BAREKENG: Journal of Mathematics and Its Applications
March 2023 Volume 17 Issue 1 Page 0495–0504
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol17iss1pp0495-0504

CLASSIFICATION OF STUNTING USING GEOGRAPHICALLY WEIGHTED REGRESSION-KRIGING CASE STUDY: STUNTING IN EAST JAVA

Atiek Iriany[1*], Wigbertus Ngabu[2], Danang Arianto[3], Arditama Putra[4]

[1,2,3,4]*Department Statistics, Faculty Mathematics and Science, Brawijaya University, Veteran Street, Ketawanggede, Lowokwaru, Malang City, 65145, Indonesia*

*Corresponding author's e-mail: ** ***atiekiriany@ub.co,id***

ABSTRACT

Article History:

Received: 21st November 2022
Revised: 5th February 2023
Accepted:15th February 2023

Keywords:

Stunting;
GWR;
GWR-Kriging

Geographically Weighted Regression Kriging (GWRK) is a special case of the Geographically Weighted Regression (GWR) model, which is modeled with the effect of spatial autocorrelation on the GWR model error. The purpose of this research is to obtain a GWRK model between the factors that affect stunting density for each site viewed from the district center point in East Java Province and to make a prediction map based on the GWRK modeling. The data used was obtained from Basic Health Research (RISKESDAS) and the East Java Health Profile Book for 2021. The units of observation in this study were 38 districts in East Java.. Based on the GWR modeling results, it was found that the GWR model error contained spatial autocorrelation so that the GWR model could be formed. From the GWRK modeling using stunting prevalence data in East Java in 2021, it was found that the GWR model was better than the global regression. Through prediction and prediction mapping formed from the GWR-Kriging modeling, it could be seen that stunting in regencies in East Java was evenly distributed. The interpolation map showed that the stunting forecasting values using the Kriging GWR interpolation ranged from 27% to 46%.

How to cite this article:

A. Iriany, W. Ngabu, D. Arianto and A. Putra., "CLASSIFICATION OF STUNTING USING GEOGRAPHICALLY WEIGHTED REGRESSION-KRIGING CASE STUDY: STUNTING IN EAST JAVA," *BAREKENG: J. Math. & App.*, vol. 17, iss. 1, pp. 0495-0504, March 2023.

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

Stunting becomes one of the health problems that contributes to a large proportion of disease and results in preventable premature death. It is a condition in children under the age of five whose height is lower than their age (World Health Organization (WHO). Malnutrition in children (stunting, wasting, and overweight) still becomes a global health problem, including in Indonesia. Stunting is a condition when children under the age of five fails to grow and develop due to repeated infections and chronic malnutrition, especially during the first 1,000 days of life (HPK) [1]. Children are classified as stunted if their height is more than two standard deviations below the height of children of their age.

In more detail, the framework for the causes of stunting in Indonesia consists of direct and indirect causes; the direct causes include nutritional intake and health status and the indirect causes include food security, social environment, health environment, and residential neighborhood [2]. Stunting is a key indicator of child welfare and it is also Sustainable Development Goal (SDG) indicator in Indonesia vision 2045. WHO mentions that in 2019, the South-East Asia region had the highest prevalence of stunting in the world (31.9%) after Africa (33,1%). Indonesia became the South-East Asian country with the sixth highest prevalence, after Bhutan, Timor Leste, Maldives, Bangladesh, and India, by 36.4% [3].

Reducing stunting is one of the global targets for Sustainable Development Goals (SDGs) and the global nutrition target in 2025. SDGs have a target to eliminate all forms of malnutrition by 2030. The global nutrition target in 2025 expects a reduction in the number of stunted children under five by 40%, a reduction in wasting to less than 5%, increased rates of exclusive breastfeeding in the first 6 months to a minimum of 50%, reduced anemia in women of reproductive age by 50%, reduced Low Birth Weight (LBW) by 30% and no increase in childhood obesity.

Stunting becomes a serious problem because it makes children susceptible to disease and experience delays in physical and cognitive growths which affect the productivity and intelligence of children in the future. It will affect reproductive development [4], teeth growth or dental caries [2]. Adverse effects arising from the stunting problem in the short term are non-optimal cognitive, verbal, and motor development, increased in mortality and morbidity, and increased health costs [5].

The integration results of the Indonesian Toddler Nutrition Status Study (SSGBI) and 2019 National Socioeconomic Survey (SUSENAS) showed that the prevalence of stunting in Indonesian children under five in 2019 was 27.67%. This number is much lower than the number found in 2018 generated from 2018 Basic Health Research (RISKESDAS) by 30.8%. Considering the decline in the prevalence rate from 2018 to 2019, it is not impossible that the 14% target for 2024 can be achieved. However, the presence of the COVID-19 pandemic has changed people's behavior patterns, including in the health sector. The COVID-19 pandemic has destroyed nutrition around the world, especially in low- and middle-income countries with the worst consequences suffered by children [6]. The strategies adopted to overcome the COVID-19 include trade restrictions, physical distancing, school closure, and lockdown. This condition has an impact on the food system, causing disruptions in the production, distribution, and sale of fresh, nutritious, and affordable food, and forcing families to depend on nutrient-poor alternatives. Precarious health systems and disrupted humanitarian response prevent access to essential nutrition services and often threaten life [7]. Social protection systems in many lower-middle-income countries are forced to bear excessive economic burden because many poor families struggle to gain access to the food and services they need during the flagging economy times [8].

East Java Province is one of the areas that has been designated as a priority area for handling stunting since 2018. The results of the 2018 RISKESDAS showed that the stunting prevalence of East Java Province reached 32.81% with the compositions of very short by 12.92% and short by 19.89%. Given the precarious effects of the COVID-19 pandemic on health, it is not impossible that the goal of reducing stunting rates will be difficult to achieve [9]. Therefore, the research was not only carry out to find factors affecting stunting toddlers in East Java Province during the COVID-19 pandemic, but also to find the challenges in doing prevention [10]. The main purpose of carrying out research on factors affecting child stunting and the challenges of stunting prevention during the COVID-19 pandemic in East Java Province are to identify and analyze factors that affect the incidence of child stunting, identify stunting prevention challenges, and formulate stunting programs and prevention strategies in East Java Province.

The stunting problem in East Java Province is not only in high numbers or percentages, but also in very high disparities among regions. The comparison among regencies/cities shows a large disparity. This inequality occurs because of the high number of stunting in certain regions. The extremely diverse conditions cause differences in each region in East Java Province and make the spatial effect problem arises because the geographical factors will affect one region to another and ultimately affect the number of stunting in East Java Province.

The approach using the spatial method is considered reasonable, given that the large disparities between stunting among regions. GWR is a spatial method involving the geographical conditions of each region as one of the factors thought to affect the dependent variable [11]. In this paper, the GWR method was adopted to find out variables affecting the stunting prevalence in East Java Province by paying attention to the site of the region to estimate the model parameters so as to be able to provide the correct results to represent the model and map the stunting percentage in East Java [12]. As a result, it is expected that the findings can be used as a reference for equitable development of stunting management in East Java.

The factors that cause stunting in each region are different because there are differences in the characteristics of a region and there is a relationship between the distances among regions. The differences in characteristics among regions cause a spatial effect called spatial heterogeneity. To overcome the spatial heterogeneity problem, we used geographically weighted regression (GWR) model which is the development of the classical linear regression model [13].

The basic for the GWR method is the proximity among regions indicated by the weighting matrix. The closer the distance among regions, the greater the weighting value [14]. The weighting function involved in the GWR analysis process is the adaptive gaussian kernel weighting function. This function has a different bandwidth at each observation site because the ability of the adaptive kernel function can be adjusted to the observation point conditions [15]. Numerous research on stunting by considering spatial effects have been carried out. One of the methods used is Geographically Weighted Regression (GWR). It produces global and local parameter estimates. The stunting research was conducted [16] using the GWR kriging method [17]. The stunting research with spatial effects modeling the stunting percentage using a global regression approach, GWR [11].

Nevertheless, unlike global regression which can be used to predict stunting at each site, the GWR model cannot be used to predict stunting occurred outside the research sample site, except by predicting the regression coefficient at that site. To overcome this problem, this paper used the Kriging predictor to predict the regression parameters.

Generally, the GWR model is used to overcome spatial heterogeneity. In a special case, error in the GWR modeling contains spatial autocorrelation, so the GWR model needs to be modified by adding spatial interpolation from the GWR model errors. The spatial interpolation method used is Ordinary kriging. This method provides the best unbiased estimates and can be classified into stochastic estimation where statistical calculations are performed to produce interpolations [17]. This method has an estimator with a minimum variance and is a linear combination of observations [18]. Moreover, this method is an interpolation technique that uses measured sample site values to estimate values at unmeasured sites using a semi variogram to obtain optimal weighting values [19]. The selection of semi variogram is not based on anything, all semi variogram modeling can be used with trial-and-error properties, but the commonly used semi variogram modelings are Spherical, Exponential, and Gaussian. The models formed will become Geographically Weighted Regression Kriging (GWRK) [18]. The GWRK model is a model formed by adding the GWR model predictions with the interpolation results of the GWR model errors.

In this research, the spatial modeling with GWRK was carried out between the response variables and predictor variable. The basis of GWRK modeling was the GWR modeling so that the modeling process started from the GWR modeling and the Ordinary Kriging interpolation was carried out on the GWR model errors.

The benefit to be achieved in this research is to provide an alternative model for determining stunting conditions by considering the spatial variations where the data are obtained.

2. RESEARCH METHODS

2.1 Global Regression

The global regression equation, usually defined using the Ordinary Least Square (OLS) parameter estimation method, can generally be written in a mathematical equation as follows.

$$y_i = \beta_{i0} + \sum_{k=1}^{p-1} \beta_{ik} x_{ik} + \varepsilon_i \quad (1)$$

where β_0 is the constant, β_i is the explanatory variable coefficient value x_i , p is the number of explanatory variables used in the model, n is the number of observations (example), and **e** is the random error assumed to spread N(0,$\sigma^2 I$) , with **e** = $(e_1, e_2, e_3, \dots, e_n)$ and I is the identity matrix. By minimizing the sum of the squared errors, the value of the parameter estimator with OLS in the form of vector is as follows.

$$\hat{\boldsymbol{\beta}}_{\boldsymbol{i}} = [\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X}]^{-\boldsymbol{1}}\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{Y} \quad (2)$$

where $\hat{\beta} = \hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_p$) is the vector p+1 as regression coefficient, X is the explanatory variable matrix sized n x(p+1) where the first column is 1 for the constant, and Y is the response variable vector.

2.2 Geographically Weighted Regression (GWR)

The GWR model is the development of the global regression model. However, in contrast to the global regression, which is generally applied at each observation site, GWR generates a local model parameter estimator for each observation site using the Weighted Least Square (WLS) method [20]:

$$\hat{\beta}_i = [X^T W_i X]^{-1} X^T W_i Y \quad (3)$$

where W_i= diag$[w_1, w_1, \dots, w_n]$ dengan 0≤ $w_1 \leq 1$ (i,j= 1,2,3,…,n)

W_i is the spatial weighting matrix of i site in which diagonal elements are determined by the proximity of i site to other sites (j site). The spatial weighting matrix (**W**) can be obtained based on distance information from neighborhood or the distance between one region and another. The bi-square weighting function is used because it involves elements of the distance between observed sites in which the value is continuous in building a weighting matrix, so each site will receive a weight according to the distance between that site and the observed site [20].

$$W_{ij}(u_i,v_i) = \begin{cases} [1 - (\frac{d_{ij}}{h})^2]2 & ; dij \leq h \\ 0 & ; dij > h \end{cases} \quad (4)$$

Where d_{ij} is the distance from i site to j site using the coordinate points. In the Bis-square weighting function, there is an optimal bandwidth parameter. The optimal bandwidth is analogous to the radius of a circle, so an observation point that is within the radius of the circle is still considered influential in forming parameters at i observation point. There are several methods that can be used to select the optimal bandwidth and one of them is using Cross Validation (CV). The calculation of CV in the panel regression model is the same as GWR, which is calculated based on the average of the dependent and independent variables for the entire time [21] and defined as follows.

$$CV = \sum_{i=1}^{n} (\bar{y}_i - \hat{\bar{y}}_{\neq i}(b)) \quad (5)$$

where $\bar{y}_i$ is the average over time of the dependent variable at the observation site i and $\hat{\bar{y}}_{\neq i}(b)$ is the estimator valuey_i with bandwidth h with on-site observation $(u_i v_i)$.

To detect globally whether GWR is better than OLS, it can be tested by the analysis of variance (ANOVA) proposed by [15].

2.3 Moran's I

Moran's I coefficient is the development of Pearson correlation on univariate series data. It is used to test spatial dependency or autocorrelation between observations or sites [22] .

The hypotheses used are:

H_0: I = 0 (there is no autocorrelation between sites)
H_1: I ≠ 0 (there is autocorrelation between sites)

With the test statistics used [22]

$$I = \frac{n\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})^2} \tag{6}$$

Description:

x_i = i location variable data (i = 1, 2, ..., n)

x_j = j location variable data (j = 1, 2, ..., n)

$\bar{x}$ = data average

w = weighting matrix

The value of I index are between -1 and 1. If I > Io, the data have a positive autocorrelation. If I < Io, the data have a negative autocorrelation.

2.4 Kriging

Kriging is a prediction or estimation method in geographic space, often known as the best linear bias predictor (BLUP). This is a geostatistical method of interpolation for random spatial process. Unlike the global regression model, the GWR model cannot be used to predict parameters other than the parameters at the research site [23]. To overcome this problem, this paper proposed the use of the spatial predictor kriging (ordinary kriging predictor) to estimate local parameters. The assumption related to the use of the predictor [24] is:

$$p(b; s_0) = \sum_{i=1}^{n} \lambda_i b(s_i), \quad \sum_{i=1}^{n} = 1 \tag{7}$$

The number of coefficients of 1 guarantees uniform unbiasedness and the optimal value $\lambda_1, \lambda_2, ..., \lambda_n$ is obtained by using the following formula.

$$\lambda_0 = \Gamma_0^{-1}\gamma_0 \tag{8}$$

Where

$\lambda_0 = (\lambda_0, \lambda_0, \dots \lambda_0, \phi)^2$

$\gamma_0 = (\gamma(S_0 - S_0), \dots, \gamma(S_0 - S_n), 1)^T$

$$\Gamma_0 = \begin{cases} \gamma(S_i - S_j) & i = 1, \dots, n; j = 1, \dots, n \\ 1 & i = n + 1; j = 1, \dots, n \\ 0 & i = n + 1; j = n + 1 \end{cases}$$

γ_0 is the fitting variogram function, $\{S_1, S_2, \dots, S_n\}$ is the spatial site and ϕ is the lagrange multiplier for the sum of lambda coefficients of 1. In this paper, some isotropic variogram functions such as linear, spherical, and exponential were tested and a variogram function providing minimum weight sum of square was chosen. The three variogram models above are as follows [25].

a. Linear Model

The equation for the circular function is:

$$\gamma(h) = \begin{cases} c_0 + c\left\{1 - \frac{2}{\pi}\cos^{-1}\left(\frac{h}{a}\right) + \frac{2h}{\pi a}\sqrt{1 - \frac{h^2}{a^2}}\right\}; h \le a \\ c_0 + c; h > a \\ 0; h = 0 \end{cases} \tag{9}$$

where $\gamma(h)$ is the semi variance of the lag h, c is a variety of *a priori* from the autocorrelation process, c_0 is the nugget variance which is the spatially uncorrelated variation at a distance less than the sampling interval and measurement error, and α is the distance parameter, range of spatial dependence and spatial autocorrelation.

b. Spherical Model

This model is one of the two most widely used models in kriging modelling science. The equation is:

$$\gamma(h)=\begin{cases} c_0+c\left\{\dfrac{3h}{2a}+\dfrac{1}{2}\left(\dfrac{h}{a}\right)^3\right\};h\le a \\ c_0+c;h>a \\ 0;h=0 \end{cases} \tag{10}$$

The symbol has the same meaning as above. This model bends more slowly when the limit is reached than the linear one.

c. Exponential Model

The exponential and spherical functions together account for most of the models installed in the kriging model. The equation is:

$$\gamma(h)=c_0+c\left\{1-\exp\left(-\frac{h}{r}\right)\right\} \tag{11}$$

where $c0$ and c have the same meaning as above, but the distance parameter is now r. The exponential model approaches its threshold more gently than the previous model and is also asymptotic, so it does not have a limited range.

2.5 Data

The data used in this research were secondary data obtained from Basic Health Research (RISKESDAS) data and 2021 East Java Health Profile Book. The observation units in this research were 38 districts in East Java.

The variables used in this research consisted of the dependent variable (Y) and five independent variables(X) such as Stunting Percentage, Coverage of K1 visits to Pregnant Women, FE Tablet Consumption, Coverage of Exclusive Breastfeeding, Coverage of Toddlers with Complete Immunization, Clean and Healthy Living Behavior.

3. RESULTS AND DISCUSSION

3.1 Multiple Linear Regression

The linear regression model is carried out by regressing the response variable, which was Stunting with all independent variables in the research. The equation of the multiple linear regression model obtained is as follows.

$$\hat{Y} = 12.542 + 0.0469X_1 - 0.1125X_2 - 0.0244X_3 - 0.0429X_4 + 0.0862X_5$$

Based on the model obtained, it can be seen that the coverage of K1 visits (X_1) and clean and healthy living behavior (X_5) had a positive relationship with stunting. However, the FE tablet consumption (X_2), exclusive breastfeeding(X_3), and complete immunization coverage (X_4) had a negative relationship with stunting. For example, the lower the percentage values of the FE tablet consumption, the greater the stunting percentage values. This multiple linear regression model yielded R^2 value by 0.5479 meaning that the independent variables in the research simultaneously affected stunting by 54.79% and the remaining 45.21% was affected by other variables outside the research variables. Thus, the Normality Assumption Test was fulfilled.

3.2 Spatial Aspect Testing

The spatial aspect testing is carried out in two steps, including spatial heterogeneity testing and spatial dependency testing.

Table 1. Spatial Autocorrelation test

Testing	P-value
Spatial Heterogeneity (Breusch Pagan	0.000354
Morans'I	0.000023

The results above shows that the p-value < α, meaning that there was a spatial effect on East Java stunting data; this could be continued with GWR modeling.

3.3 Parameter Estimation of GWR Model

After forming a weighting matrix at each site, the weighting matrix were substituted to form the GWR parameter estimation at each research site. The parameter estimation results of the GWR model can be exemplified by the GWR model formed for Pamekasan Regency.

$$\ln\left(Y_{kota\ Surabaya}\right) = 6.7563 + 1.044X_1 - 0.4867X_2 - 0.3246X_3 - 0.1064X_4 + 0.0456X_5$$

Based on the GWR model obtained, the number of stunting prevalence declined with $e^{1.044} = 2.84$ if the percentage of coverage of K1 visits to pregnant women (X_1) increased by 1% provided that other variables were constant and the effect of the site around the observed point, that was point 18 was considered constant. In addition, the decrease in the stunting prevalence to $e^{0,4867} = 1.62$ could also be done by the decrease in the FE3 tablet consumption (X_2) by 1% provided that other variables were constant and the effect of the site around the observed point, that was point 18 was considered constant. The 1% decrease in the exclusive breastfeeding (X_3) decreased the stunting prevalence by $e^{0,3246} = 1.38$ provided that other variables were constant and the effect of the site around the observed point that was point 18 was considered constant. Nonetheless, the 1% increase in the complete immunization (X_4) affected the stunting prevalence by $e^{0,1064} = 1.11$ in Pamekasan Regency provided that other variables were constant and the effect of the site around the observed point that was point 18 was considered constant. Then the 1% increase in the clean and healthy living behavior (X_5) decreased the stunting prevalence bye$^{0,0456} = 1.04$ provided that other variables were constant and the effect of the site around the observed point that was point 18 was considered constant.

Hence, the GWR prediction can be seen in the figure below.

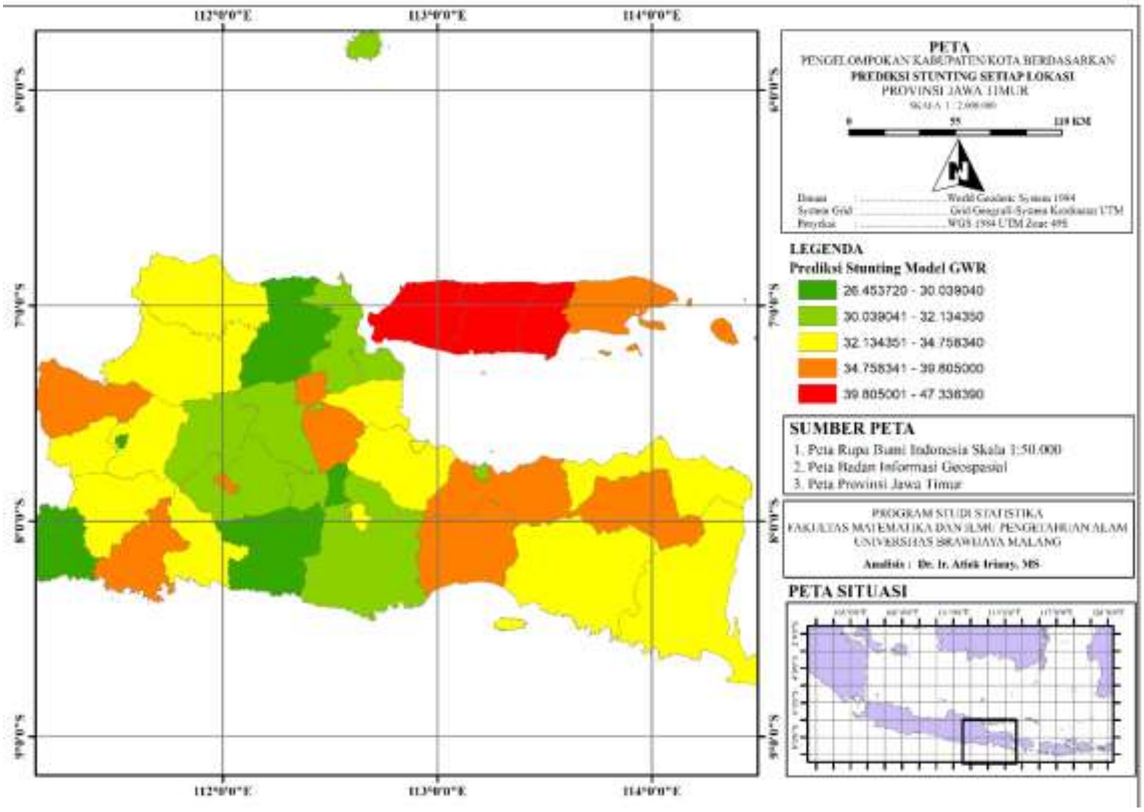

Figure 1. Stunting Prediction Map with the GWR Model

The figure above shows that the stunting predictions with the GWR model have a range with the lowest of 26% and the highest of 47%.

a. GWR Model Fit Test

The model fit test can be presented in the following **Table 2**.

Table 2. Simultaneous parameter test

Source of Diversity	Sum of Squares	Degrees of Freedom	Middle Square	F Test Statistics
OLS Residual	5.2436	6		
GWR Improvements	5.3725	19	0.282763	
GWR Residuals	1.0032	13	0.077169	3.6642

Based on the table above, the test statistics obtained the value of $F_{count} = 3.6642 > F_{(0,05;19;13)} = 2,4$, then H_0 was rejected, so the *Adaptive Bisquare Kernel* weighting affects the GWR model parameter estimation.

b. Partial testing of GWR model parameters

The significance test of the GWR model parameters was calculated, the t_{count} results obtained were compared to the value of $t_{(0,05;36)}$ = 2.03. If the value of $|t_{count}|$ was greater than the value oft_{table}, then the parameter was significant at each site. For example, we tested the significance of parameters partially at Pamekasan Regency site to find out which parameters had a significant effect on the model in Pamekasan Regency.

Table 3. Partially test parameters

Parameter	Estimator	T Test Statistics	Decision	Conclusion
$\boldsymbol{\beta_0}$	6.756	6.43	$H_0$was rejected	Significant
$\boldsymbol{\beta_1}$	1.044	4.785	H_0 was rejected	Significant
$\boldsymbol{\beta_2}$	-0.486	3.859	H_0 was rejected	Significant
$\boldsymbol{\beta_3}$	-0.324	-3.955	H_0 was rejected	Significant
$\boldsymbol{\beta_4}$	-0.106	-1.367	$H_0$was accepted	Not Significant
$\boldsymbol{\beta_5}$	-0.045	0.942	$H_0$was rejected	Not Significant

Based on the table above, the stunting prevalence in Surabaya Regency was significantly affected by the coverage of K1 visits to pregnant women (X_1), FE tablet consumption FE3 (X_2), and exclusive breastfeeding(X_3).

The determination coefficient (R^2) value with a distance weighting, which was the adaptive bisquare kernel for the GWR model was 0.97, meaning that the effects of the five independent variables on the stunting prevalence in East Java was 97% and the remaining 3% was affected by other variables outside the research.

3.4 GWR Kriging Model

Mapping with kriging interpolation used coordinate point data and Y_{pred} value data on the GWR model. The semivariogram used in this research was the exponential semi variogram. The stunting data were interpolated by the GWR Kriging and presented in the form of a forecasting map to make it more informative and useful. The stunting forecasting map is presented in the figure below.

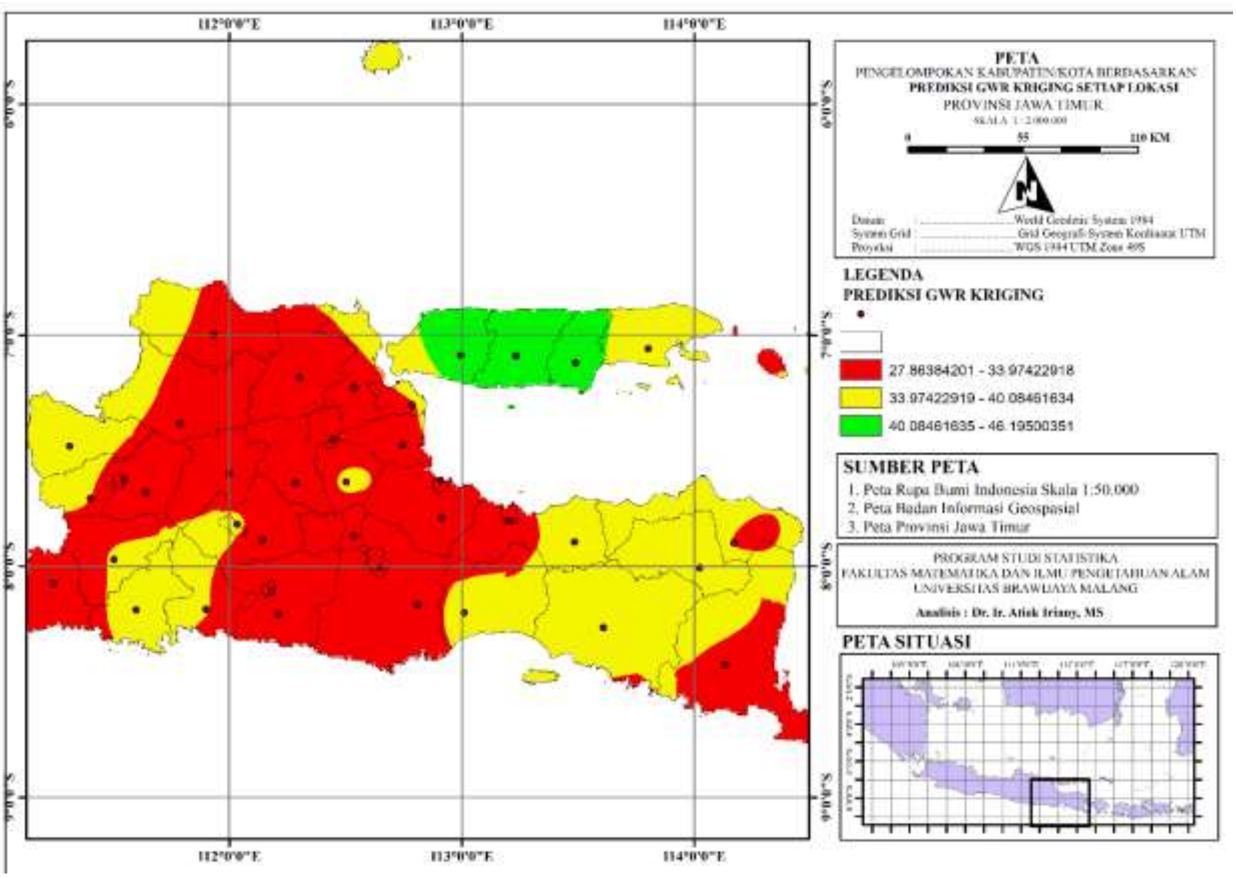

Figure 2. **Stunting Prediction Map with the GWR-Kriging model**

Based on the interpolation map above, it can be seen that the stunting forecasting values using the GWR Kriging interpolation ranged from 27% to 46%. The high stunting forecast value is presented on the green map and the low one is presented on the red map. It can be seen that only a small number of regencies in East Java have a high stunting prevalence, illustrated on the red map and located in Sampang and Pamekasan Regencies.

For example, Jember Regency which is yellow on the map is in the classification of 2 moderate stunting prevalence with a value ranging from 33 – 40. The map also shows that Jombang Regency is affected by Mojokerto Regency, Nganjuk Regency, and Kediri Regency. This can be seen from the sites of the points that are close to each other and have the same colors on the map, that is green, which is at a prevalence with a low classification, which ranges from 27% - 34%.

4. CONCLUSIONS

The results of GWR Kriging interpolation with distance weighting show that the stunting forecasting values range from 27% to 49.5%. These results indicate that the stunting forecasting values using the GWR and GWR kriging methods do not provide considerable difference.

AKNOWLEDGEMENT

We thank Universitas Brawijaya for its support to this research. This research is a doctoral grant at Faculty level at Universitas Brawijaya.

REFERENCES

[1] A. Ernawati, “Gambaran Penyebab Balita Stunting di Desa Lokus Stunting Kabupaten Pati,” *J. Litbang Media Inf. Penelitian, Pengemb. Dan IPTEK*, vol. 16, no. 2, pp. 77–94, 2020.

[2] K. Rahmadhita, “Permasalahan Stunting dan Pencegahannya,” *J. Ilm. Kesehat. Sandi Husada*, vol. 9, no. 1, pp. 225–229, 2020.

[3] R. Kim, I. Mejia-Guevara, D. J. Corsi, V. M. Aguayo, and S. V Subramanian, “Relative importance of 13 correlates of child stunting in South Asia: Insights from nationally representative data from Afghanistan, Bangladesh, India, Nepal, and Pakistan,” *Soc. Sci. Med.*, vol. 187, pp. 144–154, 2017.

[4] I. Budiastutik and S. A. Nugraheni, “Determinants of stunting in Indonesia: A review article,” *Int. J. Heal. Res.*, vol. 1, no. 2, pp. 43–49, 2018.

[5] T. Mulyaningsih, I. Mohanty, V. Widyaningsih, T. A. Gebremedhin, R. Miranti, and V. H. Wiyono, “Beyond personal factors: Multilevel determinants of childhood stunting in Indonesia,” *PLoS One*, vol. 16, no. 11, p. e0260265, 2021.

[6] D. Izwardy, “Studi Status Gizi Balita Terintegrasi Susenas 2019,” *Balitbangkes Kemenkes RI*, 2020.

[7] T. Beal, A. Tumilowicz, A. Sutrisna, D. Izwardy, and L. M. Neufeld, “A review of child stunting determinants in Indonesia,” *Matern. Child Nutr.*, vol. 14, no. 4, p. e12617, 2018.

[8] L. Fitri, “Hubungan BBLR Dan Asi Ekslusif Dengan Kejadian Stunting Di Puskesmas Lima Puluh Pekanbaru,” *J. Endur. Kaji. Ilm. Probl. Kesehat.*, vol. 3, no. 1, pp. 131–137, 2018.

[9] C. R. Titaley, I. Ariawan, D. Hapsari, A. Muasyaroh, and M. J. Dibley, “Determinants of the stunting of children under two years old in Indonesia: a multilevel analysis of the 2013 Indonesia basic health survey,” *Nutrients*, vol. 11, no. 5, p. 1106, 2019.

[10] H. Pramoedyo, M. Mudjiono, A. A. Fernandes, D. Ardianti, and K. Septiani, “Determination of Stunting Risk Factors Using Spatial Interpolation Geographically Weighted Regression Kriging in Malang,” *Mutiara Med. J. Kedokt. dan Kesehat.*, vol. 20, no. 2, pp. 98–103, 2020.

[11] A. Fadliana and P. P. Darajat, “Pemetaan Faktor Risiko Stunting Berbasis Sistem Informasi Geografis Menggunakan Metode Geographically Weighted Regression,” *ikraith-informatika*, vol. 5, no. 3, pp. 91–102, 2021.

[12] H. Al Azies, F. Cholid, and D. Trishnanti, “Pemetaan Faktor-Faktor yang Mempengaruhi Stunting pada Balita dengan Geographically Weighted Regression (GWR),” *semnaskes 2019*, pp. 156–165, 2019.

[13] W. Simeng, W. Dazhao, and H. Chang, “A comparative study of using ANUSPLIN and GWR models for downscaled GPM precipitation,” in *2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics)*, 2019, pp. 1–5.

[14] Q. Zhou, C. Wang, and S. Fang, “Application of geographically weighted regression (GWR) in the analysis of the cause of haze pollution in China,” *Atmos. Pollut. Res.*, vol. 10, no. 3, pp. 835–846, 2019.

[15] C. Zeng *et al.*, “Mapping soil organic matter concentration at different scales using a mixed geographically weighted regression method,” *Geoderma*, vol. 281, pp. 69–82, 2016.

[16] A. Y. K. Kartini and L. N. Ummah, “Pemodelan Kejadian Balita Stunting di Kabupaten Bojonegoro dengan Metode Geographically Weighted Regression dan Multivariate Adaptive Regression Splines,” *J Stat. J. Ilm. Teor. dan Apl. Stat.*, vol. 15, no. 1, 2022.

[17] Y. Sen Sun, W. F. Wang, and G. C. Li, “Spatial distribution of forest carbon storage in Maoershan region, Northeast China based on geographically weighted regression kriging model.,” *Ying Yong Sheng tai xue bao= J. Appl. Ecol.*, vol. 30, no. 5, pp. 1642–1650, 2019.

[18] S. Bahmani, S. R. Naganna, M. A. Ghorbani, M. Shahabi, E. Asadi, and S. Shahid, “Geographically weighted regression hybridized with Kriging model for delineation of drought-prone Areas,” *Environ. Model. Assess.*, vol. 26, no. 5, pp. 803–821, 2021.

[19] A. A. Rostami, M. Isazadeh, M. Shahabi, and H. Nozari, “Evaluation of geostatistical techniques and their hybrid in modelling of groundwater quality index in the Marand Plain in Iran,” *Environ. Sci. Pollut. Res.*, vol. 26, no. 34, pp. 34993–35009, 2019.

[20] A. S. Fotheringham, W. Yang, and W. Kang, “Multiscale geographically weighted regression (MGWR),” *Ann. Am. Assoc. Geogr.*, vol. 107, no. 6, pp. 1247–1265, 2017.

[21] D. A. I. M. Siti Maulina Meutuah, Hasbi Yasin, “Pemodelan Fixed Effect Geographically Weighted Panel,” *J. Gaussian*, vol. Vol 6 Nomo, pp. 241–250, 2017, [Online]. Available: https://media.neliti.com/media/publications/98983-ID-none.pdf.

[22] A. LUTFI, “Identifikasi Autokorelasi Spasial Angka Partisipasi Sekolah di Provinsi Sulawesi Selatan Menggunakan Indeks Moran.” Universitas Negeri Makassar, 2019.

[23] P. Harris, A. S. Fotheringham, R. Crespo, and M. Charlton, “The use of geographically weighted regression for spatial prediction: an evaluation of models using simulated data sets,” *Math. Geosci.*, vol. 42, no. 6, pp. 657–680, 2010.

[24] A. Muche, M. S. Melaku, E. T. Amsalu, and M. Adane, “Using geographically weighted regression analysis to cluster under-nutrition and its predictors among under-five children in Ethiopia: Evidence from demographic and health survey,” *PLoS One*, vol. 16, no. 5, p. e0248156, 2021.

[25] M. M. Fischer and A. Getis, *Handbook of applied spatial analysis: software tools, methods and applications*. Springer, 2010.