

Deterministic Economic Resilience Through Gross Regional Domestic Product Using Nonparametric Geographically Weighted Regression Spline Truncated

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ABSTRACT

Megatrends are large-scale global movements with huge impacts, influenced by socio-economic, political, ecological, and technological factors. As a developing country, Indonesia faces challenges such as political instability and limited infrastructure, so strengthening economic resilience through increasing Gross Regional Domestic Product (GRDP) is important. This research aims to analyze Indonesia's GRDP data in 2022, which shows significant spatial variability between provinces, to see the resilience of the Indonesian economy. The method used is Nonparametric Geographically Weighted Regression-Spline Truncated (NGWR-ST). The NGWR-ST approach is well-suited because it allows location-specific parameter variations, captures complex nonlinear relationships through spline functions, and minimizes the influence of extreme values using truncation. The results indicate that an optimal model is achieved with two knot points ($GCV = 0.293$) and a fixed kernel bi-square weighting function with a 19.174 bandwidth ($CV = 974.621$), providing optimal spatial weighting. Among the factors analyzed, the Human Development Index (HDI) and the Rate of Return (ROR) are identified as having a significant influence on GRDP, contributing insights for strengthening Indonesia's economic resilience. Thus, this study will contribute to formulating appropriate regional policy strategies to strengthen the economy in facing the World Megatrend in 2045.

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A. INTRODUCTION

Megatrends are large movements on a global scale that tend to have a wider and greater impact than evolution at the level of trends that tend to be dynamic with faster results (Bash et al., 2023). Megatrends have an impact and depend on four factors, namely socio-economic, political, ecological, and technological. Economic factors in megatrends are also called global economic megatrends. Part of this global economic megatrend is emerging markets. Emerging market is a term to describe countries with rapid economic growth (Dabija et al., 2023). Indonesia, as an emerging market country, faces challenges such as political instability,

currency fluctuations, legal uncertainty, and immature infrastructure. In preparation for the world megatrend, Indonesia needs to enhance its economic resilience. Economic resilience is the ability to improve the economy and prepare resources to move forward. Indonesia's economic resilience is carried out by increasing the value of the Gross Regional Domestic Product (GRDP).

GRDP is the added value obtained from all regional economic activities based on its production factors and is divided into GRDP on a constant base price and prevailing price (Novianto, 2022; Sanusi et al., 2021). GRDP itself is a regional part of the Gross Domestic Product (GDP) which is used as the main indicator in measuring the economic growth of the province (Sahputri et al., 2022). Economic growth as a mechanism for external growth per capita in the long term (Surenjani et al., 2023). GRDP is used with the consideration that it can represent each region in Indonesia which basically cannot be equated due to differences in conditions, such as topography, natural resources, infrastructure, and others. As an emerging market country, Indonesia can be resilient through the analysis of factors that affect GRDP, namely Foreign Investment (FDI), Regional Original Revenue (ROR), Domestic Investment (DDI), and Labor Force Participation Rate (LFPR). The Human Development Index (HDI) and the Proportion of Manufacturing Value Added (PMVA) to GDP are also added in this study to see the effect on GRDP.

In general, GRDP data in Indonesia in 2022 does not form a certain pattern and is inseparable from spatial influences. This pattern is reviewed through the existence of a very varied GRDP value and there are several extreme GRDP values. This can be seen in Figure 1.

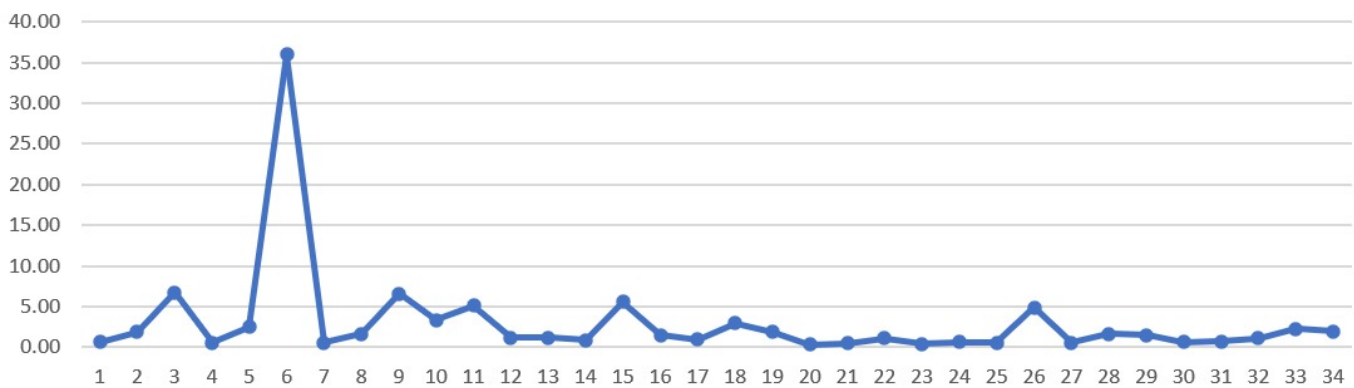


Figure 1. GRDP value pattern

Then spatial influence occur because the GRDP data used is different for each province (Mijayanti & Helma, 2021). The problem of spatial analysis, in this case a province with an unknown regression curve, can be solved using one of the spatial and nonparametric regression development methods, namely Nonparametric Geographically Weighted Regression Spline Truncated (NGWR-ST) modeling. The spline function is used to model complex and nonlinear relationships between predictor variables. It will take into account the variety of interprovincial regions in the shape and strength of the relationship. The truncated function in this method refers to the adjustment used to reduce the extreme observation effect. Therefore, these factors will be analyzed with NGWR-ST.

The NGWR-ST is a nonparametric regression approach designed for spatial analysis problems with unknown regression curves (Laome et al., 2023; Sifriyani et al., 2018). This method provides an accurate model for examining the effects of predictors such as FDI, ROR, DDI, HDI, LFPR, and PMVA on GRDP, as it uses model parameters that vary across observation locations or each province. NGWR-ST can capture localized relationships, adapt to spatial heterogeneity, and provide flexibility in modeling complex, non-linear patterns, which are essential for understanding regional variations in economic indicators like GRDP. Research using the NGWR-ST method has been conducted by Putra et al. (2023) related to morbidity in North Sumatra. The study compared Truncated Spline Nonparametric Regression (TSNR) method with NGWR-ST and obtained the result that the NGWR-ST model is the best model that can explain the effect of the predictor variable.

In this study, NGWR-ST can be applied because the characteristics of response variables (GRDP) and predictors (FDI, ROR, DDI, HDI, LFPR, and PMVA) show spatial variations throughout the region. Therefore, a study entitled "Megatrends Emerging Market: Economic Resilience Through Analysis of Determinants of Gross Regional Domestic Product with Geographically Weighted Regression Spline Truncated" was conducted. The purpose of this study is to consider spatial influences, model geographic variability in the relationship between variables, and provide the best model as an effort to identify factors that influence GRDP to build economic resilience as a developing market in preparing Indonesia to face the global economic megatrend. The difference with previous studies lies in the focus of the application of the method used. In the study conducted by Putra et al. (2023) focused on providing an algorithm

for using the NGWR-ST model for the analysis of certain case studies. This study will apply the NGWR-ST method to analyze GRDP and the factors that influence it. In addition, this study will also demonstrate how this model effectively captures significant spatial variations based on data from 34 provinces in Indonesia. Thus, this study will contribute to providing an understanding of the relationship between variables, which is expected to be a reference in formulating appropriate regional policy strategies to strengthen the economy in facing the World Megatrend in 2045.

B. RESEARCH METHOD

Explaining research chronological, including research design, research procedure (in The research method in this study was carried out using Rstudio software with the following stages:

1. Conduct descriptive analysis and data exploration based on geographic angles using thematic maps and data patterns using scatter plots.
2. Conducting spatial heterogeneity testing using the Breusch-Pagan (BP) test with the hypothesis (Rahman et al., 2023):

H_0 : $\sigma_1^2 = \sigma_2^2 = \dots = \sigma_n^2 = \sigma^2$ (there is no spatial heterogeneity)

H_1 : there is at least one $\sigma_i^2 \neq \sigma^2$ (there is spatial heterogeneity)

The value of the BP test is obtained using Equation (1):

$$BP = \frac{1}{2} f' X (X' X)^{-1} X' f \quad (1)$$

3. Detecting multicollinearity on a predictor variable with a Variance Inflation Factor (VIF) value defined using Equation (2):

$$VIF = \frac{1}{1 - R_i^2} \quad (2)$$

by R_i^2 being the value of the determination coefficient of the i th predictor variable. If the VIF value > 10 , then it can be stated that there is multicollinearity (Juarto, 2023).

4. Determining the optimal knot point using the Generalized Cross Validation (GCV) development method with Equation (3) (Putra et al., 2023):

$$GCV(K_1, K_2, \dots, K_r) = \frac{MSE(K_1, K_2, \dots, K_r)}{\left\{ \frac{1}{n} \text{tr} [I - A(K_1, K_2, \dots, K_r)] \right\}^2} \quad (3)$$

with MSE as the mean of the squares of error, I as the identity matrix, as the matrix that is sized, and $A(K_1, K_2, \dots, K_r) X (X' X)^{-1} X' n \times n X$ as the matrix that is sized $n \times (1 + (l \times m) + (l \times r))$.

5. Specifies the spatial weighting matrix between fixed kernel functions using the minimum GCV value.
6. Estimating the parameters of the NGWR-ST model using the weighted least squares method with matrix operations (Daulay & Simamora, 2023):

$$\hat{\beta}(u_i, v_i) = (X' W(u_i, v_i) X)^{-1} X' W(u_i, v_i) Y \quad (4)$$

as a vector estimating the parameters of the model and as a matrix of spatially weighted sizes $\hat{\beta}(u_i, v_i) W(u_i, v_i) n \times n$.

7. Conducting simultaneous and partial parameter significance testing.
8. Interpret the model and make conclusions.

C. RESULT AND DISCUSSION

1. Data Exploration

This research examines GRDP data from 34 provinces in Indonesia in 2022 as the response variable. The variables hypothesized to affect GRDP (Y) are FDI (X_1), DDI (X_2), LFPR (X_3), PMVA (X_4), HDI (X_5), and ROR (X_6). Data exploration

was carried out through visualization of spatial distribution grouped based on the value of each variable of 34 provinces in Indonesia, and the pattern of relationships between variables. The spatial distribution mapping of each variable is shown through the division of provinces based on three category values, namely low, medium, and high.

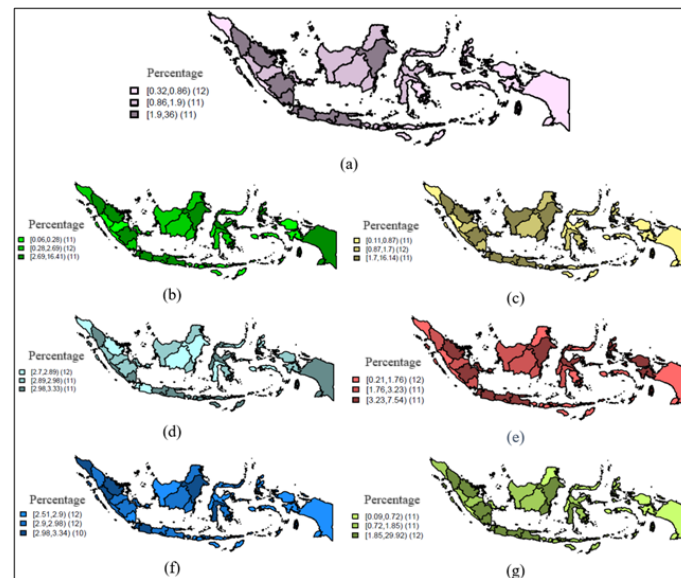


Figure 2. Spatial Distribution Map in Indonesia in 2022 (a) GRDP, (b) FDI, (c) DDI, (d) LFPR, (e) PMVA to GDP, (f) HDI, (g) ROR

Figure 2 shows the differences in spatial distribution mapping for different variables for each province. This is viewed through different colors, in this case, light for the low category, faded for the medium category, and dark for the high category. Color differences indicate differences in variable values that are inseparable from spatial dependencies. The identification of the relationship pattern between variables is shown in Figure 3.

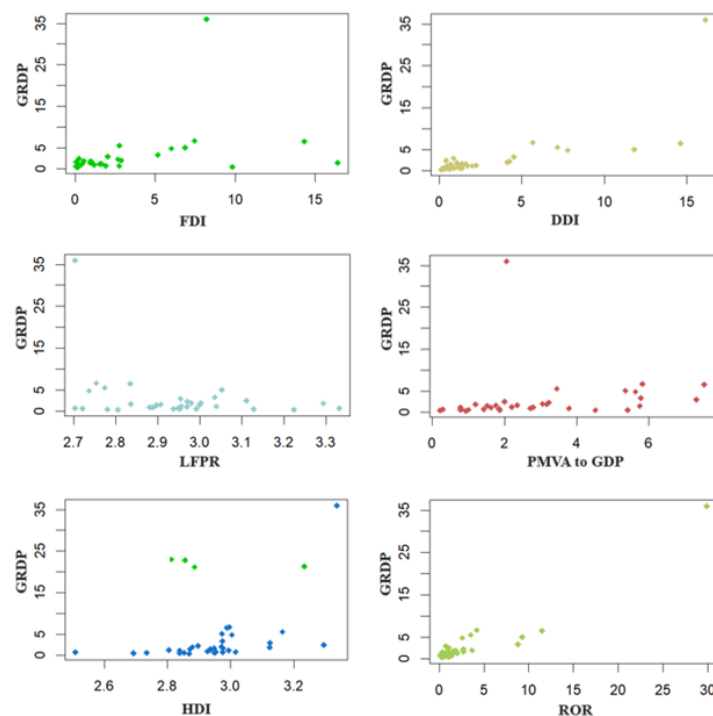


Figure 3. Scatter Plot of GRDP and Predictor Variables

Based on Figure 3, it can be seen that the relationship of each predictor variable to the response variable. The scatterplot image of each variable reveals a relationship pattern that does not follow a specific pattern, and there are extreme values, so that the analysis using nonparametric modeling can be continued.

2. Model Assumption Testing

a. Non-multicollinearity

Multicollinearity is a condition in which two or more independent variables or predictors in a model have a very high level of correlation with each other. This condition can be seen through the increase in variance in the value (VIF). If the VIF value is greater than 10, it can indicate multicollinearity in the data. The results of this assumption test can be seen in Table 1.

Table 1. Non-multicollinearity Test Results

Variable	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆
VIF	2.279	5.177	1.267	2.089	1.542	4.589

Based on Table 1, it can be seen that each predictor variable has a VIF value of less than 10. This means that there is no violation of the non-multicollinearity assumption in the data and all predictor variables can be used for further analysis.

b. Spatial Heterogeneity

The Breusch-Pagan (BP) test was used to test the effect of spatial heterogeneity, with the results shown in Table 2. The test hypotheses used are as follows:

$$H_0 : \sigma_1^2 = \sigma_2^2 = \dots = \sigma_n^2 = \sigma^2 \text{ (There is no spatial heterogeneity)}$$

$$H_1 : \text{there is } \sigma_i^2 \neq \sigma_j^2 \text{ with } i \neq j \text{ (There is spatial heterogeneity)}$$

The results of this assumption test can be seen in Table 2.

Table 2. Spatial Heterogeneity Test Results

P-Value	Information
0.032	Fulfilled

Based on Table 2, the results of spatial heterogeneity testing using the Breusch Pagan test, the resulting p-value of 0.032 is less than $\alpha = 0.050$. This means that there is sufficient evidence to conclude that there is spatial heterogeneity in the data.

3. Optimum Knot Points Selection

The number of knot points applied is limited to one to three points because the more the number of points, the more complex the resulting model pattern (Afifah et al., 2017; Zuhdi et al., 2017). The minimum GCV value in the selection of optimum knot points can be seen in Table 3.

Table 3. Optimum Knot Point Based on Minimum GCV

Number of Knot Points	GCV
1	0.706
2	0.293
3	0.295

Table 3 shows the minimum GCV value is 0.293 with two knot points used. Based on these results, two knots are needed for each predictor variable. The optimum knot point locations for each predictor variable are shown in Table 4.

Table 4. Location Point Knot Predictor Variable

Variable	Knot Point Location	
	K _{p1}	K _{p2}
X ₁	4.734	5.068
X ₂	4.691	5.018

Variable	Knot Point Location	
	K_{p1}	K_{p2}
X_3	2.883	2.896
X_4	2.306	2.455
X_5	2.745	2.762
X_6	8.616	9.225

Based on Table 4, the optimum knot point location is known for each predictor variable. This means that there are significant changes related to other variables around these points which can indicate a complex interaction between the variables.

4. Optimum Bandwidth Selection

The optimum bandwidth is determined by minimizing Cross Validation (CV) based on spatial weights. The results of calculating the CV value for the spatial weighting function can be seen in Table 5.

Table 5. Optimum Bandwidth Selection

Kernel Functions	Weighting Function	Bandwidth	CV
Fixed	Gaussian	7.223	980.792
	Bisquare	19.174	974.621
	Tricube	19.572	975.319

Based on Table 5, the minimum CV value obtained using the smallest fixed kernel bi-square is 974.621. This indicates that the weighting function to be used is a fixed kernel bi-square with a bandwidth value obtained of 19.174.

5. Model Parameter Estimation

The Model parameters are calculated based on geographical points so that model parameters vary between observation locations. In addition to these parameters, there are also parameters for each variable based on the knot point. Therefore, there are 19 parameters for each province. The model parameters can be seen briefly in Table 6.

Table 6. Model Parameters

Province	β_0	...	β_6	$\beta_{1,2}$	$\beta_{1,3}$...	$\beta_{6,3}$
Aceh	5.421	...	0.172	-0.621	1.454	...	8.255
North Sumatra	4.679	...	-0.049	-3.624	3.773	...	-5.699
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Papua	-4.199	...	0.313	3.051	-2.820	...	0

Based on Table 6, it is known that each province has a different model. This depends on the predictor variables that have a significant influence on each region. In general, the NGWR-ST model obtained is written in the following Equation 5.

$$\begin{aligned}
 y_i = & \beta_0(u_i, v_i) + \beta_1(u_i, v_i)x_{1i} + \beta_{1,2}(u_i, v_i)(x_{1i} - 4.734)_+ + \beta_{1,3}(u_i, v_i)(x_{1i} - 5.068)_+ + \beta_2(u_i, v_i)x_{2i} \\
 & + \beta_{2,2}(u_i, v_i)(x_{2i} - 4.691)_+ + \beta_{2,3}(u_i, v_i)(x_{2i} - 5.018)_+ + \beta_3(u_i, v_i)x_{3i} \\
 & + \beta_{3,2}(u_i, v_i)(x_{3i} - 2.883)_+ + \beta_{3,3}(u_i, v_i)(x_{3i} - 2.896)_+ + \beta_4(u_i, v_i)x_{4i} \\
 & + \beta_{4,2}(u_i, v_i)(x_{4i} - 2.306)_+ + \beta_{4,3}(u_i, v_i)(x_{4i} - 2.455)_+ + \beta_5(u_i, v_i)x_{5i} \\
 & + \beta_{5,2}(u_i, v_i)(x_{5i} - 2.745)_+ + \beta_{5,3}(u_i, v_i)(x_{5i} - 2.762)_+ + \beta_6(u_i, v_i)x_{6i} \\
 & + \beta_{6,2}(u_i, v_i)(x_{6i} - 8.616)_+ + \beta_{6,3}(u_i, v_i)(x_{6i} - 9.225)_+
 \end{aligned} \tag{5}$$

(u_i, v_i) symbols indicate that there is a spatial effect on the model.

6. Model Fit Testing

A goodness-of-fit test was conducted to determine the better model between the NGWR-ST model and the global regression model, yielding a p-value of $2.54 \times 10^{-47} < 0.050$, which is far below the significance level of 0.05. This extremely low p-value provides strong evidence to reject the null hypothesis, confirming that the NGWR-ST model significantly differs from and outperforms the global model in capturing spatial variability in the data. While the global regression model assumes that relationships between variables remain constant across all locations, the NGWR-ST model allows for nonparametric, location-specific relationships using truncated splines. This difference has a significant impact on this study, as the NGWR-ST model can reveal more detailed spatial patterns and provide a more accurate understanding of local variations. With this flexibility, the NGWR-ST model offers better fit and precision, facilitating more region-specific insights and supporting more targeted policies.

7. Parameter Significance Testing

The simultaneous parameter significance test aims to determine the significance of the model parameters together. The test results provide a p-value of $1.477 \times 10^{-4} < 0.050$ sufficient evidence to conclude that predictor variables simultaneously affect GRDP. The partial parameter significance test aims to identify significant predictor variables against the GRDP model formed in each province. Partial significance testing results in the formation of provincial groups based on significant predictor variables. Significant variables for each province can be observed visually in Figure 4.

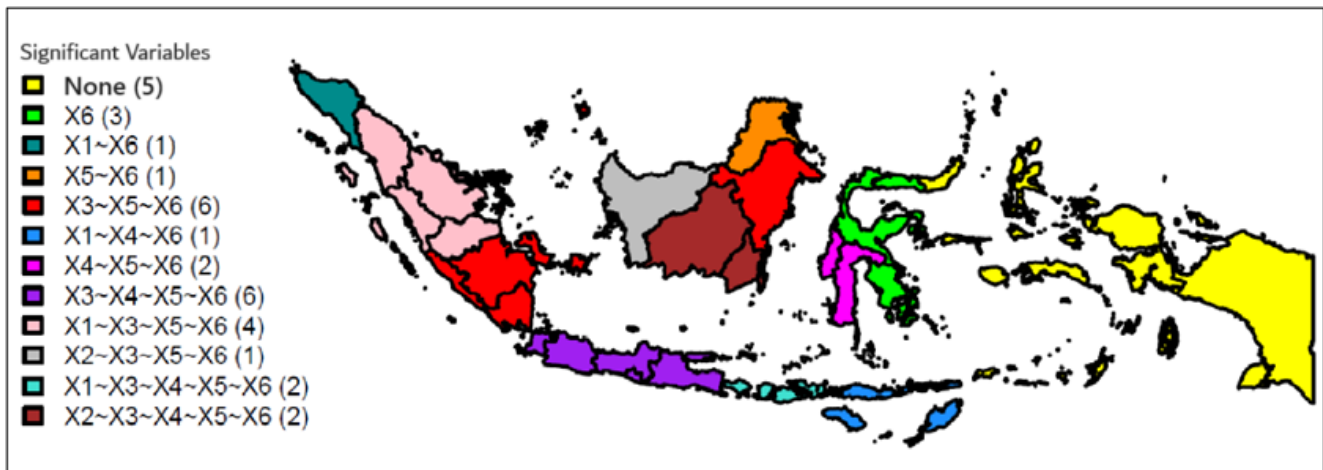


Figure 4. Spatial Distribution Map Based on Significant Predictor Variables

Based on Figure 4, the division of groups can be described as follows.

- a. Group 1 is a province (Aceh) with variables that have a significant influence on GRDP variables are FDI and ROR investment.
- b. Group 2 is a province (Bali and West Nusa Tenggara) with variables that have a significant influence on GRDP variables are FDI, LFPR, PMVA, HDI, and ROR.
- c. Group 3 is a province (DI Yogyakarta, Banten, East Java, DKI Jakarta, Central Java, and West Java) with variables that have a significant influence on GRDP variables are LFPR, PMVA, HDI, and ROR.
- d. Group 4 is a province (Bengkulu, East Kalimantan, South Sumatra, Riau Islands, Lampung, and Bangka Belitung Islands) with variables that have a significant effect on GRDP variables are LFPR, HDI, and ROR.
- e. Group 5 is a province (Central Sulawesi, Gorontalo, and Southeast Sulawesi) with variables that have a significant influence on the GRDP variable only ROR.
- f. Group 6 is a province (Riau, Jambi, North Sumatra, and West Sumatra) with variables that have a significant influence on GRDP variables are FDI, LFPR, HDI, and ROR.
- g. Group 7 is a province (West Kalimantan) with variables that have a significant influence on GRDP variables are DDI, LFPR, HDI, and ROR.
- h. Group 8 is a province (South Kalimantan and Central Kalimantan) with variables that have a significant influence on GRDP variables are DDI, LFPR, PMVA, HDI, and ROR.
- i. Group 9 is a province (North Kalimantan) with variables that have a significant influence on GRDP variables are HDI and

ROR.

- j. Group 10 is a province (East Nusa Tenggara) with variables that have a significant influence on GRDP variables are FDI, PMVA, and ROR.
- k. Group 11 is a province (West Sulawesi and South Sulawesi) with variables that have a significant influence on GRDP variables are PMVA, HDI, and ROR.
- l. Group 12 is a province (North Sulawesi, Papua, North Maluku, Maluku, and West Papua) with no variables that have a significant influence on GRDP variables

The findings of this study indicate that in general, the variables that have a significant effect on GRDP in Indonesia are ROR and HDI. The results of this study are in line with research by Dewi (2023) In analyzing the factors that influence PRDB in Indonesia from 2010 to 2020. The main difference between this research and previous research is the methodological approach used. This study uses the NGWTSR method which allows to capture significant spatial variations from 34 provinces in Indonesia. This method provides more detailed and accurate results by considering the spatial influence in the GRDP analysis. Meanwhile, Dewi's research uses a fixed effect model that does not consider spatial variation with the same detail. As such, this study provides a more comprehensive understanding of the factors that influence GRDP and how those influences vary across different regions in Indonesia.

One of the models obtained, namely the model for West Sumatra Province, has a high coefficient of determination of 97.86%. The variables that have a significant effect are the investment of FDI, LFPR, HDI, and ROR. The GRDP model of West Sumatra Province is as follows.

$$y_{32} = -31.99 - 0.058x_{1,32} - 2.459(x_{1,32} - 4.734)_+ + 2.590(x_{1,32} - 5.068)_+ - 9.934x_{3,32} + 63.934(x_{5,32} - 2.762)_+ - 0.053x_{6,32} + 7.279(x_{6,32} - 8.616)_+ - 5.556(x_{6,32} - 9.225)_+$$

8. Model Interpretation

The interpretation of the model from West Sumatra Province is explained as follows.

- a. The assumption of the predictor (x_3, x_5, x_6) is constant, then the effect of the FDI variable on GRDP can be written as follows.

$$y_{1,32} = -0.058x_{1,32} - 2.459(x_{1,32} - 4.734)_+ + 2.590(x_{1,32} - 5.068)_+$$

$$f(x) = \begin{cases} -0.058x_{1,32}, & x_{1,32} < 4.734 \\ -2.5170x_{1,32} + 11.6409, & 4.734 \leq x_{1,32} < 5.068 \\ 0.0730x_{1,32} - 1.4852, & x_{1,32} \geq 5.068 \end{cases}$$

If the FDI is less than 4.734, then each one-unit increase in FDI reduces the value of GRDP by 0.058%. Furthermore, for FDI between 4.734 and 5.068, each one-unit increase in FDI decreases the value of GRDP by 2.517%. For FDI more than 5.068, each one-unit increase in FDI increases the value of GRDP by 0.073%.

- b. The assumption of the predictor (x_1, x_5, x_6) is constant, then the effect of the LFPR variable on GRDP can be written as follows.

$$y_{3,32} = -9.934x_{3,32} + 73.866(x_{3,32} - 2.883)_+ - 60.565(x_{3,32} - 2.896)_+$$

$$f(x) = \begin{cases} -9.934x_{3,32}, & x_{3,32} < 2.883 \\ 63.932x_{3,32} - 212.9557, & 2.883 \leq x_{3,32} < 2.896 \\ 3.367x_{3,32} - 37.559, & x_{3,32} \geq 2.896 \end{cases}$$

If the LFPR is less than 2.883, then every increase in LFPR one unit decreases the value of GRDP by 9.934%. Furthermore, for LFPR between 2.883 and 2.896, each one-unit increase in LFPR increases the value of GRDP by 63.932%. For LFPR more than 2.896, each increase in LFPR one unit increases the value of GRDP by 3.367%.

- c. The assumption of the predictor (x_1, x_3, x_6) is constant, then the effect of the HDI variable on GRDP can be written as follows.

$$y_{5,32} = 20.855x_{5,32} + 43.998(x_{5,32} - 2.745)_+ - 63.934(x_{5,32} - 2.762)_+$$

$$f(x) = \begin{cases} 20.855x_{5,32}, & x_{5,32} < 2.745 \\ 64.8530x_{5,32} - 120.7745, & 2.745 \leq x_{5,32} < 2.762 \\ 0.9190x_{5,32} - 55.8112, & x_{5,32} \geq 2.762 \end{cases}$$

If the HDI is less than 2.745, then each one-unit increase in HDI increases the value of GRDP by 20.855%. Furthermore, for HDI between 2.745 and 2.762, every one unit increase in HDI increases the value of GRDP by 64.853%. For HDI more than 2.762, each one-unit increase in HDI increases the value of GRDP by 0.9190%.

- d. The assumption of the predictor (x_1, x_3, x_5) is constant, then the effect of the variable ROR on GRDP can be written as follows.

$$y_{6,32} = -0.053x_{6,32} + 7.279(x_{6,32} - 8.616)_+ - 5.556(x_{6,32} - 9.225)_+$$

$$f(x) = \begin{cases} -0.053x_{6,32}, & x_{6,32} < 8.616 \\ 7.226x_{6,32} - 62.7159, & 8.616 \leq x_{6,32} < 9.225 \\ 1.670x_{6,32} - 11.4618, & x_{6,32} \geq 9.225 \end{cases}$$

If the ROR is less than 8,616, then each one-unit increase in ROR decreases the value of GRDP by 0.053%. Furthermore, for ROR between 8,616 and 9,225, each one-unit increase in ROR increases the value of GRDP by 7.226%. For ROR more than 9,225, each one-unit increase in ROR increases the value of GRDP by 1.670%.

D. CONCLUSION AND SUGGESTION

Based on the previous results and discussions, it can be concluded that NGWR-ST is a spatial and nonparametric regression development model that can be used in determining the factors that influence GRDP as one of the efforts for economic resilience. The NGWR-ST model, which utilizes a fixed bisquare kernel as a weighting function and two knot points, is the most effective in explaining GRDP in Indonesia in 2022. In general, the factors that have a significant influence on GRDP in Indonesia are TPB and HDI. The government is advised to focus on improving the quality of education and health, which are the main components of HDI. Investment in infrastructure and technology also needs to be increased to support more equitable economic growth across regions. However, several provinces are not affected by TPB or HDI, namely North Sulawesi, Papua, North Maluku, Maluku, and West Papua. Further researchers or the government need to analyze the factors that influence GRDP in provinces that are not affected by TPB and HDI. Economic diversification and collaboration with the private sector are also important for developing new sectors, so that these provinces can increase GRDP and contribute more significantly to national economic resilience. Overall, the results of this research can be used as a reference to contribute to formulating appropriate regional policy strategies from significant factors to strengthen the economy in facing the World Megatrend in 2045.

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DECLARATIONS

AUTHOR CONTRIBUTION

In this study, the first author played a role in preparing the initial draft of the article and data analysis. The second author contributed to the development of research topic ideas, provided input on article writing, and assisted with data collection. The third author, who also acted as a writer, provided input on the case study and data analysis, and made revisions based on reviewer input.

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The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

COMPETING INTEREST

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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