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Spatial Diversity of Village Funds in Reducing Poverty in West Sumatra Province

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Abstract: One of the efforts to improve the community's welfare and poverty alleviation requires an integrated development program and synergized based on local resources. One of the efforts is the village fund program, are funds provided for villages sourced from the state budget and are used for government administration, implementation of development and empowerment of village communities. This paper examines the spatial diversity of the effectiveness of the Village Fund in reducing poverty in West Sumatra Province from 2015 to 2020 (data from the Ministry of Finance). The unit of research analysis is the regency/municipal that receives the Village Fund assistance. This study uses Geographically Weighted Regression, with dimensions of observing the allocation of Village Funds and poor people. The study results show that the Village Fund cannot reduce poverty in the beneficiary regencies/municipals. The number of Village Funds disbursed increases every year, but the number of poor people also increases; only three districts, namely Limapuluh Kota, Pesisir Selatan, and Kepulauan Mentawai, have decreased in 2020. The Village Fund Program is ineffective in reducing poverty in West Sumatra Province due to the Village Fund allocation percentage being more prominent for village government operations. The allocation of Village Funds for the administration of village government is much larger than what is mandated by law, which is 30%. The main objective of the Village Fund Program is to eradicate poverty and reduce inequality. To achieve this noble goal, it is necessary to evaluate the distribution of Village Funds. This study looks at the effectiveness of the Village Fund in reducing poverty, and looks at the spatial diversity of the effectiveness of the Village Fund in beneficiary regencies/municipals.

Keywords: Regional Development, Poverty, Geographically Weighted Regression

INTRODUCTION

Development are fundamental changes in social structure, community behaviour, national institutions, accelerated economic growth, income inequality, poverty alleviation (Todaro & Smith, 2012), and systematic and sustainable improvement in community welfare (Fudge *et al.,* 2021; Rustiadi *et al.*, 2018; Kumari & Devadas, 2017). Regional development is focused on recognizing the potential of local resources (Zasada *et al.*, 2018; Babkin *et al.*, 2017). Poverty is a problem that often occurs and has always been an issue in various countries (Gilbert, 2014), including in Indonesia. People are said to be poor if they have a low standard of living, so they cannot meet basic needs due to limited income (Zaini *et al.*, 2018).

One of the efforts to realize accelerated development and improve the community's economy in the region requires an integrated and synergized development program based

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on local resources (Friedmann & Alonso, 1964). In regional development and development, effective strategies are needed to accelerate development (Rustiadi *et al.*, 2018) and focus on competitiveness (Camagni, 2019). The main problem in regional development is development policies based on regional uniqueness and regional potential (Kuncoro, 2018). To solve the problem causes the central government, local governments, and communities to predict the potential resources used to plan and develop the regional economy (Saragih, 2015). That limited development resources require regions to prioritize resource allocation (Chulaphan & Barahona, 2018; Yusof *et al.*, 2013; Gugushvili *et al.*, 2017).

One of the efforts made by the Indonesian government to improve welfare and alleviate poverty is the Village Fund program (Arifin *et al.*, 2020; Watts *et al.*, 2019; Buku Pintar Dana Desa, 2017). Village Funds are funds provided for villages sourced from the state budget (APBN) and transferred through the Regency/City APBD for governance, implementation of development and empowerment of rural communities (Law No. 6/2014 on Villages). The allocation of the Village Fund is used 30% for the operation of village administration and 70% for community empowerment in the fields of education, health and economy, and the development of village economic infrastructure. According to Law No. 6/2014, the objectives of the allocation of the Village Fund are: 1) overcoming poverty and reducing inequality, 2) improving the quality of development planning and budgeting and empowering rural communities, 3) encouraging infrastructure development based on justice and local wisdom, 4) increasing the practice of religious values, social and cultural activities to realize increased social welfare, 5) improve services to rural communities, 6) encourage increased self-reliance and mutual assistance of village communities, 7) increase village income through BuMDes (Village Owned Enterprises). Implementation of Village Fund distribution based on justice principles, priority needs, village authority, participatory, village resource-based self-management and village typology.

The Village Fund Program has been running since 2015, amounting to 20.77 trillion for all of Indonesia. In 2016 the Village Fund disbursed by the government was 46.98 trillion, an increase of 55.8% from 2015. In 2017 there was an increase in the allocation of the Village Fund by 21.7% to 60 trillion. In 2018 there was a decrease in fund allocation by 69.1%; the amount of Village Funds disbursed in 2018 was 18 trillion. The allocation of Village Funds in 2019 increased by 73.5%, disbursed funds amounted to 70 trillion, and in 2020 there was an increase of 2.7% to 72 trillion. In line with the increase and decrease in the number of funds disbursed nationally, the Province of West Sumatra also experienced these fluctuations (Figure 1). The allocation of Village Funds in 2018 experienced a high decline from 796.5 billion in 2017 to 267 billion. In 2019 there was a high increase in the allocation of funds to 932.3 billion.

Previous research shows that village funds channelled have the opportunity to increase Village-Owned Enterprises (BUMDes) but are not followed by increased job opportunities for rural communities (Arifin *et al.*, 2020). Transparency and lack of information from the village government cause the community's understanding of the use of village funds to be still small (Solichin & Akmal, 2018). Research conducted by Rahmawati *et al.* (2021) that the application of the principle of village fund management has not been maximized; this is because it does not open up space for community roles, community participation is still passive and the focus of activities on physical development.

The Village Fund Program has been running since 2015, with an allocation of 20.77 trillion, which is channelled through the district/city local government budget (APBD) of the provinces on the island of Sumatra, based on the number of villages, West Sumatra Province is one of the recipients of village funds with a large budget allocation. West Sumatra Province is one of the recipients of the Village Fund. West Sumatra Province, which consists of 19 regencies/cities (12 regencies and seven cities), in 2015 received a fund allocation of 50.3 billion. However, of the 19 regencies and cities in West Sumatra, not all of them received village fund allocations. Only 14 regencies/cities received village fund allocations, namely Pesisir Selatan, Solok, South Solok, Mentawai Islands, Dharmasraya, Padang Pariaman, Tanah Datar, Sijunjung, Agam, Pasaman, West Pasaman. Limapuluhkoto and Kota Pariaman and Sawahlunto. Meanwhile, Padang Municipal, Solok Municipal, Padang Panjang Municipal, Bukittinggi Municipal and Payakumbuh Municipal did not get the Village Fund allocation. Regions that do not receive Village Funds because the five cities are large cities that have been independent so do not need Village Fund allocations.

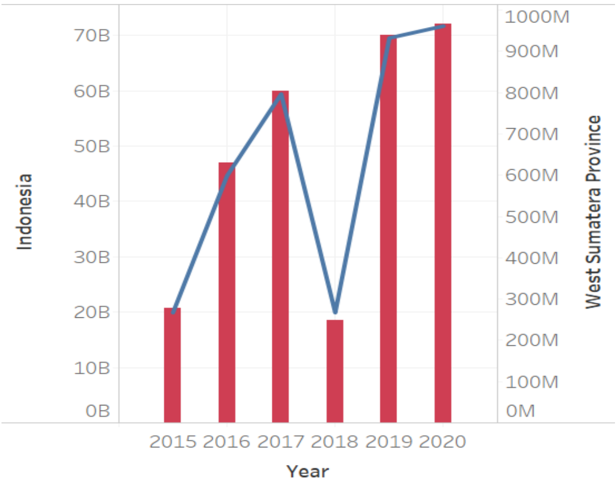


Figure 1. Village Fund Allocation Indonesia and Province West Sumatera

Figure 2 and Table 1 show the amount of the Village Fund allocation for each city district. The area that received the most funding was Pesisir Selatan Regency, and the smallest was Sawahlunto City. On average 2015 - 2017, there was an increase in the number of funds received by districts/cities and a decrease in 2018. However, several districts in 2018 even experienced an increase in the allocation of Village Funds, namely Pesisir Selatan, Pasaman and West Pasaman Regencies. In 2019, all districts and cities experienced an increase in the allocation of Village Funds.

Table 1. Village Fund Allocation Each Region 2015-2020

Region	Village Fund (Million Rupiahs)					
	2015	2016	2017	2018	2019	2020
			Regency			
Mentawai Islands	14,962.27	33,581.00	41,619.40	45,266.90	54,390.77	57,749.49
Pesisir Selatan	50,359.93	112,965.69	143,905.95	145,715.75	166,305.83	169,362.52
Solok	22,378.08	50,220.93	64,082.14	62,877.21	74,487.56	78,119.34
Sijunjung	18,156.86	40,677.75	51,629.93	49,641.00	58,787.65	59,669.31
Tanah Datar	21,830.76	48,999.84	62,469.77	56,799.30	66,854.25	68,755.68
Padang Pariaman	18,823.67	42,269.55	84,644.73	81,944.44	95,038.40	97,862.54
Agam	24,751.33	55,566.45	70,772.85	63,978.70	74,249.76	76,923.81
Lima Puluh Koto	23,740.81	53,280.09	67,871.12	64,968.67	75,446.61	78,429.45
Pasaman	11,629.29	25,551.22	35,950.81	38,829.16	48,262.08	48,576.98
South Solok	12,356.23	27,729.29	35,426.12	35,721.40	43,409.55	44,944.69
Dharmasraya	15,755.27	35,357.32	45,098.23	43,249.03	51,593.12	53,834.61
Pasaman Barat	8,728.91	19,617.11	25,253.38	36,711.43	47,238.49	48,525.15

Region	Village Fund (Million Rupiahs)					
	2015	2016	2017	2018	2019	2020
			Municipal			
Padang	0	0	0	0	0	0
Solok	0	0	0	0	0	0
Sawahlunto	8,191.43	18,396.31	23,665.86	23,477.79	28,211.22	28,923.03
Padang Panjang	0	0	0	0	0	0
Bukittinggi	0	0	0	0	0	0
Payakumbuh	0	0	0	0	0	0
Pariaman	15,339.02	34,425.08	44,148.67	41,606.56	48,050.23	49,458.81

Source: The Ministry of Finance

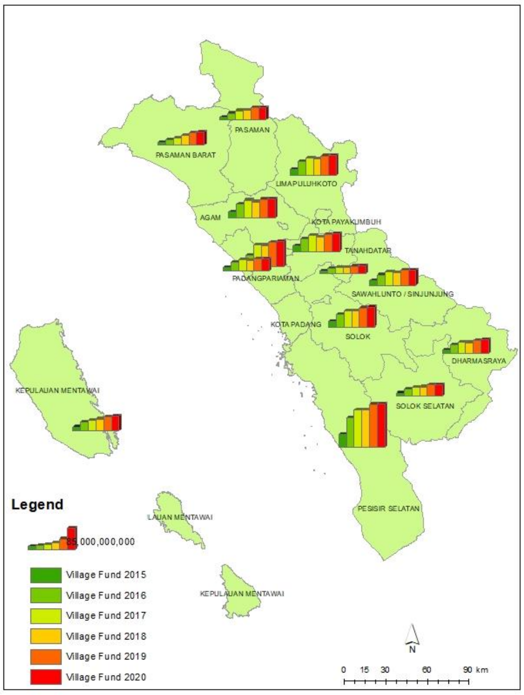


Figure 2. Village Fund Allocation Each Region 2015-2020

In this study, we want to see the effectiveness of the Village Fund on poverty/or reduction in the number of poor people in West Sumatra Province from 2015 to 2020. The level of effectiveness of the village fund is seen spatially for each district/city receiving assistance. The Geographical Weighted Regression (GWR) method approach was used in this study.

METHOD

This research was conducted in West Sumatra Province as one of the recipients of Village Fund assistance, the district/city analysis unit. The data used in this study is secondary data, namely data on the allocation of Village Funds and the number of poor people. From 2015 to 2020. Secondary data were obtained from the Ministry of Finance and simreg.bappenas.go.id. The GWR approach can see spatial diversity (Mao, Yang, & Deng, 2018) based on various kernel weighting functions (Wheeler & Paez, 2010) with fixed (fixed Gaussian) and variable bandwidth (adaptive bi-square). The GRW approach is used because it can see the spatial diversity (Mao *et al.*, 2018) the effectiveness of implementing the Village Fund program for each district/city receiving assistance. The Geographically Weighted Regression (GWR) model develops the classical regression model (Wheeler & Paez, 2010). The general form of the GWR model is:

$$lny_i = \beta_0(u_i,v_i) + \sum_{k=1}^{p} \beta_k(u_i,v_i) lnx_{ki} + \delta_i \quad (1)$$

where:

y_i	=	Observation value of response variable at the i-location
x_{ki}	=	k-clearing modifier value at the i-location (i=1,2,...,n)
(u_i, v_i)	=	Coordinates of the i-observation location
$\beta_0 (u_i, v_i)$	=	Constant/intercept GWR
$\beta_k(u_i, v_i)$	=	The value of the k-parameter at the i-location
δ_i	=	i-observation error which is assumed to be identical, independent, and normally distributed with zero mean and constant variance σ^2

The estimation of the parameters of the GWR model was carried out using the Weighted Least Squares (WLS) method by giving different weights for each observation location. For example, the weight for each observation location (*ui,vi*) is w_j (*ui,vi*), j = 1,2, …, n then the parameter at the observation location (*ui,vi*) is estimated by adding the weighting element w_j *(ui,vi*), In equation (1) and then minimize the following sum of the squares of the residuals:

$$\sum_{j=1}^{n} w_j(u_i,v_i)\varepsilon_j{}^2 = \sum_{j=1}^{n} w_j(u_i,v_i)\left[y_i - \beta_0(u_i,v_i) - \sum_{k=1}^{p} \beta_k(u_i,v_i)x_{jk}\right]^2$$

In the form of a matrix, the sum of the squares of the residuals is:

$$\begin{aligned}\varepsilon^T W(u_i,v_i)\varepsilon = y^T W(u_i,v_i)y - 2\beta^T(u_i,v_i)X^T W(u_i,v_i)y \\ + \beta^T(u_i,v_i)X^T W(u_i,v_i)X\beta(u_i,v_i)\end{aligned} \quad (2)$$

Whit:

$$(u_i,v_i) = \begin{bmatrix}\beta_0(u_i,v_i)\\ \beta_1(u_i,v_i)\\ \vdots \\ \beta_p(u_i,v_i)\end{bmatrix} dan\ W(u_i,v_i) = diag(w_1(u_i,v_i), w_2(u_i,v_i), \dots, w_n(u_i,v_i))$$

If equation (2) is derived to β^T (*ui,vi*) and the result is equalized to zero, then the parameter estimator of the GWR model is obtained.

$$\frac{\delta\varepsilon^T(u_i,v_i)}{\delta\beta^T\delta\varepsilon^T(u_i,v_i)} = 0 - 2X^T W(u_i,v_i)y + 2X^T W(u_i,v_i)X\beta(u_i,v_i)$$

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

$$\hat{\beta}(u_i,v_i) = [X^T W(u_i,v_i)X]^{-1}X^T W(u_i,v_i)y \quad (3)$$

Suppose $x_i^T = (1, x_{i1}, x_{i2}, \dots, x_{ip})$ is the first-row element of matrix X, then the predicted value for y at the observation location (*ui,vi*) is obtained in the following way:

$$\hat{y}_i = x_i^T \hat{\beta}(u_i, v_i) = x_i^T (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) y$$

Therefore, that for all observations written as follows:

$$\hat{y} = (\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n)^T = L_y \quad and$$
$$\hat{\varepsilon} = (\hat{\varepsilon}_1, \hat{\varepsilon}_2, \dots, \hat{\varepsilon}_n)^T = (1 - L)_y$$

$$L = \begin{bmatrix} x_1^T (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) \\ x_2^T (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) \\ \vdots \\ x_n^T (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) \end{bmatrix} \tag{4}$$

The GWR weighting matrix is a weighting matrix based on the proximity of the i-observation point to other observation points. The closest observation to the i-location is assumed to influence the parameter estimation at the i-location point significantly. The weighting matrix W (*ui,vi*) can be determined using a kernel function. The kernel function gives weighting according to the optimum bandwidth, whose value depends on the condition of the data. There are two types of kernels, namely fixed kernels and adaptive kernels. The fixed kernel function has the same bandwidth at each observation location. The adaptive kernel function has a different bandwidth for each observation location. The kernel functions used in GWR are:

1. Fixed kernel Gaussian

$$W_{ij} = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right] \tag{5}$$

2. Adaptive kernel Bi-square

$$W_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{b_{i(q)}}\right)^2\right]^2 & , if\ d_{ij} < b \\ 0 & , if\ other \end{cases} \tag{6}$$

Cross-validation (CV) is a process to find kernel bandwidth so that the minimum error prediction is obtained for all y(s) observations (Wheeler & Paez, 2010). CV estimation to determine minimizes the root mean squared prediction error (RMSPE), the model is:

$$\hat{\gamma} = \arg\min \sum_{i=1}^{n} [y_i - \hat{y}_{(i)}(\gamma)]^2 \tag{7}$$

Where:

$\hat{\gamma}$	=	Kernel bandwidth value that minimizes the RMSPE
$\hat{y}_{(i)}$	=	The predicted value of observation I with calibration location i left out of the estimation dataset.
γ	=	The kernel bandwidth

The corrected Akaike's Information Criterion (AIC) is an approach to estimate the kernel bandwidth not based on predicting the response variable. It is instead based on minimizing the estimation error of the response variable. It is a compromise between the goodness-of-fit of the model and model complexity, in that there is a penalty in the criterion for the effective number of parameters in the model.

$$AIC = 2nlog(\widehat{\sigma}) + nlog(2\pi) + n\left(\frac{n + trace(L)}{n - 2 - trace(L)}\right) \tag{8}$$

Where $\hat{\sigma}$is the estimated standard deviation of the error. L is the hat matrix, and the trace of a matrix is the sum of the matrix diagonal elements. The kernel bandwidth is used in the calculation of$\hat{\sigma}$ and L.

The estimated error variance is

$$\hat{\sigma}^2 = \frac{\sum_{i-1}^{n}(y_i - \hat{y}_i)^2}{\{n - [2trace(L) - trace(L^T L)]\}}$$

RESULTS AND DISCUSSION

Table 2 shows the results of the comparison of the model between Ordinary Least Square (OLS) and Geographically Weighted Regression (GWR) in looking at the spatial diversity of the effectiveness of the Village Fund in reducing poverty levels in districts/cities. The analysis results show that the GWR model is better and more accurate than the OLS model (Zhu *et al.*, 2020; Koh *et al.*, 2020; Chu *et al.*, 2019; Zhang *et al.*, 2019). The GWR model considers the spatial diversity of each coefficient, while the OLS model does not consider the spatial diversity of each coefficient. Akaike's Information Criterion (AIC) value in Table 2 shows that the GWR model has an AIC value smaller than the OLS model for each year of observation. For example, in 2015, the AIC value of the OLS model was -53.144731, and the GWR model was -53.166697; this illustrates that the AIC value of the GWR model is smaller than the OLS model with a difference of 0.021966. In 2016 the AIC value of the OLS model is -54,248999, and the GWR model is -54.269731; the difference is 0.020732. In 2017 the AIC value of the OLS model is -55.941154, and the GWR model is -57.283359; the difference is 1.342205. In 2018 the AIC value of the OLS model is -57,215042, and the GWR model is -57,215168; the difference is 0.000126. In 2019 the AIC value of the OLS model is -58.704924, and the GWR model is -58.715882; the difference is 0.010958. In 2020 the AIC value of the OLS model is -58.034818, and the GWR model is -58.046105; the difference is 0.011287. The difference in the AIC values of the OLS and GWR models shows that the GWR model is better because it is able to see spatial diversity. Based on the value of the determinant coefficient (R2), there was an increase of 0.000885 from 0.609009 to 0.609894 in 2015. In 2016 there was an increase in the value of the determinant coefficient of R2 by 0.000855, in 2017 by 0.046932, in 2018 by 0.000007, in 2019 by 0.0005997, in 2020 by 0.000631.

Table 2. Model Performance of Three Models (a) OLS, (b) FGGWR, (c) ABGWR

Time	Model	R2	AIC	RMSPE
2015	OLS	0.609009	-53.144731	0.003056
	FGGWR	0.609894	-53.166697	0.003056
	ABGWR	0.910879	-68.397009	0.004054
2016	OLS	0.611354	-54.248999	0.002891
	FGGWR	0.612209	-54.269731	0.002891
	ABGWR	0.906440	-68.464897	0.003872
2017	OLS	0.630702	-55.941154	0.002650
	FGGWR	0.677634	-57.283359	0.002758
	ABGWR	0.908398	-69.597075	0.003567

Time	Model	R2	AIC	RMSPE
2018	OLS	0.633050	-57.215042	0.002488
	FGGWR	0.633057	-57.215168	0.002488
	ABGWR	0.907330	-70.514806	0.003344
2019	OLS	0.642623	-58.704924	0.002299
	FGGWR	0.643227	-58.715882	0.002300
	ABGWR	0.910560	-72.174964	0.003079
2020	OLS	0.630265	-58.034818	0.002384
	FGGWR	0.630896	-58.046105	0.002385
	ABGWR	0.907583	-71.528410	0.003213

Source: Analysis, 2021

The GWR model uses spatial weighting by considering the spatial diversity in the regression model of each variable. The weights in the GWR model have different bandwidths so that they produce different models (Table 2). The AIC value seen, the minimum error prediction value (RMSPE) and the determinant coefficient (R2). For example, the fixed kernel Gaussian model (FGGWR) has an AIC value of -53.166697 and an adaptive bi-square (ABGWR) model of -68.397009; it shows that the AIC value of the FGGWR model is smaller than the ABGWR model with a difference of 15.230312 in 2015. The AIC value of the FGGWR model of -54.269731 and the ABGWR model of -68.464897 shows the AIC ABGWR value is smaller than the AIC FGGWR model with a difference of 14.195166 in 2016. In 2017 the AIC value of the FGGWR model was -57.283359, and the ABGWR model is -69.597075; the difference is 12.313716. In 2018 the AIC value of the FGGWR model is 57.215168, and the ABGWR model is -70.514806; the difference is 13.299638. In 2019 the AIC value of the FGGWR model was -58.715882, and the ABGWR model is -72.174964; the difference is 13.459082. In 2020 the AIC value of the FGGWR model was -58.046105, and the ABGWR model is -71.528410; the difference is 13.482305. The difference in coefficients between the GWR models illustrates that using various distance values (ABGWR) is better than using fixed distance between objects (FGGWR).

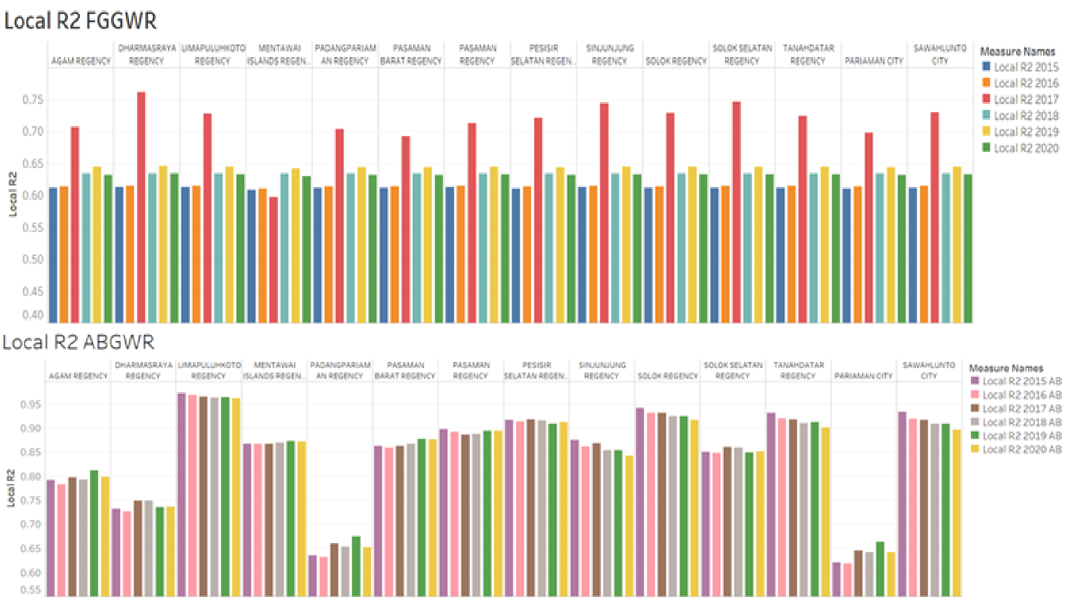


Figure 3. Coefficient Determinant R2 (a) Model Fixed kernel Gaussian, (b) Model Adaptive kernel Bi-square

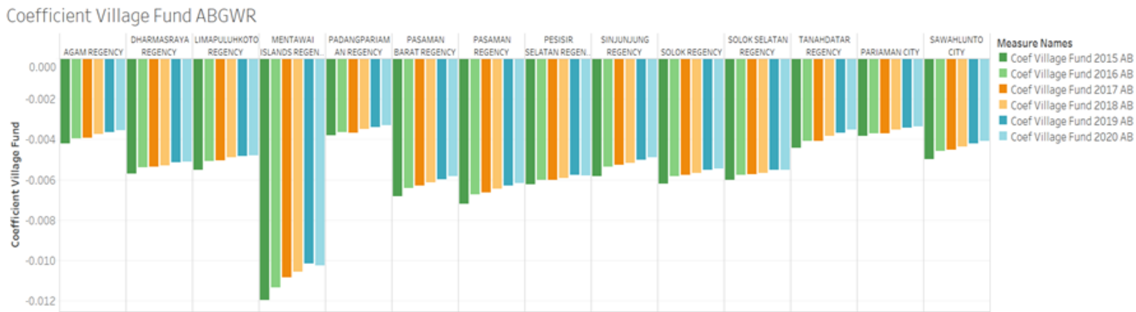
The GWR model uses spatial weighting by considering the spatial diversity in the regression model of each variable. The weights in the GWR model have different bandwidths so that they produce different models (Table 2). It can be seen from the AIC value, the minimum error prediction value (RMSPE) and the determinant coefficient (R2). The fixed kernel Gaussian model (FGGWR) has an AIC value of -53.166697 and an adaptive bi-square (ABGWR) model of -68.397009, and it shows that the AIC value of the FGGWR model is smaller than the ABGWR model with a difference of 15.230312 in 2015. The AIC value of the FGGWR model of -54.269731 and the ABGWR model of -68.464897 shows that the AIC ABGWR value is smaller FGGWR model with a difference of 14.195166 in 2016. In 2017 the AIC value of the FGGWR model was -57.283359, and the ABGWR model is -69.597075; the difference is 12.313716. In 2018 the AIC value of the FGGWR model is 57.215168, and the ABGWR model is -70.514806; the difference is 13.299638. In 2019 the AIC value of the FGGWR model was -58.715882, and the ABGWR model is -72.174964; the difference is 13.459082. In 2020 the AIC value of the FGGWR model was -58.046105, and the ABGWR model is -71.528410; the difference is 13.482305.

The value of the determinant coefficient (R2) is relatively the same in every city district because the fixed kernel Gaussian (FGGWR) model has the same bandwidth value for each observation location. The adaptive kernel bi-square (ABGWR) model has various coefficients of determinants (R2). The diversity of R2 values is due to the adaptive kernel bi-square model having different bandwidth values for each observation location.

Figure 4 shows the spatial diversity of the effectiveness of the Village Fund in reducing poverty in urban districts based on the variable coefficient of the Village Fund. The fixed kernel Gaussian model (Figure 4.a) has a Village Fund coefficient between -0.005 to -0.006. A negative value indicates an effect of the Village Fund in reducing poverty in districts/cities, but the effect is minimal. The Village Fund has a <1% effect on reducing the population in West Sumatra Province.

Figure 4.b shows the spatial diversity of the effectiveness of the Village Fund for reducing poverty based on the adaptive kernel bi-square model. The coefficient value of the Village Fund ranges from -0.003 to -0.012. Using the adaptive kernel bi-square model shows that the diversity of the effectiveness of the Village Fund is higher than the Gaussian fixed kernel model. The Village Fund in Agam Regency has no significant effect in reducing the number of poor people. Figure 4.b and Figure 5.a shows the minimal effect of the Village Fund to reduce poverty with a value of < 0.004. The coefficient value of the Village Fund has decreased from year to year; in 2015, the coefficient value of the Village Fund was -0.004195, in 2016 -0.003970, in 2018 -0.003733, in 2019 -0.003662 and 2020 -0003566. Figure 5.a shows that the number of poor people in Agam Regency continues to increase every year; this illustrates that the Village Fund has no significant effect in reducing poverty, although there is an increase in the allocation of the Village Fund.

(a)



(b)

Figure 4. Coefficient Village Fund (a) Model Fixed Kernel Gaussian, (b) Model Adaptive Kernel bi-square

The Village Fund in Dharmasraya Regency has no significant effect in reducing poverty. Figure 4.b and Figure 5.b show the minimal influence of the Village Fund with a value of < 0.006. The coefficient of the Village Fund in Dharmasraya Regency has decreased every year; in 2015, the coefficient value of the Village Fund was -0.005692, in 2016 -0.005388, in 2017 -0.005356, in 2018 -0.005290, in 2019 -0.005146, in 2020 -0.005103. Figure 5.b shows that the increase in the allocation of Village Funds from year to year has not reduced poor people. However, the Village Fund is influential in reducing poverty in 2020 due to a decrease in poor people from 71.520 people in 2019 to 71.510 people.

The Village Fund in Limapuluh Koto Regency is ineffective in overcoming poverty (Figure 4.b and Figure 5.c). The coefficient value of the Village Fund has decreased from year to year. For example, in 2015, the coefficient value of the Village Fund was -0.005502; in 2016, it was -0.005088; in 2017, it was -0.005061; in 2018, it was -0.005891; in 2019, it was -0.004837, in 2020, it was -0.004810. Therefore, increasing the number of Village Fund allocations has not reduced the number of poor people; a decrease in the number of poor people occurred in 2020 from 69,670 people in 2019 to 69,470 people.

The Village Fund in the Mentawai Islands Regency has the highest coefficient value in 2015 of -0.011962. The coefficient value of the Village Fund in the Mentawai Islands Regency is higher than other regencies/cities because it has a smaller number of poor people. Figure 4.b shows that the value of the Village Fund coefficient has decreased from year to year. In 2016, the coefficient value of the Village Fund was -0.011360; in 2017, it was -0.010833; in 2018, it was -0.010564; in 2019, it was -0.010149, and there was an increase in 2020 to -0.010269. Increasing the number of Village Fund allocations has not been able to reduce the number of poor people. Figure 5.d shows the increase in the number of poor people from year to year. The number of poor people in the Mentawai Islands Regency has decreased from 2019 - 2020 from 61,260 people to 61,090 people.

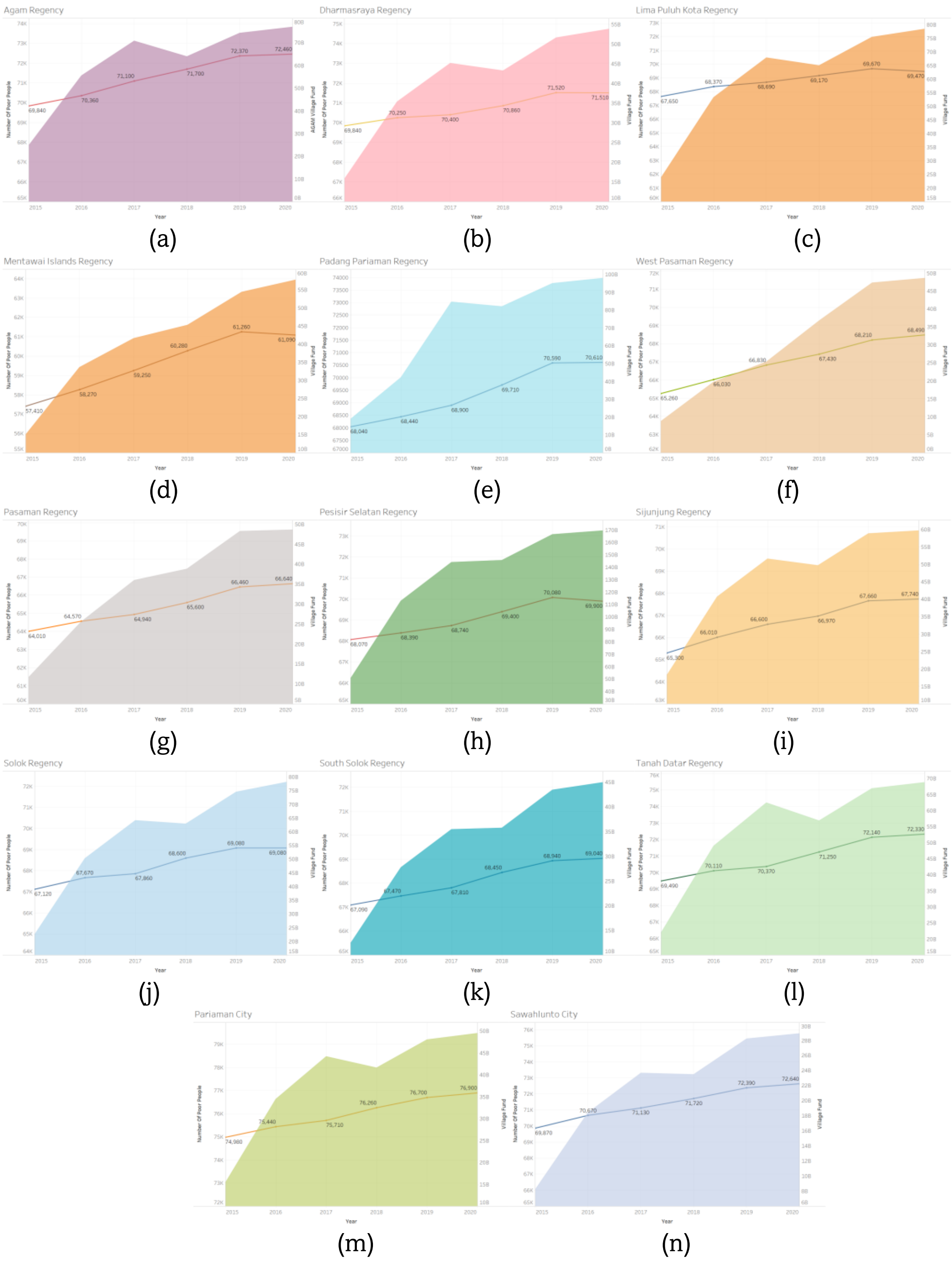


Figure. 5 Poverty vs Village Fund (a) Agam Regency, (b) Dharmasraya Regency, (c) Limapuluh Koto Regency, (d) Mentawai Islands Regency, (e) Padang Pariaman Regency, (f) West Pasaman Regency, (g) Pasaman Regency (h) Pesisir Selatan Regency, (i) Sijunjung Regency, (j) Solok Regency, (k) South Solok Regency, (l) Tanah Datar Regency, (m) Pariaman City, (n) Sawahlunto City

The Village Fund in Padang Pariaman Regency is not effective in reducing poverty. Figure 4.b shows the coefficient value of the Village Fund, which has decreased from year to year. In 2015, the value of the Village Fund coefficient was -0.003790; in 2016, it was -0.003657; in 2017, it was -0.003676; in 2018, it was -0.003476, in 2019, it was -0.003383, and in 2020 it was -0.003290. Figure 5.e shows an increase in the number of poor people, an increase in the number of Village Fund allocations each year has not reduced poverty in Padang Pariaman Regency.

The Village Fund in West Pasaman Regency is not effective in reducing poverty. Figure 4.b shows the decreasing value of the Village Fund coefficient from year to year. In 2015, the coefficient value of the Village Fund was -0.006810; in 2016, it was -0.006406; in 2017, it was -0.0063029; in 2018, it was -0.006135; in 2019, it was -0.005981, and in 2020 it was -0.005814. Figure 5.f shows the increase in the number of poor people from 65,260 people in 2015 to 68,490 in 2020. The increase in the number of Village Fund allocations has not reduced the number of poor people in the West Pasaman Regency.

The Village Fund in Pasaman Regency is not effective in reducing poverty. Figure 4.b shows the decreasing value of the Village Fund coefficient from year to year. In 2015, the coefficient value of the Village Fund was -0.007190; in 2016, it was -0.006724; in 2017, it was -0.006641; in 2018, it was -0.006647, in 2019, it was -0.006164, and in 2020 it was -0.006164. Figure 5.g shows an increase in the number of poor people from 64,010 people in 2015 to 66,640 people in 2020. The increase in the number of Village Fund allocations has not reduced the number of poor people in the Pasaman Regency.

The Village Fund in Pesisir Selatan Regency is not effective in reducing poverty. Figure 4.b shows the coefficient value of the Village Fund from year to year. In 2015, the coefficient value of the Village Fund was -.006228; in 2016, it was -0.006030; in 2017, it was -0.006013; in 2018, it was -0.005927, in 2019, it was -0.005774, and in 2020 it was -0.005810. The coefficient value of the Village Fund has increased from 2015 to 2016 by 0.000198 and from 2019 to 2020 by 0.000036. Figure 5.h shows an increase in the number of poor people from 68,070 people in 2015 to 70,080 in 2019. In 2020 the number of poor people was 69,900 people. There was a decrease in the number of poor people by 180 people in 2020. Pesisir Selatan Regency was the recipient of Village Funds, with the largest value reaching 169.4 billion in 2020. Compared to the amount of Village Funds received, it was not comparable to the decrease in poor people, which was only 0.26%.

The Village Fund in Sijunjung Regency is not effective in reducing poverty. Figure 4.b shows the decreasing value of the Village Fund coefficient from year to year. In 2015, the coefficient value of the Village Fund was -0.005838; in 2016, it was -0.005366; in 2017, it was -0.005255; in 2018, it was -0.005163; in 2019, it was -0.005011, and in 2020 it was -0.004906. Figure 5.i shows an increase in the number of poor people from 63,300 people in 2015 to 67,740 people in 2020. The increase in the number of Village Fund allocations has not reduced the number of poor people in the Sijunjung Regency.

The Village Fund in Solok Regency is not effective in reducing poverty. Figure 4.b shows the decreasing value of the Village Fund coefficient from year to year. In 2015, the coefficient value of the Village Fund was -0.006189; in 2016, it was -0.005820; in 2017, it was -0.005774; in 2018, it was -0.005675, in 2019, it was -0.005523, and in 2020 it was -0.005460. Figure 5.j shows an increase in the number of poor people from 67,120 people in 2015 to 69,080 people in 2020. The increase in the annual allocation of the Village Fund has not reduced the number of poor people in Solok Regency.

The Village Fund in South Solok Regency is not effective in reducing poverty. Figure 4.b shows the decreasing value of the Village Fund coefficient from year to year. In 2015, the coefficient value of the Village Fund was -0.006005; in 2016, it was -0.005753; in 2017, it was -0.005730; in 2018, it was -0.005637, in 2019, it was -0.005508, and in 2020 it was -0.005502. Figure 5.k shows an increase in the number of poor people from 67,090 people in 2015 to 69,040 people in 2020. The increase in the number of Village Fund allocations has not reduced the number of poor people in the South Solok Regency.

The Village Fund in the Tanah Datar district is not effective in reducing poverty. Figure 4.b shows the decreasing value of the Village Fund coefficient from year to year. In 2015, the coefficient value of the Village Fund was -0.004431; in 2016, it was -0.004081; in 2017, it was -0.004092; in 2018, it was -0.003824; in 2019, it was -0.003518, and in 2020 it was -0.003825. There was an increase in the coefficient value of the Village Fund from 2019 to 2020 of 0.000307. Figure 5.l shows an increase in the number of poor people from 69,490 people in 2015 to 72,330 people in 2020. The increase in the number of Village Fund allocations has not reduced the number of poor people in Tanah Datar Regency.

The Village Fund in Kota Pariaman is not effective in reducing poverty. Figure 4.b shows the decreasing value of the Village Fund coefficient from year to year. For example, in 2015, the coefficient value of the Village Fund was -0.003825; in 2016, it was -0.003697; in 2017 -0.003711; in 2018, it was -0.003533; in 2019, it was -0.003439, in 2020, it was -0.003353. Figure 5.m shows the increase in the number of poor people from 74,940 people in 2015 to 76,900 people in 2020. The Kota Pariaman Village Fund coefficient has the lowest value among other regencies/cities because Kota Pariaman's poor population has the highest number. Therefore, increasing the number of Village Fund allocations each year has not reduced the number of poor people in Pariaman City.

The Village Fund in Kota Sawahlunto is not effective in reducing poverty. Figure 4.b shows the decreasing value of the Village Fund coefficient from year to year. For example, in 2015, the coefficient value of the Village Fund was -0.004999; in 2016, it was -0.004587; in 2017, it was -0.004531; in 2018, it was -0.004373; in 2019, it was -0.004222, in 2020, it was -0.004090. Figure 5.n shows an increase in the number of poor people from 69,870 in 2015 to 72,640 in 2020. Therefore, the increase in the number of Village Fund allocations has not reduced the number of poor people in Sawahlunto City.

One of the Village Fund Program objectives is to overcome poverty and reduce inequality (Law No. 6/2014). However, the Village Fund in West Sumatra Province is not effective in reducing poverty. The observations show that the low level of effectiveness is due to the allocation of more than 30% of the Village Fund used for the village government's operational administration. The utilization of the Village Fund is not following the mandate contained in the law, which states that only 30% of the Village Fund is used for village government operations, and 70% is used for community empowerment. Instead, many villages in West Sumatra Province utilize up to 70% of the village fund's village administration operations. The use of Village Funds that are not following the law is due to a lack of understanding of village officials (Muhaimin, 2020) and low community understanding (Solichin & Akmal, 2018; Matridi *et al.*, 2015).

To increase the effectiveness of the Village Fund in the Provinces of West Sumatra and Indonesia in general, based on observations at the research location, the role of village experts and facilitators is crucial. The role of village experts and assistants needs special attention so that the use of village funds is effective and on target to provide technical assistance *(Watts et al.*, 2019). The Village Fund Program is inefficient to reduce poverty because the village-built business units (BUMDes) have not opened up job opportunities for rural communities *(*Arifin *et al.*, 2020), and the business fields built are not following the village's potential (Muhaimin, 2020). Based on (Solichin & Akmal, 2018) research, the community does not understand the use of the Village Fund due to the lack of information and transparency of the village government regarding the number of funds for infrastructure development. Socialization by providing clear information greatly affects the success rate of assistance programs for the poor (Solichin & Akmal, 2018; Amelia, 2019).

Learn from the experiences of several countries about the success of assistance programs for the poor and rural communities in Germany and the UK. Research conducted on several aid programs for the community to be efficient, the program must have integrity, orderly administration, community involvement in the planning process and data utilization, right on target (Zabel & Kwon, 2021; Alexiou *et al.*, 2020), the allocation of funds must be based on need (Reed *et al.*, 2020).

CONCLUSIONS

This study wants to see the efficiency of the Village Fund in reducing poverty in the Province of West Sumatra in 2015-2020. However, only 14 of the 19 regencies/cities in West Sumatra Province received assistance. Regions that do not receive Village Funds because the five cities are large cities that have been independent so do not need Village Fund allocations.

The results showed that the Village Funds distributed were not effective in reducing poverty in the Province of West Sumatra. The allocation of Village Funds distributed has increased every year but has not reduced poor people. The number of poor people in districts/cities has increased from 2015 to 2020. Factors that cause Village Funds to be inefficient in reducing poverty in districts/cities are a greater allocation of Village Funds for village government operations, greater than 30%, some areas reaching 70% utilization for village government operations.

Based on observations, to increase the effectiveness of the Village Fund in reducing poverty in West Sumatra Province is to improve the quality and quantity of village experts and assistants. The role of village experts and assistants needs special attention so that the use of Village Funds is effective and on target to provide technical assistance (Watts *et al.*, 2019). Another factor that needs to be done to increase the effectiveness of the Village Fund to reduce poverty is the fact of integrity between the government and village heads regarding improving development performance and village empowerment, and clean governance (Muhaimin, 2020).

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