Modelling Gender-Based Human Development Index in Indonesia Using Spatial Seemingly Unrelated Regression (S-SUR)

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ABSTRACT

Indonesia is one of the developing countries in Southeast Asia that still faces many problems and challenges in human development. An important indicator to assess human development in a region is the Human Development Index (HDI). Gender-based disparities in human development (gender inequality) are one of the main challenges faced by Indonesia. The Seemingly Unrelated Regression (SUR) method can only form equation models and can't accommodate spatial effects that occur in each region in Indonesia. Therefore, the Spatial Seemingly Unrelated Regression (S-SUR) model plays a crucial role in modeling gender-based HDI in Indonesia. The aim of this research is to determine the best model formed from gender-based HDI in Indonesia in 2021. The spatial weights used in the S-SUR method are the Queen Contiguity weight matrix. The best model utilized is the SUR method with spatial lag effects (SUR-SLM) with an R-Squared value of 93,13 percent for Y1 (Male HDI) and 94,96 percent for Y2 (Female HDI). The research results show that the factors influencing gender-based HDI in Indonesia are Expected Years of Schooling, Mean Years of Schooling, and Per Capita Expenditure. The more neighbors a region has, the higher the Human Development Index (HDI) will increase by rho in that region.

Keywords: *Human Development Index, Queen Contiguity, Spatial Seemingly Unrelated Regression (S-SUR).*

1. INTRODUCTION

Indonesia is one of the developing countries in Southeast Asia that still faces many issues and challenges in human development. Human development encompasses various aspects such as health, education, human rights, and gender diversity. Gender, in this case, is not just about the biological or physical differences between men and women, but it also refers to differences in roles, behaviors, activities, and social-related matters [1]. However, continuous development progress is sometimes hindered by different issues in various regions of Indonesia. This is due to regional disparities that lead to certain areas experiencing human development inequalities.

Gender inequality occurs worldwide, including in Indonesia. Gender-based human development disparities are also one of the main issues faced by Indonesia. Despite Indonesia's commitment to advancing women's rights, many challenges persist for women in the country. Limited access to education, violence against women, and gender disparities in employment are some of the gender-related issues still prevalent in Indonesia. In the 1990s, the United Nations (UN) and the United Nations Development Programme (UNDP) made a global commitment to implement gender-responsive development concepts through the use of Gender Development Index (GDI) and Gender Empowerment Index (GEM) indicators [1].

In Indonesia, from 2010 to 2021, the Human Development Index (HDI) for males consistently increased from 69.80 percent to 75.50 percent. This indicates an improvement in the social, economic, and health conditions for the male population in Indonesia during that period. Similarly, the HDI for females also

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consistently increased from 61.50 percent to 68.32 percent. This also shows an increase in access and opportunities for women in Indonesia in terms of education, health, and participation in economic and social life. Despite the improvement in HDI for both males and females, there is still a gender gap that needs attention, considering that one of the Sustainable Development Goals (SDGs) is achieving gender equality and the empowerment of women and girls [1].

Since Gender-Based HDI in Indonesia is not balanced across regions, Gender-Based HDI factors are needed. To identify the factors influencing Gender-Based HDI in Indonesia, statistical analysis is required, including accounting for regional effects. The influence of one variable on another in statistics is discussed in regression analysis, but ordinary least squares (OLS) regression analysis does not take into account the spatial element of the data used. OLS regression does not consider spatial aspects in its analysis. In general, in some previous studies, only one equation was estimated. However, as research has evolved with more complex cases, more than one equation is often estimated, and these equations are often correlated with each other. Therefore, for estimation with the OLS method, it cannot be used, and the Seemingly Unrelated Regression (SUR) method can be utilized for a system of interrelated regression equations with unbiased, linear estimators with minimum variance [2].

This research was conducted in every province in Indonesia, addressing the Human Development Index (HDI) based on gender, namely males and females, which can be modeled as two equations. For a system of interrelated regression equations, the appropriate method to use is the Seemingly Unrelated Regression (SUR) method. The first law of geography, which serves as one of the foundations for spatial analysis, was proposed by [3], stating that "everything is related to everything else, but things that are closer have a greater influence than things that are farther away." Generally, this spatial effect is commonly observed between one region and another and occurs in each cross-sectional data. If the equations are interrelated because their regression errors are correlated, the Spatial Seemingly Unrelated Regression (S-SUR) method is the most suitable to be used.

2. LITERATURE REVIEW

2.1 Spatial Weight Matrix (W)

Several methods that can be used to determine the spatial weight matrix (W) using contiguity relationship between one location and another [4] are as follows :

2.1.1. Linear Contiguity

Linear Contiguity (edge contiguity) is a weight matrix with $w_{ij} = 1$, which applies to locations located on the edge on either the left or right side of the focal location, and $w_{ij} = 0$ for other locations.

2.1.2. Rook Contiguity

Rook Contiguity (side contiguity) is a weight with $w_{ij} = 1$ for neighboring locations (commond side) with the focal location and $w_{ij} = 0$ for the other locations.

2.1.3. Bishop Contiguity

Bishop Contiguity (corner contiguity) is a weight matrix with $w_{ij} = 1$ for locations whose corner points (common vertex) meet the corners of the focal location and $w_{ij} = 0$ for other locations.

2.1.4. Double Linear Contiguity

Double Linear Contiguity (double-edge contiguity) is a weight matrix with $w_{ij} = 1$ for two entities located on the left and right sides of the focal location, and $w_{ij} = 0$ for other locations.

2.1.5. Double Rook Contiguity

Double Rook Contiguity (double-side contiguity) is a weight matrix with $w_{ij} = 1$ for two entities on the left, right, north, and south sides of the focal location, and $w_{ij} = 0$ for other locations.

2.1.6. Queen Contiguity

Queen Contiguity (side-corner contiguity) is a weight matrix with $w_{ij} = 1$ for entities that are adjacent (common side) or whose corner points (common vertex) meet with the focal location, and $w_{ij} = 0$ for other locations.

In addition to these contiguity weights, there are other types of weights known as custom weights. Custom weights consider not only the spatial proximity of regions but also factors such as economic proximity, transportation, social factors, infrastructure, or other relevant factors [5].

2.2 Spatial Dependence

Spatial dependence refers to the functional relationship between what happens in one area and another [6]. Spatial dependence occurs due to interdependence among locations within a specific region. To determine the value of spatial dependence, it is calculated using Moran's Index and Lagarange Multiplier (LM).

The use of the Lagrange Multiplier (LM) test is considered an appropriate approach for selecting a spatial regression model. Ordinary Least Squares (OLS) regression modelling should be conducted as an initial test. The Lagrange Multiplier (LM) test can be used to determine whether LM_{SLM} (spatial lag model), LM_{SEM} (spatial error model), or LM_{SARAR} (spatial autoregressive autoregressive) is significant [7].

The magnitude of significant spatial dependence in a dataset can be observed through the testing of Moran's Index [8]. The hypothesis testing is as follows :

H_0 = there is no spatial dependence
H_1 = there is spatial dependence

The test statistic used for Moran's Index is as follows :

$$Z(Ij) = \frac{[Ij - E(Ij)]}{var(Ij)^{1/2}} \sim N(0,1) \quad (1)$$

With,

$$E(I_j) = tr(MW)/(N-(M+1)) \quad (2)$$

$$var(I_j) = tr(MWMW^T) + \frac{tr(MW^2)}{d} - E(I_j)^2 \quad (3)$$

$$vM = I_N - X(X^T X)^{-1} X^T \quad (4)$$

$$d = (N-(N+1))(N-(M+1)+2) \quad (5)$$

Reject H_0, if the p-value < α.

2.3 *Spatial Seemingly Unrelated Regression (S-SUR)*

Spatial Seemingly Unrelated Regression (S-SUR) modelling fundamentally shares specifications with the general Seemingly Unrelated Regression (SUR) model but includes the addition of spatial effects in each of its equation [9]. The characteristic of this approach is the presence of limited heterogenity, assuming that regression coefficients are the same for every individual.

The general SUR model is a model that has an autoregressive structure present in both the main equations and their errors. The first type of spatial SUR model, with its autoregressive structure only in the error components, is called the SUR-SEM (Seemingly Unrelated Regression with Spatial Error Model). The second type of spatial SUR model has its autoregressive structure only in the model equations and is referred to as the SUR-SLM (Seemingly Unrelated Regression with Spatial Lag Model). Lastly, the spatial SUR model with autoregressive structure present in both the error components and the model equations is simply referred to as the SUR-SARAR (Seemingly Unrelated Regression with Spatial Autoregressive Autoregressive) model [10].

The SUR-SARAR model is a variant of the SUR model that has an autoregressive structure in both the model equations and error components. The SUR-SARAR model is an extension of the SUR model that accommodates spatial effect present in the model. The SUR-SLM model is a type of model that only has an autoregressive structure in its equations. The SUR-SEM model is a model that refers to a limited autoregressive component structure that is a present only in its errors [11].

2.4 *Model Goodnes-of-fit Test*

In general, modelling or prediction cases to determine that the obtained model is suitable or good, a measure indicating the goodness of a model is required [12]. The criterion for the goodness of the model used in this study is a higher R-squared value. The calculation of R-squared is as follows :

$$R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (6)$$

With,
SSR = Sum Square Regression
SST = Sum Square Total

3. RESEARCH METDHOLOGY

3.1 *Data Sources*

This research utilizes secondary data from the Central Bureau of Statistics for the year 2021. The dependent variables include the Human Development Index (HDI) for males and females, while the independent variables consist of various HDI indicators. In this study, 34 provinces in Indonesia are used as observation units, with a total of 340 data points included in the research dataset.

3.2 *Research Variables and Data Structure*

The variables observed in this study were the Male Human Development Index (Y1) and the Female Human Development Index (Y2). Meanwhile, Male Expected Years of Schooling (X11), Average Years of Schooling for Males (X12), Male Per Capita Expenditure (X13), Male Open Unemployment Rate (X14), Female Expected Years of Schooling (X21), Average Years of Schooling for Females (X22), Female Per Capita Expenditure (X23), Female Open Unemployment Rate (X14) as independent variables.

Table 1. Data Structure

Province	$Y_{1.i}$	$Y_{2.i}$	$X_{11.i}$	**.**	$X_{24.i}$
Aceh	$Y_{1.1}$	$Y_{2.1}$	$X_{11.1}$	.	$X_{24.1}$
Sumatera Utara	$Y_{1.2}$	$Y_{2.2}$	$X_{11.2}$	.	$X_{24.2}$
Sumatera Barat	$Y_{1.3}$	$Y_{2.3}$	$X_{11.3}$	.	$X_{24.3}$
Riau	$Y_{1.4}$	$Y_{2.4}$	$X_{11.4}$	.	$X_{24.4}$
Jambi	$Y_{1.5}$	$Y_{2.5}$	$X_{11.5}$	.	$X_{24.5}$
Sumatera Selatan	$Y_{1.6}$	$Y_{2.6}$	$X_{11.6}$	.	$X_{24.6}$
.	.	.	.	.	.
Papua	$Y_{1.34}$	$Y_{2.34}$	$X_{11.34}$	.	$X_{24.34}$

3.3 *Research Steps*

The steps in completing this research using ArcGis and Rstudio software are as follows :

Step 1 : Perform descriptive analysis and thematic map data exploration to understand the characteristics of he data for the various variables used.

Step 2 : Standardize the data to make the data units uniform.

Step 3 : Conduct correlation tests between variables.

Step 4 : Conduct multiple linear regression analysis and classical regression assumption tests.

Step 5 : Perform correlation tests between each Gender-Based Human Development Index model (gender equality correlation) in Seemingly Unrelated Regression (SUR) analysis.

Step 6 : Formulate the spatial weight matrix using Queen Contiguity.

Step 7 : Measure spatial autocorrelation using Moran's Index.

Step 8 : Conduct Lagrange Muliptlier (LM) teste to etimate S-SUR model parameters.

Step 9 : Model using the best Spatial Seemingly Unrelated Regression (S-SUR) model.

Step 10 : Interpret the model.

4. RESULTS AND DISCUSSION

4.1 *Descriptive Analysis*

Table 2. Descriptive Statistics of Research Variables with Original Data

Var	**Number of Observations**	**Mean**	**Min**	**Max**
Y_1	34	75.50	66.07	83.87
X_{11}	34	13.38	11.31	15.67
X_{12}	34	9.12	7.44	11.52
X_{13}	34	15177	10451	22910
X_{14}	34	168980	9643	1543750
Y_2	34	68.32	52.69	79.54
X_{21}	34	13.16	10.99	15.64
X_{22}	34	8.40	6.00	10.83
X_{23}	34	8629	4007	16993
X_{24}	34	88256	6700	641715

Table 2 shows that the average Human Development Index (HDI) for males is 75,50 percent, which is higher than the HDI for females, which is 68,32 percent. In the independent variables, the average Male Expected Years of Schooling is higher than Female Expected Years of Schooling, and the average Male Average Years of Schooling is higher than Female Average Years of Schooling, and the average Male Per Capita Expenditure is higher than Female Per Capita Expenditure. The same pattern is observed in the Male Open Unemployment Rate (TPT) compared to the Female Open Unemployment Rate. This indicates that gender inequality still exists between males and females.

Figure 1. Thematic Map of the Male Human Development Index in Indonesia for 2021 (Y1)

4.2 *Thematic Map Exploration*

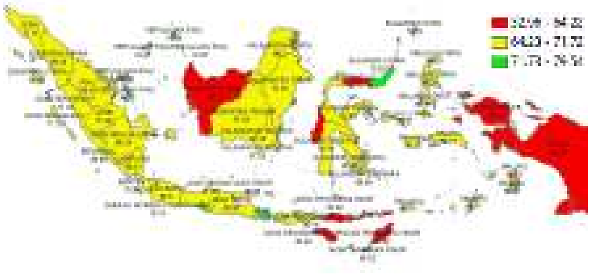

Figure 2. Thematic Map of the Female Human Development Index in Indonesia for 2021 (Y2)

In the above map, there are thematic maps of the Human Development Index (HDI) for males and females for each province in Indonesia in the year 2021, categorized into three groups: low category represented by the color red, medium category represented by the color yellow, and high category represented by the color green. The thematic map illustrates that the provinces with the highest HDI values in 2021 for both males and females are in the DKI Jakarta region, with values of 83.87 percent and 79.54 percent, respectively. Meanwhile, the provinces with the lowest HDI values in 2021 for both males and females are in the Papua region, with values of 66.07 percent and 52.96 percent, respectively.

4.3 Data Analysis

4.3.1 Correlation Test Between Variables

Table 3. Correlation of Independent Variables with Dependent Variables

Variable		Coefficients	P-value
Y_1	X_{11}	0,4778	0,0042
	X_{12}	0,7138	$2{,}142 \times 10^{-06}$
	X_{13}	0,8192	$3{,}14 \times 10^{-09}$
	X_{14}	0,1684	0,341
Y_2	X_{21}	0,5320	0,0012
	X_{22}	0,7282	$1{,}05 \times 10^{-06}$
	X_{23}	0,8858	$3{,}343 \times 10^{-12}$
	X_{24}	0,2209	0,2091

Table 3 indicates that there is a correlation between dependent and independent variables for each gender. It can also be observed that overall, there is positive correlation between dependnet and independent variables. Significant correlations exist between Y1 and X11, Y1 and X12, Y1 and X13, Y2 and X21, Y2 and X22, Y2 and X23, as evidenced by P-values < the 5% significance level.

4.3.2 Multiple Linear Regression Analysis

Table 4. Multiple Linear Regression Parameter Estimation

Variable		Coefficients	P-value
Y_1	Constant	$1{,}606 \times 10^{-15}$	1
	X_{11}	$3{,}242 \times 10^{-01}$	$7{,}32 \times 10^{-06}$
	X_{12}	$2{,}972 \times 10^{-01}$	$9{,}47 \times 10^{-05}$
	X_{13}	$6{,}514 \times 10^{-01}$	$7{,}19 \times 10^{-12}$
	X_{14}	$1{,}333 \times 10^{-01}$	0,0186
	R-Squared	0,9126	
Y_2	Constant	$3{,}369 \times 10^{-15}$	1
	X_{21}	$2{,}536 \times 10^{-01}$	$2{,}89 \times 10^{-05}$
	X_{22}	$2{,}793 \times 10^{-01}$	$3{,}99 \times 10^{-05}$
	X_{23}	$6{,}508 \times 10^{-01}$	$9{,}68 \times 10^{-13}$
	X_{24}	$1{,}255 \times 10^{-01}$	0,0125
	R-Squared	0,9346	

In the table 4, it can be concluded that using multiple linear regression analysis with a significance level of α = 5%, the variables that significantly influence Male Human Development Index (Y1) are Male Average Years of Schooling (X11), Male Expected Years of Schooling (X12), Male Per Capita Expenditure (X13), and Male Open Unemployment Rate (X14). Meanwhile, the variables that significantly influence Female Human Development Index (Y2) are Female Average Years of Schooling (X21), Female Expected Years of Schooling (X22), Female Per Capita Expenditure (X23), and Female Open Unemployment Rate (X24). The goodnes-of-fit criteria show excellent results with R-squared values 91,26 percent for the Male HDI model and 93,46 percent for the Female HDI model.

4.3.3 Test the classical assumption of multiple linear regression

Table 5. Assumption of Multiple Linear Regression

Classic Assumption	Y_1	Y_2
Normality	Normal	Normal
Heteroscedasticity	Not Happen	Not Happen
Autocorrelation	Happen	Happen
Multicollinearity	Not Happen	Not Happen

The application of linear model theory in simultaneous equation models can lead to violations of classical assumptions. This makes the use of Ordinary Least Square (OLS) estimation method inefficient. Seemingly Unrelated Regression (SUR) is an example of a simultaneous equation model developed by Zellner in which errors from different equations are allowed to be correlated. Therefore, in the SUR model, there is a violation of classical assumption, where errors become non-constant and autocorrelation occurs. Table 5 shows that there is autocorrleation in the multiple linear regression model, leading to a violation of the classical assumptions. Therefore, one method to address these violations in simultaneous equation models is to use the Seemingly Unrelated Regression (SUR) method.

4.3.4 Seemingly Unrelated Regression Analysis

Table 6. Correlation Between SUR Model Errors

Variable	Y_1	Y_2
Y1	1	0,8227
Y2	0,8227	1

In table 6, it can be seen that there is a correlation between the variables in the SUR model. The correlation between Male HDI (Y1) and Female HDI (Y2) is 0,8227. This means that the correlation between the errors of the SUR model is very strong.

Spatial autocorrelation is calculated using Moran's Index. This value can be used to determine the location of spatial clustering or spatial autocorrelation. Spatial autocorrelation is defined as the correlation between a variable and itself based on space [13].

4.3.5 Spatial Autocorrelation Testing

Table 7. Moran's Index Value

Variable	Value	P-value
Y_1	0,2541	0,0411
Y_2	0,3297	0,0124

The hypothesis used are as follows :

H_0 = No spatial dependence
H_1 = spatial dependence exist

With the testing criterion being to reject H_0 if the P-value < α (0,05) and accept H_0 if the P-value > α (0,05).

Based on the result in table 7, the Moran's Index value for variable Y1 is 0,2541 with a P-value of 0,0411, and for variable Y2, it is 0,3297 with a P-value of 0,0124, both at a significance level of 5%. In this case, the P-value < α (0,05), indicating that variables Y1 and Y2 have positive autocorrleation.

Table 8. LM Test on SUR Spatial

Testing	P-value	Conclusion
LM SUR SLM	**0,0339**	**Significant**
LM SUR SEM	0,2279	Not Significant

The hypothesis used are as follows :

H_0 = no spatial effect
H_1 = there is a spatial effect

With the testing criterion being to reject H_0 if the P-value < α (0,05) and accept H_0 if the P-value > α (0,05).

In table 8, it can be seen that the P-value for LM-SUR-SLM is 0,0339. With a P-value less than the 5% significance leel, H_0 is rejected, indicating the presence od spatial lag dependence. Therefore, it is necessary to proceed with the formation of the SUR-SLM model.

4.3.6 S-SUR Parameter Estimation

Based on the LM test results in Table 8, it can be concluded that only the SUR-SLM model is suitable for modeling the factors influencing gender-based Human Development Index (HDI) in provincial regions in Indonesia. This is because there is a spatial lag dependence with an autoregressive structure that occurs only in the main equation.

The SUR-SLM model can be formed by estimating the parameters of the SUR-SLM model by maximizing In likelihood in table 9 below :

Table 9. Estimation of SUR-SLM Model Parameters

Variable		Coefficient	P-value
Y_1	Constant	-0,0046	0,9205
	X_{11}	0,3047	$1{,}459\text{x}10^{-07}$
	X_{12}	0,3331	$6{,}717\text{x}10^{-09}$
	X_{13}	0,5367	$2{,}2\text{x}10^{-16}$
	X_{14}	0,1104	0,0277
	Rho_1	0,1285	0,0193
	R-Squared	0,9313	
Y_2	Constant	0,0013	0,9721
	X_{21}	0,2302	$2{,}307\text{x}10^{-06}$
	X_{22}	0,2620	$3{,}807\text{x}10^{-08}$
	X_{23}	0,6201	$2{,}2\text{x}10^{-16}$
	X_{24}	0,0828	0,0703
	Rho_2	0,1154	0,0278
	R-Squared	0,9496	

4.3.7 Significance Test of SUR-SLM Model Parameters

Table 10. Testing the Significance of the SUR-SLM Model Parameters

Variable		P-value	Conclusion
Y_1	Constant	0,9205	
	X_{11}	$1{,}459\text{x}10^{-07}$	Significant
	X_{12}	$6{,}717\text{x}10^{-09}$	Significant
	X_{13}	$2{,}2\text{x}10^{-16}$	Significant

	X_{14}	0,0277	Significant
	Rho_1	0,0193	Significant
	R-Squared	0,9313	
Y_2	Constant	0,9721	
	X_{21}	$2{,}307 \times 10^{-06}$	Significant
	X_{22}	$3{,}807 \times 10^{-08}$	Significant
	X_{23}	$2{,}2 \times 10^{-16}$	Significant
	X_{24}	0,0703	Not Significant
	Rho_2	0,0278	Significant
	R-Squared	0,9496	

Table 10 shows that not all independent variables have a significant impact on the dependent variables. By examining the P-values in table 10, it can be concluded that the Average Years of Schooling variable has a significant impact on Male Human Develepoment Index (Y1) and Female Human Development Index (Y2). The Average Expected Years of Schooling variable also has a significant impact on Male Human Development Index (Y1) and Female Human Development Index (Y2). Similarly, the Per Capita Expenditure variable has a significant impact on Male Human Development Index (Y1) and Female Human Development Index (Y2). However, the Open Unemployment Rate variable only has a significant impact on Male Human Development Index (Y1).

5. CONCLUSION

1. An overview of Gender-Based Human Development Index (HDI) data in Indonesia in 2021 is as follows :
    a. For males, the highest Human Development Index (HDI) value in 2021 is in the DKI Jakarta province at 83.87 percent, while the lowest HDI value is in the Papua province at 66.07 percent.
    b. For females, the highest Human Development Index (HDI) value in 2021 is in the DKI Jakarta province at 79.54 percent, while the lowest HDI value is in the Papua province at 52.96 percent.
2. The best-fitting Spatial Seemingly Unrelated Regression (S-SUR) model that was formed is the Seemingly Unrelated Regression - Spatial Lag Model (SUR-SLM) with goodness-of-fit criteria (R-Squared) values of 93.13 percent for Y1 (Male HDI) and 94.96 percent for Y2 (Female HDI). Below is the formed SUR-SLM model :
    a. Model for the Human Development Index (HDI) equation for males

$$\hat{y}_{1.i} = -0{,}0046 + 0{,}3047X_{11.i} + 0{,}3331X_{12.i} + 0{,}5367X_{13.i} + 0{,}1104X_{14.i} + 0{,}1285\sum_{j=1}^{34} W_{y_{1.i}}$$

    b. Model for the Human Development Index (HDI) equation for females

$$\hat{y}_{2.i} = 0{,}0013 + 0{,}2302X_{21.i} + 0{,}2620X_{22.i} + 0{,}6201X_{23.i} + 0{,}1154\sum_{j=1}^{34} W_{y_{2.i}}$$

3. The factors influencing the Human Development Index (HDI) for males in Indoensia in 2021 are Expected Years of Schooling (X11), Average Years of Schooling (X12), Per Capita Expenditure (X13), and the Open Unemployment Rate (X14). Meanwhile, the factors influencing the Human Development Index for females are Expected Years of Schooling (X21), Average Years of Schooling (X22), and Per Capita Expenditure (X23). Additionally, having more neighboring regions will increase the Human Development Index (HDI) by a factor of rho in that region.

6. RECOMMENDATION

1. For future researchers, it is recommended to conduct further research on the Spatial Seemingly Unrelated Regression (S-SUR) method, considering various models and different spatial weighting matrices. Panel data can be used as a research source for future studies, allowing researchers to explore broader and deeper information.
2. For the government, it is important to promote the implementation of gender mainstreaming policies in all development sectors. By encouraging the implementation of gender mainstreaming policies, the government will be better equipped to identify and address gender gaps in human development. By focusing on this, the government is expected to make significant progress in reducing gender disparities,

strengthening gender equality, and improving the quality of life for all Indonesian citizens.

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