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Poverty Modeling in Indonesia: A Spatial Regression Analysis

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Abstract

The government has made various efforts to reduce poverty in Indonesia. However, based on the World Population Review report, Indonesia is still ranked as the 73rd poorest country in the world in 2022 based on the value of gross national income. Therefore, it is necessary to identify the factors that affect poverty. This research was conducted by comparing classical, spatial lag, and spatial error regression, and the best model will be selected. The results show that the spatial error regression model is the best, based on the highest coefficient of determination and the lowest Akaike's information criterion value. Based on the best model, it is found that the expected years of schooling, the rate of gross regional domestic product, the percentage of households that have access to proper sanitation services, and the percentage of households with electric lighting sources have a significant effect on the percentage of poor people. The percentage of poor people in a province is also influenced by the percentage of poor people in the surrounding provinces. The results of this simulation can help the government take initiatives or policies aimed at reducing poverty in Indonesia based on variables that affect poverty.

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INTRODUCTION

One of the critical goals of the Indonesian government is to reduce the proportion of poor people in the country. The government has made efforts to decrease the poverty rate by implementing several empowerment programs aimed at increasing productivity and enhancing the economic capacity of the community (Gunartha & Utama, 2020). People must meet their fundamental demands for food and non-food to live a decent life. This condition is known as poverty. Low income levels that make it impossible to achieve essential living standards like health and education constitute poverty (Corral et al., 2020).

Efforts to reduce poverty align with one of the Sustainable Development Goals (SDGs), a global agenda to improve people's economic welfare. The first goal of the SDGs is to end poverty in all its forms everywhere, making poverty eradication the primary objective underlying the other goals established within the SDGs (United Nations Development Programme, 2022). According to the Republic of Indonesia Law Number 25 of 2000 concerning national development programs, the government's efforts to reduce poverty in Indonesia are divided into two main parts: protecting groups of people experiencing temporary poverty and helping those experiencing chronic poverty by empowering them and preventing new poverty.

These efforts are implemented through three programs designed to assist people experiencing poverty: the provision of necessities, the development of the social security system, and the promotion of a business culture (Mahkamah Konstitusi Republik Indonesia, 2000). However, according to the World Population Review report, in 2022, Indonesia is expected to remain the world's poorest country regarding Gross National Income (GNI), with a GNI per capita of US$3,870 in 2020. Indonesia ranks 6th in terms of low-income status compared to other ASEAN countries, trailing behind Myanmar, Cambodia, Timor Leste, Vietnam, and the Philippines (World Population Review, 2022). Although Indonesia does not rank high among low-income countries in ASEAN, the percentage of poor people in Indonesia increased by 0.03% in September 2022 compared to March 2022. As a result, the number of poor people in September 2022 reached 26.36 million, an increase of 0.20 million from March 2022 (BPS, 2022). Thus, poverty remains a severe problem in Indonesia, making it necessary to identify and address the factors influencing poverty.

Various interrelated factors influence poverty, and the quality of human resources plays a crucial role in determining an individual's income. A person's level of education is a reflection of the quality of their human resources. Higher education is expected to produce high-quality human resources, enabling individuals to become more productive, increase their income, and break free from the cycle of poverty (Arsani et al., 2020).

Individual productivity can also be enhanced with adequate facilities; one essential factor is access to electricity. Regions with good access to electricity can undoubtedly boost the productivity of individuals within their areas, leading to increased income. This, in turn, indirectly contributes to poverty reduction (Budiono et al., 2021). Health is also one of the factors that affect poverty. Health facilities and access to proper sanitation must support public health conditions. Access to adequate sanitation is one of the most critical factors for health because it is related to the environment. Poor sanitation will cause human welfare to decline, which will impact productivity and drive the quality of human resources to be low (Nawatmi et al., 2020).

Apart from health and education, poverty is also influenced by a region's economy, as seen from the gross regional domestic product (GRDP) rate in each region. An area's economy can be good if it has a high GRDP. A good economy can undoubtedly reduce the poverty rate, so the higher the GRDP of an area, the lower the poverty rate. GRDP can be used to optimize development to improve community welfare (Feriyanto et al., 2020). The identification of factors affecting poverty can be done using a regression approach.

Analysis named regression seeks to simulate the relationship between the predictor variable (X) and the response variable (Y). The presumption is that errors are independent and normally distributed with a mean of zero and a variance of σ^2 must be satisfied in a classical regression analysis (Rencher & Schaalje, 2008). However, these assumptions can often not be met, so it is necessary to develop a classical regression analysis. Spatial regression analysis is one technique that can simulate the relationship between response variables and predictor variables when there is a reasonably significant dependence on neighbouring data. Spatial regression has two types: point-based spatial regression and area-based spatial regression. Problems with spatial dependency are solved using the area technique. In contrast, those with spatial diversity are solved by utilizing the point approach. The spatial effect causes estimates using classical regression to be incorrect because they do not meet identical and independent assumptions, so spatial regression analysis is used (Grasa, 1989).

The spatial regression model consists of spatial lag and error models. The lag spatial model is a spatial model with an area approach that considers the spatial influence of lag between predictor variables or fixed changers. In contrast, the spatial error model is a spatial model in which spatial effects occur on the error changer. By looking at the value of the enormous coefficient determination (R^2) and the smallest value of Akaike's Information Criterion (AIC), the optimal model can be chosen (Anselin, 1988).

Research on the percentage of poor people was conducted by Zahra et al. (2019) using the SEM-PLS method to determine the factors that significantly influence poverty and found that improving human resources with an equitable distribution of quality education, increasing good health insurance, and the availability of decent housing can reduce poverty and improve community welfare. Liu et al. (2022) also carried out poverty modelling using the spatial econometric model method in provinces in China. The studies indicate that neighbouring regions' poverty impacts a province's poverty level. The analysis of the number of poor people was also carried out by Rahayu (2018) using multiple regression applied to case studies in Jambi Province, and the resulting model had a low coefficient of determination (R^2) value of 14.3%. According to the research, the model's ability to describe how impactful the predictor variables are on the number of poor individuals is less. Indications of the number of poor people's dependence on one region with nearby areas can explain the inability of multiple regression models to explain the factors influencing the number of poor people.

LeSage and Pace (2009) state that spatial regression methods can be used to analyze and calculate an observation that depends on other observations. The fact is that poverty in one region depends on poverty in adjacent other areas. Therefore, applying the spatial lag model is more suitable. However, suppose the error from the resulting model depends on an error in another adjacent region. In that case, the error spatial model will be more appropriately applied. Based on this explanation, this study aims to model the proportion of poor people in Indonesia using classical and spatial regression. The greatest model will then be chosen by comparing its value for the biggest coefficient of determination and the smallest AIC value. The novelty of this study is that it uses spatial lag regression and spatial error regression methods that were not used in previous studies, where spatial regression can accommodate the influence of poverty in a region with poverty in the surrounding areas.

RESEARCH METHODS

The data used in this study is related to the percentage of poor people in each province in

Indonesia in 2021. This percentage represents the portion of the population living below the poverty line, defined as the minimum monthly expenditure required to meet basic life needs, including food and non-food necessities (BPS, 2021). Data on the percentage of poor people and factors suspected to be influential are secondary data sourced from Badan Pusat Statistik (BPS.) Indonesia publications. The variables used in this study are presented in Table 1.

Table 1. Research Variables

Variable	Variable Description	Scale	Variable Type
Y	Percentage of Poor People (%)	Ratio	Continuous
X_1	Expected Years of Schooling	Ratio	Continuous
X_2	GRDP rate	Ratio	Continuous
X_3	Percentage of Households with Access to Proper Sanitation Services (%)	Ratio	Continuous
X_4	Percentage of Households with Lighting Source of State Electricity (%)	Ratio	Continuous

Source: Data Processed, 2023

The expected years of schooling are several years, which is expected to describe the length of schooling for seven and older residents. The expected years of schooling show the opportunity for children aged seven years and over to pursue formal education at any given time. The expected years of schooling to look at the development conditions in the education system at various levels. The expected years of schooling depend on the number of residents who attend school at a particular time (BPS, 2020).

The Gross Regional Domestic Product (GRDP) rate is an indicator aimed at seeing the growth of production of goods and services at a specific interval in a region. The GRDP rate can be used to measure economic progress due to national development as a reference basis for the government in estimating state revenues aimed at development planning on a national, sectoral, and regional scale. It can also be used to create sales equations that can be used to make business forecasts (BPS, 2022).

The percentage of households with access to proper sanitation services is the number of people with access to appropriate sanitation services expressed as a percentage of the total population. The requirement for sanitation facilities is considered feasible if the facility is used by the household alone or with specific other households, the facility is equipped with a gooseneck type toilet, and the facility is equipped with a landfill in the form of a septic tank. The percentage of households that have access to proper sanitation services can show the level of welfare of the population based on health aspects (BPS, 2020).

The percentage of households with a lighting source of state electricity compares the number of households with a lighting source of state electricity to the total number of households. The source of electric lighting can be obtained from electricity managed by Perusahaan Listrik Negara (PLN) or electricity managed by agencies or other parties. Sources of electric lighting managed by agencies or other parties can be in the form of lighting sources from batteries, generators, or solar power plants not managed by PLN (BPS, 2022).

The first analysis was conducted, namely modelling the percentage of people experiencing poverty using classical regression. According to Rencher & Schaalje (2008), the classical regression model consists of one response and p predictor variables. Regression models are used to create models that describe the relationship between predictor variables and response variables. The classic regression model can be written as follows:

$$y_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_p X_{ip} + \varepsilon_i \quad \text{.............} (1)$$

where i is the unit of observation (i = 1,2,…,n), y_i is the response variable on the observation to

i; X_{i1}, X_{i2}, ... , X_{ip} is a predictor variable on observation to i; $\beta_0, \beta_1, \dots, \beta_p$ is a parameter of the classic regression model; ε_i is an *error* in the observation to i. Several assumptions must be met in the classical regression model, including that errors are normally distributed with an average of 0 and variances of σ^2 ($\varepsilon_i \sim N(0, \sigma^2)$), that errors are independent, and that there is no dependency between errors ($cov(\varepsilon_i, \varepsilon_j) = 0$).

The next stage is forming a spatial weighting matrix using an area approach. According to Lee & Wong (2001), the W spatial weighting matrix is a component of an econometric spatial model that describes the relationship between one region and another. Adjacent territories will be affected more than far-flung regions. The W matrix can be formed using an area approach. The spatial weighting matrix used in this study was queen contiguity. Queen contiguity spatial weighting matrix defines $w_{ij} = 1$ for region i that intersects with region j, While $w_{ij} = 0$ for regions that $i$do not intersect with the territory$j$.

The next step is spatial dependency testing. According to LeSage & Pace (2009), the Moran index can indicate spatial effects. The Moran index is a measure that shows the spatial relationships that occur in a unit of observation. The Moran index can be mathematically written as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{j=1}^{n}(y_j - \bar{y})^2} \quad \text{..........................(2)}$$

where I is the Moran index value; w_{ij} is an element of the spatial weighting matrix of the i row and the j column; n is the number of observations; y_i is the i observation value of the response variable; y_j is the j observation value of the response variable, and $\bar{y}$ represents the average value of y on n observations. The Moran Index has values ranging from -1 to 1, and if the Moran Index is 0, there is no indication of spatial autocorrelation. Indication of spatial effects can also be done by testing the Moran index values. The test statistics used for testing Moran index values are derived in the form of standard normal random variable statistics based on the central limit theorem, with the test statistics as follows:

$$Z(I) = \frac{I - E(I)}{\sqrt{var(I)}} \quad \text{... (3)}$$

with:

$$E(I) = -\frac{1}{n-1}$$

$$Var(I) = \frac{n^2 n S_0 3 S_0}{(n^2-1){S_0}^2} - [E(I)^2]$$

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}$$

$$S_1 = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(W_{ij} + W_{ji}\right)^2$$

$$S_2 = \sum_{i=1}^{n} \left(\sum_{j=1}^{n} W_{ij} + \sum_{j=1}^{n} W_{ji}\right)^2$$

The hypotheses used in testing are:
H_0 = No spatial dependencies between regions
H_1 = There are spatial dependencies between regions.
with decision-making criteria, such as rejecting H_0 if $|Z(I)| > Z_{\alpha/2}$ or if p-value < α.

If spatial dependencies exist between regions, the next step is to test the Lagrange multiplier. According to Anselin (1988), the Lagrange multiplier test is used to identify spatial influences that occur in data on spatial lag regression models and spatial error regression models. The hypotheses used in testing for the lag spatial regression model are as follows:
$H_0 : \rho = 0$ (There is no spatial lag dependencies)
$H_1 : \rho \neq 0$ (There is a spatial lag dependency)
With Lagrange multiplier test statistics for the lag spatial regression model used, namely:

$$LM_{lag} = \left[\frac{\varepsilon' W y}{\varepsilon' \varepsilon / n}\right]^2 / D \quad \text{................................... (4)}$$

with:

$$D = (WX\beta)'[I - X(X'X)^{-1}X'](WX\beta)] + tr(W^2 + W'W)$$

with decision-making criteria, such as rejecting H_0 if $LM_{lag} < \chi^2_{1-\alpha/2}$ or $LMlag > \chi^2_{\alpha/2}$. In the spatial regression error model, the following hypothesis is used:
H_0: $\lambda = 0$ (There is no dependencies between errors)
H_1: $\lambda \neq 0$ (There is a dependency between errors)
With Lagrange multiplier test statistics for the spatial regression error model used, namely:

$$LM_{error} = \left[\frac{\varepsilon' W\varepsilon}{\varepsilon'\varepsilon/n}\right]^2 / \left[tr(W^2 + W'W)\right] \quad \text{..........(5)}$$

with decision-making criteria, such as rejecting H_0 if $LM_{error} < \chi^2_{1-\alpha/2}$ or $LM_{error} > \chi^2_{\alpha/2}$.

If the Lagrange multiplier test for the Lagrange spatial regression model is significant, it will be continued with modelling using Lagrange spatial regression. As for the Lagrange multiplier test results for the spatial error regression model, if a significant result is obtained, it will be continued using spatial error regression modelling.

According to LeSage & Pace (2009), spatial regression is one of the developments of classical regression, which in spatial regression models has accommodated the occurrence of spatial out-of-correlations in observation data. Spatial regression models are formed when $\rho \neq 0$ and $\lambda \neq 0$. The spatial regression equation can be written as follows:

$$y = \rho Wy + X\beta + u \quad \text{.................................(6)}$$

with

$$u = \lambda Wu + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 \mathrm{I}))$$

Where y is the vector of the response variable; X is a matrix of predictor variables; β is a vector of regression coefficient parameters; ρ is the autoregressive parameter of spatial lag; λ is an error spatial autoregressive parameter; u is a residual vector; ε is an error vector; W is a weighting matrix; u is assumed to have a random location effect and has spatial autocorrelation.

The lag spatial regression model is a model in which there is a spatially autoregressive form. The spatial model of lag can be written as follows:

$$\begin{cases} y = \rho Wy + X\beta + \varepsilon \\ \varepsilon \sim N(0, \sigma^2 I) \end{cases} \quad \text{...................................(7)}$$

where y is the vector of the response variable; ρ is a spatial autoregressive parameter that has a value of $|\rho| < 1$; W is a weighting matrix; X is a matrix of predictor variables; β is a vector of spatial regression parameters; ε is an error vector (Anselin, 1988). Individual testing of parameters on the lag spatial regression model was performed to determine whether each predictor variable had a significant effect on the dependent variable.

To test such hypotheses, use standard normal test statistics.

$$Z_j = \frac{\hat{\beta}_j}{\sqrt{var(\hat{\beta}_j)}} \quad \text{... (8)}$$

with decision-making criteria, such as rejecting H_0 if $|Z_j| > Z_{\alpha/2}$.

Spatial errors arise due to the dependence of the error value of one region on the error value of another adjacent region. Spatial error regression models occur when $\rho = 0$ and $\lambda \neq 0$ (Anselin, 1999). The spatial error regression model is.

$$\begin{cases} y = X\beta + u \\ u = \lambda Wu + \varepsilon \\ \varepsilon \sim N(0, \sigma^2 I) \end{cases} \quad \text{... (9)}$$

where y is the vector of the response variable; X is a matrix of predictor variables; β is a vector of spatial error regression parameters; ε is an error vector; λ is an error spatial autoregressive parameter; W is a weighting matrix; u is a residual vector; u is assumed to have a random location effect and has spatial autocorrelation. Individual testing of parameters in the error spatial regression model was performed to determine whether each predictor variable significantly affected the dependent variable.

To test such hypotheses, use standard normal test statistics.

$$Z_j = \frac{\hat{\beta}_j}{\sqrt{var(\hat{\beta}_j)}} \quad \text{...(10)}$$

with decision-making criteria, such as rejecting H_0 if $|Z_j| > Z_{\alpha/2}$.

Furthermore, the Likelihood Ratio Test (LRT) was carried out, which was used to determine the suitability of the spatial model. The test hypothesis is $H_0: \theta \epsilon \Omega_0$ versus $H_1: \theta \epsilon \Omega_1$ and the test statistics are $\lambda = \frac{L(\hat{\Omega}_0)}{L(\hat{\Omega}_1)}$ with $L(\hat{\Omega}_0) = \max_{\theta \epsilon \Omega_0} L(\Omega_0)$ and $L(\hat{\Omega}_1) = \max_{\theta \epsilon \Omega_1} L(\Omega_1)$. The critical area of the hypothesis test is H_0 which is rejected when $\lambda < c$ for $0 < c < 1$. $LRT = -2 \ln \lambda$ which is distributed as $\chi^2_{(v)}$ is the statistical likelihood ratio test (LRT). With the degree of freedom v is the sum of the parameters below H_1 is less than the number of parameters below H_0. The test criteria are H_0 rejected when $LRT > \chi^2_{(\alpha;v)}$ (Arbia, 2006).

Furthermore, calculating the coefficient of determination is carried out to determine the best regression model. The coefficient of determination is one of the measures that can be used to measure how well the model's ability to describe the diversity of the dependent variable, or the y response variable, is. The coefficient of determination can also indicate the suitability of the resulting regression model. The calculation of the coefficient of determination is carried out using the following formula:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{.......................................} \quad (11)$$

The value of the coefficient of (R^2) is between 0 and 1, where a smaller value of R^2 means that the resulting model's ability to explain variations in the y response variable is limited, while a value of R^2 that is close to one means that the capabilities of the model obtained are good (Walpole *et al.*, 2011).

Calculating the Akaike Information Criteria (AIC) value can also select the best model selection. The AIC method itself was proposed by Akaike and is based on the maximum likelihood estimation (MLE) method. The formula for calculating the AIC value is as follows:

$$AIC = -2Lm + 2m \quad \text{..................................} (12)$$

Where Lm is the maximum log-likelihood value, and m is the number of parameters in the model. The best regression model will be selected based on the model that has the smallest AIC value (Grasa, 1989).

Furthermore, the best regression model is selected by choosing a model based on the value of the most significant coefficient of determination and the smallest AIC value. The next stage tests the regression model's assumptions, namely the normality and heteroscedasticity tests on the error. The normality test determines the residual distribution of the resulting regression model. The normality test used in this study was the Jarque-Fallow test. The Jarque-Fallow test is performed by calculating the coefficients of skewness and kurtosis. The Jarque-Fallow test can be used for large samples. The normality test hypothesis is:

H_0: Normally distributed error

H_1: Error not normally distributed

with test statistics used as follows:

$$JB = n\left(\frac{s^2}{6} + \frac{(k-3)^2}{24}\right) \quad \text{..................................} (13)$$

with

$$s = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x})^2\right)^{3/2}};$$

$$k = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x})^2\right)^{2}};$$

n is the number of samples, with the critical area being the reject H_0 if $JB > x_2^2$ or *p-value* < α (Gujarati, 2006).

A heteroscedasticity test is run to see if the variance of the error produced by the model is the same (homoscedasticity), which means $var(\varepsilon_i) = E(\varepsilon_i^2) = \sigma^2$ for all i with $i = 1,2,3,\dots,n$. In this study, the heteroscedasticity test was carried out with the Breusch-Pagan test with the following hypothesis:

H_0: Error does not occur as a result of heteroscedasticity

H_1: Error does occur as a result of heteroscedasticity

with test statistics used as follows:

$$F = \frac{R^2_{\varepsilon^2/k}}{1 - R^2_{\varepsilon^2/(n-k-1)}} \sim F_{\propto.(k,n-k-1)} \quad \text{...................} (14)$$

where k is the number of predictor variables and $R^2_{\varepsilon^2}$ is the R-square value obtained from error regressing (ε^2) in the presence of k predictor variables, including intercepts. The critical area in this test is the reject H_0 if $F > F_{\propto.(k,n-k-1)}$ or *p-value* < α (Suprapto, 2004). The last stage of this study is to interpret the best regression model obtained.

RESULTS AND DISCUSSION

The analysis in this study is aimed at describing the factors that affect the percentage of poor people in Indonesia using thematic maps, modelling the percentage of poor people in Indonesia using classical regression, lag spatial regression, and error spatial regression approaches, choosing the best regression model based on criteria (R^2 and AIC), and interpreting models.

A descriptive statistical picture of the percentage of poor people and the factors suspected of influencing it, which include the expected years of schooling (X_1), GRDP rate (X_2), the percentage of households that have access to proper sanitation services (X_3), and the percentage of households with a lighting source of state electricity (X_4), is presented in Table 2.

Table 2. Descriptive research variables

Variable	Mean	Minimum		Maximum	
		Value	Province	Value	Province
Y	10.427	4.56	Kalimantan Selatan	27.38	Papua
X_1	13.214	11.11	Papua	15.64	DI Yogyakarta
X_2	4.178	-2.47	Bali	16.4	Maluku Utara
X_3	80.97	40.81	Papua	97.12	DI Yogyakarta
X_4	98.262	79.12	Papua	100	DKI Jakarta and DI Yogyakarta

Source: Data Processed, 2023

The highest percentage of poor people in Indonesia is in Papua Province, at as much as 27.38 percent, while the lowest is in South Kalimantan Province, at only 4.56 percent. The highest percentage of poor people in Papua is due to the low level of education owned by the Papuan people. Low education causes low knowledge, skills, quality, and productivity in the work environment. South Kalimantan Province has a low percentage of poor people because this province is one of the regions in Indonesia that has considerable natural resource potential, and the people of South Kalimantan can manage these resources well so that they can increase the Pace of the economy (Ramadhan, 2021).

The highest of the expected years of schooling are in DI Yogyakarta Province at 15.64, and the lowest is in Papua Province with a score of 11.11. Papua is a province with a low school period because the motivation of the Papuan people in academic terms is relatively low. Economic, social, political, and demographic conditions cause the low motivation to learn from the Papuan people (Triyanto, 2019). The high number of expected years of schooling in the province of D.I. Yogyakarta is supported by many educational institutions at various levels of education. With supporting educational facilities, the motivation of the people of DI Yogyakarta Province is high, making the value of old-school expectations in this province also high (DPAD DI Yogyakarta, 2018).

The highest GRDP rate is in North Maluku Province at 16.4, and the lowest is in Bali Province at -2.47. The high GRDP rate of North Maluku Province is supported by the mining sector and processing industry, which are running well and increasing trade activities. In addition, the Pace of GRDP in Maluku Province is also supported by an increase in foreign export demand for commodities in North Maluku Province, namely downstream nickel commodities (Bank Indonesia, 2022). Bali Province has the lowest GRDP rate because the economy in Bali Province mostly comes from the tourism sector. The COVID-19 pandemic over the past two years has caused social restrictions, so the tourism sector has greatly decreased. This makes the GRDP rate in Bali Province very low because it is in the recovery stage from the

COVID-19 pandemic conditions (Amrita et al., 2021).

DI Yogyakarta Province has the highest percentage of households with access to proper sanitation services, at 97.12, while Papua Province has the lowest, at 40.81. The low access to sanitation services in Papua is due to the relatively low level of clean-living culture and the difficulty of pure water distribution due to geographical characteristics (Rais et al., 2022). The percentage of households with the highest electric lighting source is in DKI. Jakarta and DI Yogyakarta provinces at 100 percent, while the lowest is in Papua Province at 79.12 percent. The low access to electricity in Papua is due to geographical problems, namely that the soil structure in Papua tends to be hard, making it difficult to install electricity poles. This problem will soon be resolved by constructing the Trans-Papua Road (Zuhri et al., 2019).

An overview of the percentage of poor people in Indonesia using thematic maps is presented in Figure 1.

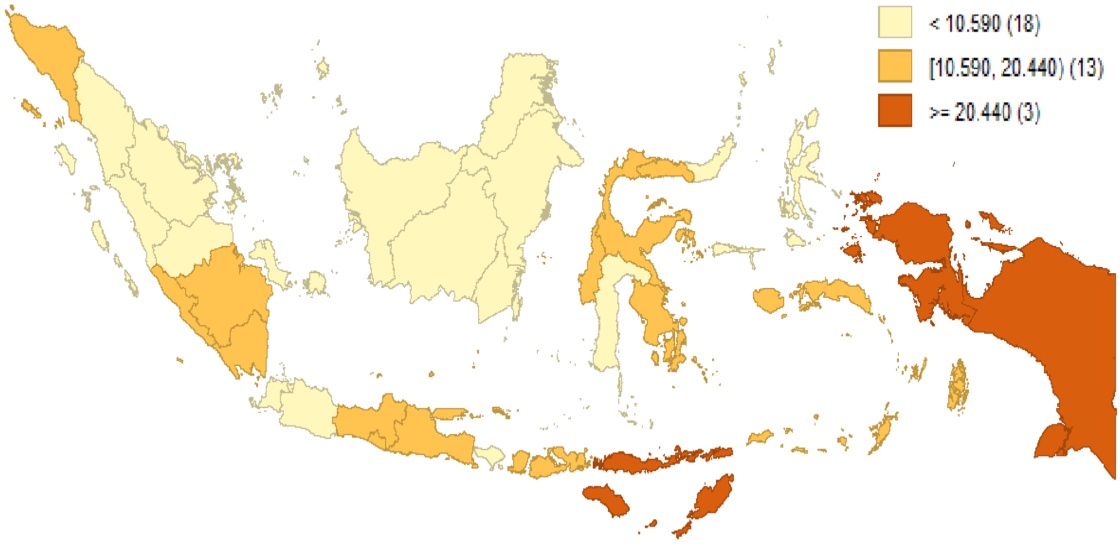

Figure 1. Thematic map of the percentage of the poor population
Source: Data Processed, 2023

The grouping of provinces in Indonesia based on the percentage of poor people uses the Natural Breaks Map method. The grouping is carried out by dividing the provinces in Indonesia into three categories: low, medium, and high. The low category is a province with a poor percentage of less than 10.59%. The moderate category is a province with a percentage of the poor population of more than or equal to 10.59% and less than 20.44%—provinces with a poor population percentage greater than or equal to 20.44% fall into the high category. Based on Figure 1, it can be seen that the percentage of poor people in Indonesia is the highest among those included in the low class, namely as many as 18 provinces, while 13 provinces have a percentage of poor people who are included in the moderate category. There are three provinces with a relatively high percentage of poor people: Papua, West Papua, and East Nusa Tenggara. Most provinces in Indonesia that are adjacent have the same colour. It shows that the adjacent provinces have almost the same percentage of the poor population. Therefore, it can be indicated that spatial autocorrelation occurs in the percentage of poor people in Indonesia.

This study used classical and spatial regression approaches to model the percentage of poor people in Indonesia. Modelling the percentage of poor people with a classical regression approach obtained the results of estimating the parameters as follows:

$$\hat{Y} = 104.309 + 2.461X_1 - 0.494\,X_2 \\ -0.158X_3 - 1.135X_4 \quad \text{.........................} (15)$$

The results of simultaneous testing of factors suspected of affecting the percentage of poor people in Indonesia using the classical regression model are presented in Table 3.

Table 3. Concurrent testing of classic regression models

Test	F-statistic	F-table ($F_{(0,05;4;29)}$)	P-value	Decision
Concurrent testing of classic regression models	11.495	2.70	0.000*	Reject H_0

Note: *significance at the test level α (5%)
Source: Data Processed, 2023

According to Table 3, the results of the simultaneous test of the classical regression model were decided to reject H_0 and it can be concluded that the four predictor variables significantly affect the percentage of poor people in Indonesia simultaneously. Individual testing was carried out to determine the real influence of each predictor variable. The results of individual tests are presented in Table 4.

Table 4. Individual testing of classic regression models

Predictor	Coefficient	t-value	P-value	Decision
Constant	104.309	4.464	0.000*	Reject H_0
X_1	2.461	2.562	0.016*	Reject H_0
X_2	-0.494	-2.391	0.024*	Reject H_0
X_3	-0.158	-1.536	0.135	Receive H_0
X_4	-1.135	-3.987	0.000*	Reject H_0

Note: *significance at the test level α (5%)
Source: Data Processed, 2023

Based on Table 4, it can be concluded that the variables of expected years of schooling (X_1), GRDP rate (X_2), and the percentage of households with a lighting source of state electricity (X_4) have a significant influence on the percentage of poor people in Indonesia, while the percentage of households that have access to proper sanitation services (X_3) does not significantly influence the percentage of poor people in Indonesia. The results of classical regression modelling have a classification precision based on the value of the coefficient of determination (R^2) of 62.23% and an AIC value of 187.191.

Assumption testing on classical regression models includes normality and homoscedasticity tests of errors. The test results of the classical regression model assumptions are presented in Table 5.

Table 5. The assumptions of classical regression models

Test	Test Statistical Value	P-value	Decision
Normality Test (Jarque-Bera)	0.7270	0.69525	Receive H_0
Homoscedasticity Test (Breusch-Pagan)	5.1289	0.27433	Receive H_0

Source: Data Processed, 2023

From the Jarque-Bera normality test in Table 5, a p-value of 0.69525 > α (5%) was obtained so that a decision could be made to accept H_0 and it can be concluded that the assumption of normality on the error is met. The results of the Breusch-Pagan homoscedasticity test obtained a p-value of 0,27433 > α (5%) so that a decision could be made to accept H_0 and it can be concluded that the assumption of homoscedasticity on the error is met. Because the assumption of the regression model has been fulfilled, equation (16) can be used to estimate the percentage of poor people in Indonesia.

Furthermore, Moran Index testing was carried out to determine the relationship between spatial autocorrelation and the percentage of poor people between provinces in Indonesia. The formation of a spatial weighting matrix is necessary for the calculation of the Moran Index. Queen Contiguity governs the formation of the spatial weighting matrix. The Moran Index test results are presented in Table 6.

Table 6. Moran's index testing

Test	Z-value	P-value	Decision
Moran's Index	2.9411	0.00327*	Reject H_0

Source: Data Processed, 2023

Based on Table 6, the decision to reject H_0 is obtained, so it can be concluded that there is spatial autocorrelation in the percentage of poor people in Indonesia.

Lagrange multiplier testing determines spatial autocorrelation in response and error variables. The results of the Lagrange multiplier test are presented in Table 7.

Table 7. Lagrange multiplier testing

Test	Test Statistical Value	P-value	Decision
LM_{lag}	4.2820	0.03852*	Reject H_0
LM_{error}	6.5454	0.01052*	Reject H_0

Source: Data Processed, 2023
Note: *significance at the test level α (5%)

From the test LM_{lag}, we obtained a p-value of 0.03852 < α (5%) so that a decision can be made to reject H_0It can be concluded that there is a spatial lag dependence on the response variable. On the test LM_{error}, we obtained a p-value of 0.01052 < α (5%) so that a decision can be made to reject H_0It can be concluded that there is a spatial dependency on model errors.

Because there is a spatial dependence of lag on the percentage of people with low incomes, the next stage is to estimate the spatial regression lag model or the Spatial Autoregressive (SAR) model. The results of the SAR model parameter estimation for the percentage of poor people in Indonesia obtained the following model:

$$\hat{Y} = 0.227Wy + 97.0861 + 2.345X_1 - 0.572\,X_2 - 0.133X_3 - 1.085X_4 \quad \text{.......................(16)}$$

One can use the Likelihood Ratio Test (LRT) to determine the suitability of the SAR model. The LRT results are presented in Table 8.

Table 8. LRT model SAR.

Test	**Test Statistical Value**	**P-value**	**Decision**
LRT	5.0158	0.02512*	Reject H_0

Source: Data Processed, 2023
Note: *significance at the test level α (5%)

From the LRT test, a p-value of 0.02512 < α (5%) was obtained so that a decision could be made to reject it H_0 and it can be concluded that the SAR model is appropriate when used to model the percentage of poor people in Indonesia.

Testing the significance of parameters on the SAR model was conducted to determine each predictor variable's real influence. The results of testing the significance of parameters on the SAR model are presented in Table 9.

Table 9. Testing the significance of parameters on the SAR model

Predictor	Coefficient	z-value	P-value	Decision
ρ	0.227	2.446	0.014*	Significant
Constant	97.086	4.839	0.000*	Significant
X_1	2.345	2.873	0.004*	Significant
X_2	-0.572	-3.257	0.001*	Significant
X_3	-0.133	-1.493	0.135	Not significant
X_4	-1.085	-4.482	0.000*	Significant

Source: Data Processed, 2023

Note: *significance at the test level α (5%)

Based on Table 9, it can be concluded that the variables of expected years of schooling (X_1), GRDP rate (X_2), and the percentage of households with a lighting source of state electricity (X_4) have a significant influence on the percentage of poor people in Indonesia, while the percentage of households that have access to proper sanitation services (X_3) has no significant influence on the percentage of poor people in Indonesia. The coefficient ρ also has a significant influence, which means that the percentage of poor people in a province is influenced by the percentage of poor people in surrounding provinces. The results of classical regression modelling have a classification precision based on the value of the coefficient of determination (R^2) of 68.13% and an AIC value of 184.175.

Assumption testing on SAR models includes normality tests and homoscedasticity tests of errors. The test results of the regression model assumptions for the SAR model are presented in Table 10.

Table 10. SAR model assumption testing

Test	Test Statistical Value	P-value	Decision
Normality Test (Jarque-Bera)	0.67073	0.7151	Receive H_0
Homoscedasticity Test (Breusch-Pagan)	6.7858	0.14765	Receive H_0

Source: Data Processed, 2023

From the Jarque-Bera normality test in Table 10, a p-value of 0.7151 > α (5%) was obtained so that a decision could be made to accept H_0 and it can be concluded that the assumption of normality on the error is met. The results of the Breusch-Pagan homoscedasticity test obtained a p-value of 0.14765 > α (5%) so that a decision could be made to accept H_0 and it can be concluded that the assumption of homoscedasticity on the error is met. Because the assumption of the regression model has been met, equation (17) can be used to estimate the percentage of poor people in Indonesia.

Furthermore, the spatial error regression model estimation is also carried out because there is a spatial dependence on the model error. The results of the estimation of Spatial Error Model (S.E.M.) parameters for the percentage of poor people in Indonesia obtained the following model:

$$\hat{Y} = 86.321 + 2.275X_1 - 0.609\,X_2 - 0.182X_3 - 0.903X_4 + u$$

$$u = 0.529\sum_{i=1,j=1}^{n} W_{ij}u_j \quad (17)$$

Use the Likelihood Ratio Test (LRT) to determine the SEM model's suitability. The LRT results are presented in Table 11.

Table 11. LRT model SEM.

Test	Test Statistica Values	P-value	Decision
LRT	9.7315	0.00181*	Reject H_0

Source: Data Processed, 2023

Note: *significance at the test level α (5%)

From the LRT test, a p-value of 0.00181 < α (5%) was obtained so that a decision could be made to reject it H_0 and it can be concluded that the SEM model is appropriate when used to model the percentage of poor people in Indonesia.

Testing the significance of parameters on the SEM model is carried out to determine the real influence of each predictor variable. The results of testing the significance of parameters on the SEM model are presented in Table 12.

Table 12. Testing the significance of parameters on the SEM model

Predictor	Coefficient	z-value	P-value	Decision
Constant	86.321	4.570	0.000*	Significant
X_1	2.275	3.254	0.001*	Significant
X_2	-0.609	-4.595	0.000*	Significant
X_3	-0.182	-2.527	0.012*	Significant
X_4	-0.903	-4.019	0.000*	Significant
λ	0.529	4.394	0.000*	Significant

Note: *significance at the test level α (5%)

Source: Data Processed, 2023

Using a α of 5% and based on Table 10, it can be concluded that the variables of expected years of schooling (X_1), GRDP rate (X_2), the percentage of households that have access to proper sanitation services (X_3), and the percentage of households with a lighting source of state electricity (X_4) have a significant influence on the percentage of poor people in Indonesia. The coefficient λ also has a significant influence, which means that the percentage of poor people in a province is influenced by the percentage of poor people in surrounding provinces. The results of classical regression modelling have a classification precision based on the value of the coefficient of determination (R^2) of 75.33% and an AIC value of 177.46.

Assumption testing on the SEM model includes a normality test and a homoscedasticity test of the error. The test results of the regression model assumptions for the SEM model are presented in Table 13.

Table 13. SEM model assumption testing

Test	Test Statistical Value	P-value	Decision
Normality Test (Jarque-Bera)	4.598	0.1004	Receive H_0
Homoscedasticity Test (Breusch-Pagan)	8.8521	0.0649	Receive H_0

Source: Data Processed, 2023

From the Jarque-Bera normality test in Table 13, a p-value of 0.1004 > α (5%) was obtained so that a decision could be made to accept H_0 and it can be concluded that the assumption of normality on the error is met. The results of the Breusch-Pagan homoscedasticity test obtained a p-value of 0.0649 > α (5%) so that a decision could be made to accept H_0 and it can be concluded that the assumption of homoscedasticity on the error is met. Because the assumption of the regression model has been met, equations (18) and (19) can be used to estimate the percentage of poor people in Indonesia.

The selection of the best regression model for the percentage of poor people in Indonesia was carried out by determining the values of the largest coefficient of determination (R^2) and each regression model's smallest Akaike's Information Criterion (AIC). Calculations (R^2 and A.I.C.) on classic regression models, S.A.R. models, and S.E.M. models are presented in Table 14.

Table 14. Value of R^2 and A.I.C.

Model	R^2	AIC
Classic Regression	62.23%	187.191
SAR	68.13%	184.175
SEM	75.33%	177.46

Source: Data Processed. 2023

Based on Table 14. it can be concluded that the best regression model is the SEM model with an R^2 of 75.33% and an AIC value of 177.46.

Based on modelling the percentage of poor people in Indonesia using spatial regression errors. The results of estimating the percentage of poor people in each province in Indonesia were obtained. A comparison of the estimated results with the actual value of the percentage of poor people in Indonesia is presented in Fig. 2.

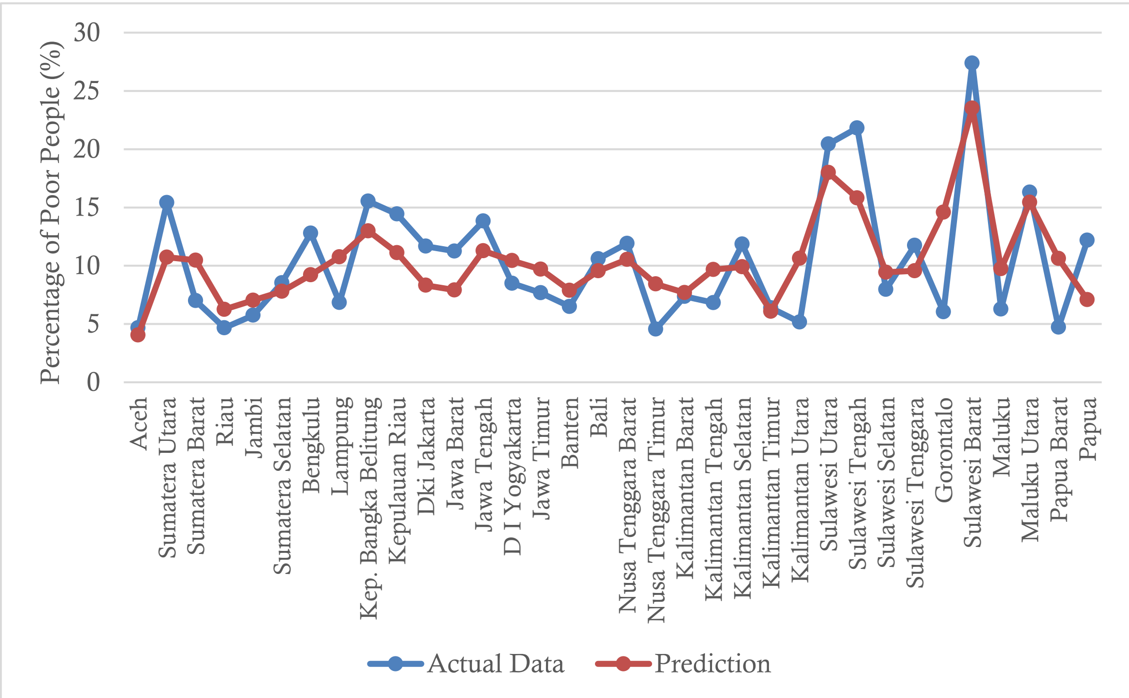

Figure 2. Comparison of actual data and predicted results

Source: Data Processed. 2023

In Figure 2. it can be seen that the results of predicting the percentage of poor people in each province in Indonesia using a spatial error regression model are not much different from the actual value, so it can be said that modelling the percentage of poor people in each province in Indonesia using spatial regression error produces a good estimated value.

Based on the SEM model. If the expected years of schooling increase by one unit in a province, the percentage of poor people in the province will increase by 2.275 points, assuming other predictor variables are considered constant. This is in line with research conducted by Sawaliyah (2022). which states that the education curriculum in Indonesia so far is still not relevant to the needs of the world of work and that there is an imbalance between the number of jobs available and the number of highly educated people, causing an increase in unemployment so that it can be said that higher education cannot guarantee the eradication of poverty.

An increase in the GDP rate of one unit in a province will reduce the percentage of poor people in the province by 0.609, assuming other predictor variables are considered constant. The GRDP rate indicates the economy in an area. The people's welfare level in the region improves when the economy increases. Improved welfare will reduce the percentage of people experiencing poverty (Dahliah & Nur, 2021).

A 1% increase in the percentage of households with access to proper sanitation services in a province would reduce the percentage of poor people by 0.182, assuming other predictor variables are considered constant. Proper sanitation services will improve people's health. If the people's health is good, it will impact the high level of productivity. A high and good level of productivity can help people improve their economy. The economic increase will help the poor escape poverty (Siddiqui, et al., 2020).

An increase of 1% in the percentage of households with electric lighting sources in a province will reduce the percentage of poor people by 0.903, assuming other predictor variables are considered constant. Access to electricity is an important aspect because it can increase economic growth. The availability of adequate electricity will increase the productivity of the people. If the productivity of the people increases, it will affect the increase in the economy of the people. Good economic growth will reduce the poverty rate in an area (Sarkodie & Adams. 2020).

The percentage of poor people in a province is also influenced by the percentage of poor people in surrounding provinces. The error values between provinces from the modelling results and spatial regression errors correlate. Based on equation (19). an error correlation value of 0.529 was obtained, which means that spatial interactions between provinces in Indonesia have a spatial influence on the percentage of poor people. Poverty in a region is influenced by poverty in the surrounding areas because poor people tend to move to neighbouring areas with lower poverty rates to look for job opportunities to get out of poverty (Alwandi & Ariputri, 2023).

Thus, efforts to overcome poverty in Indonesia by reducing the percentage of people experiencing poverty can be made by increasing the rate of GRDP, increasing the percentage of households that have access to proper sanitation services, increasing the percentage of households with lighting sources of state electricity, and increasing the expected years of schooling by improving the quality of education and providing many jobs.

CONCLUSION

The percentage of poor people in each province in Indonesia is mostly moderate. However, several provinces are still in the high category, namely Papua, West Papua, and East Nusa Tenggara. Modelling the percentage of poor people in Indonesia using classical regression methods shows that several provinces are still in the high category, namely Papua, West Papua, and East Nusa Tenggara. Modelling the percentage of poor people in Indonesia using classical regression, lag spatial regression, and spatial error regression obtained the best model as the spatial error regression model with the largest coefficient of determination value and the smallest AIC value. Spatial regression modelling shows that expected years of schooling, GRDP rates, the percentage of households with access to proper sanitation services, and the percentage of households with electric lighting sources significantly influence the percentage of poor people in Indonesia. The expected years of schooling have a positive relationship with the percentage of people with low incomes.

In contrast, the GRDP rate, the percentage of households with access to proper sanitation services, and those with electric lighting sources have a negative relationship with the percentage of people with low incomes in Indonesia. Reducing poverty can be done by increasing the rate of GRDP, the percentage of households with access to proper sanitation services, and the percentage of households with lighting sources of state electricity in each province. In education, an increase in the expected years of schooling needs to be balanced with the availability of employment so that no intellectual unemployment can increase poverty.

REFERENCES

Alwandi. M. A. & Ariputri. R. W. 2023. [*Mobilitas Pekerja Antarsektor Di Provinsi Jambi 2019-2022]*. *Media Edukasi Data Ilmiah dan Analisis (MEDIAN).* 6(1). pp. 18-34.

Amrita. N. D. A., Handayani. M. M., and Erynayati. L. 2021. [*Pengaruh Pandemi Covid-19 terhadap Pariwisata Bali]*. *Jurnal Manajemen dan Bisnis Equlibrium.* 7(2). pp. 246-256.

Anselin. L. 1988. *Spatial Econometric: Methods and Models.* Dordrecht: Academic Publishers.

Anselin. L. 1999. *Spatial Econometrics*. Dallas: Bruton Center. School of Social Sciences, the University of Texas.

Arbia. G. 2006. *Spatial Econometrics: Statistical Foundations and Applications to Regional Convergence.* Germany: Springers.

Arsani. A. M.. Ario. B. & Ramadhan. A. F.. 2020. Impact of Education on Poverty and Health: Evidence from Indonesia. *Economics Development Analysis Journal.* 9(1). pp. 87-96.

Bank Indonesia. 2022. [*Laporan Perekonomian Provinsi Maluku Utara].* [Online] Available at: https://www.bi.go.id/id/publikasi/laporan/lpp/Documents/Laporan-Perekonomian-Provinsi-Maluku-Utara-Agustus-2022.pdf [Accessed 31 January 2023].

Budiono. S.. Purba. J. T. & Purba. A.. 2021. *Fighting Poverty Gap through Literacy and Electricity: A Case from Indonesia.* Singapore. The 11th Annual International Conference on Industrial Engineering and Operations Management Singapore.

BPS. 2020. [*Persentase Rumah Tangga yang Memiliki Akses terhadap Layanan Sanitasi Layak].* [Online] Available at: https://sirusa.bps.go.id/sirusa/index.php/ indikator/1196 [Accessed 19 January 2023].

BPS. 2020. [*Harapan Lama Sekolah (HLS)].* [Online] Available at: https://sirusa.bps.go.id/sirusa/index.php/indikator/1016 [Accessed 19 January 2023].

BPS. 2021. [*Perhitungan dan Analisis Kemiskinan Makro di Indonesia].* Jakarta: Badan Pusat Statistik.

BPS. 2022. *Laju Pertumbuhan PDRB.* [Online] Available at: https://sirusa.bps.go.id/sirusa/index.php/indikator/3 [Accessed 19 January 2023].

BPS. 2022. [*Persentase rumah tangga dengan sumber penerangan listrik].* [Online] Available at: https://sirusa.bps.go.id/sirusa/index.php/variabel/7560 [Accessed 19 January 2023].

BPS. 2022. [*Persentase Penduduk Miskin September 2022 naik menjadi 9,57 persen]*. [Online] Available at: https://www.bps.go.id/pressrelease/2023/01/16/2015/persentase-penduduk-miskin-september-2022-naik-menjadi-9-57-persen.html [Accessed 20 January 2023].

Corral. P. et al.. 2020. *Fragility and Conflict: On the Front Lines of the Fight against Poverty.* Washington DC: World Bank Publications.

Dahliah. D. & Nur. A. N.. 2021. The Influence of Unemployment. Human Development Index and Gross Domestic Product on Poverty level. *Golden Ratio of Social Science and Education.* 1(2). pp. 95-108.

DPAD DI Yogyakarta. 2018. [*Sejarah Singkat Daerah Istimewa Yogyakarta].* [Online] Available at: http://dpad.jogjaprov.go.id/article/news/vieww/sejarah-singkat-daerah-istimewa-yogyakarta-1482 [Accessed 31 January 2023].

Feriyanto. N.. Aiyubbi. D. E. & Nurdany. A.. 2020. The Impact of Unemployment. Minimum Wage. and Real Gross Regional Domestic Product on Poverty Reduction in Provinces of Indonesia. *Asian Economic and Financial Review.* 10(10). pp. 1088-1099.

Grasa. A. A.. 1989. *Econometric Model Selection: A New Approach.* Kluwer: Springer Science and Business Media.

Ginting. T. A. B.. Sudibia. I. K.. Dewi . N. P. M. & Marhaeni. A. A. I. N.. 2020. The Effect of Education and Dependency Ratio on Economic Growth and Poverty in Papua. *American Journal of Humanities and Social Sciences Research (AJHSSR).* 4(6). pp. 186-195.

Gujarati. D.. 2006. *Dasar-dasar Ekonometrika.* Alih Bahasa Julius Mulyadi ed. Jakarta: Erlangga.

Gunartha. I. D. K. A. & Utama. M. S.. 2020. Community Empowerment Strategy in Poverty Treatment. *American Journal of Humanities and Social Sciences Research (AJHSSR)* . 4(9). pp. 332-344.

Lee. J.. & Wong. SWD.. 2001. *Statistical Analysis with Arcview G.I.S.* United Stated of America: John Willey and Sons.

LeSage. J. P. & Pace. R. K.. 2009. *Introduction to Spatial Econometrics.* s.l.:Boca Ration: R Press.

Liu. W.. Li. J. & Zhao. R.. 2021. The effects of rural education on poverty in China: a spatial econometric perspective. *Journal of the Asia Pacific Economy.* pp. 1-23.

Mahkamah Konstitusi Republik Indonesia. 2000. *Undang-undang Republik Indonesia Nomor 25 Tahun 2000 Tentang Program Pembangunan Nasional (Propenas) Tahun 2000-2004.* [Online] Available at: https://jdih.mkri.id/mg58ufsc89hrsg/uu25_2000.pdf [Accessed 9 November 2022].

Nawatmi. S.. Nusantara. A.. Santosa. A. B. & Muhaimin. 2020. *Determinants of Poverty in Indonesian Provinces.* Semarang. The 3rd International Conference of Banking. Accounting. Management and Economics (ICOBAME 2020).

Rahayu. Y.. 2018. Analisis Pengaruh Indeks Pembangunan Manusia. PDRB Per Kapita. dan Jumlah Pengangguran terhadap Jumlah Penduduk Miskin di Provinsi Jambi. *EKONOMIS: Journal of Economics and Business.* 2(1). pp. 165-174.

Rais. et al.. 2022. Regency Clusterization Based on Village Characteristics to Increase the Human Development Index (IPM) in Papua Province. *Jurnal Ekonomi Pembangunan.* 20(2). pp. 153-168.

Ramadhan. M.. 2021. *The Effect of Government Investment and Private Investment on Poverty Level in South Kalimantan Province.* Surabaya. Indonesia Naval Technology College International Conference on Maritime Science and Technology.

Rencher. A. C. & Schaalje. G. B.. 2008. *Linear Model in Statistics.* Second Edition ed. Inc. USA: John Wiley and Sons.

Sarkodie. S. A. & Adams. S.. 2020. Electricity access. human development index. governance and income inequality in Sub-Saharan Africa. *Energy Reports.* Volume 6. pp. 455-466.

Sawaliyah. Y.. 2022. [*Kajian Pendidikan Vokasi dan Kompetensi Ketenagakerjaan]*. *Jurnal Pendidikan dan Sosial Budaya.* 2(4). pp. 615-633.

Siddiqui. F.. Salam. R. A.. Lassi. Z. S. & Das. J. K.. 2020. The Interwined Relationship Between Malnutrition and Poverty. *Frontiers in Public Health.* 8(453). pp. 1-5.

Suprapto. 2004. *Ekonometri.* Jakarta: Ghalia Indonesia.

Triyanto. 2019. The Academic Motivation of Papuan Students in Sebelas Maret University. Indonesia. *SAGE Open.* 9(1).

United Nations Development Programme. 2022. *Sustainable Development Goals.* [Online] Available at: https://www.undp.org/sustainable-development-goals [Accessed 15 January 2023].

Walpole. R. E.. Myers . R. H.. Myers. S. L. & Ye. K.. 2011. *Probability and Statistics for Engineers and Scientists.* Ninth Edition ed. United States of America: Prentice Hall.

World Population Review. 2022. *Poorest Countries in the World 2022.* [Online] Available at: https://worldpopulationreview.com/country-rankings/poorest-countries-in-the-world [Accessed 2 November 2022].

Zahra. A.. Afifah. A. F.. Afuwu. H. & Rahma. R. A.. 2019. [*Struktur Kemiskinan Indonesia: Berapa Besar Pengaruh Kesehatan]*. Pendidikan dan Kelayakan Hunian?. *Jurnal Inovasi Ekonomi.* 4(2). pp. 67-74.

Zuhri. K.. Anggraeni. L. & Irawan. T.. 2019. Inequality in Indonesia's Electricity Access. *International Journal of Sciences: Basic and Applied Research (IJSBAR).* 48(7). pp. 237-249.