Explanatory on Rural Development Stages Using Geographically Weighted Regression based on The Integration of Socio-Economic, Demographical and Landcover Data

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Abstract. In the context of rural development, each rural area has unique characteristics in determining its development level. The monitoring on global land use–land cover (LULC), LULC change, the normalized difference vegetation index (NDVI), estimated data of crop yield and income, and demographical factors include total population and percentage growth rate during 2015 to 2020 have corresponded with the rural development stages (RDS). These parameters are used in the geographically weighted regression (GWR) has resulted that local regression gave the advantages on the perspective of how the rural areas can be managed and to what extent the environment variable can use to assist the RDS. This paper aimed to show the relationship between the RDS and through the analysis of socio-demographical, derived economic data and the trend of LULC change. The final result has shown that the rural areas located in the forested areas, have a remote location and rough topography tend to have the lowest local regression values compare by the range of R2 values at about 0 to 0.15. The GWR has shown that all explanatory variable has a weak positive correlation to the RDS, even though it shows the pattern of clustered in the entire of Way Sekampung.

INTRODUCTION

Historically, the government policies were highly successful at attracting foreign investment into several important sectors led to the rapid growth of Indonesia's manufacturing sector[1]. This policy influenced a declining share of agriculture in the total GDP at 23.2% and had fallen to 16.9% in 2000, while at the same time it still absorbed 45.1%of the Indonesian labour force[2]. Theoretically, there is no exact relationship between the economic growth on the change of the land use–land cover (LULC). But, qualitatively some studies explained it properly. For instance, at a country level, the economic development represented by gross domestic product (GDP) has grown moderately at about 5.9% to 11.5% during a decade has contributed to the change in vegetation cover. Besides that, The region with low GDP has a low degradation rate[3].

The vegetation cover is one of the major components in observing the LULC that is also used as the main factor on study a land degradation change[4]. In some cases. It is easy to explain vegetation cover by using a normalized difference vegetation index (NDVI). According to these values and it changes during a specific time, the trend on GDP can be explained[5]. The NDVI may be associated with agricultural activities which also relate to the farmers. The availability of agricultural land is very dynamic along with trends of conversion to the non-agricultural sector[6,7]. It caused the development of the agricultural sector in Indonesia to be lower compared to other sectors that contribute only 13.63% during 2014-2019. Related to agricultural GDP in Indonesia has increasing trend while agricultural contribution has a decreasing trend[8], besides other positive contributions such as yield production, reducing the poverty rate, and food sustainability index (FSI), but an exception in the agricultural employment that decreases in the decade[9].

The use of geospatial technology like remote sensing is not only limited to NDVI[10] but also there are so many approaches that can be done using the same technique for specific purposes in agricultural sectors[11,12]. Specifically to the rural development stages, a well documented has presented by Watmough et al.,[13] that focused on the socio-ecological factors for poverty prediction. Some related indicators to level wealth like local land use, agricultural productivity and family compound has fusion with a high resolution of satellite imagery. Furthermore, the study conducted by Varshney et al.,[14] have specifically shown the capability of the technology of remote sensing for addressing the poor villages by differentiating the roop type. In the context of rural development, each rural area can be classified into several groups based on the characteristics of population, environment, location and economic factors[15] and more sophisticated factors consist of rural settlement, land, industry and human settlement environment for evaluating the level of rural development can be considered to use[16]. According to Andari[17], the factors like the disparities, income per capita and poverty rate are related to RDI, Many studies tried to find the behaviour of using geospatial data to assess the economic sectors. Derived information on land surface temperature (LST) is often used for predicting people income has found in several studies that it has a significant relationship with people income[18–20]. Other studies found that climatic data such as rainfall also has a role in explaining the characteristic of income, human capital, and economic activity especially in developing countries[21–23], additionally Leroux et al. and Sruthi and Aslam proved that the NDVI may useful for predicting incomes[24].

In Indonesia, the method used for rural development assessment also named the rural development index (RDI), It is defined as an illustration of the level of village progress at a time in the region certain with a classification that is divided into three parts, namely under-developed, developing, and developed[25]. The RDI used five dimensions and forty-two indicators in basic services, infrastructure, transportation, public services, and local government. In 2018, according to the annual report provided by the Central Bureau of Statistics, there are 13.232, 54.879, and 5.559 rural areas grouped as under-developed, developing villages, and developed stages, respectively[26]. Since there are more than 70.000 rural areas divided in the form of administrative division, with more than 27,680,000 farmers[27], and each region has a unique landscape configuration that influences the richness of natural resources, so finally each rural should be decided the trends of its development. It can be varied according to the managing capability of the agricultural sectors which is supported by human quality, socio-demographical aspect and economic

This phenomenon is necessary to explain spatially, and a Geographically Weighted Regression (GWR) has chosen to describe in both statistical and spatial each factor in a point approach[28] that works based on locally linear regression[29] and developed to obtain an explanation for investigating non-stationary relations in regression analysis and of spatially varying relationships[30–32]. A study conducted by Koh et al.,[33] showed the capability of GWR to express the relationship between the NO3–N concentration and various parameters (topography, hydrology and land use) may be a great example. It is similar to the initiative in understanding the pattern on how the land use and land cover change contribute to the state of rural area development stages, along with this to what extent the population dynamic can be influenced by those changes. Other studies that utilize the same method for analyzing chemical characteristics in the river are focusing on chemical oxygen demand (COD) and biological oxygen demand (BOD)[34] and also study for malnutrition in toddlers[35].This study aimed to explain those situations based on the trends on the LULC changed, that followed by similar changes in both socio-demographical factors that represented by the number of agricultural employees and the population growth and estimated income per capita in the respective regions. All of these are used as the parameters to explain the rural development stages based ok the Geographically Weighted Regression (GWR).

METHODS

Study location

This study has taken place in the area covered by the watershed namely Way Sekampung in Lampung Province. This area is divided into several administrative regions such as South Lampung, East Lampung, Pesawaran, Tanggamus, Central Lampung Metro City, Bandar Lampung City, and Pringsewu Residence which has seventy-seven sub-district or rural areas (Fig.1). The watershed Way Sekampung is the biggest

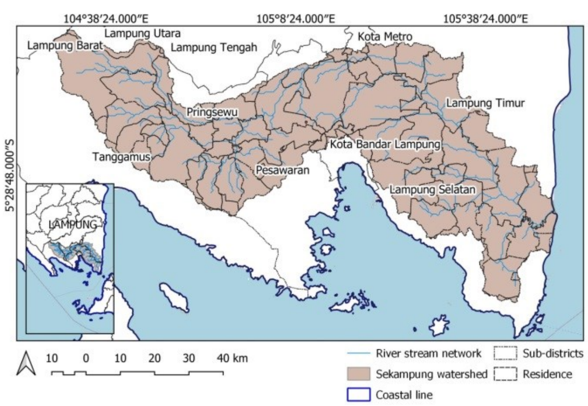

FIGURE 1. The location of way Sekampung watershed over the sub-district division in Lampung Province

Data

Data used in this study focused on the explanatory and the relation between the rural development stages during the trends of land-use and land-cover change against the socio-demographical and economic conditions. This study used several secondary data includes geospatial and non-geospatial data. A multi-temporal satellite imagery data was collected with no cost from https://earthexplorer.usgs.gov/ namely the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13Q1) especially for Normalized

Difference Vegetation Index (NDVI) used in this study at 2015 and 2019 years observations (Fig.3).

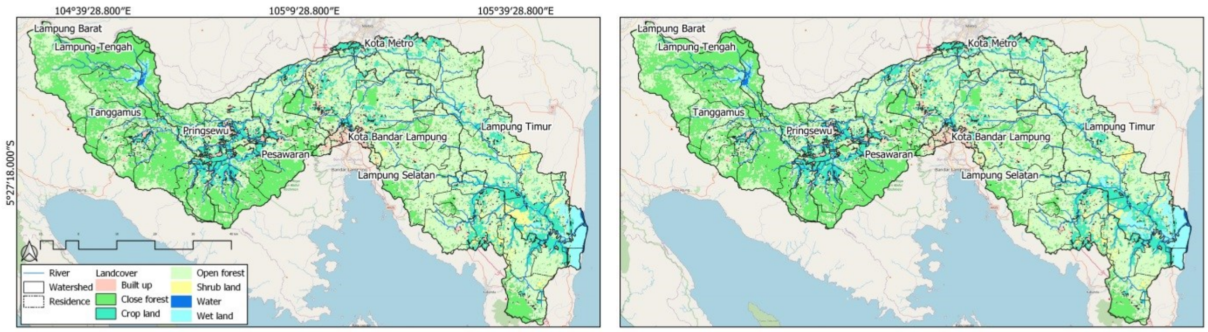

FIGURE 2. The landcover map of way Sekampung watershed in 2015-2019

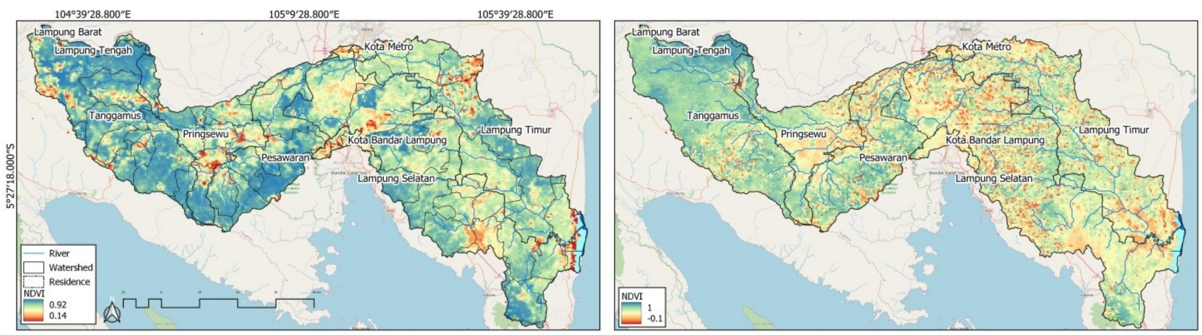

FIGURE 3. The NDVI map of way Sekampung watershed in 2015-2019

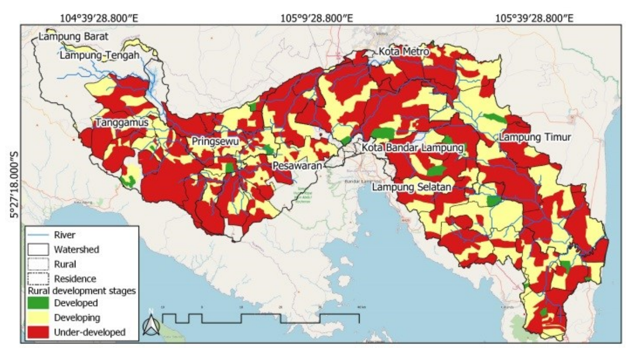

FIGURE 4. The rural development stages map of way Sekampung watershed in 2020

The NDVI values have been resampled into a range of 0-1 before using for further analysis. Additionally, a global land cover map with a global 100m resolution maps, the main inputs are PROBA-V satellite observations, organized into millions of Sentinel-2 equivalent tiles of 110x110km (Fig.2). The processing in this tiling grid, and with UTM projection, ensures high quality and facilitates the continuity with Sentinel-2 observations[36]. It has twelve classes of land cover over the Way Sekampung watershed that is simplified into seven classes includes built-up, close and open forest, cropland, shrub, water and wetland (includes paddy fields). For non-geospatial data, multi-years of total population data for each rural area from about 2015 to 2019 collected from the Central Bureau of Statistics was used together with rural development stages (Fig.3) are required for analysis.

Data Processing

1. Land cover change estimation

All raster data that includes NDVI, and land cover map are usable directly, while the attribute data for socio-economy data (population, income-percapita, and rural development) are necessary to process by attaching it into a vector file like administrative boundaries using a geographic information systems (GIS) software. Although all the raster data can use directly, for a specific purpose its should be processed to obtain some new data, For instance, the land cover data might be processed to generate the change during five years. It using a change detection method as used by many studies[37–39].

2. Yield and farmers income estimation

The NDVI has been processed to generate the predicted income per capita of farmers based on the specific land cover type. It required a separate calculation process for each type of land cover but finally will combine and covered the entire study area. For example, the entire area of wetland in the landcover maps is represented as the paddy field will be used as the boundaries to estimate the paddy rice yield using the formula proposed by Wahyunto et al.(Eq.1)[40] and then converted to predict the income per capita of farmers that live in that region (Eq.2). Where a and b is regression coefficient and $price\ per\ ton$ was obtained from interview with farmers represented relationship between NDVI and the actual yield. The exact values of a and b may varied according to the regression model. and the average price of paddy rice per ton that equal to 3.800.000 rupiahs. This method is more simplest that explained by Hendri et al., [41].

$$Paddy\ yield = a * NDVI + b \tag{1}$$

$$Farmers\ Income = Paddy\ yield * price\ per\ ton \tag{2}$$

3. Demography of rual areas in Way Sekampung

The population of each rural area is collected from multi-temporal data obtained from the Central Bureau of Statistics, and it can be directly used as attribute values of respective rural areas. In this study, each rural area is processed to get a centroid and then used as input for making a surface using an interpolation method namely inverse distance weighted (IDW). The centroid is represented as a known or observed point (z) and space between the centroid was defined as the distance (d), w_i is the weight of i-th sample point and d_{ij} is the euclidian distance from the collected data point, and p stands for power (Eq.3-5)[42]. Previously, this method was used to estimate groundwater[43], WIFI connection [44], and health analysis[45].

$$z = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{3}$$

$$w_i = \frac{1}{d_{ijp}} \tag{4}$$

$$d_{iz=\sqrt{(x_i-x_z)^2+(y_i-y_z)^2}} \tag{5}$$

All derived information obtained from the above calculation process may be used in analyzing the geographic weighted regression (WGR) using the following naming convention. The Land cover represents the land cover information map provided by a global land cover map. The Change map expresses the conversion of land cover that occurs in the study area. The NDVI is a map that shows the vegetation distribution. The Yield is an estimated crop production based on the semi-empirical paddy rice yield. The Income map is an estimated farmers income based on the function of yield and actual paddy rice price in the local market, and the Total pop and Pop growth represent the total population and its growth rate.

4. Implementation of the geographically weighted regression (WGR) algorithm

Previously introduced by Fotheringham et al[30]. The GWR used the basic form of linear regression (Eq.6) and in some cases, it may be modified into a multiple regression (Eq. 7)[34], but all these equations also required the values of weight (β), that compute separately following the weighted least square (Eq.8). The GWR is an extension of an OLS regression that allows locally varying parameters to consider a spatial non-stationary in a sample[32]. Understanding the $\beta_0(u_i, v_i)$ is an intercept value, the $\beta_k\,(u_i, v_i)$ is a coefficient of regression in the location i of the local parameters. Each location (i) has its regression model in the GWR model. The WGR needs to predict the regression coefficients, a distance-decay function (wij) is applied as a distance weighting factor between a modelled location and the observations. When sampling points are distributed irregularly, a variable bandwidth that increases the correspondence of the model is used by an adaptive weight kernel[33], where d_{ij} is the distance between observation i and j, $\theta_{i(k)}$ is the adaptive bandwidth defined by the kth nearest neighbor distance. For a case in which the distance between observations is greater than the adaptive bandwidth, the distance-decay function becomes zero (Eq. 9). The entire processes of implementation the WGR computed in the software for geographically weighted regression analysis, namely MGRM[46,47].

$$y = \beta_0 + \textstyle\sum_{i=1}^{p} \beta_i X_i + \varepsilon \tag{6}$$

$$y = \beta_0(u_i, v_i) + \textstyle\sum_{i=1}^{p} \beta_k\,(u_i, v_i) X_{ik} + \varepsilon_i \tag{7}$$

$$\beta = (X'X)^{-1}X'Y \tag{8}$$

$$w_{ij} = \begin{Bmatrix} \left(1 - \left(\frac{d_{ij}}{\theta_{i(k)}}\right)^2\right)^2 & d_{ij} < \theta_{i(k)} \\ 0 & d_{ij} > \theta_{i(k)} \end{Bmatrix} \tag{9}$$

For raster data, zonal statistic tools required for getting mean values from all parameters used include paddy rice yield and farmers income estimation, and for vector data such as change occurrence (binary map) and population, growth data are joined using a join table procedure.

RESULT AND DISCUSSION

1. The land use–land cover (LULC) change in Way Sekampung watershed

During five years of observation based on the two derived land cover maps, there is the change that occurred entirely Way Sekampung watershed. Although it is still a minor change, in the majority most of each land cover class do not change or no conversion occurs. To compare which area is experience the high conversion is located in the Lampung Timur residence. Although it has a larger size of the converted area, most of these are paddy field which has been changed naturally according to its growth pattern. Some of the researchers also stated the same when indicated the change in paddy field[48]. But entirely based on the MODIS derived land cover at 250 meters of pixel size, this area is still safe from any critical destruction (Fig.4).

FIGURE 4. The land cover change map of way Sekampung watershed in 2019

2. Estimated paddy rice yield and farmers income

As explained before that, this two estimated map derived based on the NDVI and not distinguished the variation of NDVI values according to the land cover classes. The estimated paddy yield was computed using a linear regression formula of the actual paddy rice yield per coverage area of one hectare of paddy field. Both parameters are related to farmers income. It was expected that while the paddy field size owned by farmers was larger, it would be influenced the farmer's income. Both factors are computed based on the MODIS NDVI with a sparse resolution at 250 meters.

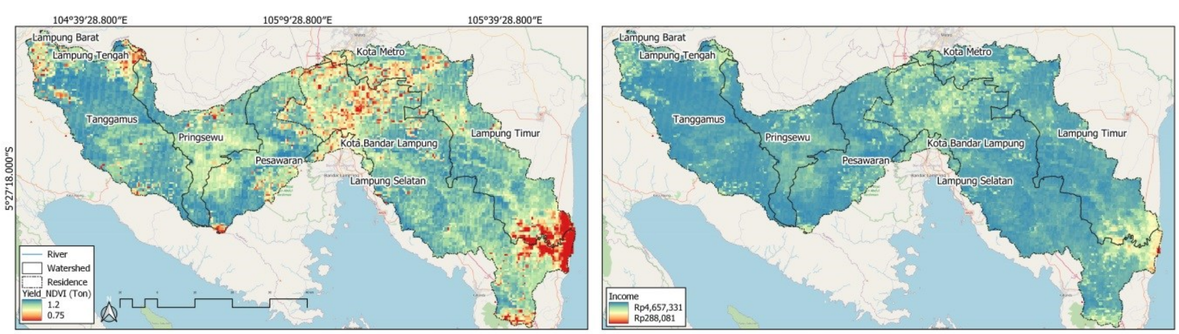

FIGURE 5. The estimated yield (left), farmers income of way Sekampung watershed in 2019

The yield distribution has a significant amount range from 0.75 to 1.2 tons per 250 meters of MODIS pixel. It is followed by the range of farmers income that starts from 288.081 to 4.657.331 rupiahs. Based on this calculation, both yield and income may be varied over the way Sekampung watershed (Fig.5). This variation occurs at the end of planting season or before the paddy rice is harvested, and made the several areas in Lampung Timur residence has a predicate of lowest paddy rice yield and farmers income.

These results might be lead to a weak accusation and potential to support a better accuracy when if the entire area of Way Sekampung are dominant by paddy fields. It does not express in that way, There are many areas are using as plantation, aquaculture, forest area that economically has their capability to give financial support when the people managing their land. In this case, the NDVI has only represented the distribution of vegetation and non-vegetation area then simplified converted as the yield and income main parameters, since all of the land use and land cover type or classes have their NDVI values. It required more detail and need more study to provide highly accurate information.

3. Demographical factors of total population and growth rate

The rural areas in way Sekampung watershed have a total population that ranges from about 1140 to 16.567 meanwhile, it also has a population growth from 0.00518 to 2.86% per year. The most populated area is located in the centre part of this region and closest to the Bandar Lampung city and does not correspond to the area with the highest population growth. This value for most regions has the lowest rate for the last five years at about lower than 0.1% per year, includes Lampung Timur, Tanggamus, and Pringsewu residences. Besides that, the Lampung Selatan residence can be classified as moderate population growth (Fig. 6).

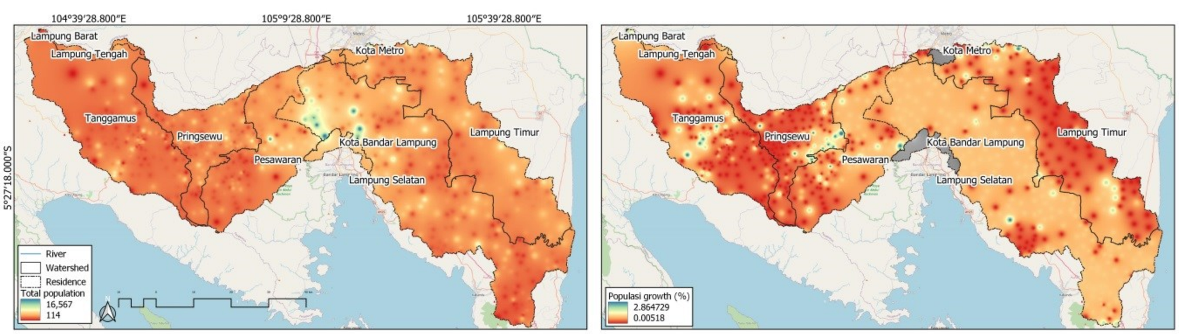

FIGURE 6. The interpolated maps of total population (left) and (right) its annual growth rate of way Sekampung watershed in 2019

4. The GWR of rural development stages

The process of obtaining the GWR is conducted in the software MGWR 2.21 using Gaussian model type, 669 as the total number of observations, 8 as several covariates, (Pop growth) are used as independent variables. The global model produced by an ordinary regression analysis was explained each explanatory variable for rural development stages in the Way Sekampung region is expressed by the value of R^2 and adjusted R^2 at 0.079 and 0.069 respectively (Tabel 1). However, these two values are lower compared to the same values obtained from a GWR that reach 0.129 and 0.018 (Tabel 2). On the other hand, the value of R^2 at 12% the selected variable used to explain the RDI in the way Sekampung is too low or weak. Besides that, It allows us to compare the values of Akaike's Information Criterion (AICc) from the same procedure, the global regression is a little higher at about 1859.432 compared with GWR at 1853.606. The contribution of independent variables are lower, but according to the p-value and considered the α values that must be greater than 0.05, these independent variables includes NDVI, Yield, Totalpop and are rejected as the null hypothesis, and two variables accepted its null hypothesis, includes the Land cover, Change, and the Income (Tabel 1).

TABEL 1. Global regression results for explanatory rural development stages (DRI) way Sekampung watershed in 2019

Global Regression Results				
Residual sum of squares:				616.101
Log-likelihood:				-921.716
AIC:				1859.432
AICc:				1861.706
R2:				0.079
Adj. R2:				0.069
Variable	Est.	SE	t(Est/SE)	p-value
Intercept	-0.000	0.037	-0.000	1.000
Land cover	0.022	0.038	0.584	0.559
Change	0.020	0.038	0.538	0.591
NDVI	-0.199	0.087	-2.294	0.022
Yield	0.264	0.098	2.688	0.007
Income	-0.159	0.094	-1.691	0.091
Total pop	0.179	0.038	4.668	0.000
Pop growth	0.116	0.038	3.080	0.002

TABEL 2. Geographically Weighted Regression (GWR) model for explanatory rural development stages (DRI) way Sekampung watershed in 2019

Geographically Weighted Regression (GWR) Results	
Coordinates type	Projected
Spatial kernel	Adaptive bi-square
The criterion for optimal bandwidth	AICc
Bandwidth used	412.000
Diagnostic Information	
Residual sum of squares	582.660
The effective number of parameters (trace(S))	22.754
Degree of freedom (n - trace(S)):	646.246
Sigma estimate	0.950
Log-likelihood	-903.049
Degree of Dependency (DoD)	0.839
AIC	1853.606
AICc	1855.431
BIC	1960.636
R2	0.129
Adj. R2	0.098

Adj. alpha (95%)	0.018
Adj. critical t value (95%)	2.380

5. Distribution maps for all variables independent

The model of GWR can be created using the maximal values of each variable that is used in explanatory the rural development stages. These values are the estimated coefficient (β) in Table 3 given a multiple regression equation and usable to estimate spatially the GWR model for RDI (Eq. 10). Since this study directly compared to models based on the global regression (OLS) and the WGR and according to the value of R^2 at 0.079 and 0.129. Although both values are lower, the WGR is better to use to estimate the DRI.

$$DRI = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 + \beta_4 * X_4 + \beta_5 * X_5 + \beta_6 * X_6 + \beta_7 * X_7 \quad (10)$$

TABEL 3. Descriptive statistic for explanatory rural development stages (DRI) way Sekampung watershed in 2019

Variable		Mean	STD	Min	Median	Max
	Intercept	-0.006	0.062	-0.146	-0.007	0.103
X_1	Land cover	0.018	0.058	-0.066	0.003	0.106
X_2	Change	-0.045	0.042	-0.086	-0.069	0.033
X_3	NDVI	-0.157	0.034	-0.206	-0.172	-0.034
X_4	Yield	0.213	0.088	0.036	0.274	0.330
X_5	Income	-0.154	0.040	-0.257	-0.155	-0.077
X_6	Total pop	0.168	0.052	0.086	0.150	0.247
X_7	Pop growth	0.125	0.044	0.063	0.106	0.235

This is important to put all the result of GWR into maps to change the statistical view into a spatial based. It was useful to create a different that use to understanding the specific information given by the model. Besides that, the GWR results shown in TABLE 1-3, there are also exist the coefficients of intersect for the dependent variable, the beta coefficient for independent variables, and both t and p values are also provided. All of these can be used as the combination model to show a predicted map of explanatory the GWR. Another way to express the GWR result is by using its local regression values. Since the GWR accommodate the local regression, these values may vary one another. In these cases, there are more than 600 rural areas or sub-districts in way Sekampung watershed, each rural area has its values for the same independent variable.

Once the values are visualized, It has already grouped into a specific range that put every single rural area into the same group based on their local values. This is likely similar to the spatial autocorrelation map of Global Moran's I that distinguished the map using four categories named HH, LL, HL, and LH[49,50]. In this case, the map explains the variation from a lower to a higher level of the particular variable that influences the stage of rural development. The maps below show a spatial distribution of independent variables based on their beta values, R^2, and the summary (Fig. 7). Not sure how to express the relationship between the values, grouped regions with the physical characteristic of land cover, but if it relates to the land cover map in Fig. 2 the qualitative explanations can be used to understand the exact meaning.

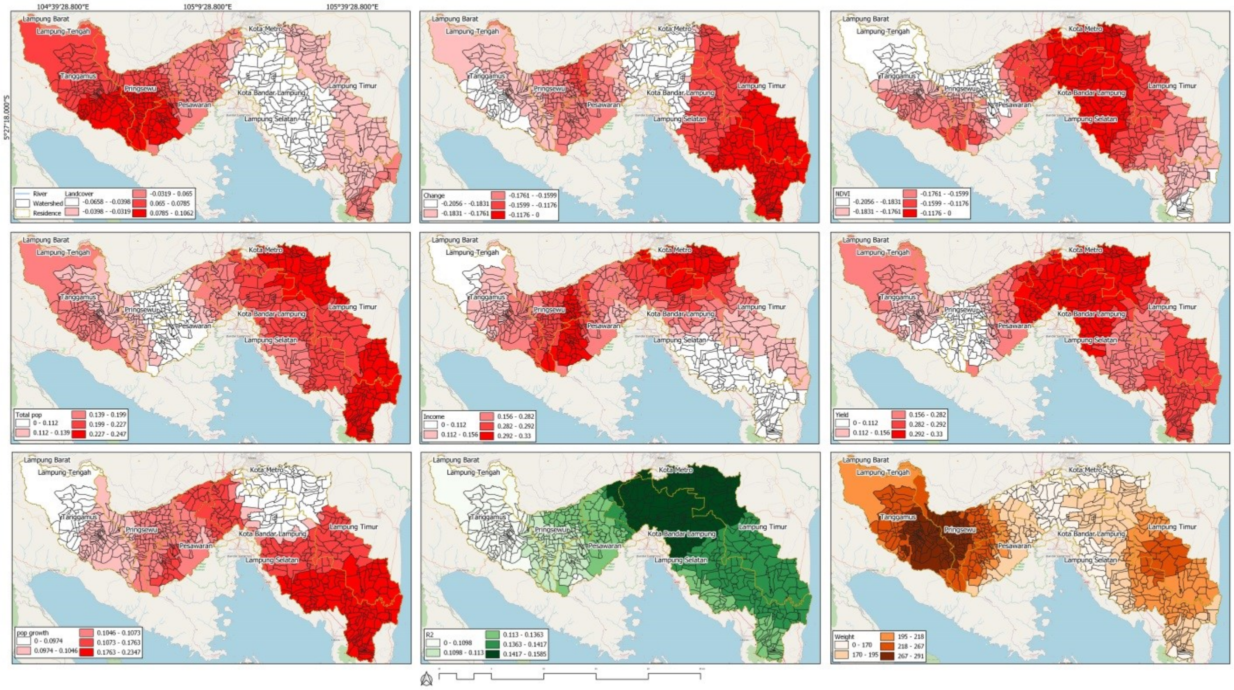

FIGURE 7. The WGR maps of independent variables are used for explanatory rural development stages. A clockwise direction from left to right: Landcover, Change, NDVI, Yields, Income, Total pop, pop growth, R^2, and Weight summary for all rural areas in of way Sekampung watershed in 2019.

The beta-values of Landcover range at about -0.0658 to 0.1062. The maximum values represent the same area where is dominated by a forest area. Since the beta values are the coefficient of Landcover to explain the rural development stages, the villages situated in this area are possible to support the development process by 0.1% and if the forest area disappeared from this area, it also affected 0.06% to decrease the same process. It seems, the forest area is important for the people, not only for supporting the economy, finance, and also to keep the area safely, Even though most of the rural areas are classified as under-developed (Fig. 4). Besides that, both Landcover and economic factors describe by Income are negatively correlated. Some of the areas with higher beta-values in Landcover are also located in the higher income area in the Income map. This explanation method is quite simple to know the relationship between two beta values from two different variables. For a comprehensive view, the GWR map compiled by R^2 values is provided with a better analysis.

The R^2 values represent the coefficient of determination for all independent variables in understanding the rural development stages. Range at about 0.0 to 0.1585 or equal to a maximum 15% those areas shaded by a darker green colour have a higher influence from all independent variable and successfully put most off the rural areas in the various stages of rural development from under-developed to developed. According to these values, the whole area is divided into five groups that have a specific range of R^2 values (Fig. 7.8). By describing the clustered map of R^2 values, in the west part of Way Sekampung some villages do not correlate with all parameters. The explanatory variable of Landcover, Change, NDVI, Yields, Income, Total pop, and Pop growth did not give any contribution for most of the villages located in the under-developed stages. In the same areas, the local regression of these parameters is lower. This situation resulted from a statistical computation process, which is mean the solution may be offered to increase the stages or the level of rural development stages in this region. As previously stated by Huang et al., [51], in some cases the utilization of land related to the development of the economy should be given priority to that of rural economy and the development of rural areas is largely dependent on land expropriation. Clearly explained by Lin et al.,[15] if the rural development tends to become a marginal sector since their location are situated near the mountainous areas, difficult to access due to the larger distance from the city center. Both situations have to consider by increasing the rural productivity in agricultural sectors. Because the rural areas with this criteria are relatively under-developed.

In contrast with other regions located between Metro and Bandar Lampung city, the rural areas tend to have higher R^2 values compared with the previous location. These areas may have the shortest distance to the city center, larger population, decrease in elevation and slope, and highest income the number of rural situated in developing stages increased while decreased in the under-developed, and it possible to create a developed rural. It may be influenced by the availability of a larger market that makes it easier to distribute the agricultural product. The study said that increasing agricultural products as part of rural development are also creating agricultural development and it means the revitalization of the economy is running well simoultanously[52]. Besides that, to achieve rural development the linkage between rural and close by small towns and urban center is crucial[53].

CONCLUSION

Study the rural development stages (RDS) based on the integration of socio-economic, demographical and landcover data is critical, but to know the intensity of these parameters to explain the RDS, the function of geographically weighted regression (GWR) has successfully described both qualitative and quantitative of all explanatory variables used. Statistically, It has shown a lower positive correlation, and spatially the local regression has grouped them into several clustered. It seems the integration of socio-economic, demographical and landcover data has the potential capability when using to explain its relationship for rural development. Although the results are not yet satisfactory, as previously expected it might have the strongest correlation between RDS and independent data. As a further consideration, some parameters might be added, the better spatial resolution of derived information obtained from satellite data must be considered, as well as the use of more statistical records in the economics factors provided by the bureau statistical agency such as the health, education, infrastructure, and human quality might be a good option to increase the GWR results.

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