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TOWARDS SPATIAL POVERTY TARGETING: IDENTIFICATION OF POVERTY CLUSTERING IN INDONESIA

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ABSTRACT

The Government of Indonesia is facing a new challenge in tackling poverty since the pace of the fall in the poverty rate has been slowing over the five years to 2020. To date, poverty alleviation programs implemented by the Government of Indonesia have been limited to large administrative areas such as the district (*kabupaten*) level. For this study, we combined the Poverty Livelihood Map of Indonesia 2015 (Poverty Maps) that measures Small Area Estimation to estimate poverty at the subdistrict (*kecamatan*) level using National Socioeconomic Survey Data (Susenas), with Census of Village Potential (Podes) datasets and Census Base Maps. This study aims to explore spatial patterns of poverty in Indonesia in relation to local geographic and demographic characteristics. We employed Global Moran's I to investigate the spatial autocorrelation of the poverty at *kecamatan* level, and Local Moran's I to detect the clustering pattern of poverty in wider geographical area in Indonesia. Furthermore, we estimated the association of poverty with spatial factors using spatial lag regression because poverty is spatially correlated across areas. The data show that hot spots of poverty are concentrated in many adjacent subdistrics and can be located across neighboring district. We found strong clusters of poverty of subdistricts in Indonesia. The spatial lag regression showed that factors such as agriculture, natural landscape (area located in uplands, woodland, sea, and river), physical infrastructures (road access and irrigation availability), access to basic facilities (health, education, and economy) are significantly correlated with poverty clustering.

Keywords: Poverty, Clustering, Spatial Analysis, Spatial Lag Regression, Local & Global Moran's I

1. INTRODUCTION

The Government of Indonesia has implemented three poverty reduction programs in the areas of food, health services, and education. The first cluster consists of health insurance (*Jamkesmas*),[1] conditional cash transfers (PKH),[2] rice subsidies for the poor (Raskin),[3] and scholarships for the poor (BSM).[4] The second cluster is a community-driven development program to alleviate poverty by having the communities design their own development agenda (PNPM).[5] The third cluster consists of a business microcredit program (KUR)[6] which is based on the empowerment of small and micro enterprises to provide access to, and strengthen, the economic environment for small- and micro-scale entrepreneurs. These programs have resulted in a fall in the national poverty rate to 10.12 per cent in 2017.

Although the national poverty rate has declined over time, the pace of the reduction in some places is much slower than others. For example, the 2017 poverty rates in eastern parts of Indonesia such as West Papua, Papua, and East Nusa Tenggara provinces are 23.12 per cent, 27.76 per cent, and 21.38 per cent respectively. These numbers are still relatively high compared to the national poverty rate and suggests that existing programs are not enough to accelerate poverty reduction in some areas and another approach is needed to solve the problem.

Bigman et al. (2000) argued that poverty tends to be concentrated in villages and certain parts of towns in most developing countries. We have made a similar assumption towards poverty in Indonesia. There has been a growing interest among scholars to study geographic targeting of small administrative areas and its use for poverty reduction efficiency and effectiveness. A study by Elbers et al. (2007) found that there are potentially large gains to be made by disaggregating to the local level in target programs. Baker and Grosh (1994) argued that geographic targeting is a useful mechanism for transferring benefits to the poor because of its simplicity and that regions can be assigned priority on the basis of existing aggregate data. Bigman et al. (2000) added that geographic targeting can reduce leakage so that a larger share of the poor population can be reached on a given budget or a larger share of this budget can reach the poor because it identifies the geographic areas where the poor are concentrated.

Hyman et al. (2005) argued that areas with high living standards are usually surrounded by neighbouring areas that have spill-over effects. Prosperous communities and households generate wellbeing in their neighbours through diffusion of innovations, social capital, trade, economies of scale, and other factors related to proximity and spatial interaction (Hyman et al. 2005). On the contrary, poor areas are often surrounded by neighbouring areas that are also poor. Poverty-stricken communities and their neighbouring areas often lack opportunities for trade and interaction (Hyman et al. 2005)

[1] *Jamkesmas: Jaminan Kesehatan Masyarakat* (Social Health Insurance).

[2] PKH: *Program Keluarga Harapan* (Family Hope Program).

[3] Raskin: *Beras Miskin* (Rice for the Poor) Program.

[4] BSM: *Bantuan Sekolah Miskin* (Cash transfer program for poor students).

[5] PNPM: *Program Nasional Permberdayaan Masyarakat* (National Program for Community Empowerment).

[6] KUR: *Kredit Usaha Rakyat* (Micro Credit Program).

We aim to examine whether poverty in Indonesia is spatially clustered by utilising the poverty estimates at *kecamatan* level from Poverty Livelihood Map of Indonesia 2015 (Poverty Maps). Furthermore, we determine how far spatial clustering correlates poverty incidences and investigate the association of geographic characteristics and its spatial clustering across *kecamatan* in Indonesia. This study suggests that, by finding poverty clusters and their contributing factors, more effective programs can be implemented to boost the poverty reduction effort.

2. DATA AND METHOD OF ANALYSIS

2.1. Data

This study utilised Podes 2014. Podes is a village-level census carried out by Statistics Indonesia (BPS).[7] Podes is a village-level dataset that covers all 74,410 villages in Indonesia. We merged the Podes dataset with poverty at the *kecamatan* level from the Poverty Livelihood Map of Indonesia 2015 (Poverty Maps). Poverty Maps applied small area statistics combining the 2010 Population Census, Susenas 2015, and Podes 2014 to estimate subnational poverty rates–particularly at *kecamatan* and village level (SMERU, 2014).

2.2. Poverty Clustering at *kecamatan* Level

Spatial clustering shows the similarity or dissimilarity of poverty in neighbouring units and spatial autocorrelation measures the strength of the spatial clustering (Cliff and Ord 1973; Getis and Ord 1992; Anselin 1995). Spatial autocorrelation is applied when the dependent variable or errors of every observation are correlated with observations or error terms of other observations. Spatial autocorrelation measures the closeness of an observation with other surrounding observations. Global Moran's I is generally applied to measure such a problem. Global Moran's Index measures the existence of spatial distribution of a variable globally. Moran's I scores are ranged from -1 to 1. A value of -1 means the data is scattered randomly while a value of 1 shows that the data is perfectly distributed spatially. We estimated the *kecamatan*-level poverty clustering using the Poverty Maps dataset. The Poverty Maps estimation combines information from Susenas with information from the population census (*Sensus Penduduk*) and Podes. A small area estimation technique is applied to estimate the *kecamatan* level poverty rates. Subdistrict poverty rates in this study are the ratio of the number of households whose expenditure per capita falls below the poverty line at *kecamatan* level.

Structurally, the poverty level of an area is related to the poverty level of the neighbouring area. In other words, we know that the structure of poverty has a spatial relationship feature. Spatial lag regression can, therefore, be utilised to model the spatial interactions of subdistrict poverty. The auto global spatial autocorrelation is calculated using Moran's I index using the following formula (Pfeiffer et al. 2008):

$$I = \frac{1}{s^2} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (Z_i - Z)(Z_j - Z)}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}$$

[7] BPS: *Badan Pusat Statistik* (Statistics Indonesia).

where

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(Z_i - \bar{Z})^2$$

n indicates the number of observations, Zi is the poverty rate for observations in location i, Zj, is the poverty rate of location j, ZBAR is the average of poverty level, and WIJ is the weight of connectivity between location i and j. The value of the Moran's I index ranges from -1 to 1. The Moran's I of 1 shows a perfect autocorrelation and -1 shows a prefect random spread (Pfeiffer et al. 2008).

The Moran's I index only provides information on whether there is or is no spatial autocorrelation of poverty between locations. To supplement this, we also need information about where the poor locations are clustered. After conducting the Global Moran's I test, the next step would, therefore, be investigating the clustering pattern by employing a local Moran's I test. The local Moran's I test is calculated by using the Local Indicator of Spatial Association (LISA) formula (Anselin 1995):

$$I_i = \frac{\sum_{j=1}^{n} W_{ij}\left(Z_i - \bar{Z}\right)(Z_j - \bar{Z})}{\sum_{i=1}^{n}(Z_i - \bar{Z})^2}$$

The LISA will provide information about the similarity of the poverty between location i and location j as well as the significance level. As with Global Moran's I, if the statistical test is not significant it means that there is no clustering pattern in the region. In other words, the poverty is randomly distributed. On the contrary, if the LISA statistical test is significant, there will be four possibilities:

1. A high-high (HH) association: this is a hot spot cluster where the LISA index in location I is higher than the overall location.
2. A low-low (LL) association: this is a cold spot cluster where the LISA index is lower than the overall location.
3. High-low outlier: in this cluster, the LISA index in location i is higher than the neighbouring location.
4. Low-high outliers: in this cluster, the LISA index in location i is lower than the neighbouring location.

In the LISA analysis, the focus is on the HH and LL association.

2.3. Spatial Lag Regression

The spatial lag regression is utilised to examine the relationship between poverty and other spatial characteristics. A spatial regression instead of linear regression is needed for two reasons: firstly, where the poverty is spatially distributed within the country. In this case, a proper consideration about spatial dependence between observations should be considered (Pisati 2001). Secondly, from the LISA analysis we found there are some regional poverty clusters, however, from the Moran's I and LISA test we cannot explain what factors are responsible for the clustering of poverty in the country. Spatial regression will, therefore, be useful for identifying factors explaining the spatial distribution of poverty. Spatial regression is able to estimate the relationship of the poverty rate as the outcome variable and some geographic and socioeconomic predictors by considering the spatial dependence among observations (Pisati 2001). This study develops spatial regression using the spatial error model. A spatial weight matrix is developed to consider the connectivity between districts. The Podes dataset is utilised to obtain subdistrict characteristics such as geography, infrastructure, population and environment, natural disasters, and education and health facilities.

The spatial lag regression is defined as:

$$y = \rho W y + x\beta + e$$

The spatial lag model reduced form equation is:

$$(I - \rho W)y = x\beta + e$$

The spatial weight matrix is defined as W with elements wij indicating whether observations i and j are spatially close.

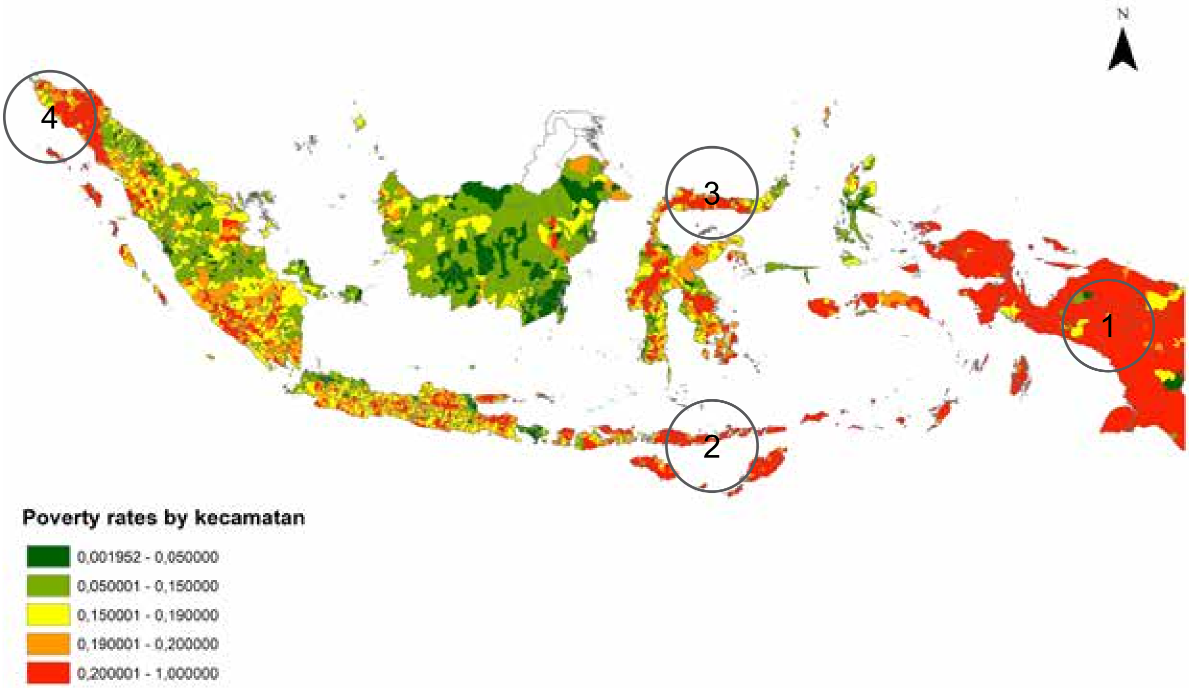
The independent variables explain the variation in the dependent variable that is not explained by the neighbours' values. The spatial dependence parameter ρ is also estimated.

3. RESULTS AND DISCUSSION

3.1. Poverty Clustering at kecamatan Level

Using a choropleth map, we can visually find a spatially distributed structure of poverty in certain regions in Indonesia by dividing the poverty rates into five categories: (i) below five per cent; (ii) five to ten per cent; (iii) ten to fifteen per cent; (iv) fifteen to twenty per cent; and (v) over twenty per cent. Figure 3.1 shows the distribution of poverty at *kecamatan* level. Cluster of poverty can be identified visually in (1) the east; (2) south; (3) top west; and (4) some small clusters spread around Java and Sumatra islands. This simple choropleth shows signs that the distribution of poverty is not spread randomly but tends to be concentrated in certain areas.

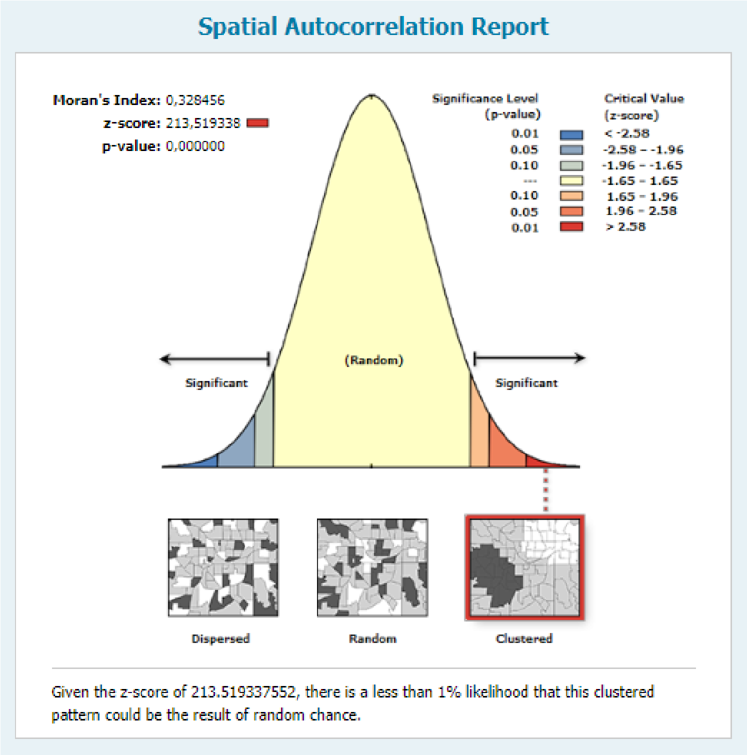
Figure 3.1: Spatial Distribution of Poverty at Kecamatan Level in Indonesia, 2015



Source: Calculated from Poverty and Livelihood Data (SMERU, 2015)

To statistically test whether the subdistrict poverty level in Indonesia is clustered, scattered or random, we used a spatial autocorrelation test of poverty using ArcMap. The test resulted in a statistically significant score of global Moran's I, which is 0.329 with the p-value of 0.0000 (Figure 3.2). Statistically significant global Moran's I verified the hypothesis of spatially distributed poor or non-poor areas across regions in Indonesia. It means a poor area is often surrounded by poor neighbours and vice versa.

Figure 3.2: Measure of Global Spatial Autocorrelation at Kecamatan Level in Indonesia, 2015



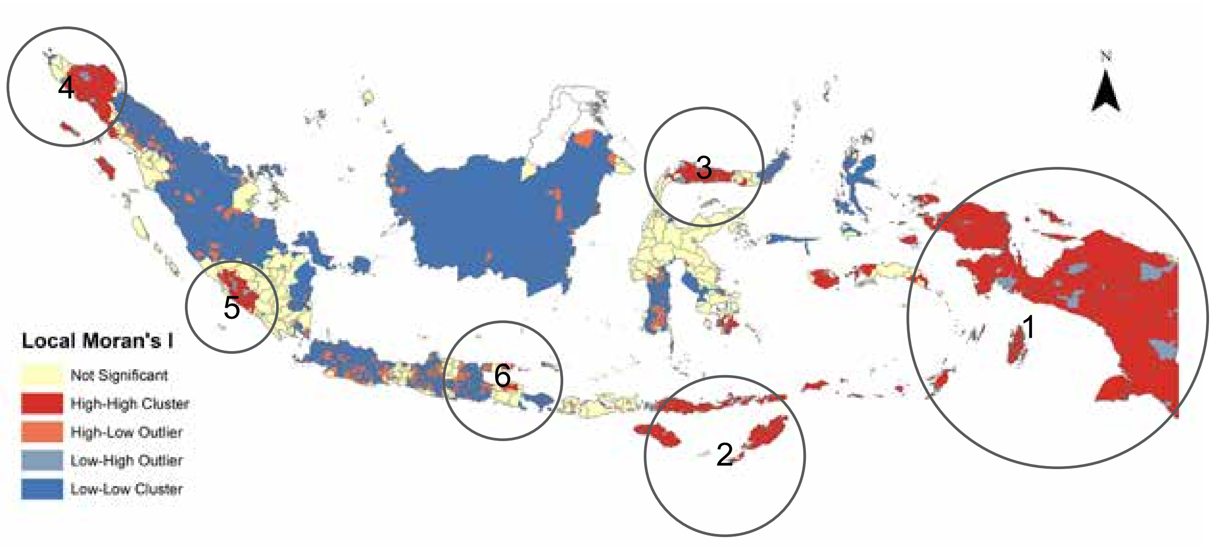
Source: Calculated from Poverty and Livelihood Data (Smeru, 2015)

Furthermore, we decompose the global spatial correlation to lower geographic coverage using LISA and plot the results in Figure 3.3. This figure suggests there are four clustering patterns of poverty: high-high, high-low, low-high, and low-low. A high-high cluster shows high subdistrict poverty with high poverty neighbours. The second group, low-high shows low subdistrict poverty with high poverty neighbours. High-low clusters show high poverty with low poverty neighbours, while low-low clusters show low poverty surrounded by low poverty neighbours.

Most of the low-low clusters are found in North Sumatra, Riau, Jambi, and South Sumatra provinces. Other low-low clusters are found in most parts of Java including Banten, West Java, DKI Jakarta, Central Java, and Yogyakarta provinces. We also found small clusters that are located across Probolinggo, Situbondo, and Bondowoso districts in East Java.

We suggest that priority attention should be given to high-high clusters of poverty, indicated by numbers 1 to 6 in Figure 3.3. These are located in Papua (1), East Nusa Tenggara Province (2), Gorontalo Province (3), Aceh Province (4), Bengkulu Province (5), and East Java Province (6). Not surprisingly, three massive clusters of poverty are found in the eastern part of the country: Papua (1), Nusa Tenggara (2), and Aceh region (4).

Figure 3.3: The Spread of Strong Poverty Clusters in Indonesia, 2015



Source: Calculated from Poverty and Livelihood Data (Smeru, 2015)

The poverty level of an area is correlated with that of the neighbouring area. In other words, the structure of poverty has a spatial relationship feature. We ran a spatial lag regression to estimate the correlation between clusters of poverty at the subdistrict level and other spatial variables.

We use the subdistrict poverty rate (p0) as a dependent variable and spatial variables as covariates. These include topography, access to river, irrigation, sea and woodland, distance to doctor, midwife and *puskesmas*, distance to primary school, distance to market, road access and electricity, share of villages with agriculture as main occupation and natural disaster.

The result is presented in Table 3.1 below.

Table 3.1: Spatial Lag Regression: Result

Spatial autoregressive model	Number of obs = 6,817		
(Maximum likelihood estimates)	Wald chi2(14) = 1,885.64		
	Prob > chi2 = 0.0000		
Dependent Variable = p0	Coef.	Std. Err.	P>|z|
Share of villages with river network	-0.008	0.003	0.012
Share of villages having irrigation network	-0.007	0.003	0.013
Share of villages whose main occupation is agriculture	0.069	0.004	0.000
Share villages with road network that is accessible all year	-0.010	0.004	0.021
Share of villages with access to PLN* electricity	-0.050	0.005	0.000
Share of villages located in mountainous area	0.007	0.003	0.027
Share of villages adjacent to sea	0.010	0.004	0.004
Share of villages located in or around woodland	0.014	0.003	0.000
Average distance of village to permanent market	0.000	0.000	0.000
Average distance of village to community health facility	0.000	0.000	0.613
Average distance of village to private doctor's practice	0.001	0.000	0.000
Average distance of village to midwife	0.000	0.000	0.064
Average distance of village from primary school	0.000	0.000	0.024
Average number of villages experiencing natural disaster in the last three years	-0.006	0.002	0.016
Intercept	0.120	0.009	0.000
Rho	0.138	0.002	0.000
sigma2	0.003	0.000	0.000

Source: author's analysis (2019)

The above table shows that, with the exception of distance to public health facilities, almost all local geographic characteristics have a significant relationship with subdistrict poverty. This result is consistent with previous research such as Murayama and Thapa (2011), Davis (1986), and Hyman et al. (2005). These findings highlight the role of local geographic conditions and infrastructure to characterise the presence of poverty clusters or poverty pockets in some regions of Indonesia.

To better understand the determinants of spatial clusters of poverty at the district level, we conducted several separated analyses for major high-high cluster areas, namely the Aceh cluster and Papua cluster to represent the west and the east region of the country.

Figure 3.4:Distribution of Poverty Clusters in Aceh Province, 2015

Source: Calculated from Poverty and Livelihood Data (Smeru, 2015)

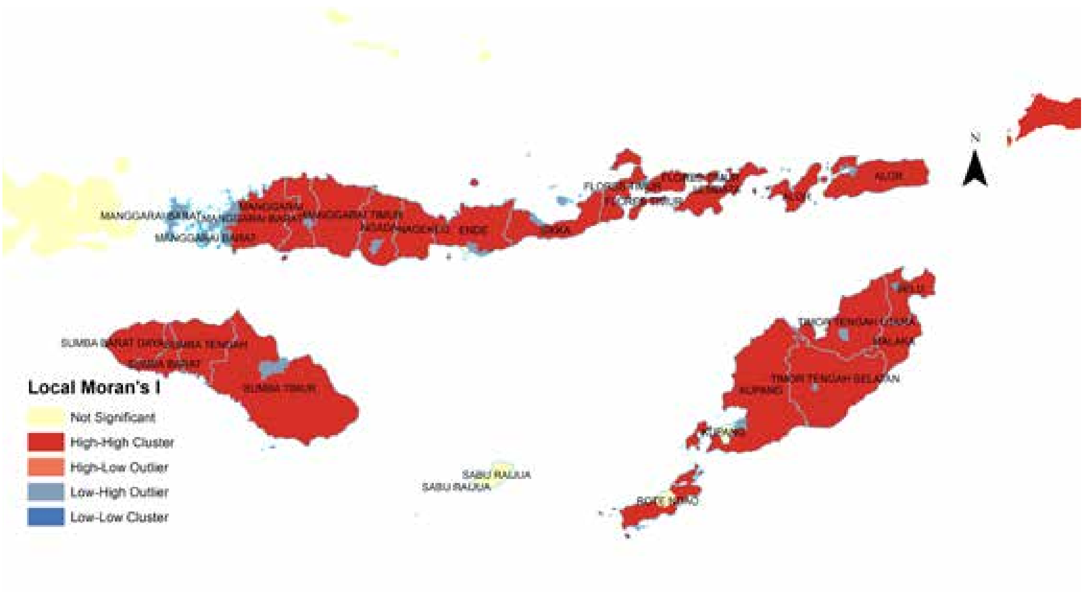
A big high-high cluster is located across Pidie, Pidie Jaya, West Aceh, Central Aceh, Bener Meriah, Bireden, Lhokseumawe, North Aceh, East Aceh, Aceh Tamiang, Gayo Lues, Southwest Aceh, Nagan Raya, Southeast Aceh, Sulubussalam, Aceh Singkil, and Simeulue districts (Figure 3.4). A low-low cluster is found in Banda Aceh and Sabang districts which is not surprising since Banda Aceh and Sabang are tourist destinations.

To examine factors which determine the high-high cluster in Aceh Province, we ran an ordinary least square (OLS) regression in 155 subdistricts. Significant correlations are found between agriculture, access to health facility, and access to a doctor with poverty rates (Table 3.1).

Local Moran's I showed that almost all districts in East Nusa Tenggara province are among in a high-high cluster (Figure 3.5). Unlike the high-high cluster in Aceh province, the OLS regression result of the high-high cluster in East Nusa Tenggara showed that there is significant correlation between poverty with irrigation access, topography, market access, health facility and doctor access, and access to primary education (Annex 1).

The road system in East Nusa Tenggara is among the worst in Indonesia (Resosudarmo and Jotzo 2009). The main highway from Kupang to Atambua on the border of Timor-Leste is well maintained, however, interior roads are frequently unsealed, irregularly serviced, and often impassable during the annual 3-4 month rainy season. Indeed, most locations off the Kupang-Atambua highway and a few other main routes can only be accessed by four-wheel drive or motorcycle, even in dry weather (Resosudarmo and Jotzo 2009).

Figure 3.5: East Nusa Tenggara Local Moran's I Result



Source: author's analysis (2019)

To examine what factors determine the high-high poverty cluster in a region, policy makers should conduct a separate regression analysis on each cluster. A qualitative analysis is also necessary to confirm the findings.

4. CONCLUSION

This study found that *kecamatan*–level poverty in Indonesia is clustered and that there are strong clusters of poverty at this administrative level. Each cluster has a different geographic endowment, therefore, local-level spatial analysis is needed to determine specific geographic characteristics that are linked to poverty. Spatial factors such as agriculture, natural landscape (upland, woodland, sea, and river), physical infrastructure (road access and irrigation availability), access to facilities (health, education, and economy) are significantly correlated with poverty clustering. By finding poverty clusters and their contributory factors, more effective programs can be implemented to boost the effort to reduce poverty.

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ANNEX

Annex 1: OLS Regression Result for HH Cluster in Aceh Province

	Number of obs	=	155
	F(18, 136)	=	2.95
	Prob > F	=	0.0002
	R-squared	=	0.2811
	Adj R-squared	=	0.186
Dependent variable =p0	Coef	Std. Err.	P>t
Share of villages with river network	-0.0131416	0.0188734	0.487
Share of villages having irrigation network	0.0192845	0.0138052	0.165
Share of villages whose main occupation is agriculture	0.2323021	0.1075864	0.033
Share villages with road network that is accessible all year	-0.0332242	0.0243716	0.175
(Share of villages with access to PLN* electricity	-0.0262783	0.0340587	0.442
Share of villages located in mountainous area	0.0075562	0.0207866	0.717
Average distance of village to permanent market	0.000322	0.0003651	0.379
Average distance of village to community health facility	-0.0029591	0.0020456	0.15
Average distance of village to private doctor's practice	0.0008836	0.0002498	0.001
Average distance of village to midwife	-0.000138	0.0001975	0.486
Average distance of village from primary school	0.0026599	0.012074	0.826
Average number of villages experiencing natural disaster in the last three years	-0.0108685	0.0137466	0.431
Number of primary school	-0.0006091	0.0011627	0.601
Total of *puskesmas*	0.0008138	0.0015695	0.605
Number of *poliklinik*	-0.0037137	0.0052951	0.484
Number of doctors and midwives	-0.0002903	0.0009392	0.758
Number of *polindes & poskesdes*	-0.0012336	0.0007369	0.096
Number of *posyandu*	0.0001308	0.0005379	0.808
Intercept	0.0871016	0.118817	0.465

Annex 2: OLS Estimation Result for East Nusa Tenggara Province

	Number of obs	=	268
	F(18, 136)	=	8.76
	Prob > F	=	0
	R-squared	=	0.3878
	Adj R-squared	=	0.3436
Dependent variable =p0	Coef	Std. Err.	P>t
Share of villages with river network	-0.0012034	0.0104823	0.909
Share of villages having irrigation network	-0.0307098	0.0122041	0.012
Share of villages whose main occupation is agriculture	0.2686013	0.0792408	0.001
Share villages with road network that is accessible all year	-0.0401405	0.0128902	0.002
Share of villages with access to PLN* electricity	-0.0061248	0.0121067	0.613
Share of villages located in mountainous area	-0.0097865	0.0088476	0.27
Average distance of village to permanent market	-0.0003885	0.0001955	0.048
Average distance of village to community health facility	-0.0013762	0.0004784	0.004
Average distance of village to private doctor's practice	0.0005695	0.0001326	0
Average distance of village to midwife	-0.0001242	0.0001056	0.241
(Average distance of village from primary school	-0.0151331	0.0166493	0.364
Average number of villages experiencing natural disaster in the last three years	-0.0031126	0.008438	0.713
Number of primary schools	0.0015836	0.0006088	0.01
Total of *puskesmas*	-0.0035938	0.00144	0.013
Number of *poliklinik*	-0.0066779	0.0052369	0.203
Number of doctors and midwives	0.0006517	0.0025878	0.801
Number of *polindes & poskesdes*	-0.0036201	0.0009393	0
Number of *posyandu*	-0.0001038	0.0003612	0.774
Intercept	0.074197	0.0805451	0.358

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