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Analysis of Regional Economic Growth Disparities in Nusa Tenggara Barat Using The Heterogeneous Coefficient Spatial Durbin Panel Model

Mawaddah Juliarti[1], Siti Hariati Hastuti[2*], Alissa Chintyana[3]

[1,2,3]Universitas Hamzanwadi, Jl. Cut Nyak Dien No.85, Pancor, Kecamatan Selong, Kabupaten Lombok Timur, Nusa Tenggara Barat
*Corresponding Author. e-mail: siti.hariatih@hamzanwadi.ac.id

ABSTRACT

Welfare for all segments of society is one of the goals of sustainable development, yet it remains an unresolved issue. In general, economic variables are divided into two types: homogeneous and heterogeneous. Heterogeneous variables are more frequently encountered in daily life because the results of their calculations tend to vary. Economic inequality is an example of a heterogeneous variable. Therefore, the urgency of this research lies in the development of the Heterogeneous Coefficient Spatial Durbin Panel Model (HCSDPM), which integrates the heterogeneous coefficient structure of the Heterogeneous Coefficient Spatial Panel Model (HCSPM) with the spatial interaction framework of the Heterogeneous Coefficient Spatial Durbin Model (HSDM). This approach allows regression coefficients to vary across regions while accounting for both direct and indirect spatial effects. Consequently, the proposed HCSDPM model is expected to provide a more accurate and representative analysis of regional economic growth disparities. Nusa Tenggara Barat (NTB) is a region characterized by high levels of economic growth inequality, which even fluctuates greatly from year to year. Therefore, this study aims to determine the factors influencing economic growth and to identify spatial disparities across regions in NTB. The analysis results show that the model's goodness of fit is around 90%. Based on these findings, regional policymakers are encouraged to prioritize improving human resources and to comprehensively adjust fiscal and investment allocations to local needs.

Keywords: heterogeneous coefficient spatial durbin panel model (hcsdpm), economic inequality, nusa tenggara barat, grdp per capita.

INTRODUCTION

Many developing countries, including Indonesia, face persistent challenges related to interregional economic growth inequality. Such disparities arise from differences in natural resource endowments and demographic conditions across regions (Novia, 2023). Economic inequality leads to unbalanced development, rising poverty rates, and declining social welfare, which in turn create economic inefficiencies and weaken social stability (Arafah and Khoirudin, 2022).

Nusa Tenggara Barat, located in the eastern Indonesia, continues to experience economic disparities, as reflected in variations in Gross Regional Domestic Product (GRDP) per capita across its regencies and municipalities (Soraya et al., 2021). Analysis of GRDP, in particular, provides a deeper perspective on how economic growth can create inequality or actually help in efforts to equalize development (Kuncoro, 2022). This is relevant because uneven economic growth often reflects structural disparities between developed and underdeveloped regions. According to Statistics Indonesia (BPS NTB, 2023) regions such as Lombok Tengah is considerably more developed than Dompu and North Lombok. Similar disparities are evident in the Human Development Index (HDI), with Mataram recording a score of 80.09 compared with only 66.62 in North Lombok. The Mean Years of Schooling (MYS) also reveal substantial educational disparities across the region (BPS, 2023).

Furthermore, regional disparities are evident in digital infrastructure. According to the OECD (2020), strong digital infrastructure enables accelerated economic transformation through increasing competitiveness, efficiency and connectivity between economic actors and the wider market. Mataram Municipality has a greater number of Base Transceiver Stations (BTS) than Dompu or Bima Municipality (Barat, 2023), influencing the pace of economic transformation through technology adoption. The high poverty rate in some areas, such as Lombok Utara (23.96%), further reflects the existence of social and economic inequality (BPS, 2024).

Most previous studies on economic inequality in Nusa Tenggara Barat have relied on homogeneous regression approaches, which fail to account for spatial heterogeneity. Spatial heterogeneity is prevalent in empirical studies because they exhibit substantial variation among units of observation. Economic inequality is a notable example of this type of variable. According to LeSage (2022) and Shin, Lee, and Ghosh (2020), the HSDM provides a more accurate framework for identifying regional differences in influencing factors and detecting spatial spillover effects. To address this issue, the present study adopts the Heterogeneous Coefficient Panel Model approach, which allows regression coefficients to vary across regions (Chudik and Pesaran, 2015). By integrating the Spatial Durbin framework with heterogeneous coefficients, this study employs the Heterogeneous Coefficient Spatial Durbin Panel Model (HCSDPM) specification (Elhorst, 2014; LeSage, 2022).

The objective of this study is to analyze patterns of interregional economic growth inequality in Nusa Tenggara Barat from 2018 to 2024, to develop the HCSDPM modeling framework, and to identify the main spatial factors contributing to economic growth disparities in NTB. HCSDPM also takes into account spillover effects, namely how economic growth in one region can affect neighboring regions (LeSage & Pace, 2009). HCSDPM is able to identify direct effects and indirect effects of economic factors, so that the interpretation of results becomes more comprehensive. Therefore, the findings of this study are expected to serve as a foundation for designing more equitable and effective regional economic development policies.

METHODOLOGY

The Heterogeneous Coefficients Spatial Panel Model is an extension of the Spatial Durbin Model (SDM) that not only accounts for spatial effects but also allows regression coefficients to vary across regions. One of its specific formulations is the Heterogeneous Coefficient Spatial Durbin Panel Model (HCSDPM) (Chudik and Pesaran, 2015).

Table 1. Research Variables

Variable	Description	Unit
(1)	**(2)**	**(3)**
Y	GRDP per Capita	Thousand Rupiah
X_1	Number of BTS Towers (BTS)	Unit
X_2	Government Expenditure (GE)	Percent
X_3	Poverty Rate (PR)	Percent
X_4	Investment (Inv)	Percent
X_5	Average Years of Schooling (AYS)	Year
X_6	Human Development Index (HDI)	-

Source: BPS (2018-2024); Satu Data NTB (2018-2024).

This study uses secondary data obtained from the official websites of Statistics Indonesia (BPS) and Satu Data NTB, covering the years 2018–2024. The data include GRDP per capita and several explanatory variables hypothesized to influence it, as presented in Table 1.

The analytical steps in this study are as follows:

1. Descriptive Analysis
   Describe the response variable and predictor variables related to interregional economic growth inequality in Nusa Tenggara Barat from 2018 to 2024.
2. Data Transformation
   Transform all variables into natural logarithmic form to stabilize variance, approximate normal distribution, and reduce potential heteroskedasticity (Gujarati, 2003; Elhorst, 2014). The transformation is given by (Wei, 2006):
   $$\boldsymbol{Z_t = \ln X_t} \tag{1}$$
3. Stationarity Test
   Conduct a stationarity test using the Im, Pesaran, and Shin (IPS) method to ensure that the panel data are stationary. Differencing is performed if non-stationarity is detected. The hypotheses are:
   H_0 :data are non-stationary (have a unit root)
   H_1 :data are stationary
   The test statistic (Im, Pesaran, and Shin, 2003) is defined as:
   $$\boldsymbol{\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_i} \tag{2}$$
   where $\boldsymbol{t_i}$ is the ADF statistic for unit *i*.
   The average statistic is then converted to a Z-statistic:
   $$\boldsymbol{Z_{IPS} = \frac{\sqrt{N(\bar{t}-(E(t_i))}}{\sqrt{Var(t_i)}}} \tag{3}$$
   Decision rule: If $\boldsymbol{Z_{IPS}} < \boldsymbol{Z_\alpha}$ or if *p-value* < α, then H_0 is rejected, indicating the panel data are stationary.
   For non-stationary variables, differencing is applied (Wei, 2006):
   $$\boldsymbol{\Delta X_t = X_t - X_{t-1}} \tag{4}$$
4. Panel Data Regression Analysis
   Estimate the panel regression using three common approaches: Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM) (Gujarati, 2003):

   a. *Common Effect Model* (CEM),
   $$Y_{it} = \beta_0 + \sum_{k=1}^{n} \beta_k X_{it} + \varepsilon it \tag{5}$$
   b. *Fixed Effect Model* (FEM),
   $$Y_{it} = \beta_{0_{it}} + \sum_{k=1}^{n} \beta_k X_{it} + \varepsilon_{it} \tag{6}$$
   c. *Random Effect Model* (REM)
   $$Y_{it} = \beta_{0_{it}} + \sum_{k=1}^{n} \beta_k x_{it} + \mu_i + \varepsilon_{it} \tag{7}$$

   The best model is selected using the Chow Test, Hausman Test, and Lagrange Multiplier (LM) Test.
5. Classical Assumption Tests
   a. Multicollinearity is checked using the Variance Inflation Factor (VIF).
   b. Heteroskedasticity is tested with the Breusch–Pagan Test.
   c. Autocorrelation is tested using the Breusch–Godfrey/Wooldridge Test for panel data.
6. Spatial Weight Matrix Formation

Construct the spatial weight matrix ($\boldsymbol{W}$) using the queen contiguity approach, where regions are considered neighbors if they share a common border or vertex. The matrix is row-standardized, ensuring each row sums to one (Getis, 2009):

$$\boldsymbol{W_{ij}} = \begin{cases} \frac{\boldsymbol{1}}{\boldsymbol{n_i}}, & \boldsymbol{if\ region\ j\ is\ a\ neighbor\ of\ region\ i} \\ \boldsymbol{0}, & \boldsymbol{otherwise} \end{cases} \tag{8}$$

7. Spatial Effect Testing
   Conduct Moran's I test to detect spatial autocorrelation and Lagrange Multiplier (LM) tests to determine the appropriate form of spatial dependence (LeSage, 1999; Anselin, 1988).
8. Spatial Panel Model Estimation
   Estimate the Spatial Durbin Model (SDM) as the initial homogeneous specification (Elhorst, 2014):

$$y_{it} = \rho \sum_{j=1}^{N} \boldsymbol{W}_{ij}\boldsymbol{Y}_{it} + \alpha + \boldsymbol{X}_{it}\boldsymbol{\beta} + \varepsilon_{it} \tag{9}$$

   If heterogeneity is significant, apply the HCSDPM formulation (Chudik and Pesaran, 2015):

$$y_{it} = \alpha_i + \psi_i \sum_{j=1}^{N} w_{ij}y_{jt} + \sum_{k=1}^{K} \beta_{k,i}x_{kit} + \sum_{k=1}^{K} \emptyset_{k,i} \sum_{j=1}^{N} w_{ij}x_{kjt} + \varepsilon_{it} \tag{10}$$

   where $\boldsymbol{y}_i$ is the vector of response values for region i, $\boldsymbol{X}_i\boldsymbol{\beta}_i$ represents the effects of predictor variables with heterogeneous coefficients across regions, $\boldsymbol{\Psi y_i}$ is the spatial autoregressive component, and σ_i^2 denotes the region-specific residual variance.
9. Interpretation of Partial Effects
   The estimated parameters are decomposed into direct and indirect (spillover) effects to capture both local and spatial impacts.
10. Model Diagnostics
    Conduct model evaluation using the Wald Test**,** Likelihood Ratio Test**,** Goodness of Fit**,** and Akaike Information Criterion (AIC) to assess model performance.

RESULTS AND DISCUSSION

1. Descriptive Analysis

Table 2. Descriptive Statistics

Variable	Min	Max	Sd	Mean
(1)	**(2)**	**(3)**	**(4)**	**(5)**
Y	10577.000	134274.000	29550.570	27108.000
X_1	45.000	399.000	107.633	193.700
X_2	0.020	1.910	0.611	0.783
X_3	8.000	29.030	4.869	14.060
X_4	0.040	90.230	18.903	10.000
X_5	5.810	10.970	1.450	7.947
X_6	63.830	81.640	4.643	70.560

Source: Author, processed (2025).

This study examines the statistical characteristics of seven key variables. The descriptive statistics indicate notable interregional disparities in both economic and social dimensions across Nusa Tenggara Barat. The GRDP per capita ranges from IDR 10,577 thousand to IDR 134,274 thousand, with a high standard deviation (IDR 29,550.57 thousand), reflecting substantial economic inequality. Similarly, other variables—such as the number of BTS towers, investment levels, and the Human Development Index (HDI)—show considerable variation among regions.

The following figure illustrates the spatial distribution of GRDP per capita during 2018–2024:

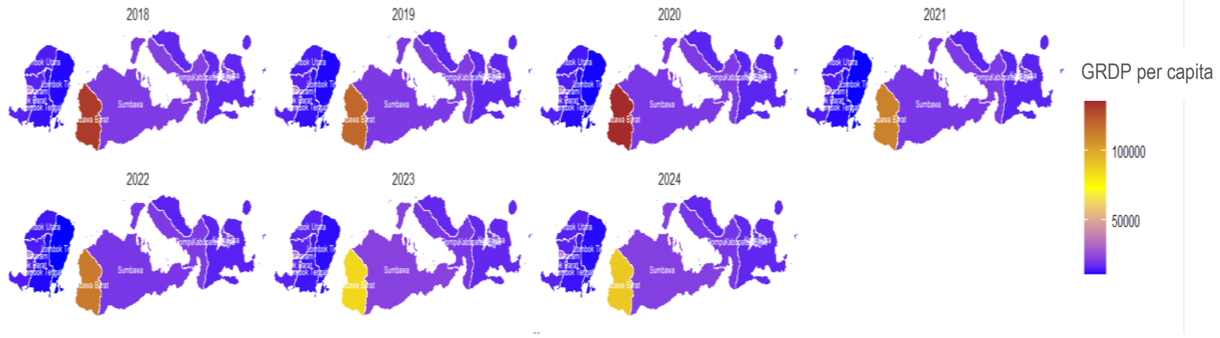

Figure 1. Spatial Distribution of GRDP Per Capita in Nusa Tenggara Barat, 2018–2024
Source: Author, processed (2025).

In Figure 1, the red–yellow shades represent regions with high GRDP per capita (such as Sumbawa and Mataram), whereas the blue–purple shades indicate regions with low GRDP per capita (such as Lombok Timur and Lombok Tengah). This spatial pattern remains consistent over time, suggesting the presence of spatial autocorrelation—where regions with similar economic characteristics tend to cluster geographically.

To enhance the quality of the analysis, all numerical variables were transformed into natural logarithms. The log transformation helps stabilize variance, reduce distributional skewness, harmonize variable scales across regions, and minimize the influence of extreme values (Elhorst, 2014; Gujarati, 2003).

2. Stationarity Test

All numerical variables were transformed into natural logarithmic form to stabilize variance, reduce skewness, and ensure proportional relationships among variables (Gujarati, 2003). This transformation was applied to the variables GRDP per capita, number of BTS towers (BTS), Government Expenditure (GE), Poverty Rate (PR), investment (Inv), Average Years of Schooling (AYS), and Human Development Index (HDI).

However, the results of the Im, Pesaran, and Shin (IPS) unit root test indicate that not all variables became stationary after the log transformation. Therefore, first differencing was applied to the non-stationary variables.

Table 3. Im, Pesaran, and Shin (IPS) Unit Root Test

Variable	**p-value**	
	ln	**ln + diff 1**
(1)	**(2)**	**(3)**
Y	2.2×10^{-16}	-
X_1	1.65×10^{-10}	-
X_2	1.618×10^{-8}	-
X_3	1.132×10^{-9}	-
X_4	1.361×10^{-7}	-
X_5	0.99	2.2×10^{-16}
X_6	1	0.087

Source: Author, processed (2025).

Based on Table 3, the variables GRDP per capita (Y), average years of schooling (AYS), and Human Development Index (HDI) required first differencing. Although the p-value for HDI remains slightly above 0.05, the variable was retained since it is significant at the 10% level ($\alpha = 0.10$) and holds substantive importance in explaining regional disparities. Consequently, the subsequent analysis employed a combination of variables in both log-transformed and first-differenced forms.

3. Panel Data Estimation

The first stage in constructing the panel data model involves specifying three model types: the Fixed Effect Model (FEM), the Random Effect Model (REM), and the Common Effect Model (CEM). Estimation was carried out using log-transformed data, after which the coefficients were back-transformed to the original scale to ensure interpretability consistent with the actual measurement units of each variable.

For variables expressed in natural logarithms (ln), the estimated coefficients represent elasticities, meaning the percentage change in GRDP per capita associated with a one-percent change in the predictor variable. In contrast, for variables expressed as first-differenced logarithms (Δln), the coefficients capture relative changes over time in relation to GRDP per capita on the original scale.

Table 4. Estimation of the Random Effect Model (REM)

Variable	**Coefficient**	**p-value**
(1)	**(2)**	**(3)**
c	248718.100	1.295×10^{-13}***
X_1	44.500	0.091
X_2	-342.000	0.368
X_3	-771.000	0.134
X_4	-24.800	0.310
X_5	-657.000	0.797
X_6	504.000	0.136

Significant at the 5% level.
Source: Author, processed (2025).

Based on Table 4, only the intercept term is statistically significant, indicating that none of the explanatory variables exerts a significant effect on GRDP per capita. This suggests that, within the current model specification, the selected predictors have not yet demonstrated the capacity to explain regional economic growth variation across districts in Nusa Tenggara Barat.

Accordingly, the estimated Random Effect Model can be expressed as follows:

$$Y = 248718.100 - 44.500X_1 - 342.000\,X_2 - 771.000X_3 - 24.800X_4 - 657.000X_5 + 504.000X_6$$

4. Model Selection for Panel Data

The selection of the most appropriate panel data model was conducted in several stages. First, the Chow Test was applied to compare the Common Effect Model (CEM) and the Fixed Effect Model (FEM). The test produced a p-value of 2.2×10^{-16}, which is smaller than the 5% significance level ($\alpha = 0.05$). Therefore, the null hypothesis was rejected, indicating that the FEM is more appropriate than the CEM.

Next, to determine whether the Fixed Effect Model or the Random Effect Model (REM) was more suitable, the Hausman Test was conducted. The result showed a p-value of 0.691, which is greater than the 5% significance level. Thus, there was insufficient evidence to reject the null hypothesis, suggesting that the Random Effect Model provides a more efficient and consistent estimation. Consequently, the REM was selected as the optimal panel data model for this study.

5. Classical Assumption Tests

After identifying the best-fitting model, a series of classical assumption tests were performed to ensure model validity. The multicollinearity test revealed that all Variance Inflation Factor (VIF) values were below 10, indicating the absence of strong linear relationships among independent variables. The Breusch–Pagan test produced a p-value of 0.127, which is greater than 0.05, confirming that heteroskedasticity is not present in the model.

However, the Breusch–Godfrey/Wooldridge test for autocorrelation yielded a p-value of 0.045 (< 0.05), indicating the presence of autocorrelation among individual errors**.** This finding strongly suggests that spatial dependence across regions must be explicitly modeled, thereby justifying the continuation of the analysis using spatial panel data modeling techniques.

6. Construction of the Spatial Weight Matrix

The first stage of spatial panel analysis involves constructing a spatial weight matrix that represents the geographical interdependence among regions. This matrix was developed using the queen contiguity approach, where two regions are considered neighbors if they share either a common border or a vertex. The resulting weights were row-standardized, ensuring that the sum of all spatial weights for each region equals one.

$$\boldsymbol{W}_{\mathbf{10\times10}} = \begin{bmatrix} 0.0 & 0.5 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.5 & 0.0 \\ 0.5 & 0.0 & 0.5 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 1.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 1.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.3 & 0.0 & 0.3 & 0.0 & 0.3 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.3 & 0.0 & 0.3 & 0.3 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.3 & 0.0 & 0.3 & 0.0 & 0.3 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.3 & 0.3 & 0.3 & 0.0 & 0.0 & 0.0 \\ 0.5 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.5 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.5 & 0.0 & 0.5 & 0.0 \end{bmatrix}$$

Figure 2. Spatial Weight Matrix
Source: Author, processed (2025).

7. Testing for Spatial Effects

A spatial autocorrelation test was conducted to examine whether the residuals of the panel data model exhibit any spatial dependency pattern. The Moran's I statistic was used for this purpose. The test yielded a Moran's I value of 0.199 with a p-value of $0.382 > \alpha = 0.05$**,** indicating that there is no significant spatial autocorrelation in the residuals of the REM model. In other words, the residuals do not exhibit a strong spatial clustering pattern.

Even though the residual autocorrelation was statistically insignificant, further testing for structural spatial dependence was still necessary. This was accomplished using the Lagrange Multiplier (LM) test, which identifies whether the spatial dependence occurs in the lag form (spatial lag model), error form (spatial error model), or a combination of both (SARMA model).

Table 5. Spatial Dependence Tests

Test Type	**Test Statistic**	**p-value**
(1)	**(2)**	**(3)**
LM *Error*	38.713	$4.91 \times 10^{-10}*$
LM *Lag*	40.778	$1.705 \times 10^{-10}*$
LM error robust	0.129	0.718
LM lag robust	2.195	0.138
SARMA	40.908	$1.309 \times 10^{-10}*$

Significant at the 5% level.
Source: Author, processed (2025).

The results in Table 5 show that both the LM Error and LM Lag tests are statistically significant (p-value < 0.05), suggesting the presence of spatial dependence through both the error and lag components. However, the robust LM tests are not significant, indicating that no single form of spatial dependence is dominant. Meanwhile, the SARMA test is significant at the 5% level (p-value $= 1.309 \times 10^{-10}$), implying a combined influence of spatial lag and spatial error effects.

Based on these findings, the Spatial Durbin Model (SDM) was selected as the most appropriate specification, as it can simultaneously capture both lag and error spatial dependencies, consistent with the diagnostic results from the LM tests.

8. Spatial Panel Estimation

After identifying the best panel data model, the analysis was extended by estimating the Spatial Durbin Model (SDM) to capture both direct and indirect (spillover) effects among regions. The estimation was performed using the transformed dataset, and the results were then back-transformed to the original data scale to ensure meaningful interpretation consistent with the units of each variable.

During the estimation stage, the variables were expressed in natural logarithmic (ln) and first-differenced logarithmic (Δln) forms. Therefore, the coefficients were not interpreted directly; instead, back transformation was applied. For variables in ln form, coefficients were multiplied by the mean of the original values, while for Δln variables, coefficients were adjusted by the ratio of value changes between consecutive periods. This process returned the estimated effects to their original measurement scale, allowing for substantive interpretation of the results.

Table 6. Spatial Panel Model Estimation Results

Variable	Coefficient	p-value
c	3280.319	2.2×10^{-16}***
X_1	97.739	0.041*
X_2	-3.976	0.124
X_3	-215.524	0.002**
X_4	-3.391	0.141
X_5	48.457	0.787
X_6	233.154	0.359
$\boldsymbol{W}X_1$	8.008	0.348
$\boldsymbol{W}X_2$	-5.781	0.079
$\boldsymbol{W}X_3$	-535.744	0.006**
$\boldsymbol{W}X_4$	-5.239	0.063
$\boldsymbol{W}X_5$	-268.399	0.297
$\boldsymbol{W}X_6$	32.099	0.918
φ	161.702	0.060
λ	-0.161	0.206

Significant at the 5% level.
Source: Author, processed (2025).

The estimation results in Table 6 show that the intercept is highly significant (p-value $= 2.2 \times 10^{-16}$), indicating that the baseline level of GRDP per capita remains substantial even when explanatory variables are not included. Among the direct effects, the number of BTS towers (X_1) and poverty rate (X_3) are statistically significant positively and negatively, respectively, suggesting that digital infrastructure supports regional economic growth, whereas higher poverty rates suppress it.

For indirect effects ($\boldsymbol{W}X$), the spatially lagged variable of poverty rate ($\boldsymbol{W}X_3$) is significant at the 5% level, indicating a negative spillover effect: regions surrounded by poorer neighboring areas tend to exhibit slower economic performance.

The spatial autoregressive parameter $\lambda = -0.161$ is not statistically significant, implying the absence of spatial autocorrelation in the dependent variable. Similarly, the spatial error coefficient $\varphi = 161.702$ is marginally significant at the 10% level, indicating that spatial error dependence is not dominant. The model's Akaike Information Criterion (AIC) value of -1477.126 indicates a strong model fit.

The resulting estimated equation is expressed as follows:

$$Y_{it} = \mu_i - 0.161\sum_{j=1}^{n} w_{ij}Y_{it} - 3280.319 + 97.739X_{1it} - 3.976X_{2it} - 215.524X_{3it} - 3.391X_{4it} + 48.457X_{5it} + 233.154X_{6it} + 8.008\sum_{j=1}^{n} w_{ij}X_{1jt} - 5.781\sum_{j=1}^{n} w_{ij}X_{2jt} - 535.744\sum_{j=1}^{n} w_{ij}X_{3jt} - 5.239\sum_{j=1}^{n} w_{ij}X_{4jt} - 268.399\sum_{j=1}^{n} w_{ij}X_{5jt} + 32.099\sum_{j=1}^{n} w_{ij}X_{6jt} + \epsilon_{it}$$

These findings emphasize the presence of both local and neighboring regional influences in determining economic growth, highlighting the importance of spatial interdependencies in regional development dynamics.

9. Spatial Heterogeneity Test

To determine whether the homogeneous SDM adequately represents regional characteristics, a spatial heterogeneity test was conducted by comparing the homogeneous and heterogeneous models. The test was performed using an F-test on the difference in Residual Sum of Squares (RSS) between the two models.

Table 7. Spatial Heterogeneity Test

Test	F-statistic	Critical Value
(1)	(2)	(3)
Slope Heterogeneity Test	372.428	1.861

Source: Author, processed (2025).

The results shown in Table 7 indicate that the calculated F-statistic exceeds the critical value (F-statistic > F-table), suggesting significant differences across regions in the effects of explanatory variables. This finding implies that the homogeneous SDM does not sufficiently capture the spatial variation present in the data. Therefore, the analysis proceeded with the Heterogeneous Coefficient Spatial Durbin Panel Model (HCSDPM) to more accurately account for local effect heterogeneity among regions.

10. Estimation of the Heterogeneous Coefficient Spatial Durbin Panel Model (HCSDPM)

The HCSDPM was selected based on the heterogeneity test results, which confirmed significant interregional differences. The estimation was carried out using the quasi maximum likelihood method. Each district or municipality in Nusa Tenggara Barat has distinct model coefficients; hence, interpretation is performed specifically for each region.

For instance, in Lombok Tengah Regency, the significance levels, coefficient directions, and spatial interaction strengths vary, reflecting unique spatial dynamics in that region. This highlights the core characteristic of HCSDPM: there is no single unified model for all regions; rather, each region possesses its own spatial dependency structure.

Table 8. Estimation Results of the HCSDPM in Lombok Tengah Regency

Variale	**Coefficient**	**p-value**
(1)	(2)	(3)
β_X_1	107.304	0.000***
β_X_2	5372.881	0.000***
β_X_3	1755.176	0.000***
β_X_4	-94.584	3.81×10^{-11}***
β_X_5	11721.725	0.000***
β_X_6	174.982	0.000***
$\emptyset W\_X_1$	-98.885	0.000***
$\emptyset W\_X_2$	-7373.934	0.000***
$\emptyset W\_X_3$	1583.098	0.000***
$\emptyset W\_X_4$	400.479	0.000***
$\emptyset W\_X_5$	-1176.434	0.000***
$\emptyset W\_X_6$	39.950	0.000***
ψ	0.899	
σ^2	0.001	

Significant at the 1% level.
Source: Author, processed (2025).

Based on Table 8, all variables are significant at the 1% level. A negative coefficient indicates that an increase in the respective variable leads to a decrease in GRDP per capita, while a positive coefficient suggests that an increase in that variable enhances GRDP per capita.

During the estimation process, variables were expressed in logarithmic and differenced logarithmic (ln and Δln) forms. Therefore, coefficients were not directly interpretable and required back-transformation. For ln variables, the exponential (antilog) function was applied to return values to their original units, while differenced log variables were interpreted as percentage changes over time, then rescaled accordingly. This approach ensures that the results can be interpreted substantively within their original measurement scale.

The resulting model for Lombok Tengah Regency after back transformation can be expressed as:

$$\begin{aligned}\hat{y}_{it}^{(Central\ Lombok)} &= a_{Central\ Lombok} + 0.899\sum_j W_{Central\ Lombok,j}y_{jt} + 107.304(X_{1it}) \\ &+ 5372.881(X_{2it}) + 1755.176(X_{3it}) - 94.584(X_{4it}) \\ &+ 11721.725(X_{5it}) + 174.982(X_{6it}) - 98.885\sum_j w_{ij}x_{1jt} \\ &- 7373.934\sum_j w_{ij}x_{2jt} + 1583.098\sum_j w_{ij}x_{3jt} \\ &+ 400.479\sum_j w_{ij}x_{4jt} - 1176.434\sum_j w_{ij}x_{5jt} + 39.950\sum_j w_{ij}x_{6jt} \\ &+ \epsilon_{it}\end{aligned}$$

The estimation results reveal a strong spatial interdependence with $\psi = 0.899$. Directly, an increase of one unit in the number of BTS towers (BTS) reduces GRDP per capita by Rp107,304, while a 1% increase in government expenditure raises GRDP per capita by Rp5,372,881. Likewise, a 1% increase in population contributes Rp1,755,176 to GRDP per capita.

Conversely, investment has a negative impact—each 1% increase reduces GRDP per capita by Rp94,584—while average years of schooling (AYS) and Human Development Index (HDI) have positive effects of Rp11,721,725 and Rp174,982, respectively.

Indirectly (spatial spillover effects), the number of BTS towers, government expenditure, and average years of schooling in neighboring regions decrease Lombok Tengah's GRDP per capita by Rp98,885, Rp7,373,934, and Rp1,176,434, respectively. Meanwhile, neighboring regions' poverty rate, investment, and HDI exert positive spillover effects of Rp1,583,098, Rp400,479, and Rp39,950, highlighting the cross-regional role of human capital quality in fostering economic growth.

11. Partial Effects

The partial effect analysis of the HCSDPM model includes both the direct effects (β) and indirect effects ($\emptyset$) of each independent variable on GRDP per capita. The direct effect reflects the influence of a variable within the same region, while the indirect effect represents its impact on neighboring regions through spatial interlinkages. As exemplified by the Human Development Index (HDI) variable, which consistently demonstrates a significant influence across model estimations, the visualization of its partial effects is presented below:

Figure 3. Direct Effect of ln_HDI
Source: Author, processed (2025).

Figure 4. Indirect Effect of ln_HDI
Source: Author, processed (2025).

The direct effect of HDI is positive and statistically significant in regions such as Lombok Tengah, Lombok Utara, and Sumbawa, underscoring that improvements in living standards directly contribute to regional economic growth. However, the indirect effects display spatial variation: regions like Sumbawa and Dompu benefit substantially from the spillover of increased HDI in neighboring areas, while Lombok Utara and Lombok Tengah exhibit negative spillover effects, indicating potential competition or unequal diffusion of development benefits across adjacent territories.

12. Model Diagnostics

To assess the adequacy of the Heterogeneous Coefficient Spatial Durbin Panel Model (HCSDPM), several diagnostic tests were conducted, including the Wald test and the Likelihood Ratio (LR) test, which evaluate the overall significance of model parameters as well as model fit assessment using the Pseudo R^2 and Akaike Information Criterion.

a. Wald test

The Wald test was used to examine whether all model parameters are jointly significant. The result yielded a test statistic of 6131.093 with a p-value = 0.000, indicating that all parameters in the

HSDM model are statistically significant at the 5% level ($\alpha = 0.05$). This confirms that the model effectively explains variations in GRDP per capita, accounting for both direct and spatial effects.

b. Likelihood Ratio (LR) Test

The Likelihood Ratio (LR) test compared the null model and the full HSDM model, as shown below:

Table 9. Likelihood Ratio Test

Test Statistic	**Value**
(1)	**(2)**
Log Likelihood Model Null	-13.385
Log Likelihood Model Full	113.718
Nilai LR Statistik	254.205
p-value	1.17×10^{-11}

Source: Author, processed (2025).

Based on Table 9, the p-value < 0.05 indicates that the HCSDPM model performs significantly better than the model without predictors.

c. Goodness of Fit and AIC

Table 10. Goodness of Fit & AIC Model

Measure	**Value**
(1)	**(2)**
R^2	0.998
AIC HCSDPM	-398.512
AIC Homogeneous SDM	73.401

Source: Author, processed (2025).

As shown in Table 10, the R^2 value of 0.998 demonstrates that the HCSDPM explains nearly all the variability in the data. Furthermore, the much lower AIC value of the HCSDPM compared to the homogeneous SDM model indicates superior model efficiency and fit. Hence, the HCSDPM is considered optimal for capturing the spatial dynamics of regional economic growth disparities.

CONCLUSION AND RECOMMENDATION

This study analyzed regional economic growth disparities in Nusa Tenggara Barat Province for the period 2018–2024 using the Heterogeneous Coefficient Spatial Durbin Panel Model (HCSDPM). The results show that regional economic growth disparities in NTB are characterized by significant spatial dependence and heterogeneous regional effects. High-GRDP per capita regions, such as Mataram City and Sumbawa Barat, formed distinct growth clusters, whereas lower-GRDP per capita regions, including Lombok Timur and Lombok Tengah, exhibited similar spatial patterns. The effects of Human Development Index (HDI), average years of schooling (AYS), government expenditure (GE), investment (Inv), and digital infrastructure (BTS) varied across regions and generated both direct and spillover effects on neighboring areas. The estimated spatial autocorrelation coefficient of 0.899 and R^2 of 0.998 indicate that the HCSDPM effectively captures regional heterogeneity and spatial interdependence in explaining economic growth disparities in NTB.

Based on these findings, regional development policies in NTB should account for spatial dependence and regional heterogeneity. Policy interventions related to human development, education, government expenditure, investment, and digital infrastructure should be tailored to local conditions while policymakers consider their spillover effects on neighboring regions.

Future research should explore spatial weight matrices based on actual socioeconomic interactions, such as trade flows, migration, and transportation connectivity. Longer observation periods and additional explanatory variables may also provide a more comprehensive understanding of regional economic disparities.

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