# Analysis of Space and Classification poverty

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### Analysis of space and classification poverty in Semarang City using spatial-logistic regression

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Abstract. The declining poverty rate becomes the priority of the Sustainable Development Goals (SDGs). In the period of 2002 - 2017 poverty rate in Central Java experienced a decrease, as similarly found in Semarang city. Examining the factors affecting the poverty classification in Semarang city, therefore, is deemed important. The analysis used in this research was conducted by examining the spatial factors and classification of poverty levels by means of the logistic model. The logistic model resulted was found to be capable of classifying the poverty levels, and the spatial model used was capable of modeling each region. In modelling the binary logistic regression, a number of factors affecting the poverty classification included the number of family members, education certificates of the head of family, the main fuel used for cooking, and listed as the receiver of the rice for poor or not. Accuracy on the classification of binary logistic regression models reached 94.9%. For spatial modeling by means of Geographically Weighted Regression (GWR), the dependent variable used referred to the number of underprivileged families in each sub-district. In GWR modeling, each sub-district had its own characteristics in modeling the number of underprivileged families in each sub-district in Semarang city.

#### 1. Introduction

Regression method refers to a statistical method to model the dependent variable with independent variables. In such method, the type of data used might be continuous and discrete. If the dependent and independent variables are continuous data, the regression method used would be simple linear regression (only containing one independent variable) or multiple linear regression (containing several independent variables). If the dependent variable is continuous, while independent variables are discrete, then the regression used is a dummy regression variable. On the other hand, if the dependent variable is discrete, while the independent variable is continuous, then logistic regression would be used. Logistic regression is able to explain the level of opportunity for each discrete occurrence on dependent variable. Based upon its scale, logistic regression can be divided into binary, multinomial, and ordinal logistic regression. Binary logistic regression is logistic regression with the dependent variable in the form of a nominal scale with only two categories, while multinomial logistic regression has more than two categories. For ordinal logistic regression, the scale of the dependent variable is ordinal. Similar with simple regression modeling, logistic regression modeling steps include determining the model, testing the significance of the model, and testing each model parameter. Logistic regression has the assumption of dependency and homoscedasticity.



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Regional-based regression model nowadays has been developed. It can be done based on a point or region. The point-based spatial regression model is known as Geographical Weighted Regression (GWR), while the region-based spatial regression model is named spatial regression. The GWR model is a regression model locally based or often referred to as local regression [5]. It illustrates that each region has its own regional characteristics to be modeled. In the GWR modeling, the location with the closest distance will be given a greater weight compared to the one with a long distance. The determination of weighting in GWR model is based on kernel; thus, it is necessary to seek the optimum bandwidth. The determination of the optimum bandwidth in the GWR model is conducted using Cross Validation (CV). If each region has its own characteristics, the GWR model will be better than the linear regression model (global regression) [3].

The declining poverty rate has become the priority of the Sustainable Development Goals (SDGs), a United Nations (UN) program to implement sustainable development in several social, economic and environmental aspects [2]. One of the targets for poverty alleviation in the SDGs program is poverty alleviation by 2030 and to provide an ascertained social protection for the poor and access improvement to basic public services.

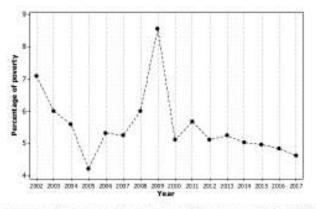


Figure 1. Percentage of poverty rate in Semarang city in 2002-2017

Figure I depicts that the poverty level in Semarang overall has experienced a decrease however in 2007-2009 the level increased. Furthermore, 2012 to 2017 saw a decrease. As revealed by Central Statistics Agency (2014), family groups based upon expenditures per capita that have been converted according to the poverty line consist of two groups: poor family and non-poor family [7]. The poverty line was used as a limit to classify poor family and non-poor family. Poor family refers to a family with an average expenditure per capita under the Poverty Line (GK) [2]. Considering that level of poverty is still high, then there is a need to find a way to identify family groups, one of which is by examining the factors that can characterize the family group. This research can be used as a public policy to government to reduce the poverty based on the factors that have impact to poverty in Semarang city [4].

#### 2. Materials and Methods

2.1. Binary Logistic Regression

Regression model is presented as follows:

 $y_i = \pi(x_i) + \varepsilon_i$ 

where  $y_i$  refers to the response variable and  $\pi(x_i)$  denotes the function estimation from the regression model. In the logistic regression model, it has been written that  $\pi(x_i) = E(y|x_i)$  to show

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that the expectation value of Y is conditionally with x. The general form of logistic regression model is presented with the equation below [1]:

$$\pi(x_i) = \frac{e^{\beta_0 + \sum_{i=1}^{n} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{n} \beta_i x_i}}$$

It was simplified using the logit transformation  $\pi(x)$ . The form of logit is presented as follows:

$$g(x) = \ln\left[\frac{\pi(x)}{1 - \pi(x)}\right] = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \text{ with } g(x) = \ln\left[\frac{P(y_i = 1|x_i)}{P(y_i = 0|x_i)}\right] = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$

Thus, the logistic regression equation can be presented in the form of:  $\pi(x_i) = \frac{e^{s(x)}}{1 + e^{s(x)}}$ 

The estimation of the logistic regression parameter was conducted using the Maximum Likelihood Estimation (MLE) method. The function of its likelihood is presented as follows:

$$\ln L(\beta) = \sum_{k=0}^{p} \left( \sum_{i=1}^{n} y_{ik} x_{ik} \right) \beta_{k} - \sum_{i=1}^{n} \ln \left\{ 1 + \exp\left( \sum_{k=0}^{p} \beta_{k} x_{ik} \right) \right\}$$

The value of parameter  $\beta$  of  $L(\beta)$  function was obtained through an iterative procedure known as *lteratively Reweighted Least Square* (IRLS) using the Newton-Raphson method by maximizing the likelihood function [1].

The parameter test was conducted to test whether variable predictor in model brought an effect on variable response. The test was conducted as follows:

Hypotheses  

$$H_0: \beta_1 = \beta_2 = ... = \beta_p = 0$$
  
 $H_1: \text{ At least there is one } \beta_k \neq 0; k = 1, 2$ 

H<sub>1</sub>: At least there is one  $p_{R}^{(n_{1})^{n_{1}}}\left[\frac{\binom{n_{1}}{n}^{n_{1}}}{\prod_{i=1}^{n}\tilde{R}_{i}^{\gamma_{i}}(1-y_{i})^{1-\gamma_{i}}}\right]$ Test statistics:  $G = -2\ln\left[\frac{\binom{n_{1}}{n}^{n_{1}}}{\prod_{i=1}^{n}\tilde{R}_{i}^{\gamma_{i}}(1-y_{i})^{1-\gamma_{i}}}\right]$ with  $n_{i} = \sum_{i=1}^{n} y_{i}$ ;  $n_{i} = \sum_{i=1}^{n} \binom{n_{i}}{1-\gamma_{i}}$ 

with  $n_1 = \sum_{i=1}^n y_i$ ;  $n_0 = \sum_{i=1}^n (1 - y_i)$ ;  $n = n_0 + n_1$ Critical region:  $H_0$  is refuted if  $G > \chi^2_{(a,p)}$  with p as the degree of freedom of many variables of predictor or if the p-value<a href="https://doi.org/10.1111/j.jeta.com">https://doi.org/10.1111/j.jeta.com</a>

#### 2.2. Geographically Weighted Regression (GWR)

Geographically Weighted Regression (GWR) method is the regression model that developed for the variable of continual response by considering the location aspect. GWR Model is a *locally linear regression* model that results in the estimator of model parameter that has the nature of locality in each spot or location. This model can be written as follows [3]:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i; \qquad i = 1, 2, ..., n$$

 $y_i$  is the observation value on the variable of response in the location *i*,  $x_i$  is the observation value on the variable of predictor *k* in the location *i*,  $\beta_0(u_i, v_i)$  is Intercept value of model regression GWR;  $\beta_k(u_i, v_i)$  is Regression parameter for each location *i*;  $(u_i, v_i)$  is Coordinate point (latitude, longitude) in the location *i* and  $\varepsilon_i$  is Residual model GWR in location-*i* assumed as IIDN (identic, independent, and normally distributed) with the mean is zero and constant variance  $\sigma^2$ . The estimation of GWR model used WLS (Weighted Least Square) by giving the different weight in each location.

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The weight of each location  $(u_i, v_i)$ , for instance, was  $w_j(u_i, v_i)$ , j = 1, 2, ..., n then, the parameter in the observation location  $(u_i, v_i)$  was estimated by adding the weight elements  $w_j(u_i, v_i)$  and then by minimizing the number of the following residual quadrate:

$$\sum_{j=1}^{k} w_{j} \left( u_{i}, v_{i} \right) \mathcal{E}_{j}^{2} = \sum_{j=1}^{k} w_{j} \left( u_{i}, v_{i} \right) \left[ y_{j} - \beta_{0}^{2} \left( u_{i}, v_{i} \right) - \sum_{k=1}^{k} \beta_{k}^{2} \left( u_{j}, v_{j} \right) x_{jk} \right]^{2}$$

or in the form of matrix, the number of its residual quadrate is:

5

$$\mathbf{W}(u_i, v_i) \mathbf{\epsilon} = \mathbf{y}^T \mathbf{W}(u_i, v_i) \mathbf{y} - 2\mathbf{\beta}^T (u_i, v_i) \mathbf{X}^T \mathbf{W}(u_i, v_i) \mathbf{y}$$

+
$$\boldsymbol{\beta}^{*}(u_{i},v_{i})\mathbf{X}^{*}\mathbf{W}(u_{i},v_{i})\mathbf{X}\boldsymbol{\beta}(u_{i},v_{i})$$

with

$$\boldsymbol{\beta}(u_i, v_i) = \begin{pmatrix} \beta_0(u_i, v_i) \\ \beta_1(u_i, v_i) \\ \mathbf{M} \\ \beta_p(u_i, v_i) \end{pmatrix} \text{ and } \mathbf{W}(u_i, v_i) = \text{diag}\left(w_1(u_i, v_i), w_2(u_i, v_i), \mathbf{L}, w_n(u_i, v_i)\right).$$

If it is derived against  $\beta^{T}(u_{i}, v_{i})$  in which the result is equalized with zero, then it would obtain the estimator of GWR model parameter as follows [3]:

$$\hat{\boldsymbol{\beta}}(u_i, v_i) = \left[ \mathbf{X}^T \mathbf{W}(u_i, v_i) \mathbf{X} \right]^{-1} \mathbf{X}^T \mathbf{W}(u_i, v_i) \mathbf{y}$$

#### 2.3. Methodology of Research

This research consisted of two parts: poverty classification modeling in Semarang city using binary logistic regression. The data of 930 families were taken from Susenas (The National Socioeconomic Survey) Semarang city. Poverty classification was based upon the expenditure per capita (food and non-food). If the expenditure per capita during a month were under the poverty line, then it would be categorized as poor. If it were above the poverty line, it would be categorized as not poor. In 2016, the value of poverty line in Semarang city was worth Rp.382.160. Here, the variables used included dependent variable with categorical values (1= poor; 0=not poor); X<sub>1</sub>: sex of family head (1=Male; 2=Female); X2; age of family head; X5: number of family members; X4: Education level of family head (1: No certificate; 2: Primary School; 3: Middle School (SMP); 4:High School (SMA); 5: Diploma (D1/D2/D3); 6: Undergraduate (S1); 7: Postgraduate (S2/S3)); X<sub>5</sub>: Is the family head working? (1: Yes; 2=No); X<sub>0</sub>=Business field (0: Unemployed ; 1=agriculture; 2=mining 3=manufacturing industry; 4: Electricity and Gas; 5: building; 6: trade, hotel and restaurant; 7: Transportation and Warehouse; 8: Finance and assurance; 9: Service); X=Occupational status (0: unemployed; own business; 2: own business assisted by temporary labours; 3: own business assisted by the permanent labours; 4: Labour/Employee/Officer; 5: Freelancer; 6: Family worker); Xs=status of house ownership (1: Personal Belonging; 2: Rent; 3: Free Rent; 4: Official Residence; 5: Other); X<sub>0</sub>=Building materials for roof (1: Concrete; 2: Ceramic Tile; 3: Metal Tile; 4: Clay Tile; 5: Asbestos; 6: Tin; 7: Bamboos; 8: Wood/Shingles; 9: Straw; 10: Others) X<sub>10</sub>=Main materials for house wall (1: concrete; 2: wood; 3: logs; 4: Other); Xii=Main Materials for House Floor (1: Marble/Granite; 2: Ceramic; 3: Tiles; 4; cemented/brick; 5: Ground; 6: Other); X12= the use of defecation facility (1:Available and used only for family members; 2: Available and used together with other family members; 3: Available as Public Toilet; 4: None); X11= Septic tank (1:cement-based tank; 2: Noncement-based tank; 3: Wastewater Treatment Plant, WWTP; 4: Pond/Farm/River/Lake; 5: Ground Hole; 6: other); X14=Drinking water source (1: Branded bottled water; 2: Refilled water; 3:Meter Tap; 4: Retail plumbing; 5: Drill Well/Pump; 6:Protected well; 7: Unprotected well; 8: Protected springs; 9:

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Other); ; X1:=Main fuel for cooking (0: Not Cooking at home; 1:Electricity; 2: 5.5-kg LPG; 3: 12-kg LPG; 4: 3-kg LPG; 5: kerosene; 6: firewood); X16= Receiving Rice for the Poor (1: Yes; 2: No).

#### 3. Results and discussions

The discussion of this paper consists of two parts: poverty classification modeling in Central Java using the Binary Logistic Regression model and Geographically Weighted Regression (GWR) modeling.

3.1. Poverty Classification Modelling using Binary Logistic Regression Model Logistic regression modeling carried out using 15 independent variables. The poverty classification logistic regression model in Central Java provided is as follows:

$$\pi(x_i) = \frac{e^{f(x)}}{1 + e^{f(x)}}$$

with  $f(x) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + L_1 + \beta_{15} X_{15}$ 

The parameter significance testing for each independent variable is as follows:

| Table 1. Significant | test for all variables in binary logist | áć |
|----------------------|---|----|
|----------------------|---|----|

| Variable     | Estimate | Standard<br>Error | Wald   | Sig.  | Decision                | Significant or not |
|--------------|----------|-------------------|--------|-------|-------------------------|--------------------|
| $X_I$        | 0.127    | 0.478             | 0.070  | 0.791 | Accepted H <sub>0</sub> | Not significant    |
| $X_2$        | -0.020   | 0.018             | 1.229  | 0.268 | Accepted H <sub>0</sub> | Not significant    |
| $X_{\beta}$  | 0.313    | 0.097             | 10.350 | 0.001 | Rejected Ha             | significant        |
| $X_4$        | -0.089   | 0.043             | 4.254  | 0.039 | Rejected Ha             | significant        |
| $X_3$        | 0.233    | 0.145             | 2.579  | 0.108 | Accepted H <sub>0</sub> | Not significant    |
| $X_0$        | -0.006   | 0.069             | 0.006  | 0.936 | Accepted H <sub>0</sub> | Not significant    |
| $X_7$        | 0.170    | 0.126             | 1.818  | 0.178 | Accepted H <sub>0</sub> | Not significant    |
| $X_{\delta}$ | 0.347    | 0.197             | 3.102  | 0.078 | Accepted H <sub>0</sub> | Not significant    |
| $X_9$        | 0.280    | 0.219             | 1.627  | 0.202 | Accepted H <sub>0</sub> | Not significant    |
| X10          | 0.229    | 0.156             | 2.163  | 0.141 | Accepted H <sub>0</sub> | Not significant    |
| X11          | 0.122    | 0.082             | 2.231  | 0.135 | Accepted H <sub>0</sub> | Not significant    |
| X12          | -0,302   | 0.232             | 1.694  | 0.193 | Accepted H <sub>0</sub> | Not significant    |
| X13          | 0.173    | 0.155             | 1,239  | 0.266 | Accepted Ho             | Not significant    |
| X14          | 0.118    | 0.112             | 1.127  | 0.288 | Accepted H <sub>0</sub> | Not significant    |
| $X_{13}$     | 0.326    | 0.133             | 6.002  | 0.014 | Rejected H <sub>0</sub> | significant        |
| X10          | -0.248   | 0.099             | 6.278  | 0.012 | Rejected Ho             | significant        |
| constanta    | -6.884   | 1.983             | 12.051 | 0.001 | Rejected Ha             | significant        |

As shown in table 1, of 16 independent variables, four variables (X3, X4, X15, and X16) were found to be the most significant in poverty classification modeling using binary logistic regression in Semarang city. Subsequently, it was to re-model the binary logistic regression model based on these four variables.

As seen in table 2,  $X_3$   $X_4$ ,  $X_{15}$  and  $X_{16}$  affected the poverty classification. Hence, the binary logistic regression model is presented as follows:

$$\pi(x_i) = \frac{e^{-3.978+0.252X_1-0.075X_4+0.439X_{10}-0.365X_{10}}}{1+e^{-3.978+0.252X_1-0.075X_4+0.439X_{10}-0.365X_{10}}}$$

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| Estimate<br>parameter | S.E.  | Wald   | Sig.  | Decision   | Significant or<br>not   |
|-----------------------|---|--|---|--|---|
| 0.252                 | 0.088   | 8.258  | 0.004   | Rejected Ho  | significant   |
| -0.075                | 0.035   | 4.578  | 0.032   | Rejected Ha  | significant   |
| 0.439                 | 0.116   | 14.353   | 0.000   | Rejected Ho  | significant   |
| -0.365                | 0.092   | 15.834   | 0.000   | Rejected Ha  | significant   |
| -3.978                | 0,738   | 29.041   | 0.000   | Rejected Ha  | significant   |
|                       | parameter<br>0.252<br>-0.075<br>0.439<br>-0.365 | parameter         S.E.           0.252         0.088           -0.075         0.035           0.439         0.116           -0.365         0.092 | parameter         S.E.         Wald           0.252         0.088         8.258           -0.075         0.035         4.578           0.439         0.116         14.353           -0.365         0.092         15.834 | parameter         S.E.         Wald         Sig.           0.252         0.088         8.258         0.004           -0.075         0.035         4.578         0.032           0.439         0.116         14.353         0.000           -0.365         0.092         15.834         0.000 | parameter         S.E.         Wald         Sig.         Decision           0.252         0.088         8.258         0.004         Rejected H <sub>0</sub> -0.075         0.035         4.578         0.032         Rejected H <sub>0</sub> 0.439         0.116         14.353         0.000         Rejected H <sub>0</sub> -0.365         0.092         15.834         0.000         Rejected H <sub>0</sub> |

**Table 2.** Significant test for  $X_{5}$ ,  $X_{4}$ ,  $X_{15}$ , and  $X_{25}$  in binary logistic

The level of accuracy for poverty classification in Central Java using the binary logistic regression is presented below.

|             | . The accuracy tab<br>uses binary logistic |         |
|-------------|--|---------|
| Observed    | Predict                                    | ed      |
|             | Non-poverty                                | Poverty |
| Non-Poverty | 878  | 5       |
| poverty     | 42   | 5       |

Table 3 depicts that the accuracy value for the poverty classification using the binary logistic regression model was 94.9%.

#### 3.2 Poverty classification modeling using Geographically Weighted Regression (GWR)

The subsequent step was to make modeling using GWR. The data used were the profile data in each of 16 districts in Semarang city in 2016. Here, the dependent variable referred to the number of underprivileged families. The dependent variable, meanwhile, consisted of the number of graduates from universities in each sub-district (X<sub>1</sub>), the number of residents working as the entrepreneurs (X<sub>2</sub>); Number of houses with wood material (X<sub>1</sub>), number of health facilities and infrastructure (X<sub>4</sub>), Number of large/medium scale industries (X<sub>3</sub>), Number of motorbikes (X<sub>6</sub>), Number of residents (X<sub>7</sub>), Number of traders (X<sub>8</sub>) and number of unpaved roads (X<sub>9</sub>). Data on independent variables were taken based on each district.



Figure 2. Spread of underprivileged in Semarang city

As shown in Figure 1, the underprivileged level in West Semarang and Tembalang sub Districts is found highest of other surrounding areas. The first step in modeling GWR was to determine the optimum bandwidth using the Golden Section-based Cross Validation). In this model, the optimum bandwidth value obtained was 0.04269 with Gaussian fix kernel function. The recapitulation of GWR model parameter estimation values is presented as follows:

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| Variable  | Minimum  | Maximum  | Mean     | Standard<br>deviation |
|-----------|----------|----------|----------|-----------------------|
| intercept | 2250.478 | 2458.905 | 2222.111 | 156.46                |
| X1        | 1769.434 | 3706.891 | 2059.135 | 492.6673              |
| $X_2$     | -334.558 | 353.1515 | -14.7225 | 106.7654              |
| X3        | 608.0416 | 1357.773 | 754.1982 | 183.8527              |
| $X_4$     | -454.426 | 116.0883 | -199.267 | 123.4586              |
| X5        | -448.935 | 104.5129 | -51.4567 | 143.8739              |
| Xe        | 592.3399 | 1289.798 | 680.642  | 86.76771              |
| X2        | -2910.15 | -1311.83 | -1592.28 | 447.9204              |
| Xi        | -1230.02 | -636.688 | -768.116 | 155.2338              |
| Xs        | -159.57  | 347.5134 | -70.159  | 65.76818              |

| Table 4 | . Summary of | estimation parameter | er GWR model |
|---------|--------------|----------------------|--------------|

In terms of the comparison between the global regression model and the GWR regression model, the F-count value was obtained by 0.4145. When compared with F-table, it was  $F_{0.05,0.4.08} = 5.964$ ; thus, it can be concluded that there was no difference between the global regression model and the GWR model. However, the AIC value of GWR model was 248.5 less than that of the global regression model at 256.2. The parameter significance in each region can be seen in the attachment. It is seen that the mark of each coefficient in each parameter was equal for all locations. Based on the attachment, some significant variables can be seen merely in certain locations.

#### 4. Conclusion

In modeling the binary logistic classification, it can be seen that the accuracy value reached 94.9%. However, it is important to note that the variable of *poor* is predicted to have more errors compared to the accurate classification. The comparison between the category of *poor* and the category of *non-poor* was much different; thus, it can be stated that the binary logistic regression model is not able to catch all categories though it had the high accuracy. The high accuracy was only dominated by one category namely *not poor*. Meanwhile, for the GWR modeling at the pre-privileged level in Semarang city, each region had its own characteristics.

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| GUNUNGPATI   | 2250.48  | 1341.57 | ŧ    | 161.50                      | 0.43    | 634.18         | 6     | -375.22 | 0.66  | 32.10   | 9010        | 864.43         | -99   | 68'1612   | 16.04  | .192.90   | 17    | 14391   | 50    |
| VELATAN  | 2280.51  | 2007/02 | 32   | 09765                       | 0.13    | 680.39         | 1.07  | -235.4k | 150-  | 70.73   | 410         | 596.87         |       | -1568.92  | -1,00  | -822.68   | 4.17  | 1810-   | 40.15 |
| NANYUMANIK.  | 2384.63  | 1933.41 | =    | 0.28                        | 0.02    | 748.14         | 1.20  | -237.00 | -0.56 | -3,46   | 10/0-       | 701.79         | 1670  | -1463.60  | -1.08  | -736.44   | H.L.  | -71.06  | 40.14 |
| <b>SAJAHMUNGKUR</b>  | 2403.76  | 1769.43 | 111  | LET.                        | 10/0    | 15958          | 951   | -172.38 | 0.42  | 10.61   | 60/0        | 717.52         | 1     | -1311.83  | 0.53   | -845.93   | 121   | 125.08  | 11.0. |
| GENRIK   | 12.348.21  | 1806.38 | EE1  | 55.03                       | 0.13    | 792.69         | 1.22  | 121/22  | 0.51  | 06.80   | 0.15        | 660.50         | 0     | 78-89E.L. | 40,998 | -815.05   | -1.18 | (EEG)   | 21.04 |
| SEDURUNDAN SEDURUNDAN  | 2385.62  | 1905,05 | 112  | 56.07                       | 0.12    | 722.70         | 1.98  | 20005   | -040  | 104.51  | 0.18        | 592.34         | 1     | -1507.59  | -0.83  | -918,23   | -1.19 | -100.73 | -0.23 |
| GA YAMBARI<br>KEMARANG   | 2357.10  | 1961.93 | 12'0 | -17.69                      | 0.04    | 12,116         | 1.38  | -26.15  | -0.18 | 12.86   | 20/0        | 201.43         |       | -1474,86  | 16'0   | 1009.57   | 621-  | 12.19   | -0.19 |
| TIMUR  | 2270.91  |         | 68/0 | 95765                       | 15.0    | 1357,777       | 191   | 116.09  | 0.21  | 16'811  | 0.45        | 10.018         |       | 2010015   | 03.0   | 1230.021  | 123   | 10/212  | 0.28  |
| CANDISARI  | 2015162  |         | 16.0 | 025.00                      | 00.05   | 924.45         | 1.42  | 124.79  | 05.0  | 12.78   | 10/0        | 717.04         | 1     | E8-21E1-  | 40.75  | 20/016/   | -126  | LTHE    | 61.04 |
| TEMBALANG<br>WIMAR ANG   | 3415.80  | 17:501  | Ξ    | 67.31                       | -0.14   | 902.60         | Ξ     | -143.87 | -0.15 | 17.9-   | 1010-       | 720.76         | 0.90  | -1383.39  | -0.88  | -842.76   | -1.19 | -109/05 | -0.23 |
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| TENGAH   | 2433.22  | 1938,76 | ₫    | 66.98                       | 61.9    | 27112          | 5     | 203.05  | 0.49  | 25.04   | -00.06      | 722.20         | 1670  | 1385.12   |        | 19.53     | 1,08  | 67.711- | 12.0  |
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| TUGU'  | TT NEW   | 2742.74 | 1.98 | 10.95                       | 0.02    | 008.04         | 1.06  | 404.00  | -0.82 | -276.88 | -0.56       | 824.86         | 1,003 | 09/0622   | 135    | 69929-    | 164r  | 10.07   | -0.10 |
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