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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.

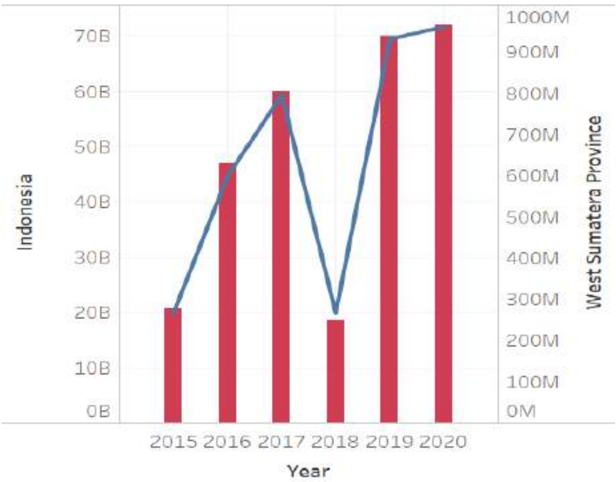



**Figure 1. Village Fund Allocation Indonesia and Province West Sumatera**

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*

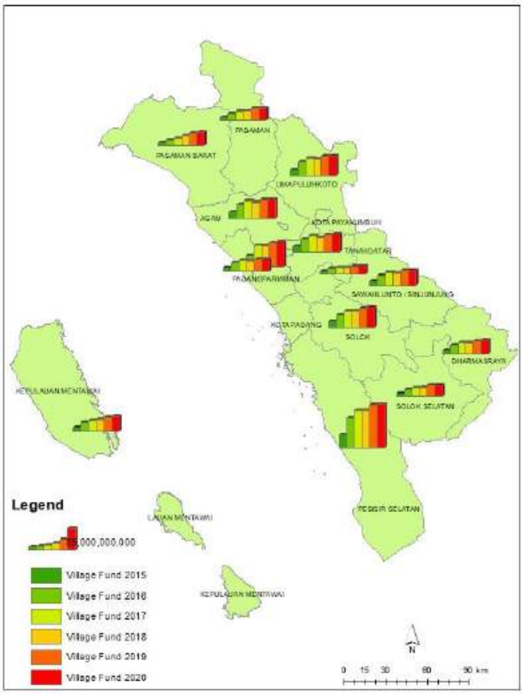



**Figure 2. Village Fund Allocation Each Region 2015-2020**

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:

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

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 |
| $\delta_i$ | = | i-observation error which is assumed to be identical, independent, and normally distributed with zero mean and constant variance $\sigma^2$ |

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:

$$\varepsilon^T W(u_i, v_i)\varepsilon = y^T W(u_i, v_i)y - 2\beta^T(u_i, v_i)X^T W(u_i, v_i)y + \beta^T(u_i, v_i)X^T W(u_i, v_i)X\beta(u_i, v_i) \quad (2)$$

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 $\beta^T (ui, vi)$ 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:

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

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

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:

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

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.

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

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).

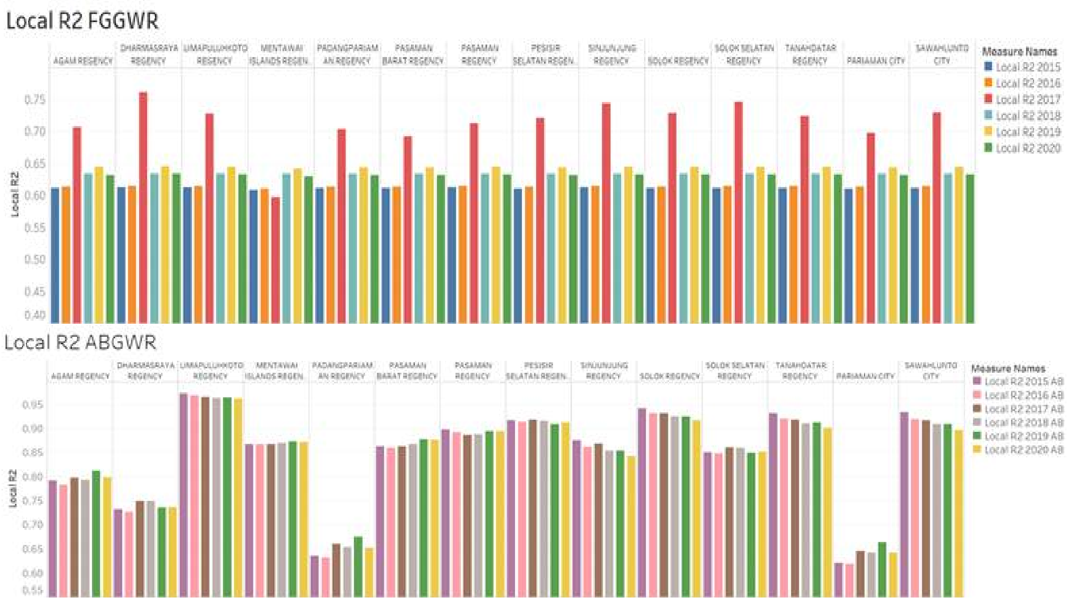


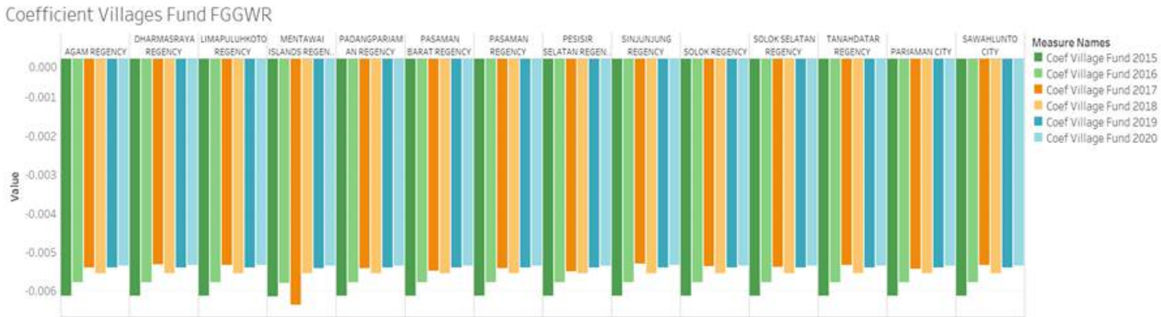

**Figure 3. Coefficient Determinant R2 (a) Model Fixed kernel Gaussian, (b) Model Adaptive kernel Bi-square**

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.

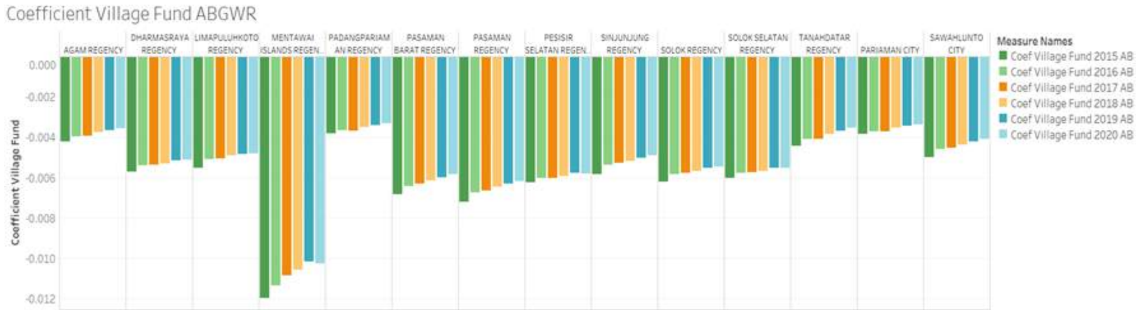
The value of the determinant coefficient (R2) is relatively the same in every city district because the fixed kernel Gaussian (FGGWR) model has the same bandwidth value for each observation location. The adaptive kernel bi-square (ABGWR) model has various coefficients of determinants (R2). The diversity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

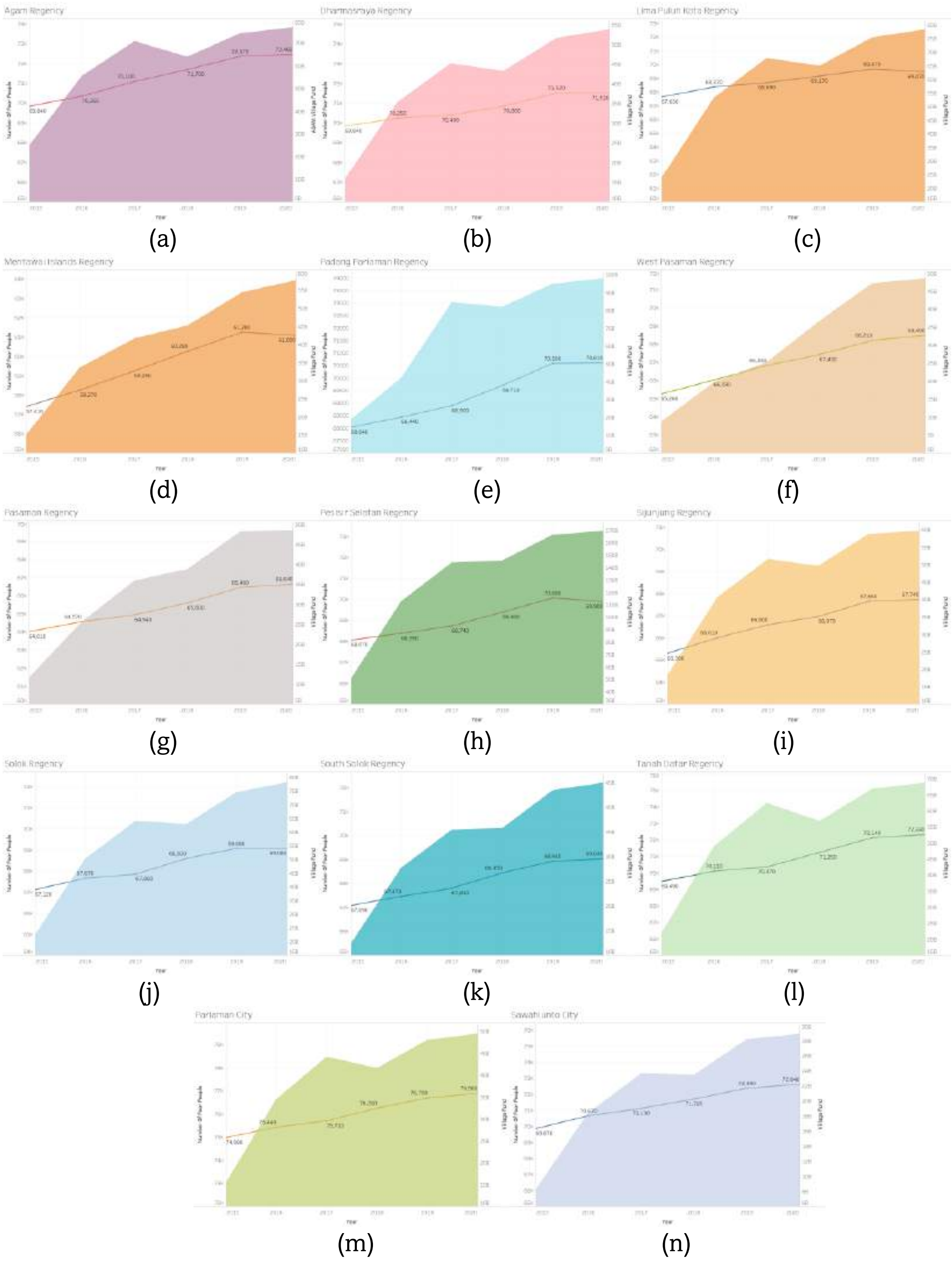



**Figure. 5 Poverty vs Village Fund (a) Agam Regency, (b) Dharmasraya Regency, (c) Limapuluh Koto Regency, (d) Mentawai Islands Regency, (e) Padang Pariaman Regency, (f) West Pasaman Regency, (g) Pasaman Regency (h) Pesisir Selatan Regency, (i) Sijunjung Regency, (j) Solok Regency, (k) South Solok Regency, (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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# Spatiotemporal Distribution Pattern and Spatial Clustering of Landslide-and Flood-Prone Areas in Metropolitan Palapa, Indonesia

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## ABSTRACT

The rapid development of urban areas is one of the driving factors for hazard exposure which causes vulnerability and environmental degradation. Environmental degradation causes vulnerability to disasters which will have implications for a decrease in economic benefits and an increase in community poverty. Landslides and floods are frequent natural disasters that cause environmental degradation. To reduce the risk of landslides and floods and formulate development policies and strategies in disaster-prone areas is necessary to identify landslides and flood areas. This study aims to identify and detect areas prone to landslides and floods in Metropolitan Palapa using GIS analysis and Moran's Local Index based on LISA statistics. The analysis results show that the northern to northeastern areas of Metropolitan Palapa (Pariaman regency and Pariaman municipal) are areas with high vulnerability to landslides, with high positive spatial associations of landslide occurrence and intensity. The area has an altitude between 350 to >1100 above sea level and a slope between 15 to >45%. Meanwhile, Padang and Pariaman municipal are areas that are vulnerable to flood hazards, and this is because these areas are lowlands/coastal areas. We can implement strategies and policies for the Palapa Metropolitan area, including a) limiting development in the northern region, b) applying engineering to areas prone to landslides by applying cut and fill techniques, c) improvement of drainage systems in areas prone to flooding; d) increase public awareness to care and provide incentives to people who care about the environment. Appropriate strategies and policies will reduce environmental degradation. We required disaster-based development planning to reduce environmental degradation, but the data is often an obstacle.

## 1. INTRODUCTION

Rapid development in urban areas is one of the factors causing damage and environmental degradation. Urban economic development is one of the engines of danger worldwide that causes urban vulnerability [1, 2]. Vulnerability will occur because urban areas are the centre of complex economic, socio-cultural, political, institutional and environmental interactions.

Urban environmental degradation occurs due to industrial growth, increased energy consumption [3], economic growth [4], population growth and utilisation of natural resources that cause a decrease in environmental quality [5, 6]. Environmental degradation causes vulnerability to disasters [7]. Ecological degradation has implications for reducing economic benefits [8] and increasing poverty, especially in developing countries [9]. Urban environmental problems are a threat to people's welfare and hinder the realisation of sustainable development [10].

Metropolitan Palapa is a strategic economic area with three administrative regions: Padang Pariaman regency, Padang municipal and Pariaman municipal. The Palapa Metropolitan administrative area consists of 32 sub-districts and 235 urban villages/nagari with the potential to be developed for trade and services, industry and tourism. A strategic area is an economic area with the potential to have a significant dual effect across sectors, regions and actors [11]. Strategic economic areas are prioritised for development [12] and have characteristics that distinguish them from the other regions [13].

The urban area in Metropolitan Palapa has developed mainly by converting land use from agricultural land to urban use, especially in urban areas. Metropolitan Palapa will continue developing with various activities as a functional area. The diversity of development activities and economic interests impacts the decline in the environment's carrying capacity [1, 14].

According to the National Disaster Management Agency (BNPB), for the past ten years (2011-2021), floods and landslides have been disasters that have frequently occurred in Indonesia. Landslides and floods represent 47% to 67% of the total disasters. The average incidence of floods reaches 30%, and landslides are 25% of the total disasters. Data for 2022 shows that the incidence of floods and landslides in Indonesia from January to August is 39% for floods and 18% for landslides.

A landslide is the movement of masses of rock, debris or soil down a slope due to the influence of gravity [15, 16]. According to Cruden and Varnes [16], the trigger for landslides is external stimuli such as high rainfall, earthquakes, changes in water levels, storms, or river erosion which causes a decrease in the strength of the slope-forming material. In addition, other factors that trigger landslides are increased human activity, population increase, urbanisation, and development in areas with high soil vulnerability.

Floods are natural disasters when overflowing rivers, lakes, and oceans inundate land caused by high rainfall. A flood is an overflow of water that submerges land and is a catastrophe for life and property that affects the environment around the world [17]. Flood is a natural disaster that is quite dangerous because it causes negative moral and material consequences [18] for human health and life, the environment, cultural heritage, economic activity and infrastructure [19, 20].

Heavy rainfall causes rivers and seas to overflow and can occur at any time of the year. Climate change will also cause sea level rise and increase the danger of flooding, especially in coastal areas [21]. Population growth and improvement of the built environment also significantly increase the risk of flooding. Apart from that, other things that can increase the risk of flooding are the shape of the land, elevation, land cover, population density and accessibility [22].

Rapid development and increasing environmental damage will cause disasters like landslides and floods. These natural disasters will become an essential issue in sustainable urban ecological management. As a result, it is necessary to identify locations prone to landslides and floods to plan appropriate disaster prevention [21-23]. This study aims to identify the spatiotemporal distribution pattern and spatial clustering of areas prone to landslides and floods in Metropolitan Palapa using Moran's Index based on Local Indicators of Spatial Association (LISA) statistics.

Mapping disaster-prone areas will assist local governments in reducing environmental degradation by making policies and strategies [24]. Among the strategies and policies that we can be implemented are establishing cooperation with areas around disaster-prone areas [10], increasing community innovation in reducing environmental degradation [25], strengthening natural resource management strategies, increasing literacy communities, and increasing community involvement [26], maintaining the presence of woody vegetation and grasslands [27].

## 2. METHODOLOGY

### 2.1 Study areas

The Study Area is located in the Palapa Metropolitan Area of West Sumatra Province, Indonesia, which consists of three regencies/cities (Figure 1). The height of the Palapa Metropolitan area varies from 0-1,650 meters above sea level. Most of the area is at an altitude of 0-200 meters above sea level (Figure 2). The land use of most of the Palapa Metropolitan area is agricultural land, with a population of between 303-34,825 people in 2021, with rainfall ranging from 228,000-398,000 millimetres per year.

The Palapa metropolitan area, which consists of three regency/municipal, 32 sub-districts and 235 urban villages and nagari, had a population of 1,437,354 people in 2021 (Figure 2a). Nagari is the division of administrative areas after sub-districts in the province of West Sumatra. The highest population is in Kuranji urban village, Padang municipal, at 34,825 people, and the area with the lowest population is in Pasir Sanur, Pariaman municipal, at 303 people. The land use of most of the Palapa Metropolitan area is agricultural land consisting of dry land agriculture and rice fields, followed by forest consisting of primary dry land forest and secondary dry land forest (Figure 2b). The slope of the Palapa Metropolitan area varies from 0 to>45%. Areas with a slope of 0 – 15% are in the coastal area, and areas with a slope of 25 to greater than 45% are in the northeast and southeast (Figure 2c). The area's altitude varies widely between 0 – 1392 above sea level (Figure 2d). Annual rainfall in the Palapa Metropolitan area is relatively high. Areas with very high rain are north and northeast (Figure 2e).


**Figure 1.** Palapa Metropolitan Location Map

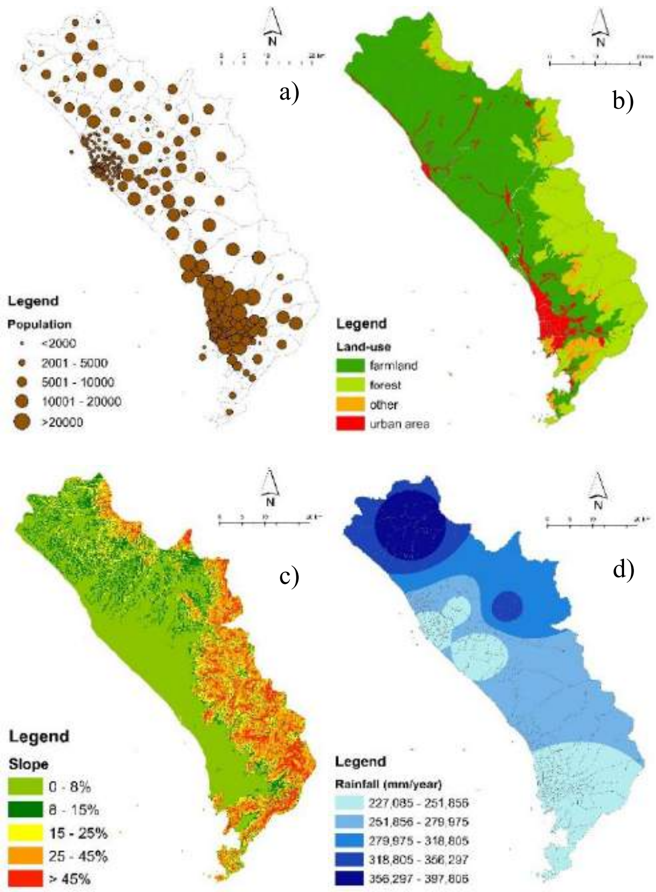



**Figure 2.** Metropolitan Palapa thematic map a) population, b) land use, c) slope, d) elevation, e) rainfall

### 2.2 Data and method

The data is on the number of landslides and floods in each village. Data were obtained from PODES (Village Potential Statistics) from 2011 to 2018 and data from the Central Bureau of Statistics (BPS) for 2021. We made the map for the distribution of landslides and floods based on the number of landslides and floods in 2011, 2015, 2017, and 2021. The unit of analysis in this study is the village level.

We used GIS analysis and Moran's Local Index based on LISA statistics to see the spatiotemporal distribution pattern and identify the spatial clustering of landslide and flood-prone areas. Local Moran Index analysis based on LISA statistics using Geographic Data Analysis (Geoda) software

The approach used in Moran's Index is a spatial autocorrelation approach [28, 29]. A positive autocorrelation will indicate that adjacent locations have similar values and tend to cluster. Negative autocorrelation indicates that adjacent areas have different values and tend to spread. The Moran Index (global index) clustering method will provide a single statistic that summarises the spatial pattern of the research area. Moran's index is used to determine whether there is a spatial relationship in an event [30-32].

The local clustering technique is carried out by examining a particular sub-region or environment in the study to determine whether the area represents a group of high values (hot spots) or low values (cold spots) [33], using the Local Indicator of Spatial Autocorrelation (LISA) [34].

This study uses the local Moran Index approach, a local spatial autocorrelation measurement based on Moran's I developed by Anselin [35] as LISA statistics [36]. LISA statistics have two characteristics: 1) each observation indicates the extent to which the spatial clustering has a significant value, and 2) the number of LISA for all observations is proportional to the global indicator of spatial association. Global spatial association shows the presence or absence of a relationship in a single event. Local spatial associations indicate the location of local clusters and spatial outliers. We can identify spatial clusters of areas, landslides and floods using the Moran Index and LISA methods.

$$I = \frac{1}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_i - \overline{x})(x_j - \overline{x})}{{S_x}^2} \qquad i \neq j$$

where,

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}$$

$$Ii = \frac{\sum_{j=1}^{n} W_{ij} \, (x_i - \bar{x})(x_j - \bar{x})}{\sum_{j=1}^{n} W_{ij} \, {S_x}^2}$$

$$= (x_i - \bar{x}) \frac{\sum_{j=1}^{n} W_{ij} (x_j - \bar{x})}{\sum_{j=1}^{n} W_{ij} \, {S_x}^2}$$

$$= (x_i - \bar{x}) \sum_{j=1}^{n} \frac{W_{ij} (x_j - \bar{x})}{W_{ij} {S_x}^2}$$

where:

$I$ = Moran's Global Index
$ii$ = Moran's Local Index
$x_i$ = value of interest of variable x for point i
$x_j$ = value of interest of variable x for point j
$\bar{x}$ = average value of x
$W_{ij}$ = continuity matrix, representing the proximity of point i's and point j's locations, with Wii = 0 for all points
$n$ = total number of points
${S_x}^2$ = variance of the observed values

The data used in the analysis is the number of floods and landslides in 2011, 2015, 2017 and 2021. Analysis of Moran's Local Index will identify the spatial clustering of areas prone to landslides and floods. Spatial clustering of the flood-prone regions will appear if the spatial association (SA) is positive with high-high (HH) or low-low (LL) types and negative values (spatial outliers) with high-low (HL) or low-high types. (LH). A positive spatial association (SA) will appear if a high value is correlated with a high-value neighbour or a low value is correlated with a low-value neighbour.

Conversely, a negative spatial association (SA) will appear when a high value correlates with a low neighbour value or a low value correlates with a high-value neighbor [33, 35]. In this study, queen contiguity will be used as a spatial weighting method to detect the spatial association of landslides and floods in Metropolitan Palapa. Queen contiguity weighting is the touch of both sides and vertex points of one region to another [33].

## 3. RESULTS AND DISCUSSION

According to Law number 26 of 2007 concerning spatial planning, an area is a geographical unit and all related elements whose boundaries and systems are determined based on administrative and/or functional aspects. Based on typology and regional classification consisting of homogeneous areas, nodal areas, planning areas, metropolitan regions, development axes, frontier regions and depressed regions [37, 38]. We developed Metropolitan Palapa as a planning area into a metropolitan area. It is essential to look at the definition of the region, typology, and regional classification to see development strategies, policies and programs related to regional development [37, 39].

The geographical position of West Sumatra Province, especially the Palapa Metropolitan area, and community activities will lead to environmental degradation, creating vulnerability to disasters, especially landslides and floods. Areas with high exposure to disasters will hinder sustainable development goals [10]. The overexploitation of natural resources can also cause environmental degradation and vulnerability to landslides and floods. Results of research conducted by Shahbaz et al. [40] and Bai et al. [41] show that the inefficient use of energy resources harms environmental quality. The development of energy-efficient technologies at production and consumption levels will significantly help reduce environmental degradation and increase productivity in the long term. In addition, the cooperation of the banking sector is also needed to provide credit relief to the energy sector and allocate funding for environmentally friendly business activities.

Çakar et al. [27] researched the relationship between human resources to environmental degradation in the European Union. The results show that human resources can reduce carbon emission levels in low-growth activities but increase carbon emissions in high-growth activities. Reducing environmental degradation is necessary to improve human resources to innovate to protect the environment.

The results of previous studies show a two-way relationship between regional growth and the environment. The results show that the level of environmental degradation and economic growth has a U-shaped relationship known as the

Kuznets Curve in the long run [42, 40]. Development is associated with reduced environmental degradation to some extent. After this threshold, increased development will increase environmental degradation.

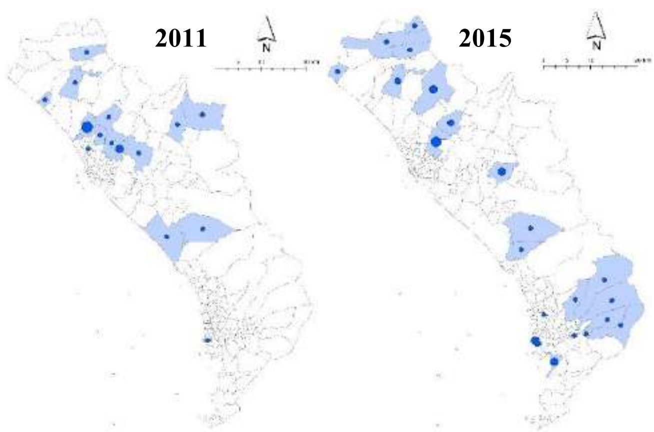
In this study, we observe the relationship between development and environmental degradation in the Palapa Metropolitan area. Landslides and floods were chosen as representatives of natural disaster hazards and are proxies for environmental degradation. The Palapa Metropolitan Area is a planning area that has been developed into a metropolitan area in West Sumatra Province. In preparing the development plan for the area, the government and the community should pay attention to reducing environmental degradation.

Regarding regional topography, the Palapa Metropolitan Area is at various altitudes and slopes, so the area is prone to landslides and floods. Population growth and rapid development are also the causes of degradation in the Palapa Metropolitan area. So it is essential to identify areas vulnerable to landslides and floods [22, 23]. Identification of landslide and flood areas will assist the government in making appropriate policies and strategies to reduce environmental degradation [42, 43].

### 3.1 Spatiotemporal distribution patterns of landslides and floods

Natural disasters are complex events and pose risks to landscape changes that cause harm to the environment, economic activities and public health [19, 44]. Landslides and floods are frequent natural disasters that cause significant losses to human life and livelihoods. Increased human activities and development further exacerbate the factors that cause landslides and floods. Landslides and floods will cause environmental degradation in the long term.

The making of landslide and flood maps needs to be done to see the extent of the landslide and flood phenomena in an area and to know the spatial distribution pattern of landslide and flood events. The landslide and flood map will be able to be developed to determine the landslide and flood zone areas and the vulnerability and risk of landslides and floods. Landslide and flood zone maps will be handy in spatial planning by local governments to formulate development policies and strategies.



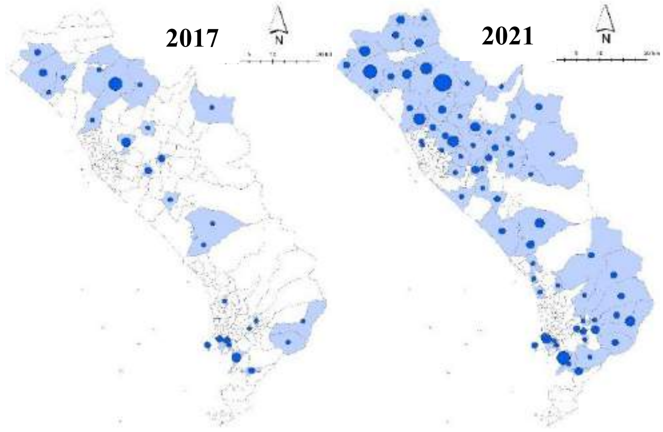




**Figure 3.** Distribution pattern of landslide in 2011, 2015, 2017 and 2021

Figure 3 shows the distribution pattern of landslides in Metropolitan Palapa in 2022, 2015, 2017 and 2021. The landslide disasters show that the number of urban villages/nagari and the area of landslides has increased and spread widely from 2011 to 2021. In 2021 most of the landslides occurred in the eastern part of the Palapa Metropolitan area. The eastern part of Metropolitan Palapa is a highland region. This area is an area with an altitude between 350 ->1100 above sea level (Figure 2d) and is on a slope of between 15 ->45% (Figure 2c), with rainfall between 227.085 to 397.806 millimetres/year (Figure 2e). The number of urban villages/nagari experiencing landslides has increased.

The complex morphology of the area causes landslides [45] at Metropolitan Palapa. The slope and altitude of the area are factors that cause landslides [46, 47]. The slope of the Palapa Metropolitan area ranges from 00 to >450, and the altitude is between 350 to >1100 masl. Areas with slopes above 150 and elevations>350 meters above sea level are in the northern to southeastern regions of Metropolitan Palapa. These areas are areas with high soil vulnerability, so landslides often occur.

The diverse topography of the Palapa Metropolitan area is exacerbated by high enough rainfall, causing landslides [48, 49]. The rain in the Palapa Metropolitan area ranges from 225,000 to >400,000 millimetres per year. The northern to eastern regions have high rainfall ranging from 320.00 to 400.000 millimetres per year. High rain will cause softening of strength and reduce slope stability, causing weakened soil cohesion [50]. Population and population density, as well as human activities, are also the causes of landslides [51]. The construction of the road network and the cutting of hilly areas are also the causes of landslides [48].

The landslide disaster in the Palapa Metropolitan area has caused a significant loss of property and life. Landslides have buried many people's houses and cut off road access. As has happened in the Sungai Sirah Kuranji Hulu urban village, Sungai Geringging sub-district, Padang Pariaman Regency, which has isolated 78 heads of families because of the material blocking the road as high as 2 meters. The landslide in Nagari Pasie Laweh, Lubuk Alung sub-district, Padang Pariaman Regency, also claimed seven lives. Losses reduce landslides; it is necessary to zone landslide-prone areas and evaluate landslide hazards [52]. The zoning of the landslide-prone regions can practically be applied to regional and infrastructure development planning in the Palapa Metropolitan area.

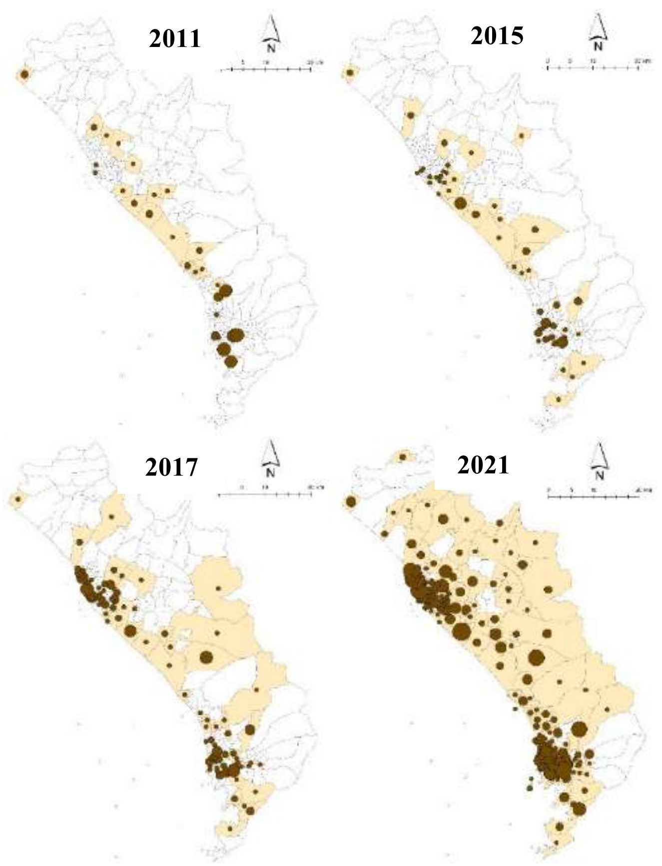



**Figure 4.** Distribution pattern of flood in 2011, 2015, 2017 and 2021

Figure 4 shows the distribution pattern of flooding in Metropolitan Palapa in 2011, 2015, 2017 and 2021. Flood disasters also show that the number of villages and areas affected by floods has increased from 2011 to 2021. Flood areas in 2011 and 2015 generally occurred in plain areas low in 2017 and 2021, spreading to the highlands. Flood events have increased; in 2011, the flooded areas were 29 urban villages/nagari increasing to 52 urban villages/nagari in 2015, rising to 94 urban villages/nagari in 2017, and becoming 196 urban villages/nagari in 2021.

The floods in the Palapa Metropolitan area caused losses to property and lives. Floods and landslides in October 2021 in Padang resulted in 8 sub-districts being affected, with water levels reaching 150 cm. The floods submerged 350 houses, 418 residents were evacuated, and two road points were affected by landslide materials. Floods in the Koto Tangah sub-district, Padang municipal, resulted in 1 person's death and two people being declared missing. Floods in Banda Gadang and Gurun Laweh urban villages, Nanggalo sub-district, Padang municipal, with a height of 200 cm. The flood that hit the Sungai Limau sub-district damaged the Belimbing River Dam. In September 2021, floods and landslides killed four people in Padang Pariaman Regency. Floods in Padang Pariaman Regency impact ten sub-districts with water levels between 75 to 200 cm. In addition to the fatalities damaged, 338 housing units, 80 hectares of agricultural land, one unit of public facilities, and one unit of educational facilities. Floods in Ulakan Tapakis sub-district, with water levels reaching 100 to 150 cm, damaged 70 houses and 17 hectares of rice fields.

Floods that occurred in the Palapa Metropolitan area were caused by high rainfall intensity. In addition to the intensity of rainfall, flooding can also be caused by land use and land cover [27], population growth and development activities [21], elevation and slope of the area, as well as drainage density [53]. The high intensity of rainfall and climate change are causing rivers to overflow and sea levels to rise, especially in coastal areas [54]. Parts of the southwest to northwest Palapa Metropolitan area are low-lying coastal areas prone to flooding [22]. Climate change causes the generation and distribution of storm waves, which has implications for the danger of flooding in coastal areas [21]. The human factor and lack of human concern for the environment further exacerbate flooding [55].

Floods are natural disasters that often occur in the Palapa Metropolitan area and the world, so it is necessary to identify and map flood-prone locations [56] to determine mitigation measures to prevent flood hazards [57]. Mapping flood-prone areas are needed to plan safety measures for both property and lives when a flood occurs. In addition, to carry out evacuation and planning shelter areas [22]. Mapping the flood area in the Palapa Metropolitan area will help the local government plan a development strategy and a strategy for building shelters.

The government can implement strategies to reduce the risk of flooding, including maintaining many perennials and grassland vegetation and providing early flood warnings [27]. It is no less important to increase public awareness of the environment. Local governments incentivise communities or groups of people who care about the environment [58].

### 3.2 Spatial clustering of areas prone to landslides and floods

The spatial clustering of areas prone to landslides and flooding in Metropolitan Palapa was carried out using the LISA method using the Local Moran Index. LISA statistical method, according to Asselin [35], serves two purposes. The first objective is to indicate the extent to which spatial areas have significant value as local indicators or hot spots. The second goal of LISA statistics is to see the effect of individual locations on global statistics and identify outliers. LISA statistics are handy for viewing spatial scrambling and identifying local hotspots. We used a randomisation approach to generate references for statistical significance values.

See the spatial clustering of the Palapa Metropolitan area as the number of landslides and floods in 2021 (Figure 5). The landslide and flood clustering maps resulting from the LISA analysis can be seen in Figures 6 and 7. Observations were made of 235 urban villages and nagari in Metropolitan Palapa.

The LISA clustering map is a map that identifies significant spatial relationships and their outliers. At the same time, the LISA significance map is a map of the significance level for each object that is interconnected with a p-value of 0.05, 0.01 and 0.001. An outlier is an area that has the opposite value to the surrounding area. The spatial relationship on the LISA clustering map consists of 1) not significant, which is an area that is not significant at the 0.05 standard quasi-significance level); 2) aloft hot spots are areas of high value surrounded by high and significant values; 3) low-low cold spots are areas that have low values surrounded by low and significant values; 4) low-high outliers are areas that have low values surrounded by high and significant values;

The results of LISA analysis using the Local Moran Index can be used to identify the spatial classification of landslides and floods in Metropolitan Palapa. Each index has a statistical test, so we can map areas with a statistically significant relationship with their neighbours and see the type of relationship.

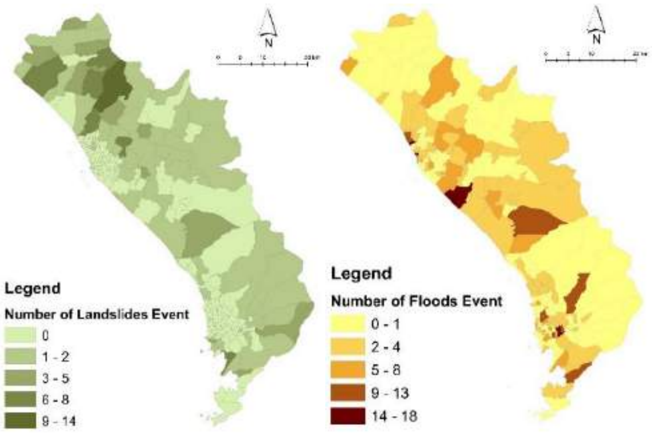



**Figure 5.** Spatial distribution of landslides and floods in 2021

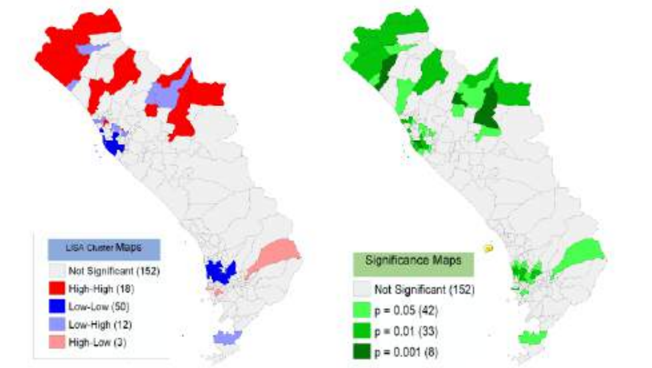



**Figure 6.** LISA cluster map and landslide significance map for 2021

Figure 5 shows the distribution of landslide and flood events in 2021 based on the number of flood events in each urban village and nagari. Figures 6 and 7 show the LISA clustering map and the landslide and flood significance map for 2021. The areas in red are hot spots representing the height-height group (HH); we can call it a positive spatial association of HH. That means that urban villages/nagari with a high incidence of landslides and floods are adjacent to areas with a high incidence of landslides and floods. The analysis results show that areas with a positive HH association with landslides are in the north and northeast of Metropolitan Palapa. Most of these areas are located in Padang Pariaman Regency and Pariaman municipal, significantly in 18 urban villages/nagari (Figure 6).

The areas in blue are cold spots representing the low-low (LL) group, and we can call it the LL positive spatial association. That means urban villages/nagari with a low incidence of landslides and floods are surrounded by areas with low incidence. The analysis results show that the landslide areas with positive spatial associations LL are located in the western and southern parts of Metropolitan Palapa (Pariaman municipal and Padang municipal) and are significant in 50 urban villages/nagari (Figure 6). Meanwhile, the positive association of LL in flood-prone areas from the west to the south of Metropolitan Palapa (Padang Pariaman regency, Pariaman municipal and Padang municipal) is significant in 9 urban villages/nagari.

Regions in purple are outliers representing the low-high (LH) group, which we call the LH negative association (Figure 7). Areas with negative associations (outliers) mean that the value representing the number of landslides and floods differs from the value representing the number of landslides and/or flooding from neighbouring areas. The negative association of LH means that areas surround areas with low landslide and flood events with high incidence. The analysis results show that the hostile association areas for landslides are in the north, northeast, southwest, the south of Metropolitan Palapa (Padang Pariaman regency, Pariaman municipal and Padang municipal) and are significant in 12 urban villages/nagari (Figure 6). Negative associations for flood LH are in the western and southern parts of Metropolitan Palapa (Pariaman municipal and Padang municipal) (Figure 7).

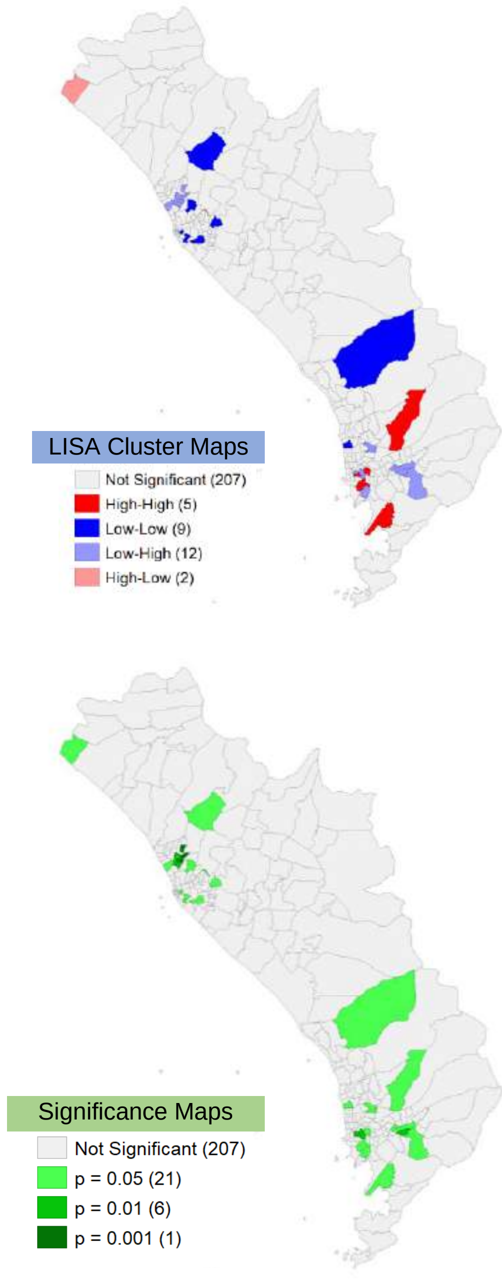



**Figure 7.** LISA cluster map and flood significance map for 2021

Regions in pink are outliers representing high-low (HL) clusters which we refer to as HL-negative associations. The negative association of HL means that an area surrounds an area with a high number of landslides and floods with a low incidence of landslides and flooding. The analysis results show that the negative association of LH landslides is in the southern part of Metropolitan Palapa (Padang municipal) and is significant in 3 urban villages (Figure 6). The negative association of flood HL was also found in the southern part of Metropolitan Palapa (Padang municipal) and was significant in 2 urban villages (Figure 7).

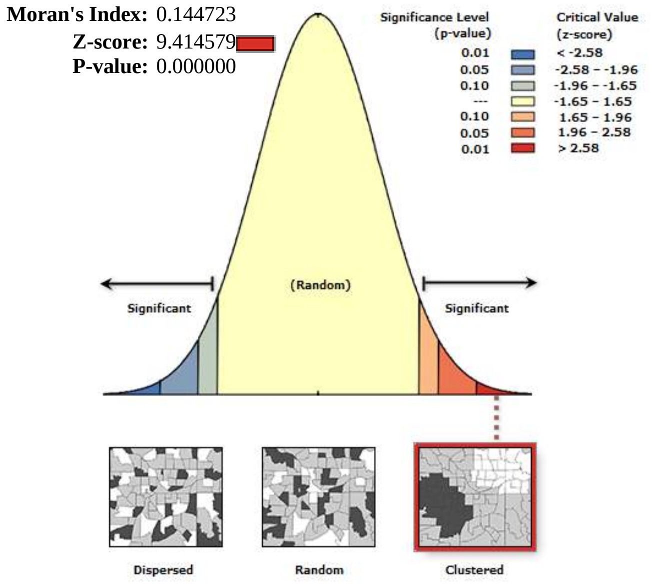



**Figure 8.** Spatial autocorrelation of landslide-prone areas

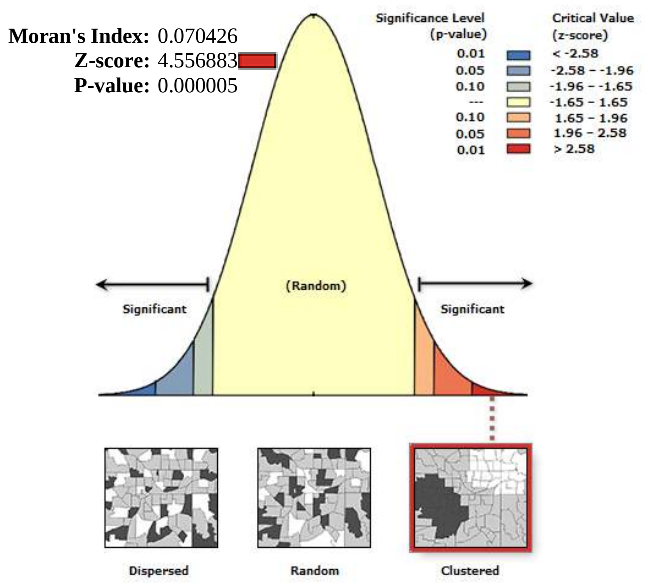



**Figure 9.** Spatial autocorrelation of flood-prone areas

Based on the significance map, we can see that the positive association of landslides was significant in 42 urban villages/nagari with a p-value of 0.05, significant in 33 urban villages /nagari with a p-value of 0.01, and significant in 8 urban villages/nagari with a p-value of 0.001 (Figure 6). Based on the significance map, we can see that there is a positive association of significant flood HH in 21 urban villages with a p-value of 0.05, significant in 6 urban villages with a p-value of 0.01, and significant in 1 urban village with a p-value of 0.001 (Figure 7).

In this study, apart from looking at the LISA statistics using the Local Moran Index, we can also look at the Global Moran Index to determine the spatial autocorrelation of landslide and flood-prone areas (Figures 8 and 9). Global Moran Index to see if the landslide and flood-prone areas are clustered, random or spread out.

Figures 8 and 9 show the spatial autocorrelation of landslide and flood-prone areas in Metropolitan Palapa. The spatial autocorrelation of the landslide-prone regions shows a Moran Index value of 0.1447 and a z-score of 9.4146, while for flood-prone areas, the Moran Index is 0.704 and a z-score of 4.5568. That means the spatial associations of landslide and flood-prone areas are clustered based on the number of landslides and floods. The existence of clustered landslide and flood-prone areas will make it easier for local governments to create development plans to realise sustainable development and establish strategies to reduce the risk of landslides and floods [10, 47] at Metropolitan Palapa.

The mapping of landslide-prone areas, which are generally located from north to southeast, will provide an overview of development planning in the area. We can implement policies and strategies to limit development in the north and southeast of Metropolitan Palapa. In addition, we propose applying technological engineering in developing the northern to southeastern areas of Metropolitan Palapa. For flood-prone areas grouped from the west to the southwest, the local government can make policies and strategies related to the drainage system.

## 4. CONCLUSIONS

The rapid development of the urban economy is one of the driving factors for hazard exposure worldwide, which causes vulnerability and environmental degradation [1]. Environmental degradation in an area causes disaster vulnerability, which will have implications for reducing economic benefits and increasing poverty. Landslides and floods are the most frequent natural disasters in Indonesia and throughout the world, which cause environmental degradation. The minimise the risks of floods and landslides, it is necessary to identify areas prone to landslides and floods. Maps of landslide and flood areas will significantly assist the government in implementing project policies and strategies to minimise hazard risks [24].

We identified local spatial associations of landslides and floods in Metropolitan Palapa using LISA statistics. The analysis results show that the area north to northeast of Metropolitan Palapa (Padang Pariaman regency and Pariaman municipal) is a high vulnerability to landslides, with a high positive spatial association of landslide occurrence and intensity. Meanwhile, Padang and Pariaman are areas that are vulnerable to flooding; this is because these areas are lowland/coastal areas. The LISA landslide and flood clustering map can be used as zoning for landslide and flood areas used for spatial planning in Metropolitan Palapa.

Strategies and policies are needed in integrated environmental planning and management to reduce the decline in social and economic benefits due to environmental degradation. Some of these things include: a) strengthening strategies for the use of natural resources that are effective and efficient; b) increasing community participation in environmental management [26]; c) increasing public awareness to care for the environment [55]; d) establishing inter-regional cooperation [10]; e) increasing community innovation [25]; f) strengthening environmental management institutions and implementing an integrated watershed approach for flood management [53]; g) maintaining the presence of woody vegetation and grasslands as well as disaster early warning [27]; h) provide incentives to communities and community groups concerned with the environment [58].

Strategies and policies we can be implemented for the Palapa Metropolitan area include: a) limiting development in the northern region; b) applying engineering to areas prone to landslides by applying cut and fill techniques; c) improvement of drainage systems in areas prone to flooding; d) increase public awareness to care and provide incentives to people who care about the environment.

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# Tipologi Wilayah dan Indeks Perkembangan Wilayah Kabupaten Dharmasraya

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**Abstract**

Kabupaten Dharmasraya sebagai salah satu beranda yang menjadi pintu masuk ke Provinsi Sumatera Barat memiliki pertumbuhan ekonomi yang cukup tinggi. Kabupaten Dharmasraya memiliki ragam potensi, karakteristik dan tipologi wilayah. Potensi yang dimiliki Kabupaten Dharmasraya menjadi daya tarik masyarakat Sumatera Barat maupun dari luar Sumatera Barat untuk menetap di wilayah tersebut. Keragaman karakteristik dan tipologi wilayah menyebabkan kebijakan dan strategi pengembangan wilayah juga beragam. Penelitian ini bertujuan untuk mengkarakterisasi formasi wilayah serta membuat Indeks Perkembangan Wilayah. Dalam mengkaji karakteristik wilayah berdasarkan aspek pembangunan yaitu kependudukan, sosial ekonomi,

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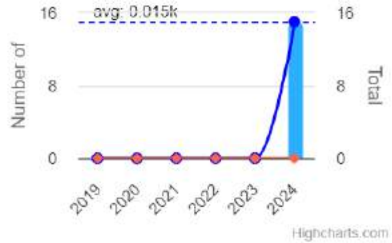


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