

Analyzing Factors Contributing to Gender Inequality in Indonesia using the Spatial Geographically Weighted Logistic Ordinal Regression Model

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Abstract—Gender inequality is a condition of discrimination caused by social systems and structures. The main objective of this research is to identify factors that influence gender inequality in each province in Indonesia and obtain classification accuracy values using Geographically Weighted Ordinal Logistic Regression (GWOLR). The dataset used in this research consists of a response variable, namely the gender inequality index where the index value is divided into ordinal categories (low, medium, and high) and four predictor variables from the dimensions of health, education, human empowerment, social-culture, and work. The results of this study show that the classification accuracy of the GWOLR model is 85%. The mapping of provinces in Indonesia based on influential variables forms three groups. The first group (brown) is influenced by the percentage of women who give birth with the assistance of health workers (X_1) and the female Human Development Index (HDI) (X_3). The second group (blue) is influenced by the ratio of women's Pure Participation Rate (APM) (X_2) and the percentage of rape crimes against women (X_4). The third group (red) is influenced by the percentage of women who give birth with the assistance of health workers (X_1), the ratio of women's Pure Participation Rate (APM) (X_2), the percentage of women's Human Development Index (HDI) ratio (X_3), and the percentage of women's rape crimes (X_4).

I. INTRODUCTION

GENDER includes inherent characteristics, behavior, differentiation of roles, positions, responsibilities, and division of labor between men and women as a result of the formation of culture or social environment in which humans grow and are raised. Gender inequality is an unfair condition caused by social systems and structures so that women and men become victims of the system [1]. Gender justice will be realized if conditions are created where the portions and social cycles of women and men are equal, harmonious, balanced, and harmonious [2]. Gender inequality is a condition of discrimination between men and women due to social systems and structures or conditions where there is a gap between men and women in family, community, national, and state life [3]. Gender justice and gender equality can be achieved by providing equal opportunities to contribute to development. Forms of gender inequality caused by gender differences are First, marginalization of access to resources, for example, information and technology, education, and employment, which results in poverty (impoverishment) and can impact both men and women. Second, subordination is an attitude of lowering social position or status. Third, stereotypes are labels

or markings of a certain group that are often detrimental and cause injustice. Fourth, violence against a person's physical and mental psychological integrity. Fifth, women have a longer and larger workload [4], [5]. Gender inequality is detrimental to all areas of development (social, economic, education, defense, and security). Gender inequality has a strong relationship with poverty and unequal access to education, health services, and access to finance [6]. The average condition of Indonesia's Gender Inequality Index (IKG) in 2022 has decreased compared to previous years. However, the condition of gender inequality in each province is still above average and many provinces still experience gender inequality towards women [7]. The issue of gender inequality became the National Medium Term Development Plan (RPJMN) for 2020-2024 and became the Sustainable Development Goals (SDGs) for 2030 so the Indonesian Government issued INPRES Number 9 of 2000 [8], [9].

According to [10] Indicators of gender inequality include risk factors in the dimensions of health (maternal mortality and adolescent fertility), empowerment (education and parliament), and the labor market. Based on BPS research in 2020, there is a negative relationship between the Gender Empowerment Index (IDG), Human Development Index (IPM), and Gender Development Index (IPG) on gender gaps in Indonesia. Indonesia's gender inequality index varies, and some provinces still have prominent levels of gender inequality. The Research conducted [11] focuses on analyzing gender gaps using spatial analysis. The findings of this research reveal that analysis using spatial methods was not applied in this research. The spatial data used is only a description of the location of gender inequality without discussing spatial statistical analysis. The results of the OLS global regression model show that important factors that influence gender inequality are the percentage of individuals aged ten years and over who have never received a formal education, the number of women aged 20-24 years who married or lived together before the age of 18, and the percentage of women aged 20-24 years. 24-year-olds who married or lived together before the age of 18. Births that occur outside health facilities, HDI of the female population, and IDG influence gender inequality in Indonesia. This research only produced a goodness of fit model of 74.48%, this is because there are still alternative statistical methods that can provide more accurate results, namely by using spatial statistical analysis methods. Each province in Indonesia has unique characteristics and conditions that can influence gender inequality. The Central Statistics Agency (Badan Pusat

Statistical) categorizes the gender inequality index into four categories ranging from low to high [12]. The appropriate method for analyzing spatial data with an ordinal categorical response variable is Geographically Weighted Ordinal Logistic Regression (GWOLR)[13], [14]. The GWOLR model in the case of human index development using exponential kernel function weighting shows superior classification accuracy compared to ordinal logistic regression, as measured by the Apparent Error Rate (APER) which reaches 86.84% [15]. Other research using the GWOLR method can map very well, namely 94.7% [16].GWOLR method is better than ordinal logistic regression [?]. The main objective of this research is to identify factors that influence gender inequality in each region in Indonesia and obtain classification accuracy values in mapping gender gaps in each province in Indonesia using Geographically Weighted Logistic Ordinal Regression.

II. METHODOLOGY

A. Logistic Ordinal Regression

The ordinal logistic regression method is a statistical technique used to analyze response variables with an ordinal scale, comprising three or more categories. In this model, predictor variables can include both categorical and continuous data, involving two or more variables [19]. The logistic regression model can be referred to as the logit model. If the response variable employs an ordinal scale with 'L' categories and 'X' refers to the vector of independent variables in 'n' observations, the OLR (Ordinal Logistic Regression) model can be formulated as follows equation (1):

$$\text{logit}[P(Y \leq l | \mathbf{x}_i)] = \ln \left[\frac{P(Y \leq l | \mathbf{x}_i)}{1 - P(Y \leq l | \mathbf{x}_i)} \right] = \beta_{0l} + \mathbf{x}_i^T \boldsymbol{\beta}_k \quad (1)$$

With $l = 1, 2, \dots, L - 1, i = 1, 2, \dots, n, k = 1, 2, \dots, p, P(Y \leq l | \mathbf{x}_i)$ describes the cumulative probability that is less than or equal to the l-category on x_k .

B. Geographically Weighted Logistic Ordinal Regression

The GWOLR model is a fusion of the Geographically Weighted Regression (GWR) model and the ordinal logistic regression model [16]. The purpose of the GWOLR model is to depict the relationship between an ordinal-scaled response variable and predictor variables, where each regression coefficient depends on the location of the observed data [20]. If the response variable consists of L categories, then the GWOLR model will be used for site I, This can be expressed as Equation (2) [13]:

$$\text{logit}[P(Y \leq l | \mathbf{x}_i)] = \ln \left[\frac{P(Y \leq l | \mathbf{x}_i)}{1 - P(Y \leq l | \mathbf{x}_i)} \right] = \beta_{0l}(u_i, v_i) + \mathbf{x}_i^T \boldsymbol{\beta}_k(u_i, v_i) \quad (2)$$

The cumulative probability of the g-the response category can be expressed as equation (3)

$$P(Y \leq l | \mathbf{x}_i) = \frac{\exp(\beta_{0l}(u_i, v_i) + \mathbf{x}_i^T \boldsymbol{\beta}_k(u_i, v_i))}{1 - \exp(\beta_{0l}(u_i, v_i) + \mathbf{x}_i^T \boldsymbol{\beta}_k(u_i, v_i))}, \quad l = 1, 2, \dots, L - 1 \quad (3)$$

The probability of the response variable at the location-I belonging to category l can be expressed as equation (4)

$$\pi_l(\mathbf{x}_i) = \frac{\exp(\beta_{0l}(u_i, v_i) + \mathbf{x}_i^T \boldsymbol{\beta}_k(u_i, v_i))}{1 - \exp(\beta_{0l}(u_i, v_i) + \mathbf{x}_i^T \boldsymbol{\beta}_k(u_i, v_i))}, \quad l = 1, 2, \dots, L - 1 \quad (4)$$

The GWOLR model utilizes the Weighted Maximum Likelihood Estimation (MLE) method. Subsequently, a likelihood function in the form of ln is constructed by transforming the original likelihood function. The weighting factors in the GWOLR model are associated with geographic locations, with each location having distinct values that reflect local characteristics within the GWOLR model. Consequently, a weighting scheme is applied to the likelihood of the GWOLR model. Parameter estimation is performed by calculating the first partial derivative of the weighted ln-likelihood equation with respect to the parameter to be estimated, followed by equating the derivative to zero. Due to the nonlinearity of this initial partial derivative, the solution employs the Newton-Raphson iteration method

Hypothesis testing on the GWOLR model includes testing the suitability between the GWOLR model and the ordinal logistic regression model, testing parameters simultaneously, and testing parameters individually. The goodness of fit test of the GWOLR model and Ordinal Logistic Regression model. This test aims to test the significance of geographical factors. The hypothesis used is [21]:

$H_0 : \beta_k(u_i, v_i) = \beta_k$ [there was no difference between the GWOLR model and the ordinal logistic regression model].

$H_1 : \text{At least one } \beta_k(u_i, v_i) \neq \beta_k$ [There are differences between the GWOLR model and the ordinal logistic regression model] Test statistics as equation (5) :

$$F = \frac{D(\hat{\phi})/df_1}{D(\hat{\phi}^*)/df_2} \quad (5)$$

Reject H_0 if $F_{\text{ount}} > F_{(\alpha, df_1, df_2)}$ In the study by [18] , weighting functions generate different parameter estimations for each observation. According to [15]the Kernel Exponential function dan Gaussian function can be a weighting function. Fixed Gaussian kernel weighting function can be written as follows equation(6)

$$w_j(u_i, v_i) = \exp \left(-\frac{1}{2} \left(\frac{d_{ij}}{b} \right)^2 \right) \quad (6)$$

Fixed exponential kernel weighting function can be written as follows equation (7)

$$w_j(u_i, v_i) = \exp \left(-\left(\frac{d_{ij}^2}{b^2} \right) \right) \quad (7)$$

With $d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}$, which represents the distance between locations (u_i, v_i) and (u_j, v_j) And b as a known non-negative parameter commonly called the smoothing parameter (bandwidth). Selecting an optimal bandwidth is crucial in ensuring the model's accuracy towards the data. Bandwidth can be achieved by utilizing Cross Validation (CV) as follows equation (8) [22]

$$CV(b) = \sum_{i=1}^n (y_i - \hat{y}_{\neq i}(b_i))^2 \quad (8)$$

A simultaneous test is utilized to assess the collective significance of the variable parameters in the GWOLR model, which

does not appear to be modifying the subject. The hypothesis is as follows [14]:

$H_0 : \beta_1(u_1, v_1) = \beta_2(u_2, v_2) = \dots = \beta_k(u_i, v_i) = 0$ (No variables that affect the model)

$H_1 : \text{at least one of } \beta_k(u_i, v_i) \neq 0$ (at least there is one predictor variable that affects the model)

Test Statistics as equation (9) [23]

$$G^2 = -2 \left(\ln L(\widehat{\Omega}) - \ln L(\widehat{\omega}) \right) \quad (9)$$

Where $L(\widehat{\Omega})$ maximized value of the likelihood function below H_0

$L(\widehat{\omega})$ maximized value of the likelihood function under the population Reject H_0 if $G^2 > \chi^2_{(\alpha, df)}$ where $df = \text{trace}(S)$ where S is a matrix with the i -th row and j -th column elements, namely:

$$S_{ij} = R_{ij} \frac{Z_j(u_i, v_j)}{Z_j(u_i, v_j)}$$

where R is a matrix with the i -th row element $R_{ij} = \mathbf{x}_i \mathbf{X}^T \mathbf{W}(u_i, v_j) dA(u_i, v_j) \mathbf{X}^{-1} \mathbf{X}^T \mathbf{W}(u_i, v_j) dA(u_i, v_j)$ Afterward, the significance of the parameters is tested individually or partially with the following hypotheses [24]:

$H_0 : \beta_k(u_i, v_i) = 0, i = 1, 2, \dots, n; k = 1, 2, \dots, p$ (No variables that affect the response)

$H_1 : \beta_k(u_i, v_i) \neq 0$ (Variable predictor affects the response variable)

Test Statistics as equation (10):

$$Z_{\text{count}} = \frac{\widehat{\beta}_k(u_i, v_i)}{SE(\widehat{\beta}_k(u_i, v_i))} \quad (10)$$

H_0 rejected if $|Z_{\text{count}}| > Z_{\alpha/2}$ According to [25] the best regression model is determined by comparing the ordinal logistic regression model and GWOLR. One of the criteria used to select the best model is the model that achieves the highest classification accuracy. In this study, the classification accuracy is measured using APER (Apparent Error Rate). [21] The corresponding error rate can be obtained by calculating the APER value. Hence, to determine the classification accuracy, one can use 1-APER.

TABLE I: Confusion matrix table of the classification

Observation		Actual Class		
		Class=1	Class=2	Class=3
Prediction	Class =1	F11	F12	F13
	Class=2	F21	F22	F23
	Class=3	F31	F32	F33

Referring to Table II, mistakes made in categorizing objects can be computed through APPER [26], which is described as Equation (11)

$$APER = \frac{F12 + F13 + F21 + F23 + F31 + F33}{F11 + F12 + F13 + F21 + F22 + F23 + F31 + F32 + F33} \times 100 \quad (11)$$

Meanwhile, to assess the accuracy of the classification, the following Equation (12) can be used:

$$\text{Total Accuracy Rate} = 1 - APER \quad (12)$$

C. Source Data and Variables

This research uses a combination of secondary data sourced from the Central Statistics Agency (BPS) and the Ministry of Women's Empowerment and Child Protection (KemenPPPA). Data was obtained through the website www.bps.go.id, the gender gap publication book by BPS and the gender publication book by Kemenpp-pa. The experimental units are locations in 34 provinces in Indonesia. as depicted in Fig. 1

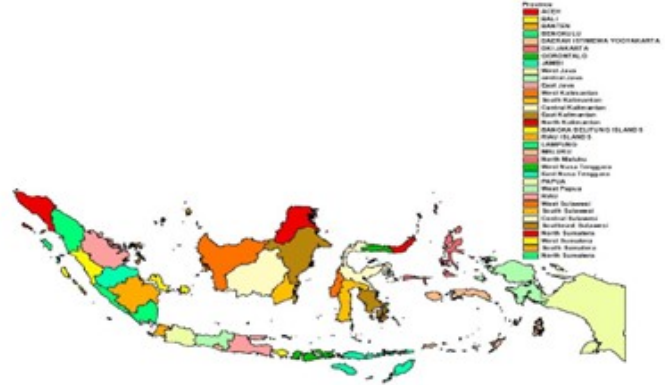


Fig. 1: Research data collection locations in 34 provinces in Indonesia

The dataset in this study consisted of response variables, namely the gender inequality index [12], where the index values were divided into three categories with ordinal scale, namely.

- 1) low (IKG < 0.3999)
- 2) medium (IKG 0.400-0.449 and
- 3) high (IKG > 0.450)

while the predictor variable consisted of The percentage of women aged 15-49 giving birth with assistance from healthcare personnel (X_1), the Ratio of net enrollment rate (APM) of women in Higher Education (X_2), the Percentage of Human Development Index (IPM) Women (X_3); Percentage of rape crimes against women (X_4); per-centage of women's involvement in parliament (X_5) and location factors point of Latitude and Point of Longitude. The analysis steps in this study, as illustrated in the flowchart Fig. 2

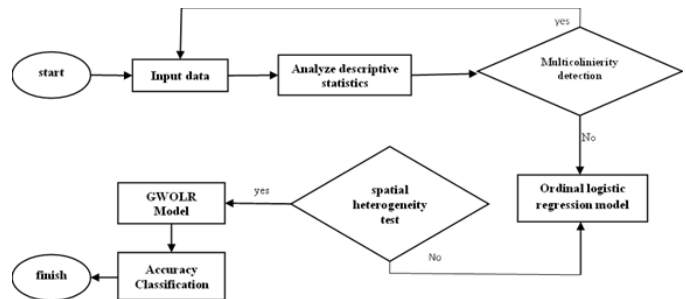


Fig. 2: Flow chart of research analysis steps

III. RESULT

The gender inequality index is categorized into three, namely (1) low (IKG < 0.3999); (2) medium (IKG 0.400-

0.449) and (3) high ($IKG > 0.450$), as presented in Fig. 3. Based on Fig 3. The gender gap situation in every province



Fig. 3: Description of the gender inequality index in Indonesia in the year 2022.

in Indonesia has shown improvement from year to year. In 2022, the highest gender inequality index was 0.492, which marked a decrease compared to the 2021 figure of 0.506. This highest index was observed in Southeast Sulawesi. On the other hand, Bali Province consistently had the lowest gender inequality index from 2021 to 2022. Several provinces in Indonesia exhibit low gender inequality, including Aceh, North Sumatra, Riau, West Sumatra, Lampung, Banten, Java Island, Bali, East Nusa Tenggara (NTT), West Nusa Tenggara (NTB), Gorontalo, Yogyakarta Special Region (DIY), and Jakarta. However, there are provinces that require immediate attention from the government due to their high gender inequality levels. These provinces are primarily located in the Eastern Indonesia (WIT) region, comprising Maluku, North Maluku, West Papua, and Papua, as well as the Central Indonesia region (WITA), including Jambi, Bengkulu, West Kalimantan, Central Kalimantan, Southeast Sulawesi, and West Sulawesi. Additionally, provinces with moderate gender gaps are closely monitored to prevent them from falling into the high inequality category. These provinces include South Sumatra, West Java, Banten, West Nusa Tenggara, South Kalimantan, North Kalimantan, and Southeast Sulawesi. Based on the examination of multicollinearity, it was found that the values of the Variance Inflation Factor (VIF) for each predictor variable are below 10. Therefore, it can be concluded that there is no significant correlation between the predictor variables. Ordinal Logistic Regression (OLR) model on the Gender Inequality Index in Indonesia as in equation (13):

$$\begin{aligned} \text{logit}[P(Y \leq 1|x)] &= -66,551 - 0,401 - 0,016X_2 - 0,366X_3 - \\ &\quad 0,620X_4 - 0,046X_5 \\ \text{logit}[P(Y \leq 2|x)] &= -66,551 - 0,401 - 0,016X_2 - 0,366X_3 - \\ &\quad 0,620X_4 - 0,046X_5 \end{aligned} \quad (13)$$

In the OLR model, the factors that influence global gender inequality in Indonesia are obtained. The percentage of women aged 15-49 giving birth with assistance from healthcare personnel (X_1), the Percentage of Human Development Index (IPM) Women (X_3), and Percentage of rape crimes against women (X_4). Next, The initial step in modeling the gender inequality index in each province of Indonesia is to determine the geographical locations based on Latitude and longitude in each region. Based on the results of the Breusch-Pagan test, it can be concluded that spatial heterogeneity exists in each province in Indonesia. Then, the Euclidean distance is calculated from locations i and j . Subsequently, the optimal bandwidth is determined using the Cross Validation (CV) method. Using an optimal bandwidth of 1.091, the best weight

matrix is obtained by incorporating the Euclidean distance and the optimal bandwidth into the exponential kernel weighting function. The weights obtained for each research location are then used to estimate the GWOLR parameters in each province of Indonesia using Newton Raphson iteration. After getting the GWOLR model estimation, tests are conducted to determine the similarity between the GWOLR model and the Ordinal Logistic Regression model regarding overall and individual parameter levels involved. The following are the hypotheses used to test the equivalence between the GWOLR model and the Ordinal Logistic Regression model can be presented Table II.

TABLE II: test of equality between the GWOLR model and the Ordinal Logistic Regression model.

Model	Devians	Df	Deviant/Df	F
OLR	30.276	56	0.541	4.077
GWOLR	27.004	203.65	0.133	

The computed F test value for testing the equivalence between the GWOLR and Ordinal Logistic Regression models is 4.007. The added F test value is greater than the critical F value of F (0.05; 56; 203.65), which is 1.39. Therefore, it can be concluded that there is a significant difference between the GWOLR and Ordinal Logistic Regression (OLR) models. The modeling of the Gender Inequality Index in the provinces of Indonesia in 2022 yields significantly different results between the GWOLR and Ordinal Logistic Regression models. The following is the simultaneous testing of the parameters of the GWOLR model in this study is obtained. G^2 statistic value is 49.661, compared to the χ^2 (0.05; 5.534) value of 11,889. Therefore, the G^2 statistic value is greater than the χ^2 (0.05; 5.534) value. Hence, it can be concluded that at least one predictor variable significantly influences the Gender Inequality Index in the provinces of Indonesia. The partial testing of the parameters of the GWOLR model is conducted using the following hypotheses:

$$\begin{aligned} H_0 : \beta_k(u_i, v_i) &= 0, i = 1, 2, \dots, 34; k = 1, 2, \dots, 5 \\ H_1 : \beta_k(u_i, v_i) &\neq 0 \end{aligned}$$

Each province in Indonesia has a different model, resulting in other significant variables. For example, testing will be conducted on the parameter β_k that influences variable H_1 for each i, k with $i = 1, 2, \dots, 34$ and $k = 1, 2, \dots, 5$. Assuming that β_k at the eleventh location (u_{11}, v_{11}) representing East Java province has a significant effect, the Z-test values can be observed in Table III.

GWOLR model on the Gender Inequality Index in East Java Province (11th location) as in Equation (14):

$$\begin{aligned} \text{logit}[P(Y \leq 1|x)] &= 85,14 - 0,6783X_1 - 0,1783X_2 - 0,2007X_3 \\ &\quad + 0,0494X_4 - 0,006X_5 \\ \text{logit}[P(Y \leq 2|x)] &= 80,32 - 0,6783X_1 - 0,1783X_2 - 0,2007X_3 \\ &\quad + 0,0494X_4 - 0,006X_5 \end{aligned} \quad (14)$$

Based on the model and Table 3, the variables that influence the GWOLR model in East Java Province are The predictor variables that influence the Gender Inequality Index in East Java Province are the percentage of women aged 15-49 years who gave birth with the assistance of health workers (X_1) and the percentage of women on the Human Development Index

TABLE III: Partial Parameter Significance Test in Location of East Java Province

Parameter	Estimate	SE	Zccount	P-Value	Odd ratio
$\beta_{01}(u_{11}, v_{11})$	85,14	24,456	0,905	0,817	-
$\beta_{02}(u_{11}, v_{11})$	80,32	23,45	1,208	0,886	-
$\beta_1(u_{11}, v_{11})$	-0,6783	0,2345	-2,893	0,001*	1,971
$\beta_2(u_{11}, v_{11})$	-0,1783	0,1732	-1,029	0,152	1,195
$\beta_3(u_{11}, v_{11})$	-0,2007	0,1003	-2,001	0,002*	1,222
$\beta_4(u_{11}, v_{11})$	0,0494	0,0426	1,160	0,877	1,051
$\beta_5(u_{11}, v_{11})$	-0,006	0,1153	-0,052	0,479	1,006

*Significant of $\alpha = 5\%$

(HDI) (X_3). A one percent decrease in the percentage of ever-married women aged 15-49 years whose childbirth is assisted by health workers (X_1) is associated with East Java being 1.971 times more likely to become a high gender inequality area. Similarly, a one percent decrease in the percentage of women in the Human Development Index (HDI) (X_3) is associated with the East Java region being 1.222 times more likely to become a high gender inequality area. Mapping of provinces based on significant variables in the GWOLR model can be seen in Fig 4. The comparison of model logistic regression

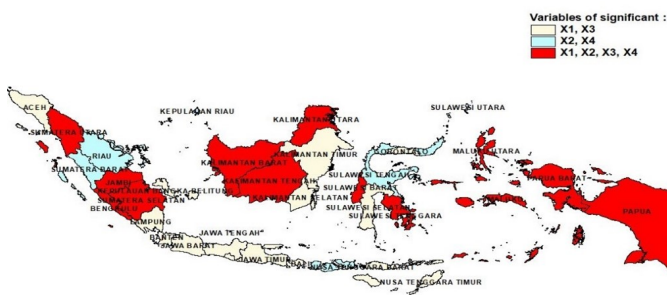


Fig. 4: Mapping of provinces based on significant variables in the GWOLR model using the Expo-nential Kernel Function weighting

and GWOLR is conducted by comparing the accuracy rate and the error value (APER) in classification as present-ed by Table IV.

TABLE IV: shows that in modeling the Gender Inequality Index, the use of the GWOLR model yields a higher classification accuracy than the ordinal logistic regression model. The GWOLR model is more suitable for modeling the Gender Inequality Index in Indonesian provinces than the ordinal logistic regression model.

Model	APER	Accuracy
Ordinal Logistic Regression	18%	82%
GWOLR	15%	85%

IV. CONCLUSION

The Factors that influence the Gender Inequality Index according to the GWOLR model can be categorized into several dimensions, such as Health, Educa-tion, Community Empowerment, and Socio-Culture. The factors that influence the Gender Inequality Index in each province are different.

The mapping of provinces in Indonesia based on influential variables forms three groups.

The first group (brown) is influenced by the percentage of women aged 15-49 years who gave birth with the assistance of health workers (X_1) and the share of women’s Human Development Index (HDI) (X_3). Provinces included in group one are Aceh, Bali, DI Yogyakarta, DKI Jakarta, Gorontalo, Central Java, East Java, East Kalimantan, Bangka Belitung Islands, Riau Islands, Lampung, East Nusa Tenggara, Riau, South Sulawesi, North Sulawesi, West Sumatra, South Sumatra, and North Sumatra.

The second group (blue) is influenced by the ratio of pure enrollment rates (APM) of women in higher education (X_2) and the percentage of rape crimes against women (X_4). Provinces in the second group are West Java, South Kalimantan, North Kalimantan, West Nusa Tenggara, and Central Sulawesi.

The third group (red) is influenced by the percentage of women aged 15-49 years who gave birth with the assistance of health workers (X_1), the ratio of the Pure Participation Rate (APM) of women in higher education (X_2), the percentage of the Human Development Index ratio (HDI) of women (X_3), and the percentage of rape crimes against women (X_4). Provinces in the third group are Banten, Bengkulu, Jambi, West Kalimantan, Central Kalimantan, Maluku, North Maluku, Papua, West Pa-pua, West Sulawesi, and Southeast Sulawesi.

Modeling the factors influencing the 2022 Gender Inequality Index using the GWOLR method with exponential kernel weighting has proven to be superior to using ordinal logistic regression based on classification accuracy values. These findings are consistent with previous research [15], [16]. The results obtained show that the GWOLR model is superior to the global ordinal logistic regression model. How-ever, the level of accuracy obtained in this study does not exceed previous research. The research produced a classification accuracy of 85%.

REFERENCES

- [1] S. D. Judiasih, “Implementasi Kesetaraan Gender Dalam Beberapa Aspek Kehidupan Bermasyarakat Di Indonesia,” ACTA DIURNAL Jurnal Ilmu Hukum Kenotariatan, vol. 5, no. 2, Art. no. 2, Jun. 2022, doi: 10.23920/acta.v5i2.904.
- [2] A. Rahim, “Gender Dalam Perspektif Islam,” SOSIORELIGIUS: JURNAL ILMIAH SOSIOLOGI AGAMA, vol. 3, no. 1, Art. no. 1, Oct. 2018, doi: 10.24252/sosioireligius.v3i1.6372.
- [3] S. Ponthieux and D. Meurs, “Chapter 12 - Gender Inequality,” in Handbook of Income Distribution, A. B. Atkinson and F. Bourguignon, Eds., vol. 2. Elsevier, 2015, pp. 981–1146, doi: 10.1016/B978-0-444-59428-0.00013-8.
- [4] G. Valsecchi, V. Iacoviello, B. Jacques, I. Borinca, and J. M. F. Pichastor, “Men’s Gender Norms and Gender-Hierarchy-Legitimizing Ideologies: The Effect of Priming Traditional Masculinity Versus a Feminization of Men’s Norms,” Gender Issues, vol. 40, no. 1, pp. 465–480, 2023, doi: 10.1007/s12147-022-09308-8.
- [5] N. I. Fadila, C. S. Riyanto, I. M. C. Avisya, B. C. Irianti, and D. O. Radianto, “Kesetaraan Gender,” Humantech: Jurnal Ilmiah Multidisiplin Indonesia, vol. 2, no. 8, Art. no. 8, Jun. 2023.
- [6] V. Aprilia and M. Triani, “Analisis Pengaruh Ketimpangan Gender, Rasio Ketergantungan Dan Kesehatan Terhadap Kemiskinan Di Indonesia,” Jurnal Kajian Ekonomi dan Pembangunan, vol. 4, no. 3, Art. no. 3, Sep. 2022, doi: 10.24036/jkep.v4i3.13772.
- [7] BPS RI, “Indeks Ketimpangan Gender (IKG) 2022,” www.bps.go.id, 2023.

- [8] F. Razi, Rencana Strategis Kementerian Agama Tahun 2020-2024. Jakarta: Kementerian Agama Republik Indonesia, 2020.
- [9] Tim Kemen PPPA, Pembangunan Manusia Berbasis Gender. Jakarta: Kementerian Pemberdayaan Perempuan dan Perlindungan Anak Republik Indonesia, 2022. [Online]. Available: <https://www.kemenpppa.go.id/>
- [10] BPS, Kajian Penghitungan Indeks Ketimpangan Gender 2021. Jakarta: BPS Republik Indonesia, 2021.
- [11] Marsono, "Deteksi Spasial Pada Model Indeks Ketimpangan Gender Indonesia," Buana Gender, vol. 6, no. 1, pp. 49–66, 2021.
- [12] TIM BPS RI, Kajian Penghitungan Indeks Ketimpangan Gender 2022. Jakarta: BPS-Statistics Indonesia, 2022. [Online]. Available: <https://www.bps.go.id/publication/>
- [13] S. Zuhdi, D. R. S. Saputro, and P. Widyaningsih, "Parameters Estimation of Geographically Weighted Ordinal Logistic Regression (GWOLR) Model," J. Phys.: Conf. Ser., vol. 855, p. 012064, Jun. 2017, doi: 10.1088/1742-6596/855/1/012064.
- [14] R. Amalah, A. K. Jaya, and N. Sirajang, "Pemodelan Geographically Weighted Logistic Regression dengan Metode Ridge," ESTIMASI: Journal of Statistics and Its Application, pp. 130–143, Aug. 2023, doi: 10.20956/ejsa.v4i2.12250.
- [15] R. N. Pradita, H. Yasin, and D. Safitri, "Pemodelan Faktor-Faktor Yang Mempengaruhi Indeks Pembangunan Manusia Kabupaten/Kota Di Jawa Timur Menggunakan Geographically Weighted Ordinal Logistic Regression," Jurnal Gaussian, vol. 4, no. 3, Art. no. 3, Jul. 2015, doi: 10.14710/j.gauss.4.3.639-650.
- [16] V. F. Rochmah and V. Ratnasari, "Pemodelan Ketahanan Pangan di Jawa Timur Menggunakan Metode Geographically Weighted Ordinal Logistic Regression (GWOLR)," JSSITS, vol. 8, no. 2, pp. D397–D404, Feb. 2020, doi: 10.12962/j23373520.v8i2.47021.
- [17] M. Fathurahman, "Hypothesis testing of Geographically weighted bivariate logistic regression," Journal of Physics: Conference Series, vol. 1417, pp. 1–8, 2019, doi: 10.1088/1742-6596/1417/1/012008.
- [18] A. R. Wardani, N. Gusriani, and D. A. Kusuma, "Pemetaan Zonasi Resiko Covid-19 Di Provinsi Jawa Barat Menggunakan Model Geographically Weighted Ordinal Logistic Regression (GWOLR)," Teorema: Teori dan Riset Matematika, vol. 7, no. 1, pp. 193–204, 2022.
- [19] M. Sari and P. Purhadi, "Pemodelan Indeks Pembangunan Manusia Provinsi Jawa Barat, Jawa Timur dan Jawa Tengah Tahun 2019 dengan Menggunakan Metode Regresi Logistik Ordinal," Jurnal Gaussian, vol. 10, no. 1, Art. no. 1, Feb. 2021, doi: 10.14710/j.gauss.10.1.149-158.
- [20] V. N. Mishra, V. Kumar, R. Prasad, and M. Punia, "Geographically Weighted Method Integrated with Logistic Regression for Analyzing Spatially Varying Accuracy Measures of Remote Sensing Image Classification," Journal of the Indian Society of Remote Sensing, vol. 49, no. 5, pp. 1189–1199, 2021, doi: 10.1007/s12524-020-01286-2.
- [21] G. Dong, T. Nakaya, and C. Brunndon, "Geographically weighted regression models for ordinal categorical response variables: An application to geo-referenced life satisfaction data," Computers, Environment and Urban Systems, vol. 70, pp. 35–42, Jul. 2018, doi: 10.1016/j.compenurbsys.2018.01.012.
- [22] A. S. Fotheringham and T. M. Oshan, "Geographically weighted regression and multicollinearity: Dispelling the myth," Journal of Geographical Systems, vol. 18, pp. 303–329, 2016.
- [23] Syinfi, Pemodelan Rata-rata Umur Kawin Pertama (UKP) Wanita Di Provinsi Jawa Timur Tahun 2012 Dengan Pendekatan Geographically Weighted Ordinal Logistic Regression (GWOLR), Thesis Program Statistika. Surabaya: ITS, 2015.
- [24] A. Fadliana, H. Pramoedyo, and R. Fitriani, "Implementation Of Locally Compensated Ridge-Geographically Weighte Regression Model In Spatial Data With Multicollinearity Problems(Case Study: Stunting among Children Aged under Five Years in East Nusa Tenggara Province)," MEDIA STATISTIKA, vol. 13, no. 2, pp. 125–135, Dec. 2020.
- [25] S. H. Hasanah, "Perbandingan Metode Klasifikasi Artificial Neural Network Backprogration dan Regresi Logistik (Studi Kasus: Bank Internasional Indonesia)," Jurnal Statistika dan Matematika, vol. 1, no. 1, Feb. 2019, doi: 10.32493/sm.v1i1.2372.
- [26] C. Anselin, Spatial Econometrics: Methods and Models. Netherlands: Kluwer Academic Publishers, 2013.
- [27] R. Aldila, M. Cahya, and K. Suryadi, "Spatio-Temporal Analysis for Detecting COVID-19 Spreading Pattern in Indonesia," Journal of Mathematical and Fundamental Sciences, vol. 52, no. 3, pp. 250–268, Aug. 2020, doi: 10.5614/j.math.fund.sci.2020.52.3.5.
- [28] J. S. Long, Regression Models for Categorical and Limited Dependent Variables. California: SAGE Publications, Inc., 1997.