BAREKENG: Journal of Mathematics and Its Applications
June 2026 Volume 20 Issue 2 Page 1099–1110
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol20iss2pp1099-1110

A MODIFIED GEOGRAPHICALLY AND TEMPORALLY WEIGHTED REGRESSION MODELING ON OPEN UNEMPLOYMENT RATE IN SOUTH SULAWESI

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Article Info

Article History:
Received: 30th April 2025
Revised: 20th June 2025
Accepted: 19th September 2025
Available online: 18th January 2026

Keywords:
GTWR;
Mahalanobis distance;
Open unemployment rate;
Spatial temporal.

ABSTRACT

The Open Unemployment Rate (OUR) in Indonesia is still a challenge despite a decline, namely 4.82% in February 2024 and around 7.2 million unemployed people. The main cause of the OUR is the imbalance between the number of the workforce and the availability of jobs. This issue is directly related to the Sustainable Development Goals (SDGs), especially Goal 8 which focuses on the creation of decent jobs and economic growth. South Sulawesi Province has experienced a spike in the OUR in the last five years, especially due to the Covid-19 pandemic which caused the poverty rate to decline to 6.31% in 2020. Along with economic recovery, this figure decreased to 4.19% in August 2024. Although low, the thickness of the layer remains a concern because 4 out of 100 people have not been absorbed in the labor market. Therefore, it is important to identify the factors that influence the OUR in South Sulawesi in order to design a reduction strategy. Various factors that influence the OUR include the human development index, percentage of poor people, average length of schooling, life expectancy, population density, and regional gross domestic product. To analyze the influence of these factors, this study uses the Geographically and Temporally Weighted Regression (GTWR) method which can capture spatial and temporal variations. Modifications are made using the Mahalanobis distance to consider inter-regional correlation and the Locally Compensated Ridge (LCR) approach to overcome high collinearity in the data. The data used comes from the Central Statistics Agency of South Sulawesi Province. Meanwhile, partial testing obtained each observation of the influencing factors varying from 2020 to 2023. In general, the factors that significantly influence the open poverty rate in South Sulawesi in 2020-2023 are the human development index, percentage of poor people, average length of schooling and life expectancy.

How to cite this article:

S. Siswanto, N. Sunusi, A. I. Yunita, M. R. Davala, A. M. A. Baso and Nurfadilah ., "A MODIFIED GEOGRAPHICALLY AND TEMPORALLY WEIGHTED REGRESSION MODELING ON OPEN UNEMPLOYMENT RATE IN SOUTH SULAWESI ", *BAREKENG: J. Math. & App.*, vol. 220, no. 2, pp. 1099-1110, Jun, 2026.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

The Open Unemployment Rate (OUR) in Indonesia is currently still a serious problem, although it has decreased. In February 2024, the OUR was recorded at 4.82%, which shows improvement compared to the higher figures in previous years. However, with the number of unemployed people around 7.2 million, the challenge to reduce this figure remains. This includes those who are unemployed, looking for work, preparing a business, or those who are not looking for work because they feel unworthy or have been accepted but have not started [1]. The main cause of open unemployment is related to the imbalance between the number of workers and the available jobs [2]. Therefore, the OUR is one of the focuses in the Sustainable Development Goals (SDGs), especially Goal 8 which focuses on Decent Work and Economic Growth.

Reducing the OUR is a crucial step to achieve the 8 SDGs goals, because high unemployment rates indicate a lack of productive employment opportunities for individuals. South Sulawesi Province is one of the provinces that has experienced fluctuations in the OUR figure in the last five years, mainly influenced by the impact of the Covid-19 pandemic. In 2020, the OUR peaked at 6.31% due to the large number of layoffs and reductions in the workforce. However, along with the economic recovery, the OUR decreased until August 2024 reaching 4.19% [3]. Although the OUR figure is relatively low, it is still one of the focus problems faced by the government. This is because there are still 4 out of 100 people who are not absorbed by the labor market. Therefore, strategic steps are needed to overcome this, namely by knowing the factors that influence the OUR in South Sulawesi.

Several factors that are thought to influence OUR are the human development index, the percentage of poor population and the average length of schooling [4]. In addition, other studies also state that OUR is also influenced by life expectancy, population density and gross regional domestic product at current prices [2]. These factors allow for diversity that influences OUR in one region with another and is also influenced by time [5]. Thus, a method is needed that can accommodate this, namely Geographically and Temporally Weighted Regression (GTWR). The advantage of the GTWR method is that it is able to produce a model that is local in each location and time [6].

The GTWR method has been used by [7] in identifying factors that influence the human development index in Bengkulu. Although it obtained good results, the method has not considered factors that are correlated between regions. Thus, a modification is needed in the estimation process, namely the calculation of distance using the Mahalanobis distance. The advantage of this distance is that it takes correlation into account, making it more accurate in measuring differences between data points in a multivariate space [8]. Even considering the correlation relationship between variables, it is not always effective in handling very high collinearity. Therefore, an approach is needed that can overcome this, namely the Locally Compensated Ridge (LCR). This approach produces a local ridge bias to adjust for the impact of high collinearity between factors so that the estimation results are more accurate [9].

The approach has been proven by [10] using LCR in Geographically Weighted Regression (GWR) to analyze factors influencing malaria outbreaks in DakNong Province, Vietnam. The results stated the LCR approach was able to improve the suitability of the results and was good in measuring malaria incidence. Another study was conducted by [11] using the same approach in analyzing factors influencing the distribution of stunting prevalence in toddlers in East Nusa Tenggara Province. The results stated that the LCR-GWR model produced better predictions than the GWR model.

Therefore, identifying the factors that influence OUR in South Sulawesi was carried out in this study using the GTWR method by modifying the distance calculation using the Mahalanobis distance and the Locally Compensated Ridge penalty. This was done to obtain a good estimate in identifying factors that influence OUR by overcoming data characteristics that are influenced by region, time and also high correlation. Thus, that the strategy that will be produced from this analysis can be used to reduce OUR, especially in South Sulawesi and will contribute to supporting SDGs point 8.

2. RESEARCH METHODS

2.1 Data Sources

The research data comes from the official website of the Central Statistics Agency of South Sulawesi Province (https://sulsel.bps.go.id/id). The range of data years used is from 2020 to 2023. This study uses one response variable and six predictor variables which can be seen more clearly in Table 1.

Table 1. Data Source

Variable	Information	Unit
Y	Open Unemployment Rate	Percent (%)
X_1	Human Development Index	Index
X_2	Percentage Of Poor Population	Percent (%)
X_3	Average Years of Schooling	Year
X_4	Life Expectancy	Year
X_5	Population Density	people/km²
X_6	Gross Regional Domestic Product at Current Prices	Billion Rupiah

Source: Central Statistics Agency of South Sulawesi 2024

2.2 Stages of Analysis

The stages carried out in this research are written as follows:

1. Conduct data collection
2. Identify the effects of spatial and temporal heterogeneity and multicollinearity on the data.
3. Calculating the Mahalanobis distance by taking into account the variance and correlation between variables.
4. Perform Geographically and Temporally Weighted Regression modeling using Mahalanobis distance on the data.
5. Calculating the local lambda value based on the beta parameter value obtained from Geographically and Temporally Weighted Regression modeling using Mahalanobis distance.
6. Perform Locally Compensated Ridge-Geographically and Temporally Weighted Regression modeling with Mahalanobis distance.
7. Perform partial testing on the LCR-GTWR model using the following formula in Eq. (1).
$$t = \frac{\hat{\beta}_k(u_i, v_i, t_i, \lambda_i)}{se_{\hat{\beta}_k}}, \tag{1}$$
with hypothesis
H_0: $\beta_k(u_i, v_i, t_i, \lambda_i) = 0$ (model parameters β_k at location and time (u_i, v_i, t_i) has no significant effect on the model)
H_1: $\beta_k(u_i, v_i, t_i, \lambda_i) \neq 0$ (model parameters β_k at location and time (u_i, v_i, t_i) has significant effect on the model)
with,
$i = 1,2, \dots, n\, ; k = 1,2,3, \dots, p$
8. Interpret the model obtained and draw conclusions.

2.3 Multicollinearity

Multicollinearity is a condition when two or more predictor variables are closed or interrelated. This can affect the modeling in regression which results in instability of the resulting estimates [12]. To detect multicollinearity, it can be done by calculating the Variance Inflation Factors (VIF) value. The formula can be seen in Eq. (2).

$$VIF_k = \frac{1}{1 - R_k^2}. \tag{2}$$

R_k^2 refers to the local coefficient of determination which shows the relationship between x_k and other predictor variables in each region [13].

2.4 Mahalanobis Distance

Mahalanobis distance is the distance between two points involving variance and can reduce the deviation of the distance caused by linear combinations. This distance calculates the variance which will later be used to form the covariance matrix of the data [14]. Thus, this distance applies a weight scheme to the data. The equation is written in Eq. (3).

$$d_{ij} = \sqrt{\frac{(u_i - u_j)^2 + (v_i - v_j)^2}{cov(u_{ij}, v_{ij})}}, \tag{3}$$

where $\boldsymbol{d_{ij}}$ is the distance between the $\boldsymbol{i}$-th location and the $\boldsymbol{j}$-th location based on the coordinate points.

2.5 Geographically and Temporally Weighted Regression

Geographically and Temporally Weighted Regression (GTWR) is a method designed to overcome non-stationarity data from both spatial and temporal aspects simultaneously, which is a development of Geographically Weighted Regression (GWR) [15]. The GTWR model for p predictor variables with response variables located at the location for each observation can be expressed in Eq. (4).

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i. \tag{4}$$

$i = 1,2, \dots, n\,; k = 1,2,3, \dots, p$

x_{ik} is the observed value of the k-th predictor variable at the i-th observation, y_i is the observed value of the i-th response variable, $\beta_k(u_i, v_i, t_i)$ regression coefficient of the kth predictor variable at the i-th observation location and i-th time and ε_i is the residual value. In addition, in the GTWR model, spatial weighting is very important because it explains the extent of spatial influence between regions [16]. The weighting is obtained through the kernel function, where the kernel function used is the Fixed Gaussian Kernel which is stated in Eq. (5).

$$w_j(u_i, v_i, t_i) = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}^{ST}}{h}\right)^2\right], \tag{5}$$

where h is the spatial-temporal bandwidth value and d_{ij}^{ST} is the distance between the i-th location and the j-th location [17].

2.6 Ridge Regression

Ridge regression is one method used to overcome multicollinearity in data by reducing all regression coefficients towards zero [18]. This is done to reduce large data variance so that multicollinearity can be overcome. In general, ridge regression is written in Eq. (6).

$$\hat{\beta}_R = (X^T X + \lambda I)^{-1} X^T Y \tag{6}$$

With a value of $\boldsymbol{0 < \lambda < 1}$ as the ridge bias parameter calculated to ensure the stability of the $\boldsymbol{\hat{\beta}_R}$ value [19]. To calculate the local ridge value (for each observation), Eq. (7) is used.

$$\lambda = \frac{p\,\hat{\sigma}^2}{\hat{\beta}_{WLS}^T (X^T X)\,\hat{\beta}_{WLS}} \tag{7}$$

$\boldsymbol{p}$ indicates the number of parameters $\boldsymbol{\hat{\beta}}$ without including $\boldsymbol{\hat{\beta}_0}$, $\boldsymbol{\hat{\sigma}^2}$ is the Mean Square Error (MSE), and $\boldsymbol{\hat{\beta}_{WLS}}$ is the estimate obtained through the WLS method [20].

2.7 Locally Compensated Ridge-Geographically and Temporally Weighted Regression

Geographically Weighted Ridge Regression (GWRR) is a method that applies one bias coefficient for each region. However, this is considered less efficient in overcoming multicollinearity problems because the level of collinearity in each observation is different and also does not consider temporal effects. Thus, a method was developed, namely Locally Compensated Ridge-Geographically Weighted Regression (LCR-

GTWR). The calculation of the bias coefficient value in this method is carried out for each region based on the level of collinearity of each observation [21]. The LCR-GTWR model is written in Eq. (8).

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_k^p \beta_k(u_i, v_i, t_i, \lambda_i)x_{ik} + \varepsilon_i \tag{8}$$

with $\boldsymbol{\beta_k}(\boldsymbol{u_i}, \boldsymbol{v_i}, \boldsymbol{t_i}, \boldsymbol{\lambda_i})$ being the local regression coefficient for the $\boldsymbol{k}$-th predictor variable at location $\boldsymbol{i}$ and $\boldsymbol{\lambda_i}$ being a particular value of the ridge bias coefficient at location $\boldsymbol{i}$.

2.8 Spatial Heterogeneity

Heterogeneity effects are effects that indicate the existence of diversity between locations. Thus, each location has a different structure and relationship parameters. Testing the effect of spatial heterogeneity is done with the Breusch-Pagan (BP) test. The hypothesis used in this test is

H_0 : $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2$ (No spatial heterogeneity exists)

H_1 : there is at least one $\sigma_i^2 \neq \sigma_j^2$ with $i \neq j$ (spatial heterogeneity exists)

The value of the BP test is calculated using Eq. (9).

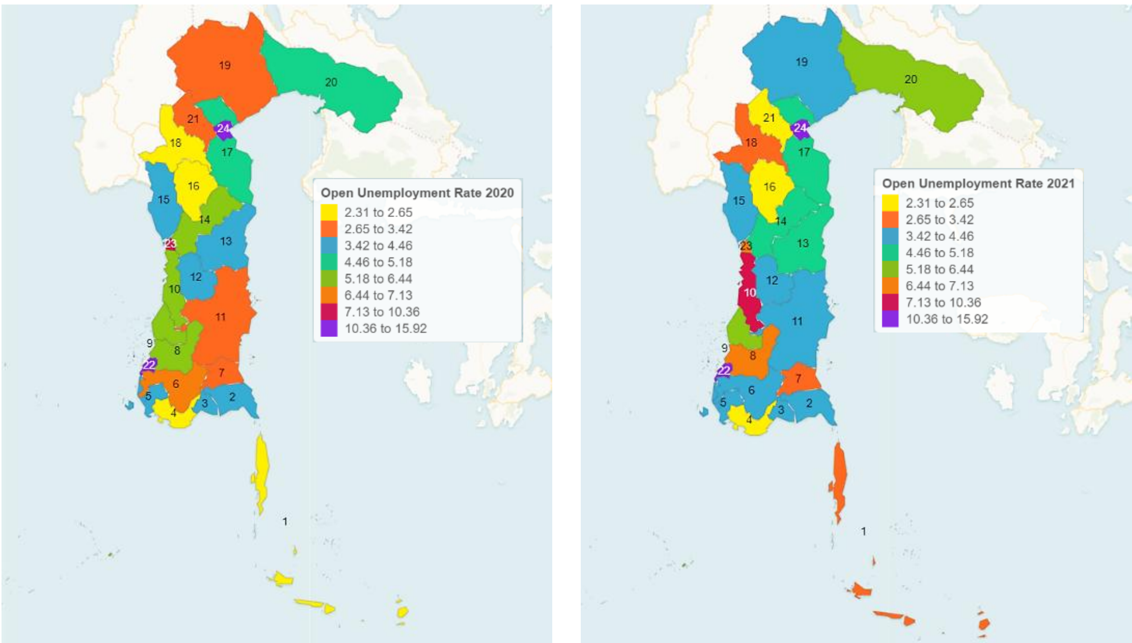
$$BP = \frac{1}{2} f^{\mathrm{T}} \mathrm{Z}(\mathrm{Z}^{\mathrm{T}}\mathrm{Z})^{-1}\mathrm{Z}^{\mathrm{T}} f + \left(\frac{1}{T}\right)\left(\frac{\varepsilon^T W \varepsilon}{\sigma^2}\right)^2 \sim \chi^2_{(\alpha)} \tag{9}$$

With vector f is $f_i = \left(\frac{e_i^2}{\sigma^2} - 1\right)$ and $T = tr[W^T W + W^2]$. While ε is residual vector ε_i of size $n \times 1$, f^T is $(f_1, f_2 \dots f_n)$, Z is standardized X matrix, of size $n \times (p+1)$, W is weight matrix W_i of size $n \times n$, and e_i^2 is residuals for the i-th observation from the regression estimation results using OLS. The decision making in this test is to reject H_0 if the value of $BP > \chi^2_{\alpha,p}$ or if the $p - value < \alpha$ with p is the number of predictor variables [22].

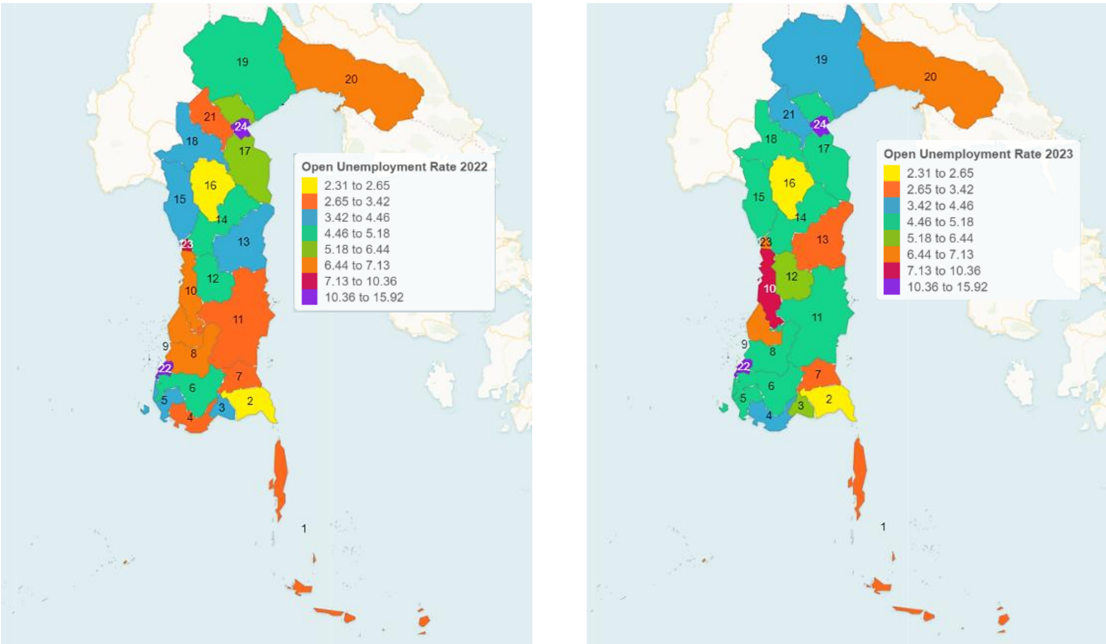
3. RESULTS AND DISCUSSION

3.1 Data Exploration

Data exploration was conducted using thematic maps. The distribution of open unemployment rates in South Sulawesi can be seen in Fig. 1.



(a) (b)



(c) (d)

Description:

1. Selayar Islands	13. Wajo
2. Bulukumba	14. Sidrap
3. Bantaeng	15. Pinrang
4. Jeneponto	16. Enrekang
5. Takalar	17. Luwu
6. Gowa	18. Tana Toraja
7. Sinjai	19. North Luwu
8. Maros	20. East Luwu
9. Pangkep	21. North Toraja
10. Barru	22. Makassar City
11. Bone	23. Parepare City
12. Soppeng	24. Palopo City

Figure 1. Distribution of Open Unemployment Rate in South Sulawesi
(a) 2020, (b) 2021, (c) 2022 and (d) 2023

The images in Fig. 1 shows the distribution of open unemployment rates in South Sulawesi from 2020 to 2023. Each color listed in the region illustrates the high or low level of open unemployment in that region. Changes in figures occur each year due to factors that influence the OUR each year. One factor that influences the spike in OUR is Covid-19 which occurred in 2021. The area with a high OUR rate each year is Makassar City until 2023 reaching 10.60. In addition, areas that consistently have low OUR rates each year are Enrekang Regency and Bulukumba Regency until 2023 reaching 1.53 and 1.31 respectively.

3.2 Assumption Testing

3.2.1 Spatial Heterogeneity

Spatial heterogeneity effect testing was conducted to determine whether there was location diversity in the data. This test uses the Breusch-Pagan test on all observations. The results of this test are shown in Table 2.

Table 2. Spatial Heterogeneity Test Result

Test Statistics	*p-value*	Decision
12.9480	0.0438	Reject H_0

Table 2 show that the $p-value = 0.0438 < \alpha = 0.05$, so the conclusion is to reject H_0. This means that there is spatial heterogeneity in the data or there is diversity between locations.

3.2.2 Temporal Heterogeneity

The temporal heterogeneity test aims to see whether the data has temporal diversity or not. The temporal heterogeneity test aims to see whether the data has temporal diversity or not. This test is also carried out using the Breusch-Pagan test, the results of which are written in Table 3.

Table 3. Spatial Temporal Test Results

Test Statistics	*p-value*	Decision
56.0890	6.61×10^{-13}	Reject H_0

Table 3 show that the $p - value = 6.61 \times 10^{-13} < \alpha = 0.05$, so the conclusion is to reject H_0. This means that there is spatial temporal in the data or there is diversity between time. Temporal heterogeneity testing is carried out using the boxplot diagram in Fig. 2.

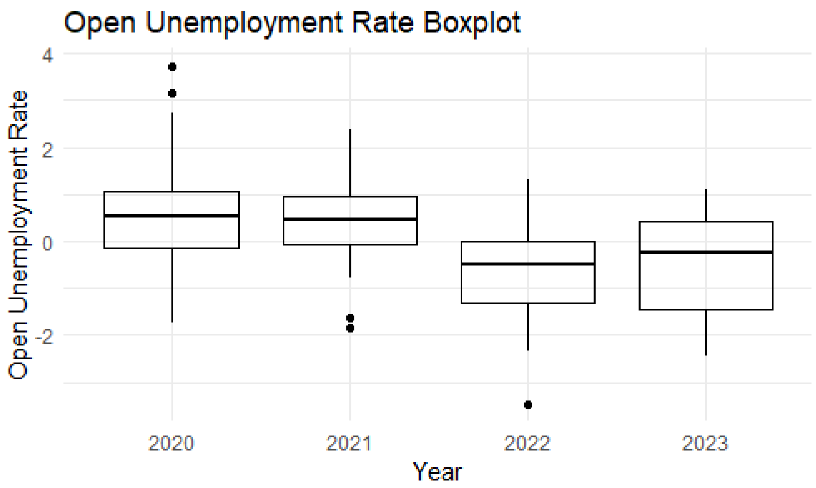


Figure 2. Open Unemployment Rate Boxplot

The image in Fig. 2 shows that the OUR in South Sulawesi from 2020 to 2023 has changed as indicated by the median value of the data over time. In addition, the boxplot diagram also explains that the OUR in South Sulawesi in 2020-2022 has decreased. This is due to significant economic recovery efforts and support from various sectors in South Sulawesi during the Covid-19 period, including social assistance and stimulus programs that support job creation. However, in 2023 there was an increase in the OUR figure triggered by global economic uncertainty, changes in government policy, and uneven economic recovery in various sectors.

3.3 Multicollinearity Detection

Multicollinearity detection in data is done by looking at the Variance Inflation Factor (VIF) value of each variable. This aims to test the correlation between predictor variables. If there is a VIF value of more than 10, then it can be said that multicollinearity occurs. The VIF values for each variable are shown in Table 4.

Table 4. VIF Value of Predictor Variables

Variable	VIF	Decision
$\boldsymbol{X_1}$	15.3630	Multicollinearity Occurs
$\boldsymbol{X_2}$	1.7230	No Multicollinearity Occurs
$\boldsymbol{X_3}$	11.1510	Multicollinearity Occurs
$\boldsymbol{X_4}$	1.6040	No Multicollinearity Occurs
$\boldsymbol{X_5}$	3.0150	No Multicollinearity Occurs
$\boldsymbol{X_6}$	2.8860	No Multicollinearity Occurs

Table 4 shows that variables X_1 and X_3 have VIF values greater than 10 with values of 15.3628 and 11.1508 respectively. The VIF value is relatively high, so it can cause the regression coefficient to be unstable and the results are biased. Therefore, the locally compensated ridge method will be used later to overcome this problem.

3.4 Geographically and Temporally Weighted Regression Model Analysis Using Mahalanobis Distance

Previously, spatial and temporal heterogeneity assumption testing and multicollinearity detection were conducted on the variables used. The results met the requirements and there was multicollinearity in the data so that the analysis was continued. The summary of the GTWR model parameters using the Mahalanobis distance are written in Table 5.

Table 5. GTWR Model Parameter Summary Mahalanobis Distance

Variable	Minimum	Maximum	Mean	Std. Deviation
Constant	-0.0968	0.2932	-0.0014	0.0393
X_1	-0.5491	1.6715	0.3689	0.4202
X_2	-0.9192	2.5576	0.1152	0.6340
X_3	-1.9863	6.0396	0.3675	1.2273
X_4	-1.8994	0.1516	-0.3524	0.3900
X_5	-1.696×10^{-1}	6.732×10^{-2}	-1.659×10^{-3}	0.0259
X_6	-0.2657	0.4331	-0.0167	0.1064

The parameter estimates β_0 for each observation of the open unemployment rate in the South Sulawesi region ranges from -0.0968 to 0.0393. Meanwhile, the predictor variables vary for each observation with an average positive value. This indicates that the higher the value of each predictor variable, the higher the open unemployment rate in South Sulawesi. The parameter estimates for one of the areas obtained, namely Makassar City in 2023, are written in Table 6.

Table 6. GTWR Model Parameters Mahalanobis Distance for Makassar City in 2023

Parameters	Estimated Value
β_0	0.0001
β_1	-0.0090
β_2	0.0149
β_3	-0.0005
β_4	0.0054
β_5	0.0001
β_6	0.0639

Thus, the model for Makassar City in 2023 can be written as follows.

$$\hat{y}_{94} = 0.0001 - 0.0090X_1 + 0.0149X_2 - 0.0005X_3 + 0.0054X_4 + 0.0001X_5 + 0.0639X_6$$

3.5 Calculation of Locally Compensated Ridge Value

After obtaining the parameters from the GTWR model using the previous Mahalanobis distance, calculations were carried out on the lambda values for each region and time. The calculation of the lambda value is carried out using the estimated value obtained previously and using Eq. (7). The results obtained are written in Table 7.

Table 7. Local Lambda Values for each Region and Year

Region	Year	λ	Year	λ	Year	λ	Year	λ
Selayar Island	2020	0.0997	2021	0.0000	2022	0.0000	2023	0.0001
Bulukumba	2020	0.0013	2021	0.0050	2022	0.0010	2023	0.0009
Bantaeng	2020	0.0008	2021	0.0031	2022	0.0009	2023	0.0007
Jeneponto	2020	0.0233	2021	0.0544	2022	0.0978	2023	0.0578
Takalar	2020	0.0412	2021	0.0463	2022	0.0763	2023	0.0274
Gowa	2020	0.0172	2021	0.0201	2022	0.0151	2023	0.0146
Sinjai	2020	0.0417	2021	0.0590	2022	0.0422	2023	0.0536
Maros	2020	0.0134	2021	0.0004	2022	0.0174	2023	0.0148
Pangkep	2020	0.0513	2021	0.0458	2022	0.0680	2023	0.0314
Barru	2020	0.0517	2021	0.0455	2022	0.0661	2023	0.0564
Bone	2020	0.0513	2021	0.0454	2022	0.0653	2023	0.0530
Soppeng	2020	0.0396	2021	0.0475	2022	0.0829	2023	0.0486
Wajo	2020	0.0329	2021	0.0187	2022	0.0364	2023	0.0215
Sidrap	2020	0.0378	2021	0.0480	2022	0.0845	2023	0.1141
Pinrang	2020	0.0087	2021	0.0067	2022	0.0758	2023	0.0162
Enrekang	2020	0.0033	2021	0.0050	2022	0.0044	2023	0.0055

Region	Year	λ	Year	λ	Year	λ	Year	λ
Luwu	2020	0.0074	2021	0.0056	2022	0.0074	2023	0.0035
Tana Toraja	2020	0.0433	2021	0.0504	2022	0.0625	2023	0.0512
North Luwu	2020	0.0479	2021	0.0521	2022	0.0558	2023	0.0529
East Luwu	2020	0.0034	2021	0.0061	2022	0.0051	2023	0.0057
North Toraja	2020	0.0041	2021	0.0003	2022	0.0002	2023	0.0008
Makassar City	2020	0.0351	2021	0.0448	2022	0.0773	2023	0.1126
Parepare City	2020	0.0513	2021	0.0455	2022	0.0666	2023	0.0377
Palopo City	2020	0.0503	2021	0.0637	2022	0.0812	2023	0.0910

The values obtained in Table 7 are then used for further analysis, namely the GTWR model analysis with Mahalanobis distance combined with local ridge values.

3.6 Analysis of Geographically and Temporally Weighted Regression Models Using Mahalanobis Distance and Locally Compensated Ridge Penalty

Next, after obtaining the local lambda value of each observation area and time, the parameter estimation calculation is carried out. The calculation is carried out using Eq. (8). The following details of the calculation results are written in Table 8.

Table 8. Summary of LCR-GTWR Model Parameters Mahalanobis Distance

Variable	Minimum	Maximum	Mean	Std. Deviation
Constant	-50.0400	110.7000	12.7500	38.9054
X_1	-0.8314	0.7126	0.1825	0.2439
X_2	-0.6166	0.4441	-0.0788	0.2251
X_3	-0.9622	3.7677	0.8127	0.8315
X_4	-1.8009	0.5199	-0.3853	0.5625
X_5	6.767×10^{-5}	2.178×10^{-4}	1.942×10^{-5}	5.113×10^{-5}
X_6	-0.0560	0.0529	0.0116	0.0224

Table 8 shows that the estimated value of the parameter β_0 for each observation of the open unemployment rate in the South Sulawesi region ranges from -50.0400 to 110.7000. Meanwhile, the predictor variables vary for each observation with an average positive value. This can be interpreted that the higher the value of each predictor variable, the higher the open unemployment rate in South Sulawesi. The parameter estimates for one of the areas obtained, namely Makassar City in 2023, are written in Table 9.

Table 9. LCR-GTWR Model Parameters of Mahalanobis Distance for Makassar City in 2023

Parameters	Estimated Value
β_0	41.4818
β_1	0.2042
β_2	-0.2287
β_3	1.0495
β_4	-0.8229
β_5	0.0001
β_6	0.0019

Thus, the LCR-GTWR Mahalanobis Distance model for Makassar City in 2023 can be written as follows

$$\hat{y}_{94} = 41.4818 + 0.2042X_1 - 0.2287X_2 + 1.0495X_3 - 0.8229X_4 + 0.0001X_5 + 0.0019X_6$$

The results obtained were 96 models with variables that influenced each observation and time. Several LCR-GTWR model results from location and time observations indicate an inverse relationship between variables such as the percentage of poor people (X_2) and life expectancy (X_4). This occurs due to complex spatial and temporal variations and the presence of non-linear variable interactions. The increase in the percentage of poor people (X_2) that is not in line with the influence of the OUR occurs due to local dynamics influenced by external factors such as migration, structural economic changes, or policy interventions that have not been fully accommodated in the model. Furthermore, the Ridge penalty used in this model to address multicollinearity can change the sign of the coefficients, resulting in the estimated results showing effects in the opposite direction to the initial hypothesis. Similarly, the inverse relationship of the life expectancy variable (X_4) could indicate short-term versus long-term effects, as well as hidden variables that also influence these spatial-temporal outcomes. The distribution of significance of these variables is visualized through a thematic map in Fig. 3.

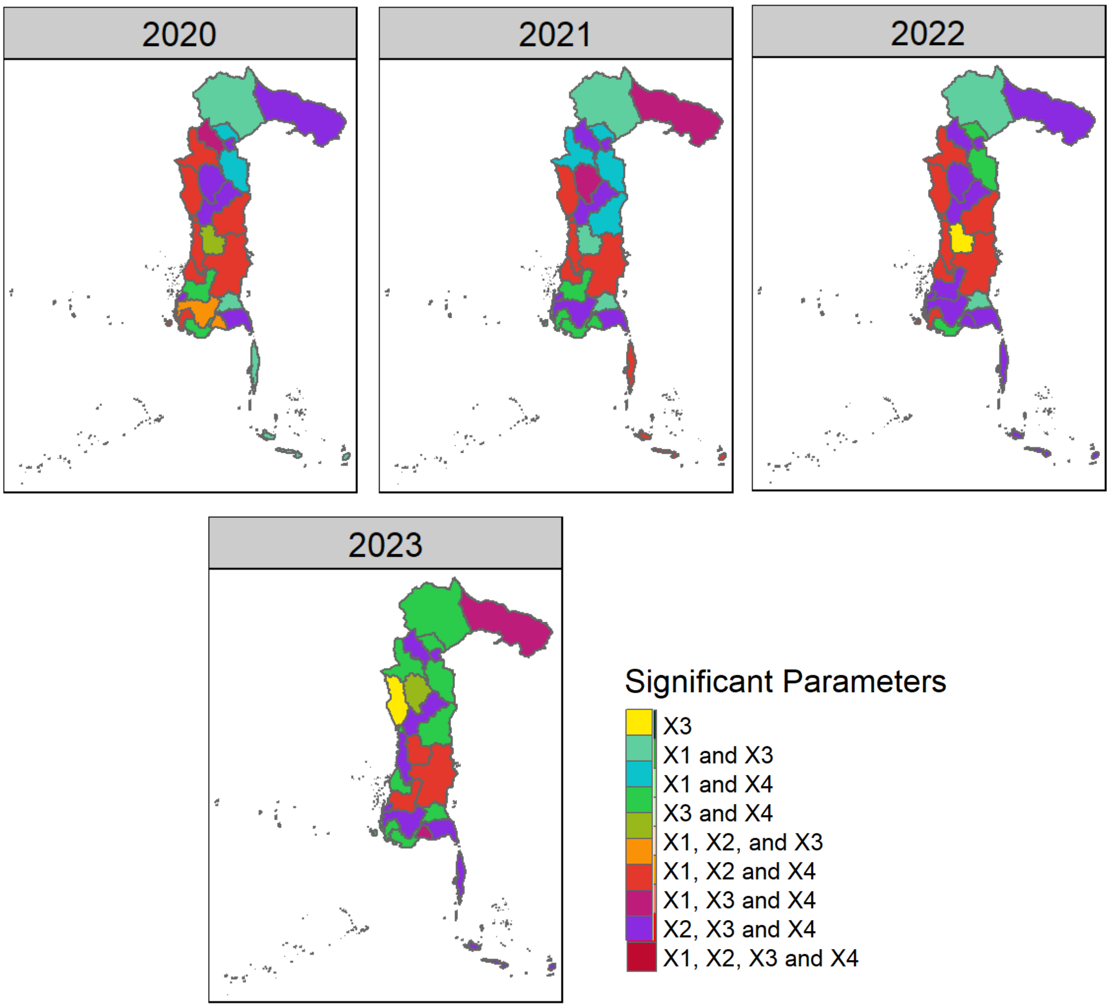


Figure 3. Distribution of Significant Variables in Each Observation

The image in Fig. 3 shows the distribution of the significance of variables in each observation and time that varies from 2020 to 2023. It can also be seen that in general the variables that affect the open unemployment rate in South Sulawesi are the human development index (X_1), the percentage of poor people (X_2), average length of schooling (X_3), and life expectancy (X_4). These four variables are influential because of their role in shaping the quality of human resources and socioeconomic conditions that determine people's ability to enter the labor market.

The human development index (X_1) describes overall human development that includes education, health, and standard of living; the higher the human development index, the higher the quality of the labor force and thus the greater the chance of being absorbed in the labor market. The percentage of poor people (X_2) has a direct negative impact on employment opportunities because poverty limits access to resources, education and training needed to compete in the workforce, increasing the risk of unemployment. Average years of schooling (X_3) provides an indication of the level of formal education attained, where longer education will improve skills and knowledge that facilitate job search and adaptation to market needs. Meanwhile, life expectancy (X_4) reflects the level of public health and longer productive years, allowing workers to stay longer and be more productive in the workforce. Better health also strengthens physical and mental endurance. Thus, these factors can be focused on by the government in making strategic policies to reduce unemployment in South Sulawesi.

3.7 Model Goodness of Fit Test

The goodness of fit test is conducted to determine how good the model is produced and can be used. This test is conducted using the Root Mean Square Error (RMSE) and the Akaike Information Criterion (AIC). RMSE measures how much error there is between the value predicted by the model and the actual value and the AIC value measures the quality of the model by considering the complexity of the model and how well the model explains the data. The two calculation results are written in Table 10.

Table 10. Model Goodness of Fit Test

Model	Metric	
	RMSE	**AIC**
GTWR Mahalanobis Distance	4.9791	27521.0600
LCR-GTWR Mahalanobis Distance	0.0857	457.6431

The model is said to be good at making predictions when the RMSE and AIC values are lower. Table 10 shows that the GTWR Mahalanobis Distance model combined with LCR is better than the model without using LCR. This is proven by the RMSE and AIC values obtained by the model. Thus, the LCR-GTWR with Mahalanobis Distance is able to explain the level of open poverty in South Sulawesi from 2020 to 2023.

4. CONCLUSION

The modified Mahalanobis distance Locally Compensated Ridge-Geographically and Temporally Weighted Regression model can explain the Open Unemployment Rate in South Sulawesi well from 2020 to 2023. This is evidenced by the results of the general model evaluation which obtained small RMSE and AIC values of 0.0857 and 457.6431, respectively, resulting in 96 varying models. Factors that have a significant influence on the Open Unemployment Rate in South Sulawesi in 2020-2023 in general are the human development index, life expectancy, percentage of poor population and average length of schooling. Based on these factors, the strategies that can be carried out are improving the quality of education and skills, strengthening the health sector, poverty alleviation based on productivity, regional economic diversification and strengthening data and sustainable policy coordination. This can be used as a reference in making strategies to reduce the decline in the open unemployment rate in South Sulawesi.

Author Contributions

Siswanto Siswanto: Conceptualization, Methodology, Writing-Original Draft, Software, Validation. Nurtiti Sunusi: Data Curation, Resources, Draft Preparation. Andi Isna Yunita: Formal Analysis, Validation. Muhammad Ridzky Davala: Software, Visualization. Andi M. Alfin Baso: Validation, Writing-Review and Editing. Nurfadilah Nurfadilah: Validation, Writing-Review and Editing. All authors discussed the results and contributed to the final manuscript.

Funding Statement

The author would like to thank Hasanuddin University for support and funding through the Hasanuddin University Revenue Fund through contract number 01260/UN4.22/PT.01.03/2025.

Acknowledgment

The research team would like to express our deepest gratitude to the individuals and institutions that have made important contributions to the success of our research.

Declarations

The authors declare that he/she has no conflicts of interest to report study.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools were used solely for language polishing purposes, including grammar, spelling, and clarity. All scientific content, data analysis, interpretation of results, and conclusions were entirely developed by the authors, and we have fully reviewed and approved the final manuscript.

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