Spatial Evapotranspiration Modeling Assisted With Landsat 8 Image Using Sebal And Geographically Weighted Regression Methods In Magelang District

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Abstract. Information about evapotranspiration is very important in relation to vegetation because it can be used for planning both in urban planning and agriculture. Magelang Regency has a lot of vegetated green land, both agricultural and non-agricultural and has no information about evapotranspiration. The calculation of evapotranspiration uses the SEBAL (Surface Energy Balance Algorithm for Land) method and modeling uses the GWR (Geographically Weighted Regression) model. Calculation and modeling assisted by QGIS 2.14, QGIS 3.6, SPSS 20, and GWR 4.09 applications. The results showed that (1) GWR evapotranspiration model with significance (sig.) 5% is divided into 3 sub-district groups according to the significant variables in the sub-district (2) NDVI and Surface Albedo variables have a small effect on a global scale and have a large effect on a local scale.

1. Introduction
Water is a fundamental element for every living thing on the surface of the earth and water is also a need that must be met by living things. Water is very important for living things, so water management and development is needed so that water resources can be available at any time. Water resource management is closely related to climate. Climate has a role in the process of the hydrological cycle. The origin of water has several sources, one of which comes from the hydrological cycle. The hydrological cycle has parts that support each other so that rain occurs. The part of the hydrological cycle that has a role in supplying water vapor to become rainwater is evaporation and evapotranspiration.

Soil surface evapotranspiration (ET) is the process of transferring large volumes of water from soil evaporation and transpiration of vegetation to the atmosphere [1]. Evapotranspiration is not only important for the global biogeochemical cycle, evapotranspiration also plays a major role in the energy balance of the earth's surface [2]. About 75% of the total precipitation is returned (evapotranspiration) by plants and soil [3] so that the calculation of evapotranspiration is very important, especially for agriculture because it can calculate water supply, the amount of water that becomes steam into the atmosphere and urban planning. Information regarding evapotranspiration is needed by people who are in the agricultural sector to have a plan regarding the development and maintenance of their agriculture. Information that can be mapped and very important for agriculture is evaporation mapping.
(evapotranspiration) because the amount of water that evaporates will have an impact on the amount of water available and needed by plants to grow. One of the regions in Indonesia that has quite extensive agricultural land is Magelang Regency. The agricultural area in Magelang Regency consists of wet and dry land, the distribution covers all districts except Ngablak and Pakis districts. The districts with the largest agricultural land area are Salaman, Mungkid, Mertoyudan, Secang, Grabag, Dukun, Bandongan and Kajoran Districts. Wet and dry agricultural land in Magelang Regency is managed to support the protection of sustainable food agriculture land covering an area of approximately 42,070 hectares spread across 21 districts. Agricultural land in Magelang Regency experienced land conversion with the percentage of land conversion into buildings based on the results of the research, namely 412.65 ha (66.91%) irrigated rice fields, 47.07 ha (7.54%) rainfed rice fields, 24.00 ha moor (3.84%), mixed gardens 114.47 ha (18.34%), grasslands and shrubs 21.96 ha (3.36%) [4].

Evapotranspiration cannot be measured directly, but it is concluded through the calculation method [5]. There are still evapotranspiration data processing which is manual calculation from several climate stations such as using the evaporation pan. The calculation of evapotranspiration can be done using the Lysimeter Calculation tool, the Eddy Correlation Technique, and the Bowen Ratio Technique. This method is accurate but in a wider area it will be inaccurate. This limitation is what motivates the calculation to be developed using remote sensing data from satellites in a wider area coverage [6]. Remote Sensing has advantages apart from its wide area coverage but also because it is very effective in measuring evapotranspiration. Remote Sensing is also low cost, fast and accurate timing. In addition, Remote Sensing data are available globally [7] making it easier to obtain data. Remote Sensing and GIS can be integrated in processing spatial and attribute data in order to obtain appropriate and accurate results. The interactions between factors are so complex that it is difficult to calculate and predict them. GIS is able to simplify the complexity of the spatial data so that it can be analyzed quickly, precisely, and accurately by using modeling [8] One popular type of modeling, namely GWR (Geographically Weighted Regression) spatial modeling is used to determine regression models by paying attention to spatial aspects in the form of relationship between one region and another. The GWR model is a local form of regression. The GWR model allows the researcher to assess the possible spatial variations in the relationship between the dependent and independent variables across the observation area. The basic idea of the GWR model is to consider elements of geography or location as a weight in estimating the model parameters. This model is a locally linear regression model which produces a model parameter estimator that is local for each point or location where the data is collected. The dependent variable is predicted by the independent variable, each of which has a regression coefficient depending on the location where the data is observed [9]. This modeling can be used to model the results of the calculation of evapotranspiration using the SEBAL (Surface Energy Balance Algorithm for Land) method.

The surface energy balance model simulates the micro-scale energy exchange process between the soil surface and the near-ground atmosphere layer. These processes include radiation, sensible heat, latent heat, and subsurface heat exchange processes. The calculation of a spatially distributed energy budget will require spatial data from sources such as satellite imagery, models that measure and use different model parameters in the simulation. [10] The data required in the SEBAL method are routine weather data such as wind speed, humidity, radiation, sun, and air temperature. No data on land use, soil type, or hydrological conditions are required to apply SEBAL [11]. Image data that can support infrared-based evapotranspiration calculations include Landsat 8 OLI / TIRS imagery. The capacity of Landsat 8 imagery to estimate evapotranspiration using Remote Sensing is quite satisfactory [12].

2. Research Methods

2.1. Data Sources and Research Variables
This study used daily weather data on January 19, 2020, which was recorded online at Mlati Weather Station, Sleman. The spatial data used in this study is a map database of Magelang Regency and Landsat 8 OLI / TIRS imagery on January 19, 2020 recording date with wrs path 120 and wrs row 65.
variables used in this study are Evapotranspiration (Y), NDVI Vegetation Index (X1) and Surface Albedo (X2).

2.2. Research methods
The stages of research carried out to obtain model results that can explain the relationship between variables that affect evapotranspiration in Magelang Regency are as follows:

2.2.1. NDVI Vegetation Index Calculations
Vegetation Index is an index used to predict the variation in the characteristics of vegetation. Vegetation index information to distinguish vegetation and other land uses can be done with the NDVI (Normalized Difference Vegetation Index) formula as follows:

\[
NDVI = \frac{NIR - RED}{NIR + RED}
\]  

Where: NIR is the near infrared channel and RED is the red band [13]

2.2.2. Calculation of Surface Albedo
Surface albedo is the ratio of the returned radiation flux to the radiation flux that occurs in the solar spectrum. Surface albedo has a role in the occurrence of soil heat. The formula for calculating the surface albedo is as follows:

\[
\alpha = \frac{\alpha_{\text{path radiation}}}{\tau_{\text{sw}}} 
\]

Where: \(\alpha_{\text{path radiation}}\) is the average portion of incoming solar radiation in all bands that are scattered back to the satellite before it reaches Earth's surface and \(\tau_{\text{sw}}\) is the transmissivity of the atmosphere

2.2.3. Calculation of Plant Reference Evapotranspiration Value (ETo)
The plant reference evapotranspiration (ETo) can be determined either from weather data or from the evaporation pan. ETo can also be estimated from the loss of evaporation from the water surface. ETo calculations use the FAO Penman-Monteith method which has a standard for calculating the ETo value [14].

2.2.4. Calculation of Evapotranspiration by SEBAL (Surface Energy Balance Algorithm for Land) Method
The calculation of evapotranspiration can use the SEBAL (Surface Energy Balance Algorithm for Land) method. The SEBAL model evapotranspiration calculation is done with the help of the spatial data processing application QGIS 2.18, 3.6, Grass 7.2 and the SEBAL module python coding script. The equation for the SEBAL method is as follows:

\[
\lambda ET = R_n - G - H 
\]

Where: \(\lambda ET\) is the latent heat flux (W / m2), \(R_n\) is the net radiation flux at the surface (W / m2), \(G\) is the ground heat flux (W / m2) and \(H\) is the sensible heat flux to the atmosphere (W / m2).

2.2.5. Data Normality Testing, Local Multicollinearity, Autocorrelation and Heteroscedasticity
Before doing data modeling, several tests were conducted to be able to do modeling. The tests are in the form of normality test, multicollinearity test, autocorrelation test, heteroscedasticity test. In this study, the Kolgomorov-Smirnov data normality test method was used with a significance level of 5%.

2.2.6. Spatial Evapotranspiration Modeling GWR (Geographically Weighted Regression) Model
Mathematically, the GWR (Geographically Weighted Regression) model can be written as follows:

\[
y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \epsilon_i 
\]
Where: \( Y_i \) is the observed value of the-i location response variable, \( X_{ik} \) is the value of the-k predictor variable at the-i observation location, \((u_i,v_i)\) are the coordinates of the (longitude, latitude) observation location, \( \beta_0(u_i,v_i) \) is the coordinate / intercept of GWR, \( \beta_k(u_i,v_i) \) is the regression coefficient \( k \) at the-i-th observation location and \( \varepsilon_i \) is the error at location which is assumed to be identical, independent, and normally distributed with the mean zero and constant variance (IIDN \((0, \sigma^2)\)) [15]

### 2.2.7. Calculation of the GWR Weighting Function

One of the weighting methods commonly used is the gaussian kernel. The Gaussian weighting function will give zero weight when location \( j \) is at or outside radius \( b \) from location \( i \), whereas if location \( j \) is within radius \( b \), it will get a weight that follows the Gaussian function, as follows:

\[
\begin{align*}
    w_{ij} &= e^{-1/2 \left( \frac{d_{ij}}{b} \right)^2} \\
    d_{ij} &= \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}
\end{align*}
\]

(5) (6)

Where: \( w_{ij} \) is the weighting function, \( b \) is the radius of comparison, \( j \) is Euclid's distance and \((u_i, v_j)\) is the coordinates of location \( i \) and \( j \).

### 2.2.8. Bandwidth Selection

Bandwidth can be regarded as the radius of interaction in the area. A wide bandwidth value can cause the model to be biased and smooth, but if the bandwidth value is narrow, the model depends on the characteristics in the area. Cross validation is a method that can be used as a criterion for obtaining the optimum bandwidth. The optimum bandwidth is used to produce the minimum cross validation coefficient. with the coefficient formula as follows:

\[
    CV = \sum_{i=1}^{n} [y_i - \hat{y}_i(b)]^2
\]

(7)

Where: \( y \neq i \) is the prediction value \( y_i \) (fitting value) with the observation at location \( i \) omitted from the prediction process and \( b \) is the radius of comparison.

### 2.2.9. GWR Model Suitability Testing

The suitability test (F test) of the GWR model was conducted to determine whether the GWR model was significantly better at modeling data (the relationship between the independent and dependent variables) than the OLS model. The formulation of the hypothesis is:

- \( H_0 \): GWR and OLS models are the same in modeling data
- \( H_1 \): The GWR model is significantly better at modeling data

The null hypothesis can be rejected if the value of \( F_{\text{count}} \) is greater than \( F_{\text{table}} \) (\( F_{\text{count}} > F_{\text{table}} \)). \( F_{\text{count}} \) is the statistical value of the F test and \( F_{\text{table}} \) is the value of the F distribution of degrees of freedom (DF1; DF2).

### 2.2.10. Partial Testing of the GWR Model Variables

The variable partial test (t test) was conducted to determine the significant variables of the GWR model in each observation area. The t test is done by comparing the t-count value with the t-table value on the basis of decision making, if the t-count value is greater than the t-table value (\( t_{\text{count}} > t_{\text{table}} \)) then the \( j \)-variable has a significant effect in the observation area.

### 2.2.11. Testing the Spatial Model of Evapotranspiration

The GWR spatial model can be known better than the OLS model by comparing four alternative measures that consider three indicators such as R-square, AIC, RSS, and BIC / MDL. The GWR model will be better than the OLS model if the R-square value of the GWR model is greater than the R-square model of the OLS model (R-square model GWR > R-square model OLS). This comparison illustrates...
that the GWR model is much better than the OLS model which does not pay attention to spatial elements or the diversity of observed areas. The results of the comparison are strengthened by the comparison of the AIC, RSS, and BIC / MDL values which are a function of the weighting in the model. If the AIC, RSS, and BIC / MDL values of the GWR model are lower than the AIC, RSS, and BIC / MDL values of the OLS model (AIC, RSS, and BIC / MDL of the GWR model > AIC, RSS, and BIC / MDL of the OLS model),

3. Result and Discussion
The initial stage carried out in this study was to process the weather and spatial data into the NDVI vegetation index value and surface albedo to find the evapotranspiration value. In this study, the calculation of the NDVI vegetation index, surface albedo and evapotranspiration used the QGIS 2.14 and 3.6 application with the annoying python coding script developed by Wagner Wolff [16] and Rafael Tieppo [17] in order to obtain the NDVI, Albedo, and Evapotranspiration index results per district. which is presented in the following table:

| Table 1. NDVI Vegetation Index, Albedo and Evapotranspiration Index data by district |
|---------------------------------|-----------------|-----------------|-----------------|
| sub-district         | Coordinate X | Coordinate Y | NDVI | Albedo | Evapotranspiration |
| Nguluwar       | 420446        | 9152419       | 0.601955679 | 0.136324366   | 4,204425223   |
| Ngablak        | 430656        | 9182129       | 0.570099042 | 0.16124729    | 5,195991043   |
| Borobudur      | 411157        | 9157190       | 0.645782624 | 0.150673376   | 4,840524585   |
| Srumbung       | 429819        | 9160370       | 0.664102298 | 0.1406966003  | 5,450545428   |
| Salam          | 423710        | 9156353       | 0.617036863 | 0.137734977   | 4,371749121   |
| Dukun          | 431744        | 9165558       | 0.638230267 | 0.139919195   | 5,857745794   |
| Muntilan       | 419023        | 9160872       | 0.552787339 | 0.143852451   | 3,718333839   |
| Mungkid        | 417433        | 9164052       | 0.583036024 | 0.14262657    | 4,355209526   |
| Sawangan       | 430405        | 9170998       | 0.639543365 | 0.137100596   | 5,864547974   |
| Mertojoyan     | 411826        | 9166312       | 0.593292432 | 0.15088806    | 4,006644167   |
| Candimulyo     | 423543        | 9170915       | 0.719016705 | 0.1322704444  | 5,882813565   |
| Pakis          | 431577        | 9176438       | 0.651394023 | 0.134941896   | 6,153909743   |
| Grabag         | 425049        | 9183301       | 0.680835285 | 0.130137763   | 5,989527199   |
| Windsusari     | 408395        | 9180455       | 0.668718496 | 0.139679443   | 5,853360041   |
| Tegalrejo      | 420028        | 9175601       | 0.679406893 | 0.137624452   | 5,536195754   |
| Bandongan      | 408897        | 9175685       | 0.647570246 | 0.140646337   | 5,3090004     |
| Secang         | 420613        | 9181794       | 0.591159131 | 0.134935956   | 4,997323644   |
| Kaliangkrik    | 405134        | 91750999      | 0.658707779 | 0.145282494   | 5,897064158   |
| Tempuran       | 407140        | 9166814       | 0.682386967 | 0.139025727   | 5,256295577   |
| Salaman        | 405633        | 9160956       | 0.664382526 | 0.142026074   | 5,112738942   |
| Kajoran        | 400528        | 9170831       | 0.699023464 | 0.135280007   | 6,074401564   |

The next stage in this research is to conduct some data testing before modeling. Some of the results of the data testing are as follows:

| Table 2. Normality Test Data |
|-----------------------------|
| Evapotranspiration Residue |

5
Based on the output in Table 41, it is known that the Asymp. Sig (2-tailed) significance value of 0.829 is greater than 0.050 (0.829 > 0.050), so according to the basis for decision making in the One Sample Kolmogorov-Smirnov normality test, it can be concluded that the data is normally distributed. Further analysis can be carried out, namely multicollinearity analysis. The multicollinearity test results are presented in Table 3 as follows:

**Table 3. Tolerance and VIF values Variable Free**

| No. | Variable                          | Tolerance | Decision       | VIF   | Decision       |
|-----|----------------------------------|-----------|----------------|-------|----------------|
| 1.  | NDVI Vegetation Index (X1)       | 0.723     | Tolerance value> 0.10 means no multicollinearity | 1.383 | VIF value <10 means there is no multicollinearity |
| 2.  | Surface Albedo (X2)              | 0.723     |                | 1.383 |                |

(Data does not contain multicollinearity)

Based on the results of Table 42, it is known that the Tolerance value of the vegetation index variable (X1) and surface albedo (X2) is 0.723. Tolerance value of 0.723 is greater than 0.10 (0.723 > 0.10), according to the basis for decision making, the independent variable data does not have multicollinearity. This conclusion is reinforced by the results of the VIF value of the independent variables (X1 and X2) of 1.383, according to the basis for decision making, the independent variable does not have multicollinearity. The next test, namely the autocorrelation test between data. The results of the autocorrelation test are presented in Table 4 as follows:

**Table 4. Independent Variable Autocorrelation Test**

| No. | Variable          | DW  | T  | K  | DL | DU | 4-DW | 4-DL | 4-DU |
|-----|-------------------|-----|----|----|----|----|------|------|------|
| 1.  | Vegetation Index  | 2.590 | 21 | 2  | 1.1246 | 1.5385 | 1.41 | 2.8754 | 2.4615 |
| 2.  | Surface Albedo    |     |    |    |    |    |      |      |      |

Table 4 shows the values of the Durbin-Watson autocorrelation test. The DW (Durbin-Watson) value is 2.590 which comes from 21 samples with 2 independent variables. The value of DL (Durbin Lower) is 1.1246, DU (Durbin Upper) is 1.5385, (4-DW) is 1.41, (4-DL) is 2.8754, and (4-DU) is 2.4615. If the DW value is greater than DU (2.590 > 1.5385), the conclusion is that there is no positive and negative autocorrelation. These results indicate that the DW value is greater than the DU value. This basis is what researchers use to continue research. The last test is the heteroscedasticity test. The test results are presented in Table 5 as follows:

**Table 5. Heteroscedasticity Test (Glejser)**

| Model                        | Sig. |
|------------------------------|------|
| Constant                     | 0.862|
| NDVI Vegetation Index (X1)   | 0.309|
| Surface Albedo (X2)          | 0.406|

Based on Table 44, it is known that the significance value (sig.) Of the NDVI vegetation index variable (X1) is 0.309 and the significance value (sig.) Of the surface albedo variable (X2) is 0.406. In accordance with the basis of heteroscedasticity test decision making, if the significance value is greater than 0.05, the data does not have heteroscedasticity. The significance value (X1) 0.309 is greater than 0.05 (0.309 > 0.05) and the significance value (X2) 0.406 is greater than 0.05 (0.406 > 0.05), it can be
concluded that the research data does not have any heterocedasticity symptoms. After passing several tests, modeling can be continued.

The next step is to find the optimum bandwidth by looking at the smallest CV value. This study uses a Gaussian adaptive kernel type. The search results are as follows:

| No. | Name                  | Result |
|-----|-----------------------|--------|
| 1   | Best Bandwidth Size   | 3      |
| 2   | Minimum CV            | 0.185  |

Table 6 shows that the bandwidth value in this modeling is 3. The bandwidth value of 3 means the 3 closest neighbors (sub-districts) which significantly affect a district, for example in the GWR model the evapotranspiration value in Muntilan District is influenced by 3 other districts such as Mungkid, Salam, Dukun. The bandwidth value of 3 can be said to be narrow (small), which means that the GWR model will depend on the characteristics of the observation area. The determination of the bandwidth is in accordance with the minimum CV value of 0.185. The next step of GWR modeling is testing the GWR model whether the GWR model is better than the OLS model in modeling data or what is commonly called the F-Test. The F-test is carried out by looking at the results of the F-test ANOVA Table which is presented in Table 7 below:

| No. | Source          | SS   | DF | MS  | Fcount | FTabel |
|-----|-----------------|------|----|-----|--------|--------|
| 1   | Global Residual | 4,665| 18 |     |        |        |
| 2   | GWR Improvement | 4,162| 11 | 0.378| 5,241  | 3.55   |
| 3   | Residual GWR    | 0.503| 6  | 0.072|        |        |

Based on Table 7, it is known that the value of Fcount is greater than FTabel (5,241> 3.55), so that the null hypothesis can be rejected, which means that the GWR model can explain the relationship between the predictor variables and the response variable better than the global regression model. After the F-test (suitability) of the model, a partial t-test is then performed for each variable. The t-test is done by comparing the value of t count is greater than t table (t count> t table) with a significance of 5%. Partial testing in Ngluwar District as a sample for the GWR model as shown in Table 8 below:

| No. | Variable       | Coefficient | theitung | t table |
|-----|----------------|-------------|----------|---------|
| 1   | Intercept      | -4.57253    | -1.362075| 0.68836 |
| 2   | NDVI (X1)      | 14.265941   | 6.605984 |         |
| 3   | Albedo (X2)    | 2.325665    | 0.120826 | |
| 4   | Local R2       | 0.938075    |          |         |

Table 8 shows that the NDVI variable has a t-count value of 6.605984 and albedo has a t-count value of 0.120826 with a t-table value in this GWR model is 0.68836. Based on the basis of decision making, the NDVI variable has a significant effect on evapotranspiration in Ngluwar District (6.605984> 0.68836) while the surface albedo variable has no significant effect on evapotranspiration in Ngluwar District (0.120826> 0.68836). NDVI and surface albedo variables have an R-square value of 0.938, which means that these variables simultaneously (together) have an effect on evapotranspiration in Ngluwar District by 94% (93.8%). The results of the partial test then form 3 groups of districts, namely districts that are influenced by 2 independent variables, sub-districts that are influenced by the NDVI vegetation index variable and sub-districts that are not influenced by 2 variables. These results are presented in table 9 below:
Table 9. Subdistrict Groups according to Significant Variables

| No. | Significant Variables | sub-districts |
|-----|-----------------------|---------------|
| 1.  | NDVI and Albedo        | Serumbung, Salam, Bandongan and Kaliangkrik |
| 2.  | NDVI                  | Ngluwar, Ngablak, Borobudur, Dukun, Muntilan, Mertojordan, Candimulyo, Grabag, Windusari, Tegalrejo, Secang, Tempuran, Salaman and Kajoran |
| 3.  | There are no significant variables | Sawangan and Pakis |

Based on Table 9, 3 groups of sub-districts were formed which have the same significant variables that affect evapotranspiration in Magelang Regency. The advantage of the GWR model is that the data obtained can be used and displayed in the form of a thematic map as shown in the following figure:

Figure 1. Map of Local Significant Variables of Evapotranspiration in Magelang Regency

Writing the GWR model in Ngluwar District based on the results of the variable partial test can be written as follows:

$$ Y_{Ngluwar} = -4.57253 + 14.26594X_{1Ngluwar} $$

The GWR model for Ngluwar District above explains that evapotranspiration will increase by 14.26594 percent if the percentage of the NDVI vegetation density index increases by one percent. The writing of the GWR model for each district is presented in Table 10 as follows:

Table 10. Similarities of the GWR Model for Each District in Magelang Regency

| No. | sub-district | The GWR Evapotranspiration Model Equation |
|-----|--------------|------------------------------------------|
| 1.  | Ngluwar      | $$ Y_{Ngluwar} = -4.57253 + 14.26594X_{1Ngluwar} $$ |
2. Ngablak $\gamma_{\text{Ngablak}} = 0.460992 + 8.040957X_{1\text{Ngablak}}$

3. Borobudur $\gamma_{\text{Borobudur}} = -2.179644 + 13.127731X_{1\text{Borobudur}}$

4. Srumbung $\gamma_{\text{Srumbung}} = -8.094273 + 16.317505X_{1\text{Srumbung}} + 20.671994X_{2\text{Srumbung}}$

5. Salam $\gamma_{\text{Salam}} = -7.799461 + 15.754234X_{1\text{Salam}} + 19.149443X_{2\text{Salam}}$

6. Dukun $\gamma_{\text{Dukun}} = 6.477171 + 5.4005X_{1\text{Dukun}}$

7. Muntilan $\gamma_{\text{Muntilan}} = -2.426599 + 13.116907X_{1\text{Muntilan}}$

8. Mungkid $\gamma_{\text{Mungkid}} = -2.426599 + 12.052746X_{1\text{Mungkid}}$

9. Sawangan $\gamma_{\text{Sawangan}} = 9.083786$

10. Mertoyudan $\gamma_{\text{Mertoyudan}} = 1.027299 + 11.888648X_{1\text{Mertoyudan}}$

11. Candimulyo $\gamma_{\text{Candimulyo}} = 0.881438 + 9.623253X_{1\text{Mungkid}}$

12. Pakis $\gamma_{\text{Pakis}} = 7.540954$

13. Grabag $\gamma_{\text{Grabag}} = -1.535918 + 9.244204X_{1\text{Grabag}}$

14. Windusari $\gamma_{\text{Windusari}} = -2.959963 + 12.816733X_{1\text{Windusari}}$

15. Tegalrejo $\gamma_{\text{Tegalrejo}} = 2.292194 + 7.821521X_{1\text{Tegalrejo}}$

16. Bandongan $\gamma_{\text{Bandongan}} = -11.023869 + 19.116307X_{1\text{Bandongan}} + 128.216185X_{2\text{Bandongan}}$

17. Secang $\gamma_{\text{Secang}} = -0.10842 + 8.039527X_{1\text{Secang}}$

18. Kaliangkrik $\gamma_{\text{Kaliangkrik}} = -7.799461 + 15.754234X_{1\text{Kaliangkrik}} + 19.149443X_{2\text{Kaliangkrik}}$

19. Tempuran $\gamma_{\text{Tempuran}} = -0.696998 + 13.148116X_{1\text{Tempuran}}$

20. Salaman $\gamma_{\text{Salaman}} = -0.808486 + 12.76885X_{1\text{Salaman}}$

21. Kajoran $\gamma_{\text{Kajoran}} = -7.875864 + 17.238589X_{1\text{Kajoran}}$

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