inflation is high, the resulting economic pressure can reduce a city's resilience to disasters (Tam et al. 2021).

Gini Index (X2) is the second variable analyzed. This variable measures the level of income inequality in Jakarta, which is important in the context of disaster risk. These inequalities can influence how vulnerable different groups of society are to disasters and how quickly they can recover post-disaster (Yousof, Altun, and Hamedani 2021). A high Gini Index can indicate a gap in abilities between community groups in dealing with disasters. The third variable is Number of Villages Affected (X3), which calculates the number of villages or sub-districts in Jakarta affected by the disaster. This variable provides an idea of how widely the disaster impact is distributed in the city area. This is important for understanding the geographic scope of disasters and assists in strategic planning for disaster mitigation and management in the most vulnerable areas (Bista 2020).

Then Total Casualties (X4) recorded the number of fatalities and injuries resulting from the disaster. It is a direct measure of the human impact of a disaster and is one of the most important indicators in assessing the severity of a disaster. The number of victims provides a real perspective on the consequences of a disaster and the effectiveness of existing response systems. Analysis of these variables will provide in-depth insight into the dynamics of disaster risk in Jakarta (Dhiman et al. 2020). By understanding how each of these factors interact and contribute to disaster risk, this research aims to develop more effective strategies for reducing risk and increasing cities' resilience to disasters.

Below is a table that summarizes the main variables used in this research. This table provides a brief description of each variable, which includes Disaster Risk as the dependent variable, and Inflation Rate, Gini Index, Number of Villages Affected, and Total Casualties as independent variables. This explanation is intended to provide a clear picture of each factor that will be analyzed in relation to disaster risk in DKI Jakarta

Table 3.1 Research Data Variables

Variable	**Information**
Y	Disaster Risk
X1	Inflation Rate
X2	Gini Index
X3	Number of Villages Affected
X4	Total Casualties

In order to provide a deeper understanding of the dynamics of disaster risk in DKI Jakarta, the following graph is presented illustrating the relationship between disaster risk and economic and social indicators from 2005 to 2022. This graph displays the trend of Disaster Risk along with related variables such as Inflation Rate, Gini Index, Number of Villages Affected, and Total Casualties. This visual analysis will help explore how these factors interact over time and provide important insights into their potential influence on disaster risk in the region.

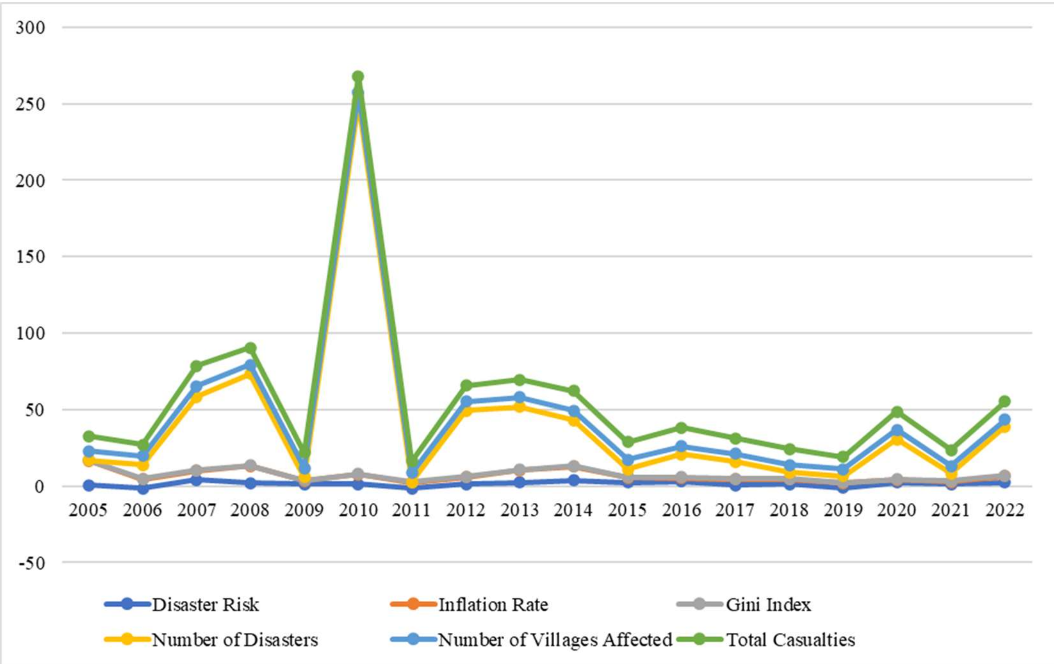

Figure 1. Research Data Graph

The graph above provides data visualization that illustrates the relationship between disaster risk and various economic and social variables in DKI Jakarta from 2005 to 2022. Through this graph, we can interpret the trends and patterns that emerge from the data. In the graph, it can be seen that Disaster Risk, depicted by the blue line, shows fluctuations from year to year. However, there was a very striking peak around 2007, indicating a major disaster or series of disasters that had a significant impact that year. This could be related to an extraordinary natural disaster or infrastructure crisis that results in major damage and loss.

Meanwhile, the Inflation Rate, shown by the orange line, appears to be fluctuating steadily without any dramatic spikes similar to those shown by Disaster Risk. This indicates that although the inflation rate plays a role in the economic condition of DKI Jakarta, there is no direct indication that inflation has a direct impact on disaster risk in the observed time period. The Gini Index, represented by the gray line, also shows a relatively stable trend. This suggests that income inequality in Jakarta may not have experienced drastically significant changes over those years, or that the changes that did exist did not have a strong direct correlation with the frequency or severity of disasters.

The number of Villages Affected, marked with the light blue line, appears to follow a similar pattern to Disaster Risk, although it is not well intensity the peak was seen in 2007. This could indicate that when disasters occur, their scope tends to be broad, affecting many villages or sub-districts. Total Casualties, shown by the green line, generally appear to be correlated with Disaster Risk, although with smaller scale differences. This shows that as disaster risk increases, the number of victims tends to increase as well, although not always proportionally. Interpretation of the graph above provides an illustration that disaster risk in DKI Jakarta is influenced by various social and economic factors, but there is no single variable that is consistently able to explain variations in Disaster Risk over the time observed. These relationships, which are complex and multifaceted, underscore the importance of deeper analysis to understand the dynamics of disaster risk in this city.

3.2. Correlation Analysis

The scatter plot matrix seen below illustrates the relationship between important variables in this study, including Disaster Risk, Inflation Rate, Gini Index, Total Casualties, and Number of Villages Affected. This visual analysis is very useful in identifying patterns and relationships between variables, which allows us to see how strong the relationship is between economic and social factors and disaster risk in DKI Jakarta.

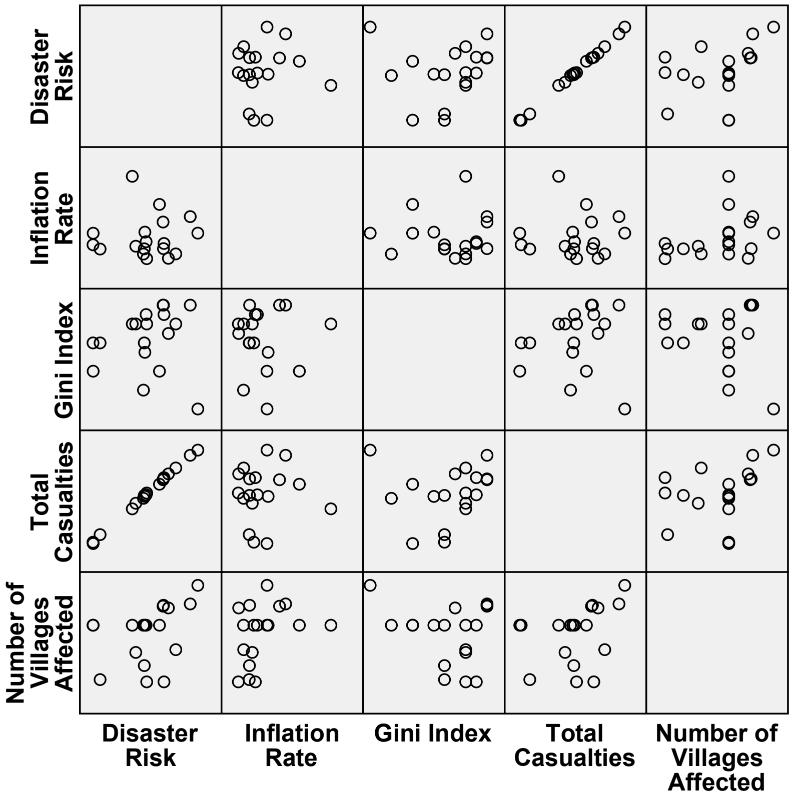

Figure 3.2 Variable Correlation Scatterplot

The displayed scatter plot matrix is a powerful visual tool for revealing the correlation between various variables related to disaster risk. From the distribution of points in the plot, an initial picture of the relationship between each pair of variables can be obtained. In examining the plot between Disaster Risk and other variables such as Inflation Rate, Gini Index, Total Casualties, and Number of Villages Affected, there does not appear to be a pattern that shows a strong linear correlation. If a correlation exists, it may be non-linear or may require the use of advanced statistical methods to identify the relationship. The plot comparing Disaster Risk with the Inflation Rate and Gini Index shows a relatively scattered distribution of points, indicating that there is no clear direct relationship between these economic variables and disaster risk. This may indicate that economic factors do not directly or alone determine disaster risk. This could be because economic factors such as inflation and income inequality influence disaster risk through more complex mechanisms that are not visible just by simple correlation analysis.

Meanwhile, the relationship between Disaster Risk with Total Casualties and Number of Villages Affected seems to be more convergent than the others, but still does not show a clear pattern leading to a positive or negative correlation. This may indicate that while disaster events certainly impact the number of victims and affected villages, other factors not included in this analysis may play a more significant role in determining the scale and impact of a disaster. An in-depth analysis of the relationship between variables in the context of disaster risk in DKI Jakarta has been carried out and is presented in the form of a correlation table below. This table describes the statistical relationship between disaster risk variables and the inflation rate, Gini index, number of affected villages, and Total Casualties. Pearson correlation coefficients and their corresponding significance values will guide in understanding the strength and relevance of the relationships between these variables, providing a more concrete basis for previous interpretations based on scatter plots.

Table 3.2 Correlation Values Between Variables

		Disaster Risk	Inflation Rate	Gini Index	Number of Villages Affected	Total Casualties
Disaster Risk	Pearson Correlation	1	,053	,099	,367	,999**
	Sig. (2-tailed)		,834	,697	,134	,000
	N	18	18	18	18	18
Inflation Rate	Pearson Correlation	,053	1	,008	,352	,027
	Sig. (2-tailed)	,834		,974	,151	,914
	N	18	18	18	18	18
Gini Index	Pearson Correlation	,099	,008	1	-,219	,122
	Sig. (2-tailed)	,697	,974		,383	,631
	N	18	18	18	18	18
Number of Villages Affected	Pearson Correlation	,367	,352	-,219	1	,342
	Sig. (2-tailed)	,134	,151	,383		,164
	N	18	18	18	18	18
Total Casualties	Pearson Correlation	,999**	,027	,122	,342	1
	Sig. (2-tailed)	,000	,914	,631	,164	
	N	18	18	18	18	18

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation table presented provides more specific statistical information about the relationship between disaster risk variables, inflation rate, Gini index, number of affected villages, and Total Casualties. By using the Pearson correlation coefficient and associated significance values, we can interpret the strength and statistical significance of the relationships between these variables. First, the relationship between Disaster Risk and Total Casualties is very strong, with a correlation coefficient close to 1 (0.999) and very high significance ($p < 0.01$). This indicates an almost perfect and statistically significant relationship between the two variables. In other words, increases in disaster risk tend to be associated with increases in the number of victims, indicating that the higher the disaster risk, the greater the likelihood of fatalities and injuries.

In contrast, the relationship between Disaster Risk and the Inflation Rate and Gini Index appears to be weak, with a very low correlation coefficient (0.053 for the Inflation Rate and 0.099 for the Gini Index) and not statistically significant ($p > 0.05$). This confirms the initial interpretation of the scatter plot which shows that there is no significant correlation between disaster risk and economic factors such as inflation and income inequality. Meanwhile, the relationship between Disaster Risk and Number of Villages Affected has a moderate correlation coefficient (0.367) but is not statistically significant ($p > 0.05$). This suggests that while there may be a trend that higher disaster risk is associated with a greater number of affected villages, this relationship is not strong enough to be confirmed as significant in the analyzed sample.

The correlation table supports the findings from the scatter plot by showing that Total Casualties has a very strong and significant relationship with Disaster Risk. On the other hand, economic variables such as the Inflation Rate and Gini Index do not show a significant relationship, confirming that economic factors may play a role in a broader and more complex context that has not been fully explored in this analysis. This highlights the importance of considering additional factors or interactions between variables to gain a more comprehensive understanding of disaster risk in DKI Jakarta.

3.3. Multiple Linear Regression Analysis

Below is a descriptive statistical table that details the main characteristics of the data set used in this research. This table provides the mean, standard deviation, and number of observations for important variables such as Disaster Risk, Inflation Rate, Gini Index, Number of Villages Affected, and Total Casualties. This information provides a basis for understanding the distribution and diversity of data that will be further analyzed in the context of disaster risk in DKI Jakarta.

Table 1.3 Descriptive Statistics

	Mean	Std. Deviation	N
Disaster Risk	1,3456	1,63599	18
Inflation Rate	5,3583	3,72420	18
Gini Index	,3944	,03185	18
Number of Villages Affected	5,8056	,64034	18
Total Casualties	10,5461	1,64481	18

The descriptive statistical tables presented provide an important summary of data relating to disaster risk and other related factors in DKI Jakarta. This table shows the average value (mean), standard deviation (standard deviation), and number of observations (N) for each variable studied. Starting with the Disaster Risk variable, we see that the average disaster risk has a relatively low value on the scale used, with a mean of 1.3456. However, the high standard deviation, namely 1.63599, indicates significant variation in disaster risk between different observations. This large variability may reflect differences in the intensity or frequency of disasters over time, suggesting that there are certain years with particularly high or low disaster risk.

For the Inflation Rate, the average is 5.3583 with a standard deviation of 3.72420, which indicates that the inflation rate in Jakarta varied quite widely during the period studied. This variability can reflect changes in economic conditions that impact the prices of goods and services, which of course has implications for people's purchasing power and the allocation of resources for disaster mitigation and management. Meanwhile, the Gini Index has an average of 0.3944 with a relatively low standard deviation of 0.03185, indicating that income inequality in Jakarta was relatively stable during the period studied. This stability in inequality may indicate that there are no drastic changes in income distribution that could affect social vulnerability to disasters.

By looking at the Number of Villages Affected, the average is 5.8056 with a standard deviation of 0.64034. This figure illustrates that the average number of villages affected by disasters is not very high, but there is still significant variation, which may be related to different scales or types of disasters. Total Casualties shows a high average of 10.5461 with a standard deviation of 1.64481, indicating that the impact of disasters on fatalities tends to be significant and also varied. This high average casualty score reflects that when a disaster occurs, the consequences are serious and require in-depth attention from disaster risk management.

Table 3.4 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	1,000[a]	1,000	1,000	,02644	1,669

a. Predictors: (Constant), Total Casualties, Inflation Rate, Gini Index, Number of Villages Affected

b. Dependent Variable: Disaster Risk

The model summary table presented above provides the results of the regression analysis that has been carried out to understand the influence of predictor variables on Disaster Risk as a response variable. The results show a perfect R value, namely 1.000, which indicates a perfect correlation between the predictor variables and Disaster Risk. The also perfect R Square value, 1.000, confirms that the regression model can explain 100% of the variation in Disaster Risk, which is a very rare situation in real-world data and may indicate overfitting or data error.

An adjusted R Square of also 1.000 supports this finding, indicating that adjustment for the number of predictors in the model did not change the proportion of variance explained by the model. In other words, every variable included as a predictor in the model has a significant contribution to the explanation of Disaster Risk. The very low Standard Error of the Estimate, namely 0.02644, indicates that the model estimate is very close to the true value. This shows that the model has high precision in predicting Disaster Risk based on the predictor variables used.

The Durbin-Watson value is close to 2, namely 1.669, indicating the absence of significant autocorrelation in the model residuals. In the context of regression analysis, this means that the assumption of independence of observations is not violated, and the predictions produced by the model are not influenced by predictions made earlier in the data sequence.

Table 3.5 ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	45,491	4	11,373	16268,471	,000[a]
	Residual	,009	13	,001		
	Total	45,500	17			

a. Predictors: (Constant), Total Casualties, Inflation Rate, Gini Index, Number of Villages Affected

b. Dependent Variable: Disaster Risk

The ANOVA (Analysis of Variance) table displayed provides the results of statistical analysis to evaluate the regression model that has been developed. This table helps determine whether the overall regression model is statistically significant in predicting Disaster Risk based on the selected predictor variables. The Sum of Squares (SS) for the regression, which is very high at 45.491 compared to the residual SS of almost zero (0.009), indicates that the regression model explains almost all of the variability in the data. This is indicated by the Mean Square (MS) value, which is the ratio of SS to degrees of freedom (df). The MS for the regression is very high (11.373) compared to the MS for the residual (0.001), confirming that the variability explained by the model is very significant compared to the variability not explained by the model.

The very large F value (16268.471) and very low significant (Sig.) value ($p < 0.001$) confirms that the regression model we have is very statistically significant. This extreme F value usually indicates that the predictor variables included in the model have a very strong influence in predicting the dependent variable, namely Disaster Risk. However, these very extreme values, both for F and for R Square in the previous model table, may raise suspicions about possible overfitting or problems in the data. In good research practice, results of this kind would trigger further investigation to ensure that the model has been appropriately tested and validated, thus ensuring that the model not only explains the existing data sample but can also be generalized to the wider population.

The ANOVA table above is used for the F test, namely testing the feasibility of the overall model from the regression coefficient to find out whether Inflation (X1), Gini Index (X2), Number of Villages Affected (X3) and Total Casualties (X4), together affects Disaster Risk (Y).

Hypothesis:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4$$

$$H_1 : \text{there is at least one } \beta_k \neq 0$$

$$\left(\beta_1 \neq 0 \text{ or } \beta_2 \neq 0 \text{ or } \beta_3 \neq 0 \text{ or } \beta_4 \neq 0 \text{ or } \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq 0\right)$$

It appears that the Sig value. = 0.000 < 0.05, meaning that at the 95% confidence level Ho is rejected. Thus, there is at least one significant one. So that further analysis can be carried out.

Table 3.6 Regression Analysis Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-8,967	,113		-79,322	,000
	Inflation Rate	,009	,002	,021	4,975	,000
	Gini Index	-1,003	,213	-,020	-4,713	,000
	Number of Villages Affected	,036	,012	,014	2,990	,010
	Total Casualties	,991	,004	,996	231,273	,000

a. Dependent Variable: Disaster Risk

The coefficient table from the regression analysis displayed provides detailed information about the influence of each independent variable on the dependent variable, Disaster Risk. In this table, we see the Unstandardized Coefficients (B), Standard Error, Standardized Coefficients (Beta), t value, and significance level (Sig.) for each predictor variable and constant. The regression model constant, or intercept, has a very negative value (-8.967) with a high level of significance ($p < 0.001$). This shows that when all independent variables are zero, the Disaster Risk value is expected to decrease by 8.967 points, an assumption that may be unrealistic in a practical context but shows the importance of the independent variables in the model.

The inflation rate (Inflation Rate) has a positive coefficient (0.009), indicating that for every unit increase in the inflation rate, Disaster Risk increases by 0.009 units. This coefficient is statistically significant, but the low Beta value (0.021) indicates that its effect on Disaster Risk is relatively small compared to other variables. The Gini Index, which measures income inequality, has a negative coefficient (-1.003) that is also significant, indicating that increases in income inequality are actually associated with decreases in Disaster Risk, an interesting and perhaps controversial finding that requires further research to fully understand.

Number of Villages Affected has a positive coefficient (0.036) which shows that the more villages affected by a disaster, the higher the Disaster Risk, with a fairly strong level of significance ($p = 0.010$). This is consistent with the intuition that disasters that are broader in scope tend to increase overall risk. Most notable is the coefficient for Total Casualties, which is very high (0.991) with a Beta close to 1 (0.996), indicating that Total Casualties is the most dominant predictor of Disaster Risk in this model. The very high t value and significance level close to zero confirms that the relationship between Total Casualties and Disaster Risk is very strong and statistically significant.

These results overall indicate that the model has a very good fit to the data and that Total Casualties is the main determining factor in the prediction of Disaster Risk according to this model. However, as stated previously, perfect fit must be checked carefully to ensure that there are no problems such as overfitting or errors in the data that could affect the validity of the model.

Based on the Coefficients table above, it appears that the value of

$$\hat{\beta}_0 = -8,967,\ \hat{\beta}_1 = 0,009,\ \hat{\beta}_2 = -1,003,\ \hat{\beta}_3 = 0,036,\ \text{and } \hat{\beta}_4 = 0,991.$$

The significance of the four coefficients can be determined using the T test.

1) Hypothesis Test for β_0

$$H_0 : \beta_0 = 0$$
$$H_1 : \beta_0 \neq 0$$

Because the Sig value = 0.000 < 0.05, then Ho is rejected, meaning that the regression line does not pass through the starting point (a significant constant entered into the regression model).

2) Hypothesis Test for β_1

$$H_0 : \beta_1 = 0$$
$$H_1 : \beta_1 \neq 0$$

Because the Sig value = 0.000 < 0.05, then Ho is rejected, meaning the coefficient of β_1 is significantly included in the model, in other words the Inflation variable (X1) influences Disaster Risk.

3) Hypothesis Test for β_2

$$H_0 : \beta_2 = 0$$
$$H_1 : \beta_2 \neq 0$$

Because the Sig value = 0.000 < 0.05, then Ho is rejected, meaning the coefficient of β_2 is significantly included in the model, in other words the Gini Index variable (X2) influences Disaster Risk.

4) Hypothesis Test for β_3

$$H_0 : \beta_3 = 0$$
$$H_1 : \beta_3 \neq 0$$

Because the Sig value = 0.010 < 0.05, then Ho is rejected, meaning the coefficient of β_3 is significantly included in the model, in other words the variable Number of Affected Villages (X3) influences Disaster Risk.

5) Hypothesis Test for β_4

$$H_0 : \beta_4 = 0$$
$$H_1 : \beta_4 \neq 0$$

Because the Sig value = 0.000 < 0.05, then Ho is rejected, meaning the coefficient of β_4 is significantly included in the model, in other words the Total Casualty variable (X4) influences Disaster Risk.

The final model for Disaster Risk is as follows:

$$\hat{Y} = -8,967 + 0,009\ X1 - 1,003\ X2 + 0,036\ X3 + 0,991\ X4$$

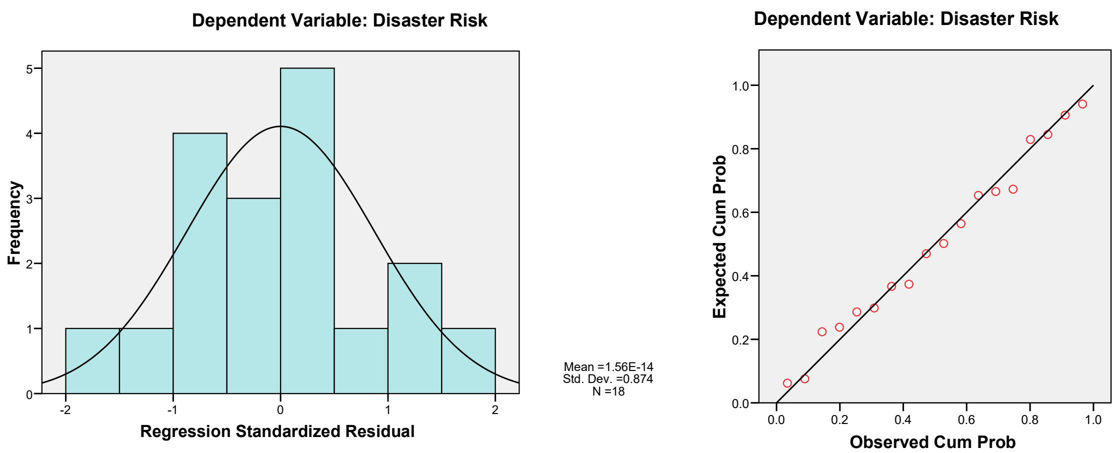

Figure 3.3 Normality Diagram

The image displayed consists of two plots related to the residual analysis of the regression model for the dependent variable Disaster Risk. The first plot is a histogram of standardized residuals with a superimposed normal distribution curve, and the second plot is a P-P (Probability-Probability) plot for model residuals. The histogram of standard regression residuals shows the frequency of residuals at various intervals (Yousof, Altun, and Hamedani 2021). Ideally, if the residuals are normally distributed, the histogram will resemble a bell shape (normal curve) and the residuals will be centered around zero (Dhiman et al. 2020). In this case, the histogram shows some deviation from a normal distribution with residuals tending to be concentrated in certain intervals more than others, although there is still a general impression of a symmetric distribution with a mean very close to zero, as indicated by the very small mean value (1.55E-14). The standard deviation of the residuals was 0.874, indicating variation in the residuals. The P-P plot, on the other hand, is a diagnostic tool that compares the cumulative distribution of residuals (Observed Cum Prob) with the expected cumulative distribution of a normal distribution (Expected Cum Prob). In a perfect representation, the points on the P-P plot will fall exactly on the diagonal line indicating a perfect fit to a normal distribution. In this graph, although the points are not exactly on the line, they tend to follow the diagonal line quite closely, indicating that the assumption of normality of residuals is not too far off the mark.

These two plots provide evidence that the residuals from the regression model are quite close to the assumed normal distribution. Although there are some deviations from perfect normality visible in the histogram, the P-P plot shows that the fit to a normal distribution is quite good. The assumption of normality of residuals is important in linear regression because it supports the validity of statistical tests such as t and F tests used to assess the significance of regression coefficients. However, this conclusion should be considered critically in light of the previously identified perfect R and R Square values, which may indicate that further analysis is required to ensure proper interpretation of the model. Based on the histogram and scatter plot above, it can be seen that the data is spread around the diagonal line and follows the direction of the diagonal line, so the regression model has normal residuals.

3.4. Strategic Decision Making

The results of the multiple regression analysis that has been carried out offer important insights into the factors that influence Disaster Risk. It was found that the variables Total Casualties, Inflation, Gini Index, and Number of Affected Villages had a significant correlation with the level of Disaster Risk, providing clear direction for the government and related institutions in setting intervention priorities and resource allocation for disaster mitigation. Total Casualties, as the variable that has the most significant influence on Disaster Risk, emphasizes the need for effective disaster management strategies. This strategy must include increasing public preparedness and awareness regarding preventive measures, rapid response when a disaster occurs, as well as reliable infrastructure and communication systems. Developing training programs and regular disaster simulations can be one way to prepare the community to face emergency situations.

In an economic context, the Inflation and Gini Index variables highlight the importance of economic stability and social equality in reducing disaster risk. Uncontrolled inflation can weaken the economic capacity of regions and individuals to recover after disasters, while high economic inequality can increase the vulnerability of poor groups to disasters. Therefore, economic policies that ensure fair income distribution and stable price control need to be strengthened. Meanwhile, the number of affected villages highlights the importance of a segmented and localized approach in disaster risk management. This means that each village must have a disaster mitigation and preparedness plan tailored to the specific characteristics and risks it faces. Increasing local capacity, both in human resources and infrastructure, will be key in minimizing the impact of disasters.

By considering these factors simultaneously, stakeholders in all sectors can build a comprehensive disaster management system. This system must be interdisciplinary, combining public health, economic and social policies, and integrating community participation in every aspect of disaster risk management. Only through a collaborative and integrated approach can we reduce Disaster Risk and build more resilient communities. Stakeholders in all sectors need to work together in disaster risk management efforts by paying attention to the four independent variables together. It is important to carry out a comprehensive disaster risk analysis by involving all stakeholders and taking into account factors that influence disaster risk, including Inflation (X1), Gini Index (X2), Number of Affected Villages (X3) and Total Casualties (X4). In this case, there needs to be coordination and synergy between the government, society and the private sector in efforts to manage disaster risk.

IV. Conclusion

Based on the analysis and discussion of disaster risk in DKI Jakarta, it emphasizes that the complexity of disaster risk is not only influenced by natural factors, but also by various economic and social elements. Multiple regression analysis carried out revealed that Total Casualties, Inflation, Gini Index, and Number of Affected Villages had a significant correlation with disaster risk. In this case, Total Casualties stands out as the most influential factor, indicating the importance of effective disaster management strategies, which include increasing community preparedness and awareness, rapid response when disasters occur, and building resilient infrastructure and communication systems. On the economic side, the inflation rate and Gini Index highlight how important economic stability and social equality are in reducing disaster risks. Economic instability and income inequality can increase vulnerability to disasters, especially among poor groups.

In addition, the focus on the number of affected villages points to the importance of a segmented and localized approach in disaster risk management, with increasing local capacity being the key to minimizing the impact of disasters. From a strategic perspective, the integration of public health, economic, social policies and active community participation are important elements in a comprehensive disaster management system. This collaborative and integrated approach is vital to reducing disaster risks and building more resilient communities. The importance of cooperation between all stakeholders in disaster risk management efforts cannot be ignored, given the need to consider all factors that influence disaster risk, including economic and social factors. Thus, disaster risk management in DKI Jakarta requires comprehensive analysis, good coordination and synergy between government, society and the private sector to face this complex and dynamic challenge.

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REFERENCES

[1] Bista, Raghu Bir. 2020. “Does Disaster Change Income and Wealth Distribution Toward Extremity of Inequality and Poverty? Analysis of Flood and Landslides in the Vulnerable Locations of Nepal.” Forum for Social Economics 0(0): 1–15. https://doi.org/10.1080/07360932.2020.1715810.

[2] Cao, Yu, Cong Xu, Nur Mardhiyah Aziz, and Syahrul Nizam Kamaruzzaman. 2023. “BIM–GIS Integrated Utilization in Urban Disaster Management: The Contributions, Challenges, and Future Directions.” Remote Sensing 15(5): 1–35.

[3] Dhiman, Harsh S. et al. 2020. “Wind Turbine Gearbox Condition Monitoring Based on Class of Support Vector Regression Models and Residual Analysis.” Sensors (Switzerland) 20(23): 1–17.

[4] Dwirahmadi, Febi et al. 2023. “Linking Disaster Risk Reduction and Climate Change Adaptation through Collaborative Governance: Experience from Urban Flooding in Jakarta.” Geosciences (Switzerland) 13(11).

[5] Dwirahmadi, Febi, Shannon Rutherford, Dung Phung, and Cordia Chu. 2019. “Understanding the Operational Concept of a Flood-Resilient Urban Community in Jakarta, Indonesia, from the Perspectives of Disaster Risk Reduction, Climate Change Adaptation and Development Agencies.” International Journal of Environmental Research and Public Health 16(20).

[6] Fauzia, Qanita, Fatma Lestari, and Devi Partina Wardani. 2022. “Analysis of Fire Risk Assessment in South Jakarta 2021.” Jurnal Ilmu Kesehatan Masyarakat 13(1): 26–38.

[7] Firdausi, Nobella, Fatma Lestari, and Avinia Ismiyati. 2021. “Disaster Preparedness Analysis of Public Health Centers in DKI Jakarta Province in 2020.” International Journal of Safety and Security Engineering 11(1): 91–99.

[8] Hidayat, Hisyam Yusril, Syarif Amr Hasyemi, and Muhammad Galih Saputra. 2020. “The Strategies and Challenges of Non-Governmental Organization Roles in Flood Disaster Management in Jakarta.” Natapraja 8(2): 94–105.

[9] Jülich, Sebastian. 2015. “Development of a Composite Index with Quantitative Indicators for Drought Disaster Risk Analysis at the Micro Level.” Human and Ecological Risk Assessment 21(1): 37–66.

[10] Priscannanda, Farizzy, and Hilwati Hindersah. 2022. “Identifikasi Kemampuan Berbagai Jenis Green Infrastructure Dalam Upaya Mengurangi Banjir Pada Das Ciliwung Hilir DKI Jakarta.” Jurnal Riset Perencanaan Wilayah dan Kota C: 23–35.

[11] Rahayu, H. P. et al. 2020. “A Micro Scale Study of Climate Change Adaptation and Disaster Risk Reduction in Coastal Urban Strategic Planning for the Jakarta.” International Journal of Disaster Resilience in the Built Environment 11(1): 119–133.

[12] Tam, Doan Ho Dan, Nguyen Phuc Phuong Vy, Nguyen Thi Xuan Tham, and Hoang Thi Ngoc Thang. 2021. “Trade and Income Distribution: Is Natural Disaster an Actor?” Economics and Business Administration 11(1): 60–72.

[13] Tarigan, S. D., and S. Mahera. 2020. “Assessing Urban Water Security: Case Study Jakarta.” IOP Conference Series: Earth and Environmental Science 477(1).

[14] Yan, Yan et al. 2023. “Quantitative Estimation of Pipeline Slope Disaster Risk in China.” International Journal of Disaster Risk Science 14(2): 298–312. https://doi.org/10.1007/s13753-023-00462-5.

[15] Yousof, Haitham M., Emrah Altun, and G.G. Hamedani. 2021. “A New Extension of Fréchet Distribution with Regression Models, Residual Analysis and Characterizations.” Journal of Data Science 16(4): 743–70.