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Geographically Weighted Panel Regression Modeling On The Effect Of Natural Disaster Factors On The Gini Ratio In Indonesia

Oktaviana Nur Rohmatulillah✉ [1], Dwi Endah Kusrini [1]

[1]Department Of Business Statistics, Institute Technology Sepuluh Nopember, Surabaya, Indonesia

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✉ oktaviana12002@gmail.com

Abstract: Indonesia is a country with a high risk of natural disasters, ranking second with the highest disaster risk index in the world, reaching 43.50%. In the period 2015-2024, tens of thousands of disaster events were recorded in various provinces, which had a significant impact on socio-economic aspects. The severity of economic losses caused by natural disasters has redistributed income inequality and poverty levels, where vulnerable groups have become even more vulnerable, while non-vulnerable groups with better adaptive capacities have become even less vulnerable. Therefore, this study aims to analyze the impact of natural disasters, including disaster risk, social, and economic aspects, on income inequality in Indonesia using the Geographically Weighted Panel Regression (GWPR) method to examine regional differences. The analysis results show that the impact of natural disasters, which includes aspects of disaster risk, social and economic aspects, causes an increase in the Gini ratio. It is known that the disaster risk index variable, population density, percentage of unexpected costs, and distribution of ADHB GRDP according to household expenditure have a significant effect on the Gini ratio using a random effect model. Using the GWPR method shows better performance than the random effect panel data regression model with an *adjusted* R2 value of 93,86% considering the error or random effect. The results indicate that inter-regional income inequality is shaped not only by economic factors, but also by regional disaster vulnerability and fiscal capacity for recovery.

Keywords: Natural Disasters, Geographically Weighted Panel Regression (GWPR), Gini Ratio.

1. Introduction

Indonesia's geographical location, which is crossed by the Pacific Circum or Pacific Ring of Fire, is a meeting point for active tectonic plates and is located in the tropics along the equator, making it prone to various natural disasters (Fuady et al., 2021). Natural disasters that frequently occur in Indonesia are classified into hydrometeorological disasters and geological disasters. Hydrometeorological disasters include drought, flooding, storms, forest fires, El Niño, La Niña, and landslides which are attributed to climate change in tropical regions. Geological disasters include earthquakes, tsunamis, liquefaction, and volcanic eruptions caused by the Pacific Ring of Fire and plate convergence (Idroes et al., 2023). Over the past ten years, there have been 35,180 natural disasters affecting 33 million people, causing displacement, injuries, and even deaths (BNPB, 2025). Based on the latest data, the Disaster Risk Index (IRB) shows that all regions in Indonesia are at moderate to high risk in 2024 (BNPB, 2025). Natural disasters in Indonesia, whether small or large in scale, have a negative impact on society because disasters themselves cause economic, social, and cultural disruption in both the short and long term (Puja Ilham, 2023). When a natural disaster occurs, the losses incurred include damage to infrastructure, loss of jobs, and damage to productive assets such as agricultural land, livestock, fisheries, and buildings. Based on research related to natural disasters and poverty in Indonesia, natural disasters have a negative and significant impact on income (Putra, 2017). This means that disasters not only reduce household income but may also generate broader social problems, including social jealousy and inequality, particularly when post-disaster recovery and development are unevenly distributed.

The ongoing impact of natural disasters can significantly affect poverty and inequality (Desinta & Sitorus, 2021). The Gini coefficient measures economic and social inequality, allowing assessment and comparison of income differences between regions. In one study, (Brata, 2022) found that meteorological disasters in Indonesia, such as storms or droughts, exacerbate income inequality, especially in densely populated areas, due to their greater economic disruption. The latest data indicate that Indonesia’s Gini ratio remains in the moderate category (RINI et al., 2022). These conditions suggest that increasing disaster frequency and intensity may heighten economic vulnerability and widen social and economic inequality, particularly among groups with limited capacity to recover.

Inequality is a key issue in sustainable economic recovery after a natural disaster(Tselios & Tompkins, 2019). Within the Sustainable Development Goals (SDGs) framework, reducing inequality is essential for promoting inclusive economic growth and poverty alleviation, especially in regions exposed to disaster risk. However, the impact of disasters on inequality may differ across provinces because each region has different levels of disaster exposure, population density, economic structure, and fiscal capacity. Therefore, modeling is needed to measure the extent to which the Gini ratio in each Indonesian province is affected by disaster-related and socioeconomic factors. This approach allows the relationship between disasters and inequality to be examined more systematically with spatial model. In addition, spatial modeling is relevant because each region has distinct geographical characteristics and economic capacity. The results can support the formulation of long-term, region-based strategic policies, rather than relying only on temporary post-disaster countermeasures (Tasri et al., 2022).

Based on this research gap, this study applies spatial mapping and Geographically Weighted Panel Regression (GWPR) to analyze the effect of natural disasters on income inequality, measured by the Gini ratio, across Indonesian provinces. The study covers 34 of Indonesia's 38 provinces, leaving out four new provinces (South Papua, Central Papua, Highland Papua, and Southwest Papua) because of limited data, and uses information from 2015 to 2024. We used a method that looks at both where and when changes happen, called

Geographically Weighted Panel Regression, to understand these effects. The results show that disasters affect inequality differently across provinces. Some areas see more inequality after disasters, while others change little. By pointing out these differences, the study gives policymakers clear information to help them plan for disaster risk, improve recovery, and address inequality after disasters.

2. Methods

The research was conducted using secondary data taken from the official websites of the Central Statistics Agency (BPS), the National Disaster Management Agency (BNPB), and djpk.kemenkeu. The endogenous variable is the Gini ratio (Y), with five exogenous variables: disaster risk index (X1), population density (X2), the distribution of Gross Regional Domestic Product at Current Market Prices (GRDP ADHB) by household expenditure (X3), percentage of unexpected regional budget expenditure (X4), and open unemployment rate (X5). In this context, the endogenous variable refers to the main variable being explained by the model, whereas exogenous variables refer to external explanatory factors assumed to influence changes in the Gini ratio. The research began with the following steps.

2.1. Data Collection

This study uses secondary data obtained from various websites, namely the Central Statistics Agency (BPS), the National Disaster Management Agency (BNPB), and djpk.kemenkeu. The data used is panel data observed from 2015 to 2024. The research object used is 34 provinces in Indonesia, so the total data used is 340. The variables used will be explained in Table 1 as follows.

Tabel 1. *Research Variable*

Variable	Description	Scale	Unit
y_{it}	Gini Ratio	Ratio	Indeks
x_{1it}	Risk Index Variable	Ratio	Indeks
x_{2it}	Population Density	Ratio	People/km^2
x_{3it}	Distribution Of ADHB GRDP According to Household Expenditure	Ratio	Persentage
x_{4it}	Percentage Of Unexpected Costs in The Regional Budget	Ratio	Persentage
x_{5it}	Open Unemployment Rate	Ratio	Persentage
u_{it}	Latitude Coordinates	-	-
v_{it}	Longitude Coordinates	-	-

Based on the research variables that use data from each province over a ten-year period and utilize spatial aspects, the Geographically Weighted Panel Regression (GWPR) method is the most appropriate method. This method is the result of a combination of the Geographically Weighted Regression (GWR) model and panel data regression. The advantage of this combination lies in its ability to capture spatial variation, intertemporal variation, and inter-individual variation, thereby improving the accuracy of the estimation.

2.2. Method Of Analysis

2.2.1 Data Panel Regression

Panel data regression is an analysis that uses combined data from time series and cross-sectional data. Using panel data can detect and measure the effects of data that cannot be measured by time series or cross-sectional data. In general, panel data offer various statistical and economic-theoretical advantages. One key advantage is their ability to explicitly capture individual heterogeneity by incorporating variables that are specific to each individual within econometric models (Supianti, 2023). The following is the general form of a panel data regression model.

$$Y_{it} = \alpha + \boldsymbol{\beta}'\boldsymbol{X}'_{kit} + \varepsilon_{it} \tag{1}$$

There are three methods used to estimate panel data regression models: the Common Effect Model, the Fixed Effect Model, and the Random Effect Model. The selection of panel data regression models uses the Chow test, Hausman test, and LM Test to determine the most effective panel data regression model estimation results in explaining the model. In addition, in the formation of panel data regression models, the assumptions of normality, non-multicollinearity, and homoscedasticity are assumptions that must be met in panel data regression.

2.2.2 Geographically Weighted Panel Regression (GWPR)

The Geographically Weighted Panel Regression (GWPR) method is a model development that combines the Geographically Weighted Regression (GWR) model with panel data regression. The advantage of combining these two methods is that they can capture spatial variation, intertemporal variation, and interindividual variation, thereby improving the accuracy of estimates (Rusgiyono & Prahutama, 2021). The following is an explanation of the Geographically Weighted Panel Regression (GWPR) model.

a. Selected Spatial Weighting

In the GWR model, the weighting scheme is essential because it represents the spatial location of each observation. Weights are determined by calculating the Euclidean distance between locations i and j, as shown in Equation(Nasri et al., 2023a).

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \tag{2}$$

The next step is to determine the bandwidth parameter, which can be specified as a fixed value for the entire model or allowed to vary depending on the density of observation points at each location. The optimal bandwidth value can be selected using several criteria, including cross-validation (CV), generalized cross-validation (GCV), Akaike information criterion (AIC), and corrected Akaike information criterion (AICc) methods (Koç, 2022). One bandwidth selection method is to use the cross-validation approach, which has the advantage of avoiding models that are too closely fitted to the data itself, so that the CV value for the kernel function parameter can select the optimal parameter value. The cross-validation criterion is formulated as follows.

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(b)]^2 \tag{2}$$

where $\hat{y}_{\neq i}(b)$is the fitted value of y_i by omitting the i the point from the process.

The spatial weighting function has a problem, namely discontinuity, whereby when the regression point shifts slightly, the estimated coefficient can change drastically. To that end, one way to overcome weight discontinuity is by defining w_{ij} as a continuous function of distance d_{ij} between *i* dan *j.* Here is an explanation of several continuous weighting functions.

- *Fixed Gaussian*

$$w_{ij} = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right] \tag{3}$$

- *Fixed Bisquare*

$$w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{b}\right)^2\right)^2, & for\ d_{ij} \leq b \\ 0 & , for\ d_{ij} > b \end{cases} \tag{4}$$

- *Fixed Tricube*

$$W_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{b}\right)^3\right)^3, & for\ d_{ij} \leq b \\ 0 & , for\ d_{ij} > b \end{cases} \tag{5}$$

- *Adaptive Gaussian*

$$W_{ij} = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b_j}\right)^2\right] \tag{6}$$

- *Adaptive Bisquare*

$$W_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{b_j}\right)^2\right)^2, & for\ d_{ij} \leq b \\ 0 & , for\ d_{ij} > b \end{cases} \tag{7}$$

- *Adaptive Tricube*

$$W_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{b_j}\right)^3\right)^3, & for\ d_{ij} \leq b \\ 0 & , for\ d_{ij} > b \end{cases} \tag{8}$$

b. GWPR Model Parameter Estimaton

GWPR model parameter estimation uses the weighted least squares (WLS) approach. The weights are assigned differently for each location, individual, and time. The estimator for the regression coefficient in GWPR is described as follows (Ananda et al., 2023)

$$\hat{\beta}(u_{it}, v_{it}) = (\boldsymbol{X}^T \boldsymbol{W}(u_{it}, v_{it})\boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{W}(u_{it}, v_{it})\boldsymbol{Y} \tag{9}$$

$\hat{\beta}(u_{it}, v_{it})$ Vector of local regression coefficients, sized p x 1 and $\mathbf{W}(u_{it}, v_{it})$ Explaining the diagonal matrix with diagonal elements is the geographical weighting of each data point for individual unit-i and time-t.

c. GWPR Model Parameter Signification Test

The explanation of the diagonal matrix with diagonal elements is the geographical weighting of each data point for individual unit-*i* and time-*t*.

- GWPR Model Goodness of Fit

Suitability testing is conducted by testing parameter compatibility simultaneously. The hypothesis used is explained as follows (Rusgiyono & Prahutama, 2021).

Hypothesis:

H_0 : $\beta_k(u_{it}, v_{it}) = \beta_k$, i = 1, 2, ..., n dan k = 1, 2, ...p

(There is no significant difference between the panel regression model and GWPR)

H_1 : at least one $\beta_k(u_{it}, v_{it}) \neq \beta_k$

(There is a significant difference between panel regression models and GWPR)

$$F = \frac{\text{SSE}(H_1)/\text{df}_1}{\text{SSE}(H_0)/\text{df}_2} \tag{10}$$

With a significant level set at α, then Reject H_0 if F < $F_{1-\alpha, df1, df2}$ or *P-value* > α.

- *Partial Testing of Significance of GWPR Model*

Partial testing is used to determine the independent variable x_k that affects location ke-i. The hypothesis used is described as follows (Rusgiyono & Prahutama, 2021).

Hypothesis:

H_0 : $\beta_k(u_{it}, v_{it}) = 0$, k= 1, 2, ..., p

H_1 : At least one $\beta_k(u_{it}, v_{it}) \neq 0$, k = 1, 2, ..., p

Test Statistics:

$$t = \frac{\hat{\boldsymbol{\beta}}_k(u_{it}, v_{it})}{se\left(\hat{\boldsymbol{\beta}}_k(u_{it}, v_{it})\right)} \tag{11}$$

If a significant level set at α, then Reject H_0 |*t*| > t α/2, df

d. Selection Of the Best Model

The best model can be selected using the coefficient of determination method, which describes how well the model explains the dependent variable. An important characteristic of the regression coefficient is that as the number of regressors increases, the coefficient decreases, R^2 almost always increases and never decreases. The value of the coefficient of determination is explained in the following equation(Nasri et al., 2023b).

$$R^2 = 1 - \frac{\text{SSE}}{\text{SST}} \tag{12}$$

3. Results and Discussion

3.1 Panel Data Model Formation

Panel data regression analysis was conducted prior to GWPR analysis, whereby this method would yield the best regression model on the impact of natural disasters on the Gini ratio. Panel data regression parameter estimation consists of three types of estimation, namely CEM, FEM, and REM, which will be explained as follows.

a. *Common Effect Model* (CEM)

Panel data regression modeling on factors suspected to influence the Gini index in Indonesian provinces yielded the following CEM model.

$$y_{it} = 0{,}369325 - 0{,}000396x_1 + 0{,}00000259x_2 + 0{,}000735x_3 - 0{,}001867x_4 - 0{,}000217x_5 + \varepsilon_{it}$$

The disaster risk index variable, the percentage of unexpected costs in the regional budget, and the open unemployment rate have negative variable coefficients, meaning that when these variables increase, the Gini ratio will decrease, while the population density variable and the distribution of regional gross domestic product according to household expenditure will have the opposite effect.

b. *Fixed Effect Model* (FEM) Individu

Panel data regression modeling of factors suspected to influence the Gini ratio index of provinces in Indonesia yielded a Fixed Effects Model with individual effects as follows.

$$y_{it} = 0{,}258149 + 0{,}000186x_1 + 0{,}00000801x_2 + 0{,}001048x_3 - 0{,}003613x_4 - 0{,}001840x_5 - 0{,}041898D_1 - 0{,}034378D_2 - 0{,}0046897D_3 - 0{,}000267D_4 - 0{,}0026688D_5 - 0{,}0014058D_6 - 0{,}018058D_7 - 0{,}027197D_8 - 0{,}093372D_9 + 0{,}006523D_{10} - 0{,}060245D_{11} + 0{,}033453D_{12} + 0{,}003993D_{13} + 0{,}022110D_{14} + 0{,}005399D_{15} + 0{,}023779D_{16} + 0{,}019253D_{17} - 0{,}019774D_{18} - 0{,}022479D_{19} - 0{,}005073D_{20} + 0{,}008792D_{21} + 0{,}013635D_{22} - 0{,}019427D_{23} + 0{,}028925D_{24} - 0{,}000938D_{25} + 0{,}036556D_{26} + 0{,}046828D_{27} + 0{,}060364D_{28} + 0{,}013185D_{29} + 0{,}054059D_{30} - 0{,}038954D_{31} + 0{,}068555D_{32} + 0{,}056632D_{33} + \varepsilon_{it}$$

In this Fixed Effect Model (FEM), the disaster risk index variable, the population density variable, the distribution of regional gross domestic product, and the percentage of unexpected costs in the regional budget show a positive influence, meaning they can increase the Gini ratio. Conversely, the open unemployment rate has the opposite effect (a negative influence). The dummy variables act as the fixed effects for each respective province.

c. *Random Effect Model* (REM)

The estimation of the panel data random effect regression parameters for the Gini ratio index is shown in the following model.

$$y_{it} = 0{,}266742 + 0{,}000168x_1 + 0{,}00000477x_2 + 0{,}000987x_3 - 0{,}003604x_4 + 0{,}001732x_5 + w_{it}$$

In this Random Effect Model (REM), the disaster risk index variable, the population density variable, the distribution of regional gross domestic product, and the open unemployment rate show a positive influence, meaning they can increase the Gini ratio. Conversely, the percentage of unexpected costs in the regional budget has the opposite effect (a negative influence). The element referred to is the combination of the model error and the individual error effect, which contains all the influences not explained by the variables in the model, but which still affect the result (the Gini ratio) in each province and year. After the panel model was formed, the Chow test, Hausman test, and LM test were conducted to determine the best estimation model using panel data regression. The test results can be seen in Table 1.

Tabel 2. Regresion Panel DataTest

Chow Test		Hausman Test		LM Test	
P-value	0,000	P-value	0,2184	P-value	0,000

Based on Table 1, a P-value < 0.05 was obtained in the Chow test, so FEM was selected in the first test. The next tests were conducted, namely the Hausman test with a P-value > 0.05 and the LM Test with a P-value < 0.05, which showed that the REM model was selected.

In the REM model, significance tests will be conducted both simultaneously and partially to see whether natural disaster impact variables have a significant effect on the Gini ratio in Indonesia. Simultaneous tests are used to determine the simultaneous effect of natural disaster impact variables on the Gini ratio, using a significance level of 5%, showing an F-test statistic value of 12.623, which is greater than $F_{(0{,}05;5;334)}$ as large as 2,241 and reinforced by a P-value of 0,000, which is smaller than 0.05, so it can be decided H_0 rejected, which means that there is at least one natural disaster impact variable that significantly affects the Gini ratio. After simultaneously finding at least one natural disaster impact variable that significantly affects the Gini ratio, a partial test is conducted to determine whether each variable has a significant effect or not, as follows.

Table 3. Significant Test of Partial Regresion Panel Data

Variable	|t|	$t_{\left(\frac{0{,}05}{2}\right);334)}$	P-value	Decision
Intersep	17,302	1,967	0,0000	H_0 rejected
Risk Index Variable	2,651	1,967	0,0084	H_0 rejected
Population Density	2,036	1,967	0,0425	H_0 rejected
Distribution Of ADHB GRDP According to Household Expenditure	4,815	1,967	0,0000	H_0 rejected
Percentage Of Unexpected Costs in The Regional Budge	3,371	1,967	0,0008	H_0 rejected
Open Unemployment Rate	1,646	1,967	0,1006	H_0 not rejected

This shows that the disaster risk index variable, population density, distribution of ADHB GRDP according to household expenditure, and percentage of unexpected costs in the regional budget have a T statistic greater than the T table and are reinforced by a P-value smaller than alpha 0.05, which means that these four variables are significant to the Gini ratio in Indonesia, while the open unemployment rate variable is the opposite. Based on the significant variables, a random effect model can be formed as follows.

$$y_{it} = 0{,}271230 + 0{,}000176x_1 + 0{,}00000501x_2 + 0{,}0001040x_3 - 0{,}003542x_4 + w_{it}$$

The equation w_{it} in the model shows the value of individual random error (ε_{it}) which indicates the extent of the difference in the random error component in each province from the intercept value for all provinces in Indonesia, which is 0.2712. Based on the random error values for each province, Aceh Province has a random error value of -0.040, which shows how far the random error component of Aceh Province differs from the intercept value, as is the case with other provinces.

Next, panel data regression assumptions were tested to ensure that the resulting model had accurate, unbiased, and consistent estimates. Based on the results of these assumption tests, it can be concluded that the residuals are normally distributed, there is no multicollinearity between independent variables, and the residual variance is not constant. The complete analysis results are presented in Tables 4, 5, and 6.

Tabel 4. Normality Asumption

Kolmogorof Smirnov	
KS	0.027

The normal distribution assumption test is used to determine whether the residuals of the selected REM model follow a normal distribution or not. Based on Table 4, KS is 0.027, which is smaller than $D_{(0{,}05;340)}$ of 0,073 and the p-value 0> 0.05, so it can be concluded that the residuals are normally distributed.

Tabel 5. Multicolinearity Asumption

Variable	VIF
x_1	1,0537
x_2	1,0384
x_3	1,0401
x_4	1,0594

Furthermore, Table 5 shows the VIF values of the five variables used, where all five variables have values greater than 10, so it can be said that there is no indication of multicollinearity in the random effect panel data regression model.

Tabel 6. Spatial Heterogenity Asumption

Breusch Pagan test	
BP	23,394
P-value	0,0001106

Meanwhile, the Breusch-Pagan test result in Table 5 shows that the p-value < 0,05, which is rejected at a significance level of 5%. This indicates that the Random Effect Model (REM) experiences heteroscedasticity caused by differences in spatial characteristics between regions. Therefore, this study uses the Geographically Weighted Panel Regression (GWPR) method as an alternative approach because the assumption of non-heteroscedasticity in the REM model is not met.

3.2 Formation of the GWPR-REM Model

GWPR analysis on the REM model can first determine the location points of each province in Indonesia in the form of longitude and latitude coordinates. Once the location points have been determined, the Euclidean distance or distance between locations can be calculated, which will later be used in GWPR analysis.

3.2.1 The Spatial Weighting Function of Random Effect: Impact of Natural Disasters on the Gini Ratio

Next, in estimating the model parameters, it is necessary to determine the observation location for each province in Indonesia, followed by selecting the optimum bandwidth by checking the Cross Validation (CV) score, AIC, and R-Square in the weighting function. The results of weighting with the Kernel function can be seen in Table 6.

Tabel 1. Spatial Weighting Function

	Kernel					
	Fixed			Adaptive		
	Gaussian	Bisquare	Tricube	Gaussian	Bisquare	Tricube
CV	0,0723	0,0903	0,0932	0,1733	**0,0587**	0,0600
AIC	-2044,94	-1971,37	-1965,92	-1645,11	**-2193,776**	-2186,92
R-square	0,9326	0,9147	0,9134	0,7443	**0,9595**	0,9587

Table 6 shows that the adaptive bisquare kernel spatial weighting function was selected for the random effect of natural disasters on the Gini ratio because it produced the minimum CV value, the largest R-square, and the minimum AIC compared to other spatial weighting functions. Furthermore, the GWPR analysis will use the selected adaptive bisquare kernel weighting function.

3.2.2 Significance of GWPR Random Effect Parameters: Impact of Natural Disasters on the Gini Ratio

GWPR testing with the REM model includes model fit testing and model parameter significance testing. Model fit testing is used to determine whether there are differences between the random effect panel model and the GWPR model simultaneously. The results show that the F test statistic value is 0.617786, which is smaller than $F_{(0,95;224,4367;335)}$ of 0,8158 so it can be concluded H_0 is rejected, which means that there are at least natural disaster impact variables that have a significant effect on the significant difference between the panel regression model and GWPR.

Next, a partial significance test of the GWPR model parameters was conducted to determine the predictor variables or natural disaster impact variables that significantly affect the Gini ratio in each province in Indonesia. The results are as follows.

Tabel 7. Significance Test of Partial GWPR

Province	$\|t(\hat{\beta}_1)\|$	$\|t(\hat{\beta}_2)\|$	$\|t(\hat{\beta}_3)\|$	$\|t(\hat{\beta}_4)\|$	$t_{0,05;225}$	Variable Significant
Aceh	1,809	**2,787**	0,393	0,523		x_2
Bali	0,734	0,655	0,298	0,720		-
Banten	**3,360**	**2,931**	0,214	**2,002**		x_1, x_2, x_4
Bengkulu	0,561	0,038	1,339	0,400		-
Di Yogyakarta	0,054	**3,751**	1,443	**3,385**		x_2, x_4
Dki Jakarta	**3,216**	0,359	**2,313**	1,509		x_1, x_3
Gorontalo	0,091	1,146	0,661	0,038		-
Jambi	0,338	1,573	**2,002**	0,686		x_3
Jawa Barat	0,892	0,550	0,051	0,758		-
Jawa Tengah	0,420	**3,603**	1,564	**3,612**		x_2, x_4
Jawa Timur	**4,911**	0,775	1,589	1,506		x_1
Kalimantan Barat	0,309	1,429	0,958	0,469		-
Kalimantan Selatan	**2,197**	0,591	0,154	0,679		x_1
Kalimantan Tengah	0,737	0,095	0,054	0,433		-
Kalimantan Timur	**2,507**	**7,722**	0,934	0,650		x_1, x_2
Kalimantan Utara	**2,615**	**7,900**	**2,148**	1,102	1,971	x_1, x_2, x_3
Kep. Bangka Belitung	**2,672**	**7,213**	**2,045**	**3,597**		x_1, x_2, x_3, x_4
Kep. Riau	0,077	0,461	0,484	1,206		-
Lampung	0,297	**5,391**	**2,976**	1,610		x_2, x_3
Maluku	0,530	**6,536**	**4,296**	0,478		x_2, x_3
Maluku Utara	0,984	**11,157**	0,557	**2,073**		x_2, x_4
Nusa Tenggara Barat	0,186	0,707	0,414	1,307		-
Nusa Tenggara Timur	0,442	**2,696**	0,183	1,339		x_2
Papua	1,420	0,733	0,642	0,916		-
Papua Barat	**2,467**	1,607	0,038	0,503		x_1
Riau	**2,988**	0,773	1,895	1,006		x_1
Sulawesi Barat	**2,202**	1,803	**2,222**	0,994		x_1, x_3
Sulawesi Selatan	**3,299**	**2,233**	1,882	1,344		x_1, x_2
Sulawesi Tengah	0,464	1,343	**5,125**	1,319		x_3
Sulawesi Tenggara	0,956	**2,262**	**2,227**	0,276		x_2, x_3
Sulawesi Utara	0,036	1,642	1,090	0,679		-
Sumatera Barat	**3,202**	0,544	0,707	0,188		x_1
Sumatera Selatan	1,324	0,749	0,456	0,071		-
Sumatera Utara	**2,524**	0,288	0,712	0,082		x_1

It is known that several provinces have similar variables that affect the Gini ratio, while other provinces differ, and there are provinces that do not have research variables that affect the ratio, namely 11 out of 34 provinces. This difference is caused by the GWPR regression T-value being smaller than the T-table value. The diversity of coefficients indicates structural instability and suggests spatial heterogeneity or differences in characteristics between regions. For this reason, provinces will be grouped based on similarities in variables that affect the Gini ratio as follows.

Tabel 8. Significance Test of Partial GWPR

Group	Region	Variable
1	Sumatera Selatan, Bengkulu, Kepulauan Riau, Jawa Barat, Bali , Nusa Tenggara Barat, Kalimantan Barat, Kalimantan Tengah, Sulawesi Utara, Gorontalo, Papua	-
2	Sumatera Utara, Sumatera Barat, Riau, Jawa Timur, Kalimantan Selatan, Papua Barat	x_1
3	Aceh, Nusa Tenggara Timur	x_2
4	Jambi, Sulawesi Tengah	x_3
5	Kalimatan Timur, Sulawesi Selatan	x_1, x_2
6	DKI Jakarta, Sulawesi Barat	x_1, x_3
7	Lampung, Sulawesi Tenggara, Maluku	x_2, x_3
8	Maluku Utara, Jawa Tengah, DI Yogyakarta	x_2, x_4
9	Kalimantan Utara	x_1, x_2, x_3
10	Banten	x_1, x_2, x_4
11	Kepulauan Bangka Belitung	x_1, x_2, x_3, x_4

Based on Table 8, it is known that several provinces have similar variables that affect the Gini ratio, while other provinces differ. However, there are provinces that do not have research variables that affect the ratio, namely 11 out of 34 provinces. To make it easier to identify the grouping of provinces based on groups, the provinces in Indonesia will be mapped as shown in Figure 1 below.

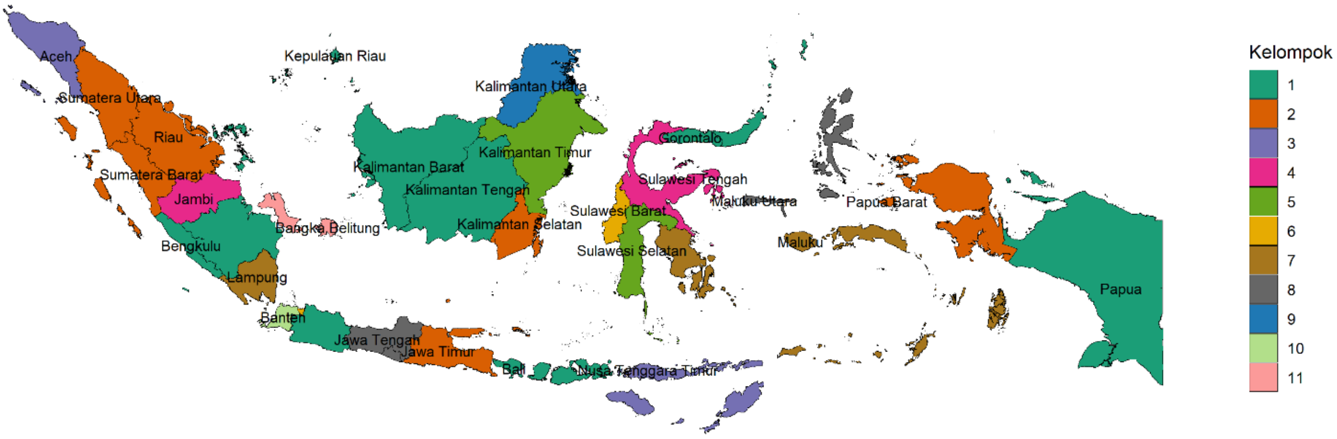

Figure 1. Mapping of GWPR Result

The clustering results indicate that the effects of the disaster risk index, population density, the distribution of per capita GRDP by household expenditure, and the percentage of the provincial budget allocated to unforeseen expenses on the Gini coefficient vary across provinces. In eleven provinces, namely South Sumatra, Bengkulu, Riau Islands, West Java, Bali, West Nusa Tenggara, West Kalimantan, Central Kalimantan, North Sulawesi, Gorontalo, and Papua, the four variables do not have a significant effect. These findings indicate that income inequality in these regions may be more influenced by factors outside the model, such as local economic structure, infrastructure quality, access to education, labour market characteristics, and regional development policies. This aligns with(Kurniawan et al., 2019), who state that provinces in Indonesia do not always follow the same path of socioeconomic convergence, so the causes of inequality may differ across regions.

In provinces with high disaster risk, inequality can happen because low-income groups are more likely to suffer when disasters hurt the economy. Damage to property, lost daily income, interrupted work, and the cost of rebuilding after disasters can make the gap between the poor and richer people even wider. This supports (Brata, 2022) findings that natural disasters can widen income differences in Indonesia, though the effect depends on the type of disaster and local conditions. However, we should think about these results more (Wang & Zhao, 2023) found disasters do not always have the same effect; government support and transfers can help reduce some of the differences caused by disasters.

Population density is a significant variable in several provinces because inequality tends to increase when population growth is not accompanied by equitable access to employment, public services, housing, transportation, and economic centers. In addition to population factors, the significance of the distribution of ADHB GRDP (Gross Regional Domestic Product at current market prices) by household expenditure indicates that inequality is also linked to the concentration of purchasing power and economic activity in specific regions. Furthermore, economic growth does not automatically reduce inequality if it is concentrated only in growth centers. Lastly, the percentage of the regional budget allocated to unforeseen expenses (funds set aside for unexpected events or emergencies) reflects the region's fiscal capacity to respond to shocks, particularly disasters. If the allocation is inadequate, vulnerable groups may experience a slower recovery, potentially leading to increased inequality.

Overall, the clustering pattern of provinces that are partially geographically adjacent suggests the presence of spatial effects. Adjacent provinces tend to share similarities in disaster risk, economic structure, population mobility, and interregional economic interactions. Therefore, income inequality in Indonesia cannot be explained by a single factor, but rather through the interaction between disaster risk, demographic pressures, economic activity, and fiscal capacity. Consequently, policies to reduce inequality need to be formulated based on regional characteristics, rather than using a uniform approach for all provinces.

3.2.3 Selection of the Best Model: Random Effect Model and GWPR Random Effect for the Impact of Natural Disasters on the Gini Ratio

The best model is used to determine the goodness of the model produced by the impact variables of natural disasters on the Gini ratio in Indonesia using the GWPR random effect, which is better than the simple random effect panel regression model. It is known that the panel data regression results have a model goodness of 14.63%, while the GWPR random effect model is 93,86%, which shows that the GWPR model can explain better than just using the panel alone. The GWPR model goodness of 93,86% shows that the four natural disaster impact variables that have been weighted with a weighting matrix and random effect are able to explain the Gini ratio, while the rest is explained by other variables outside the model.

4. CONCLUSION

The Geographically Weighted Panel Regression (GWPR) Random Effect approach yielded a high model goodness of fit. This indicates that the impact of natural disasters on the Gini ratio, in terms of risk, social, and economic factors, varies across provinces. Some provinces show a significant influence, while others do not. This forms several groups with distinct regional characteristics. The research findings indicate that the disaster risk index, population density, the distribution of Gross Regional Domestic Product at Current Market Prices (GRDP ADHB) by household expenditure, and the percentage of local budget (APBD) for unforeseen expenditures have a significant effect on the Gini ratio. This finding affirms that inter-regional income inequality is influenced not only by economic factors but also by the level of regional vulnerability and capacity to cope with and recover from natural disasters. Regions with high disaster risk, large population density, and low fiscal capacity tend to experience an increase in inequality after disasters. This is due to asset damage, decreased economic activity, and limited resources for recovery. These findings emphasize the importance of a spatial approach in understanding interregional income inequality.

This study, however, has various limitations, especially in terms of coverage of study, data, and research methodology. Further research is recommended to deepen the analysis with more specific variables related to the type of disaster and regional capacity. From a policy perspective, local governments need to formulate strategies according to the characteristics of each region, such as strengthening emergency budgets in high-risk areas, controlling density in vulnerable zones, and encouraging economic diversification and strengthening household purchasing power. This approach is not only responsive to disasters but also contributes to reducing income inequality among communities.

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