International Journal of Psychosocial Rehabilitation, Vol. 24, Issue 04, 2020
ISSN: 1475-7192

Geography Determinant Affecting Child Poverty in East Nusa Tenggara-Indonesia

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Abstract--- *Children are the population group that experience the most impact of poverty. The purpose of this study was to determine the factors that affect child poverty spatially in a specific location in the sub-district at Indonesia. The data was gained from integrated data from the Poor Handling Program, covering 306 districts in East Nusa Tenggara, Indonesia. The analysis used in this study is the Geographically Weighted Regression (GWR) method. The results showed that the burden of dependents, child labour, elderly workers, agricultural sector workers, non-agricultural sector workers, et cetera, have effected child poverty in East Nusa Tenggara. Therefore, it is strongly suggested that both central and regional governments, as policymakers, need to pay attention to aspects of spatial heterogeneity of the determinants of child poverty.*

Keywords--- *Child Poverty, Child Labor, Older Workers, Geographically Weighted Regression, East Nusa Tenggara-Indonesia.*

I. INTRODUCTION

Poverty, in all forms and dimensions, including extreme poverty for all people wherever they are, is the biggest global challenge. Being free of poverty is also an indispensable requirement for sustainable development. Poverty has been a global problem in developed and developing countries (Leung &Shek, 2016). In 2015, the International Poverty Line was updated from $ 1.25 to $ 1.90 per person, per day. The data shows that nearly 383 million children live in extreme poverty with less than $ 1.90 per person per day (UNICEF & the World Bank Group, 2016). A series of child poverty estimation, conducted by the World Bank, shows that around 20% of children, who belong to low and middle-income countries, have lived in poverty(Newhouse, Suarez-Becerra, & Evans, 2016).

The national population poverty rate in Indonesia has dropped from 24 % in 1998 into 10.86 %in 2016. From the total number of people who lived in poverty, in Indonesia, 40.22 % (11.26 million) of them were children. However, in the last five years, poverty reduction has occurred slowly. In addition, the majority of the population is still included in the vulnerable groups.

When the poverty line is multiplied by two (2 GK), then it is found that almost 60 % of Indonesian children live at a cost below23.625 IDR per day. This shows that vulnerable poor currently have precarious and insecure incomes (BPS, 2017). East Nusa Tenggara is one of the provinces in Eastern Indonesia with high percentage of poor children. Reviewing the distribution of poverty in Indonesia, the child poverty rate in East Nusa Tenggara Province is 26.42 % (Central Bureau of Statistics, 2017). This shows that child poverty is very sensitive to changes in the

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DOI: 10.37200/IJPR/V24I4/PR201497
Received: 16 Jan 2020 | Revised: 17 Feb 2020 | Accepted: 26 Feb 2020

International Journal of Psychosocial Rehabilitation, Vol. 24, Issue 04, 2020
ISSN: 1475-7192

poverty line. In other words, many Indonesian children are vulnerable to falling into poverty if economic conditions worsen.

UNICEF & SMERU (2013) argue that more than half of children in developing countries grow in poverty. This poverty makes children lose the abilities to survive. It makes children be more vulnerable to exploitation, abuse, discrimination, and stigmatization. Undeniable, children are the population group that feels the most impact of poverty (double vulnerable). Every child, who lives in a poor household, is vulnerable to multidimensional pressure that can affect their future. Furthermore, poverty prevents children from growing and developing according to their maximum potential.

Childhood poverty is the root of adult poverty. Poor children are more likely to have worse adult outcomes than non-poor children (Duncan et al. 1998; Oshio et al., 2009; Ratcliffe and McKernan 2010). The statement also refers to lower success in the labour market. Poor children tends to fail in labour market than non-poor children (Gregg and Machin, 1998). Poor children, with lack of access to survival, are likely to grow into poor adults who will be more likely to move poverty to their children when they become parents (Moore, 2005; Bird, 2007).

Studies of child poverty show that children poverty occurs not only in third world countries but also in developed countries (Gordon et al., 2003; Eurochild, 2007; Roelen 2010). Poverty during childhood raises several policy challenges. Even, developed countries such as the United States have not escaped the problem of children poverty. The cause of children poverty is the composition of the household and parental labour market participation. This problem is not insurmountable. It is proven that many of these losses can be overcome with appropriate public policies (Smeeding and Th'evenot, 2016).

Poverty in children is closely related to the characteristics of parents and the household where they live. This is in accordance with the result of study conducted by Nichols (2008). Using logistic regression, Nichols (2008) has found that the dominant factor affecting child poverty is the economic condition of the family which is constrained due to local government policies. Also, it was found that parental education and employment also influence the probability of reducing children poverty. Begum et al. (2012), in their research on Economic Growth and Child Poverty Reduction in Bangladesh and China, showthat economic growth can reduce child poverty. However, this is not always true.

Child poverty is found to be more widespread in Bangladesh than in China. There are many problems for rural children in both countries. To understand changes over time and between countries in child poverty, it is also necessary to consider changes or differences in income distribution as well as in demographic composition. It is a multidimensional problem since many factors cause children to be poor. A child's household condition, both from a monetary and non-monetary approach, dramatically influences whether a child is weak or not. Characteristics of the household, include household sex, the number of household members, and the job of the head of the household determine the poverty of the child. The proportion of poor children tends to be higher for the female.

Isdijoso et al. (2013) review the dimensions of poverty and disparity faced by children in Indonesia The results of the study indicate that the prevalence of deprived children in Indonesia is still relatively high. A condition that can be seen from the high proportion of children living below the international poverty line (international poverty

DOI: 10.37200/IJPR/V24I4/PR201497
Received: 16 Jan 2020 | Revised: 17 Feb 2020 | Accepted: 26 Feb 2020

line), which is \$ 2 per capita per day, is still more than 50 % (in 2009). Besides, the gap between the different characteristics of lowest poverty rates provinces and the highest poverty rates provinces, is wider than the gap between urban and rural conditions. Generally, poverty and deprivation experienced by children in the territory of East Indonesia, including East Nusa Tenggara region, is worse than the other regions in Indonesia.

One assumption with global regression modelling is that the relationship between child poverty and its determinants is globally constant. In some cases, this is appropriate, but in other cases, the static spatial model parameters serve to obscure local heterogeneity. There is significant variation that can lead to misleading and possibly counterproductive results. To overcome this weakness, statistical geographers offer Geographically Weighted Regression (GWR), a non-stationary geographic modelling technique designed to explore spatial heterogeneity in geographical datasets. GWR describes local variations that would be obscured by global models.

GWR is a prominent technique of the current study since the relationship between child poverty and its determinants is not stationary. The main objective of this research is to use the GWR to explore and analyse the specific effects of sub-district locations between child poverty and several determinants including the burden of dependents, poor child labour, poor elderly workers, poor agricultural sector workers, poor non-agricultural sector workers.

The analysis was carried out in a single framework and the results visualised on a series of maps. Overall, the motivation underlying this research is to take into account the spatial variation of the factors that influence child poverty, which has been largely ignored by traditional regression-based model studies.

II. RESEARCH METHOD

The data in this study were sourced from the Integrated Database for Poor Handling Program. The data coverage consists of 306 districts in the East Nusa Tenggara region as the province with the highest child poverty rates. The data include the number of children, child workers, elderly workers, agricultural sector workers, and the number of non-agricultural sector workers.

If the analysis uses the Ordinary Least Squares (OLS) model, then the relationship between the factors that cause poverty is the same in all regions. The relationship might differ by region, and therefore, raise to spatial non-stationarity. To overcome spatial non-stationarity, a Geographically Weighted Regression (GWR) model was used. In this model, the magnitude of the influence of each factor on poverty varies because it depends on the location where the data is taken.

Using the method of GWR, as proposed by Fotheringham et al. (2002),it is found that one can extend previous models of spatial inquiry by allowing the explanatory variables affect to change over geographical space rather than assuming that the variables have the same influence over all locations. This is fluently referenced from correcting for spatial autocorrelation that exists in the data. Traditionally methods for correcting for autocorrelation such as spatial error component models (Anselin, 1988) returns global parameters and does not allow for spatial variations in parameter values. The GWR model specification is presented as follows.

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \quad \ldots\ldots(1)$$

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Or more generally:

$$y_i = \beta_0(u_i v_i) + \sum_k \beta_k(u_i v_i) + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

In which $(u_i v_i)$ indicates that location of the point and $\beta_k(u_i v_i)$ is a realization of the function $\beta_k(u_i v_i)$ at point *i*. GWR recognizes that spatial variation in the parameters might exist and provides the models with a way that they can be recognized. The GWR model used in this study is as follows:

$$y_i = \beta_0(\mu_i, v_i) + \beta_1(\mu_i, v_i)X_1 + \cdots + \beta_5(\mu_i, v_i)X_5 + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

β is the regression coefficient, and ε is the residual. 55 is child poverty in sub-district i, □1 is a burden on dependents in sub-district i, 52 is child labour in sub-district i, 5 3 is theelderly worker in sub-district i, □4 is agricultural sector worker in sub-district i, 55 is non-agricultural sector worker in sub-district i.

An issue that can be raised is that in equation two, there more unknowns variables. Fotheringham et al. (2002) acknowledge this and do not consider the coefficients to be random; instead, they view them as a function of locations in space. In this model, the data closer to location i are weighted more heavily in the estimation than those further from i. the model is very similar to weighted least square in its operation. The weighting scheme can be written as follows:

$$\hat{\beta}(u_i v_i) = (\text{X'W } (u_i v_i)\text{X})^{-1}\text{X'W}(u_i v_i)\text{Y} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

The estimations are weighted according to the *n* by *n* matrix $\text{W}(u_i v_i)$ in which the diagonal elements are zero and the diagonal elemets are the weighting of each of the *n* observations for regression point *i*. This can be more clearly explained by considering the OLS equation:

$$\text{Y} = \beta\text{X} + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(5)$$

In which the β vector of parameters is estimated by,

$$\hat{\beta} = (\text{X'X})^{-1}\text{X'Y} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...(6)$$

The GWR extension of this is,

$$\text{Y} = (\beta \otimes \text{X})1 + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(7)$$

Each element of β is multiplied by the corresponding element of X. the matrix β now has *n* sets of parameters and the following form:

$$\beta = \begin{pmatrix} \beta_0(u_1 v_1) & \ldots & \beta_k(u_1 v_1) \\ \vdots & \ddots & \vdots \\ \beta_0(u_n v_n) & \ldots & \beta_k(u_n v_n) \end{pmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

Each parameter above is then estimated using

$$\hat{\beta}(i) = (\text{X'W (i) X})^{-1}\text{X'W(i)Y} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(9)$$

In which i represents a row in the matrix in 8 and W (i) is an *n* by *n* spatial weighting matrix of the form.

$$\text{W (i)} = \begin{pmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{in} \end{pmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

W is the weight given to data point n for location i. The function of the weighting scheme is Gaussian. The

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observation is defined as:

$$w_{ij} = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right] \qquad (11)$$

d is the distance between observation i and location j and b is the bandwidth, estimated by minimising the Akaike Information Criterion (AIC). The spatial weighting scheme in GWR can be made to adapt themselves to the size variations in the density of the data; larger bandwidths in sparser areas, and smaller in more highly concentrated areas. The essential idea is that for each regression pointi, there is an area of influence around I described by the weight in the estimation of the parameters than other. This will be used to highlight the degree of misspecification in the global model.

The technique of GWR allows the investigation of the demographic and employment roles as well as access to primary and public facilities in changing poverty patterns. It allows the influence of the explanatory variables to change over the geographical space rather than assuming that it has the same structure at all locations. In addition, by allowing parameter values to vary by geographic location, one can visually map individual parameter within a geographical information system (GIS). Such visual representation provides a powerful means to better understand the influence of the exogenous variables on poverty patterns.

III. Results And Discussion

Breusch-Pagan and White test results have shown that the OLS model does not meet spatial assumptions homoscedasticity (stationarity) at a significant level of 1%. Besides, the spatial autocorrelation test showed the Moran's Test I, Lagrange Multiplier (Lag), Lagrange Multiplier (SARMA) has a value of ρ-value <α (0.01). Thus it can be concluded that there is spatial autocorrelation. Non-Stationarity and spatial autocorrelation are violations of OLS assumptions. It makes the result of OLS is being biased and misleading the test results (Fox et al. (2001) and Zhang et al. (2004) in Shrestha (2006). OLS results in the use of OLS models, which are not appropriate need to be evaluated (Foody (2003) in Shrestha(2006)). The next step is to make GWR model (Nakaya et al., 2016). The estimation results of the GWR model using Windows Software Application for Geographically Weighted Regression (GWR4.09) is presented in the following table.

Table 1: Estimated Parameters of the GWR and OLS Models

Variable	OLS	$\hat{\beta}$GWR$[\beta\langle\widehat{\mu_i , v_i}\rangle]$		Sign $\hat{\beta}$ GWR = $\hat{\beta}$ OLS (%)	$\hat{\beta}$ GWR Sig. at $\propto$ = 5% (%)
		Min. Local	Max.Local		
Intercept	-38.816066***	-135.794063	49.956682	86.60	32.68
Dependency load	0.916352***	0.824478	0.961888	100	100
Child Labor	0.135179***	-0.271274	0.631047	42.48	48.04
Elderly workers	-1.202115***	-0.605039	-0.905031	100	100
Agriculture sector workers	0.052295***	-0.007209	0.193334	98.37	86.93
Non-agricultural sector workers	-0.000400	-0.107745	0.166312	17.32	58.82

*** = significant at 1% level ** = significant at 5% level

Source: Processed Data Result, 2019.

Table 1 shows that spatially, the burden of load effect on child poverty with a minimum regression coefficient of

DOI: 10.37200/IJPR/V24I4/PR201497
Received: 16 Jan 2020 | Revised: 17 Feb 2020 | Accepted: 26 Feb 2020

0.824478, a maximum of 0.961888 and significant at the 5% level of 100% from 306 districts. The yellow area (in the following Figure 1) shows a significant positive effect on child poverty in a spatially specific location in 306 districts in East Nusa Tenggara.

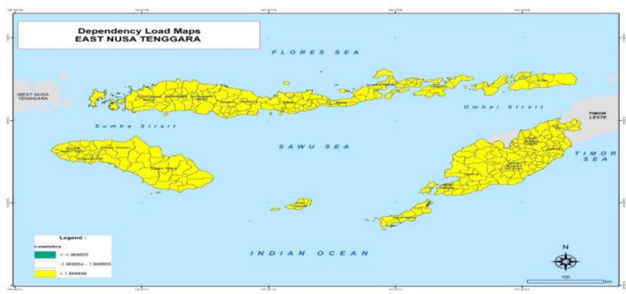

Fig. 1: The Significance of the Burden of Dependents on Child Poverty

The result of the current study is supported by research from Kim Rockli et al. (2016) and Dartanto and Otsubo (2016). They state that one of the determinants of poverty is the household size or the number of family members. According to Sachs (2006) and Jhingan (2002), poverty traps are caused by demographic traps, especially when low-income families have many children, causing problems in the provision of food, housing, household equipment, capital equipment, education and health.

Conditions in East Nusa Tenggara show that, in large families, the number of dependents is not only from a large number of children but also from parents and close relatives. In impoverished households, the average number of household members is six people, whereas in vulnerable households, the average number of household members is four people. The high dependency burden on poor and vulnerable low-income families causes the basic needs of children cannot be fulfilled adequately. Consequently, poor children are increasingly trapped in the cycle of poverty.

The problem of high dependency burden is caused by uncontrolled rate of birth. There are still many couples of childbearing age do not use the tools or methods of family planning. Therefore, they are not able to reduce the birth rate, even burdensome poor and near-poor families who tend to have a large number of dependents. This problem requires a strategy from the government of Indonesia, both central and district/city to the district and village levels. The Family Planning Program needs to be promoted continuously. Furthermore, health workers should continue to provide counselling to couples of childbearing age.

Poor and vulnerable poor couples are the main target since the information and knowledge about family planning are still low for them. If the program is carried out routinely and on target, then in the medium and long term, the burden of dependents on poor and near-poor families can be reduced. Reducing the burden of dependents can increase the fulfilment of basic needs and in the future, especially for children, to get out and avoid the pitfalls of poverty. Besides, it is necessary to pursue productive employment for workers who bear the cost of living for those who do not work (dependent burden), in this case, children and the elderly.

Table 1 shows that the child labour variable was spatially influencing child poverty with a minimum regression coefficient of -0.271274, a maximum of 0.631047, and significant at the 5% level of 48.04% (from 306 districts). Next, the following Figure 2 shows the significant positive influence found in 42 districts spread in western Flores

Island, eastern Sumba Island and SabuRaijua Island (in the yellow area). The significant negative influence of the green colour area is found in 105 districts spread on Timor Island, while 159 districts have no effect. It is shown in the white colour area spread on Flores Island, Lembata, Alor, Rote Ndao, and parts of Sumba Island.

Fig. 2: Significance of the Influence of Child Labour on Child Poverty.

The influence of child labour variables on poverty was significantly positive in various districts of western Flores Island and Eastern Sumba Island and Sabu Raijua Islands. This condition shows that child labourers do not get wages and work in unproductive sectors so that they do not earn income to meet the needs of children and their families. Moreover, a significant adverse effects are found in 105 sub-districts on Timor Island, that child workers can provide additional income to support themselves and even their families so that they can help reduce poverty.

Children tend to work when families experience crop failure, adults are unemployed, and low adult market wages cause families to become weak. Therefore, children work to be able to meet family needs or reduce family poverty. Ray (2000), Beegle et al. (2006), Duryea (2007), in Jacklin (2015) state that many economists believe that poverty is the main reason for child labour. Many children work to ensure the survival of their families and their children, but child labour today leads to poverty tomorrow. Child labour alleviates poverty and produces inter-generational poverty traps. However, a policy prohibiting child labour from working, even if it is conducted, can jeopardise the welfare of children and their families rather.

Endrawati's (2011) research results show that children work to not only fulfilling their own needs but also to meet the economic needs of the family. Low household income or family income makes the family mobilise all family members to work for fulfilling their daily needs, including mobilising children under working age (Suhu, 2013).

Conditions in East Nusa Tenggara show that child labour in poor families is more prevalent in rural areas. Children cannot withstand the effects of household poverty. Therefore, poverty that occurs in households has a significant influence on children. When a person lives in a low-income family, he experiences poverty. When poor and near-poor households do not have enough money, they cannot meet children's food, clothing, health and education needs. Also, children in poor households tend to be more vulnerable to poverty, especially if poor households experience unexpected events such as drought, rising food prices, and so on. In this condition, poor households can survive, but their children are forced to quit school to work for supplementing household income. Child labour is spread in various sectors such as agriculture, et al. For children who live in urban areas, they tend to be more absorbed in the non-agricultural sector.

DOI: 10.37200/IJPR/V24I4/PR201497
Received: 16 Jan 2020 | Revised: 17 Feb 2020 | Accepted: 26 Feb 2020

If child labour is seen as a reflection of poverty, it is recommended that the emphasis is on poverty reduction and not the direct handling of child labour problems. Child labourcan not be prevented, at least in the short term. It mus be more emphased on mitigating measures such as regulations that can prevent child abuse and provide a variety of support services for working children.

Next, as shown, Table 1 reveals the spatial variable of elderly workers. It has an effect on child poverty with a minimum regression coefficient of -0.605039, a maximum of -0.905031 and significant at the 5% level of 100% (from 306 districts). Significant adverse effects on spatial poverty in specific locations in 306 districts of East Nusa Tenggara are shown in the green area of Figure 3

Fig. 3: Significance of the Effect of Elderly Workers on Child Poverty.

The results of the analysis of the influence of the elderly worker variable on child poverty are significantly negative. It means that if older workers do work, it will reduce the poverty of children. The results of this study are in accordance with Affandi's (2009) research. Affandi (2009) states that elderlyare still working to fulfill their economic needs. Physically and mentally, the elderly are still able to carry out daily activities. Affandi (2009) states that there are many reasons for older people who still working. The reason includes physically and mentally.

The reason for the elderly work is to support themselves. Even, a few older people still support the family of their children and grandchildren who live with them. Generally, the elderly who live in rural areas still do work activities, and usually, they work in the agricultural sector. In the other side, the elderly who live in urban areas are generally involved in industry. This condition is also experienced by elderly workers in East Nusa Tenggara. Since there is contribution of elderly workers to meet the needs of families including the needs of children and grandchildren, the policy strategy, adopted by the central and regional governments, is to provide social protection programs. Besides, the empowerment program is based on the potential of local resources following the skills and physical conditions of the elderly.

Table 1 shows that the spatial variability of the agricultural sector workers has an effect on child poverty with a minimum regression coefficient of -0.007209 to a maximum of 0.93334, and significant at the 5% level of 86.93% from 306 districts. Next, in the following Figure 4, it is shown that there is a significant positive effect on child poverty in a spatially specific location in 266 districts. It is shown by the scattered yellow areas on Timor, Sumba, central and eastern Flores Island, Lembata Island, Alor, and Rote Ndao. There is no effect found in 40 districts indicated white areas. They are scattered in western Flores Island, SabuRaijua Island, eastern Alor and western Rote Ndao.

DOI: 10.37200/IJPR/V24I4/PR201497
Received: 16 Jan 2020 | Revised: 17 Feb 2020 | Accepted: 26 Feb 2020

Fig. 4: Significance of the Influence of Agricultural Sector Workers on Child Poverty.

The results of this study were supported by researches conducted by Takahiro and Dariwardani (2013) and Amarasinghe et al. (2005). In the other side, Nazara (2007) argues that poverty is always associated with the type of work in agriculture for rural areas. Suryahadi et al. (2006), argue that during the period of 1984 and 2002, both in rural and urban areas, it is proven that the agricultural sector was the leading cause of poverty. The study also shows that the agricultural sector contributes more than 50 % to total poverty in Indonesia. The high level of poverty in the agricultural sector causes poverty among household heads or residents who work in the agricultural sector to be higher than those who work in other sectors. Broeck and Maertens (2017)support the view that moving out of agriculture / small farmers is an excellent strategy to escape poverty for resource-poor households.

Poor residents in East Nusa Tenggara generally work in the agricultural sector which is identified with poverty. The magnitude of the poverty rate in the agricultural sector is related to the ability of the agricultural sector as a buffer for unemployment. Central and regional government policy strategies are needed to increase the incomes of poor workers in the agricultural sector. Agricultural sector development policy facilitated by the central and regional governments, followed by efforts of farmers or poor agricultural workers, include: empowerment of the food crops subsector covering rice and secondary crops consisting of corn, soybeans, peanuts, green beans, cassava, sweet potatoes; the horticultural crops sub-sector includes vegetables and fruits and medicinal plants, the estate sub-sector includes coffee, cocoa, coconut, cashew, candlenut, and the livestock subsector includes large, medium and poultry; and fisheries subsector. This empowerment is based on integrated local resources; ranging from farming subsystems, management subsystems, marketing subsystems that are integrated with supporting subsystems and services including mentoring and training, strengthening microfinance institutions and research and development.

Table 1 shows that the spatial variable of non-agricultural sector workers affected child poverty with a minimum regression coefficient of -0.107745, a maximum of 0.166312 and significant at the 5% level of 58.82% from 306 districts. Figure 5 shows the significant negative effect found in 30 districts on the western part of Flores on the green area. The significant positive influence of the yellow area is found in 150 subdistricts spread on the eastern part of Flores Island, Lembata Island and Timor Island and no effect on white colour is found in 126 districts spread on Sumba Island, central Flores, Alor Island and SabuRaijua.

DOI: 10.37200/IJPR/V24I4/PR201497
Received: 16 Jan 2020 | Revised: 17 Feb 2020 | Accepted: 26 Feb 2020

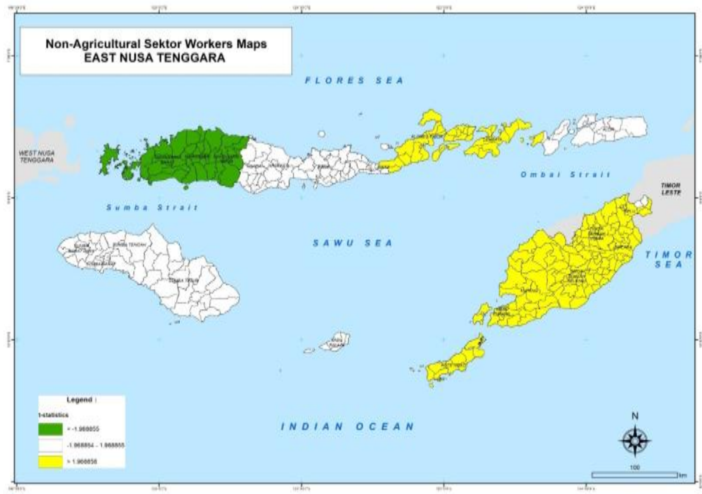

Fig. 5: Significance of the Influence of Non-Agricultural Sector Workers on Child Poverty.

The significant positive effect of the non-agricultural sector workers variable can be observed that poor workers who are absorbed by productivity are still deficient. Besides, the amount is still low since the non-agricultural sector demands adequate quality and expertise or skills, while poor workers cannot meet these qualifications. Non-agricultural sector workers consist of the mining and quarrying sector, manufacturing, electricity and gas, building/construction, trade, hotels and restaurants, transportation and warehousing, information and communication, finance and insurance, education services, health, society, government and individual. Takahiro and Dariwardani (2013), who conducted a study of chronic poverty and temporary poverty in Indonesia, showed that rural households whose heads work in the trade, service and financial sectors tend to have a lower chance of becoming poor than those working in the agricultural sector. Suryhadi et al. (2006) found that poverty among heads of households working in the agricultural sector was higher than those working in other sectors.

Conditions in East Nusa Tenggara show that employment in the industrial sector that develops in rural areas is small and landless farmers entering the small industry sector and the home industry is for survival or workers in the small industry sector. It is illustrated that the development of rural home industries that have lower incomes than farm labourers provides evidence that industries in rural areas are generally places where workers are sent from the agricultural sector. Most small businesses and even micro-businesses that employ family labour are only a means of survival. Facing problems like this, the effort to revitalise the development of small-scale industries and households based on local resources is a policy instrument that should be carried out by the central and regional governments of Indonesia. It is to improve the welfare of the community. Furthermore, small and household industries play a significant role in poverty alleviation because they are labour-intensive, require relatively little capital and a level of simple technology that makes it possible to work on the grassroots, both urban and rural.

IV. CONCLUSION

Spatially, the influence of dependent load, child labour, elderly workers, agricultural sector workers, non-agricultural sector workers on poverty varies individually in the location of sub-districts. The dependent load variable has a positive effect in all districts, while the elderly worker variable has a negative effect on the magnitude

DOI: 10.37200/IJPR/V24I4/PR201497
Received: 16 Jan 2020 | Revised: 17 Feb 2020 | Accepted: 26 Feb 2020

of the effect varying in each district. The variable of the agricultural sector workers has a significant positive effect on some sub-districts in East Nusa Tenggara except on the western island of Flores. The child labour variable has a significant positive effect in various districts of western Flores Island, East Sumba Island, Sabu Island and Raijua, while the significant negative effect is found in Timor Island, with different magnitude of influence. The variable of non-agricultural sector workers has a significant negative effect in several sub-districts of the western part of Flores, while the positive effect is significant in several sub-districts in the eastern part of Flores, Lembata and Timor. The results of this study provide direction for both central and regional governments in determining policies that should pay attention to aspects of the spatial heterogeneity of the sub-district area from various determinants of child poverty so that policies are right on target and children can be avoided and escape the poverty trap.

V. ACKNOWLEDGEMENTS

This study was funded by Yayasan Pendidikan Katolik Arnoldus and Widya Mandira Catholic University, Kupang, Indonesia.

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Received: 16 Jan 2020 | Revised: 17 Feb 2020 | Accepted: 26 Feb 2020

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