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Spatial Modeling of Infant Mortality Rate In South Central Timor Regency Using GWLR Method With Adaptive Bisquare Kernel And Gaussian Kernel

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ABSTRACT

Geographically Weighted Logistic Regression (GWLR) was regression model consider the spatial factor, which could be used to analyze the IMR. The number of Infant Mortality as big as 100 cases in 2015 or 12 per 1000 live birth in South Central Timor Regency. The aim of this study was to determine the best modeling of GWLR with fixed weighting function and Adaptive Gaussian Kernel in the case of infant mortality in South Central Timor District in 2015. The response variable (Y) in this study was a case of infant mortality, while variable predictor was the percentage of neonatal first visit (KN1) (X1), the percentage of neonatal visit 3 times (Complete KN) (X2), the percentage of pregnant get Fe tablet (X3), percentage of poor families pre prosperous (X4). This was a non-reactive study, which is a measurement which individuals surveyed did not realize that they are part of a study, with analysis unit in 32 sub-districts of South Central Timor Districts. Data analysis used open source program that was Excel, R program, Quantum GIS and GWR4. The best GWLR spatial modeling with Adaptive Gaussian Kernel weighting function, a global model parameters GWLR Adaptive Gaussian Kernel weighting function obtained by g (x) = 0.941086 - 0,892506X4, GWLR local models with adaptive Kernel bisquare weighting function in the 13 Districts were obtained $\mathrm{g(x)} = \beta_0 - \beta_0 \mathrm{X}_4$, factors that affect the cases of infant mortality in 13 sub-districts of South Central Timor Regency in 2015 was the percentage of poor families pre prosperous.

Keywords: Kernel, Adaptive bisquare, GWLR, Infant mortality

INTRODUCTION

Statistical modeling method by taking into account the spatial factor for each observation had developed by Geographically Weighted Regression (GWR) method. Through GWR, a model for geographic location dependent to data sets or geographically data based would be observed (Fotheringham, et.al, 2002). The GWR method was a development of global regression for continuous response variables to predict the models of data sets that had a binary response variable through a logistic model. This method was called Geographically Weighted Logistic Regression (GWLR) (Atkinson et.al., 2003).

GWLR statistical methods had advantages that if spatial data was heterogeneity if one independent variable got an unequal response at different locations in one research area, local form from logistic regression with observe to locations assuming that data had Bernoulli distribution, response variables (Y) are categorized, and predicted variables with response variables whose respective regression coefficients depend on the location of the data observed (Fotheringham, et al 2002). In this method, the parameter appraisal used weighting function. GWLR method parameters required weighting matrix that was weighting on the data in accordance with the proximity of the observation location. Fixed Kernel function had the same bandwidth at every point of the location, whereas the Kernel adaptive function had different bandwidth for each point of sight location. Weighting functions are often used Kernel Gaussian function and Kernel bisquare function. Both weighted functions were influenced by a measure of neighborness (neighborhood size) or commonly called as bandwidth. Bandwidth was used are the bandwidth that could minimize the value of cross validation obtained using Golden Section Search.

Infant mortality was a death that occurs in infants aged 0 -11 months (including neonatal). While the infant mortality rate is the number of infants aged 0 -11 months who died in an area at a certain period per number of live births in the region and at a certain time in 1000 live births (Ministry of Health RI, 2014). Infant mortality cases in East Nusa Tenggara Province fluctuated from 2013 to 2015, by 2013 cases of infant mortality decreased to 1,286 deaths or 13 per 1000 live birth and subsequently in 2014 infant mortality increased to 1,280 cases or 14 per 1000 live birth, then in 2015 increases to 1,388 (11 per 1000 live birth). Targeted in the strategic plan of East Nusa Tenggara Provincial Health Office in 2015 that the rate of infant mortality was targeted to drop to 1,305, but the target was not reached (deviation by 83 cases).

The trend of infant mortality rate in South Central Timor Regency was increasing in 2013 the number of infant mortality decreased from 125 to 96 cases, and in 2014 increased but in 2015 decreased. The drastic increase occurred from 2011 to 2012 from 66 to 125 cases. The number of infant mortality 100 cases in 2015 or 12 Per 1000 live birth, while the target of South Central Timor Regency in 2015 is 85 cases of infant mortality or 10 Per 1000 live birth. Geographical and topographic conditions with different demographic characteristics allowed variables that affect infant mortality among 32 sub-districts was different in South Central Timor Regency. Different IMRs in each sub-district had the possibility of different characteristic of each location of observation, So that the problem solved of infant mortality could not be generalized in every area of 32 sub-districts.

This study aimed to analyze the parameters on the best GWLR model to determine the factors affecting infant mortality rate in 32 sub-districts of South Central Timor Regency.

METHODS

This was a non-reactive study, which is a measurement which individuals surveyed did not realize that they are part of a study. The design of this study used secondary data from the health and population profile of South Central Timor Regency in 2015. The unit of analysis in this study was 32 sub-districts on infant mortality rate. Infant mortality rate in the sub-district, if 0 = Infant Mortality < 10 Per 1000 live birth or 1 = Infant Mortality Rate ≥10 Per 1000 live birth. Predictor variables affecting infant mortality are percentage of first neonatal visit (KN1) (X1), percentage of neonatal visit 3 times (KN Complete) (X2), percentage of pregnant get Fe tablet (X3) and percentage of poor family pre prosperous (X4) . Data analysis used open source program that was Excel, R program, Quantum GIS and GWR4 (to analyze the GWLR model with Kernel weighting function). The analysis steps (1) the area of South Central Regency on the thematic map falling into the category had the same color gradation and categorically had a different color, (2) testing the presence or absence of multicolinearity on predictor variable using correlation coefficient value and VIF values, (3) analyzed the GWLR model with the following steps: determining *ui* and *vi* based on southern latitude and east longitude in each sub-district in South Central Timor Regency, calculated euclidian distance between observation site based on geographical location, determine the bandwidth based on the distance of the central location with the nearest neighbor (q), calculated the weighting matrix by using the function that was entering by the euclidian distance and bandwidth into the adaptive bisquare Kernel and adaptive Gaussian Kernel for i = 1,2,3, ..., 32 then one location j would be obtained a weighting of 32, estimating the parameters of the GWLR model, performing simultaneously and partial test parameters, analyzing the goodness of fit test on the GWLR model and determining the best regression model by compared the GWLR model with the smallest AIC criteria, and made the best thematic modeling map of infant mortality rate.

RESULTS

Infant Mortality Description in South Central Timor Regency

Infant mortality rate in 2015 was targeted as 85 cases or if converted 10 per 1000 live birth. The number of live births 8,254. Infant mortality rate in 32 sub-districts was calculated by comparison of infant mortality reported in 2015 by community health centres to Health Department of South Central Timor Regency, based on sub-district with live birth rate in each sub-district by 2015 stated per 1000 live birth. Results of infant mortality rate calculated per sub-district were categorized into categories, if 0 = infant mortality <10 per 1000 live birth or 1 = infant mortality rate ≥10 per 1000 live birth. In 2015 the number of infant mortality amounted to 100 cases or 12 Per 1000 live birth. The spread of infant mortality in South Central Timor Regency could be described as below.

Figure 1 showed that from 32 sub-districts that included infant mortality rate ≥ 10 per 1000 live birth of 23 sub-districts wasdescribed in red zone, while 9 sub-districts whose infant mortality rate <10 per 1000 live birth were describe with green zone. South Central Timor Regency had 71.8% infant mortality cases. Factors predicted to affect infant mortality rate in South Central Timor Regency which was a predictor variable in this study as many as 4 variables. Here is the distribution of the 4 predictor variables:

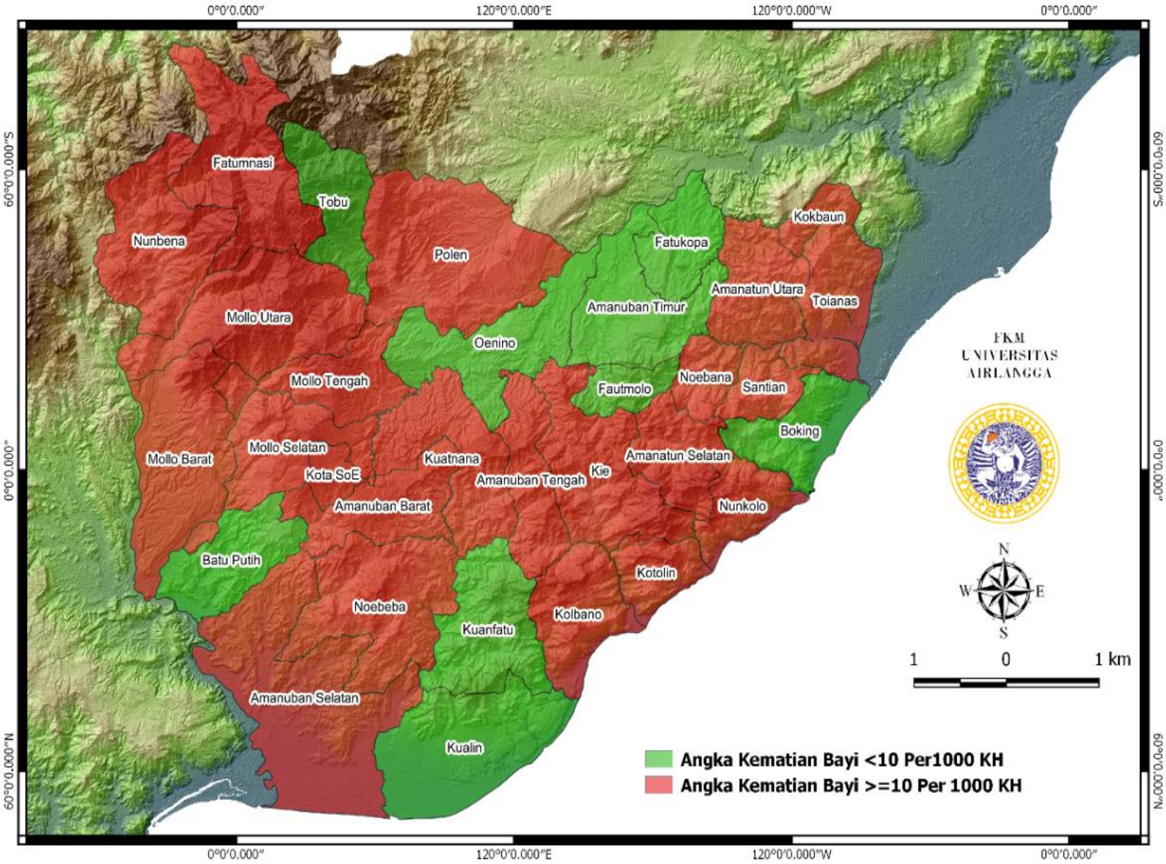

Figure 1. Map of infant mortality distribution by sub-district

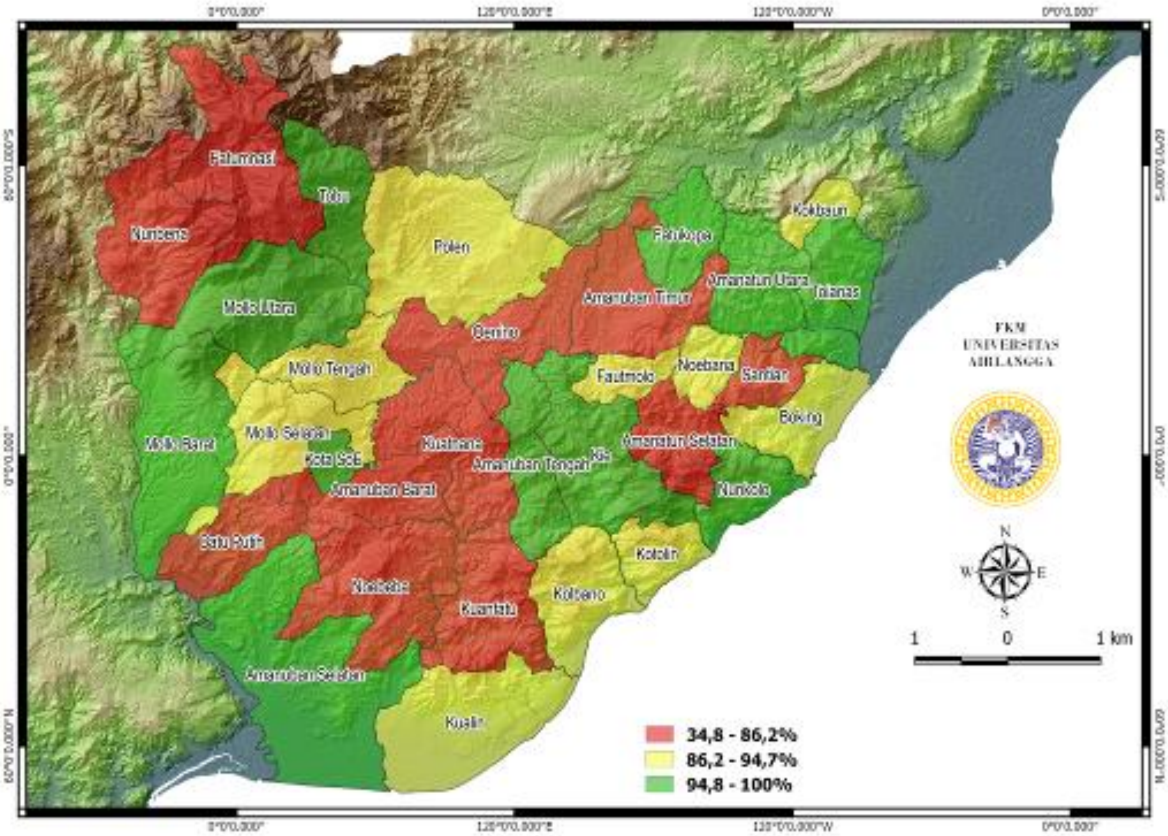

Figure 2. Thematic map of infant mortality distribution by the neonatal first visit variables

Figure 2 showed the percentage of neonatal first visit distribution (KN1) in red zone, yellow zone and geographically influenced zone) There are 11 sub-districts in red zone with coverage of 34.8% - 86.2%, from 11 neighborhood sub-districts that are Nunbena, Fatumnasi, Batuputih, West Amanuban, Kuatnana, Noebeba, Kunfatu, Oenino, East Amanuban, Southern Amanatun and Santian. Likewise the yellow and green zones of each sub-district had an influence due to the affiliation.

Figure 3 showed the spread percentage of neonatal visits 3 times (complete KN) in the red zone, yellow and green zone that geographically tends to affect each other. There are 11 sub-districts in the red zone with coverage of 47.13% - 79.4%, from 11 neighborhood sub-districts that are Fatumnasi, Nunbena, SoE, West Amanuban and Kuatnana. Likewise, the yellow and green zones of each sub-district had an influence due to neighborhood.

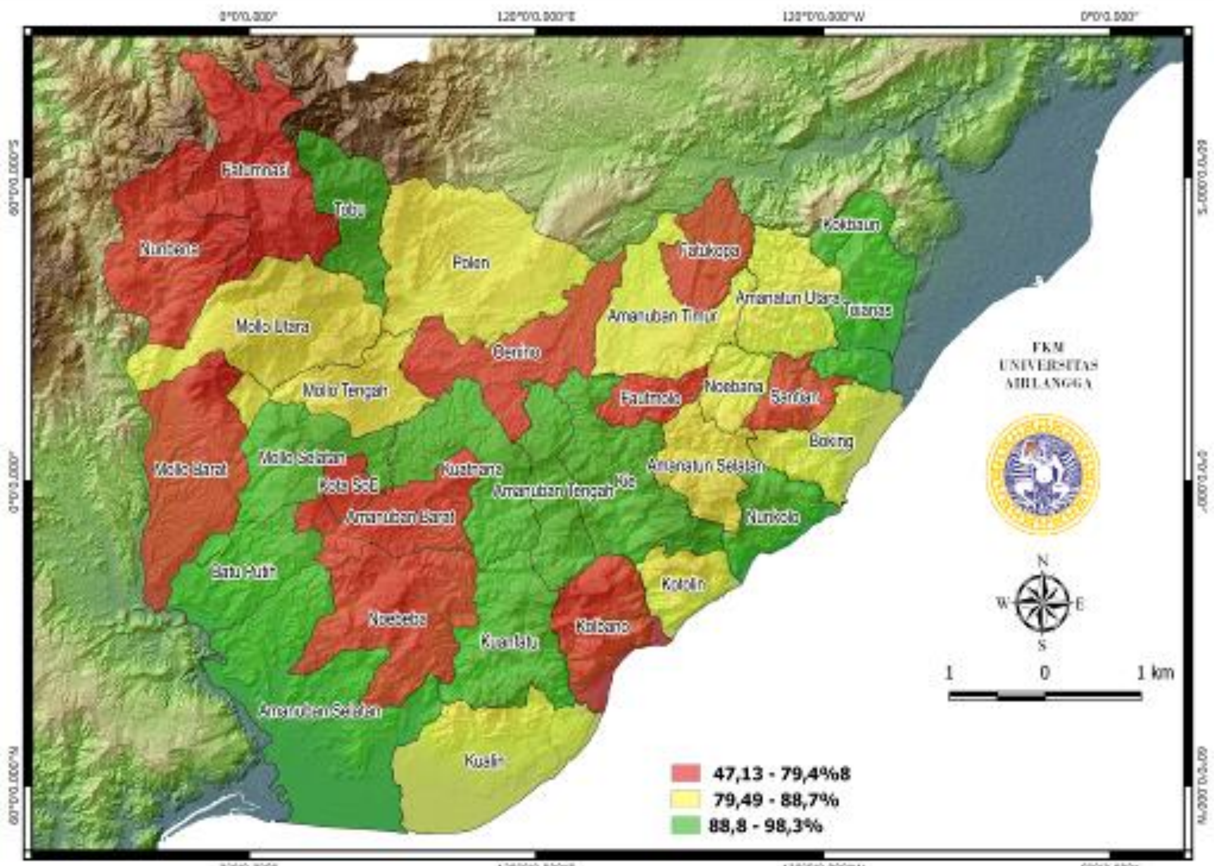

Figure 3. Thematic map of neonatal visit 3 times (complete KN)

Figure 4 showed the percentage distribution of pregnant getting Fe tablets, in red , yellow and grren zone areas that geographically tends to affect each other. There are 11 sub-districts in the red zone, with coverage of 26.20% - 64.40%, from 11 neighborhood sub-districts that are Kuatnana, Kuanfatu, Nunkolo, Boking, Santian, North Amanatun, Fatukopa and Kokbaun. Likewise, the yellow and green zones of each sub-district had an influence due to neighborhood.

Figure 5 showed the percentage distribution of poor pre prosperous family in red, yellow and green zone. Geographically, they tend to influence each other. There are 11 sub-districts in the red zone with coverage of 24.17% - 55.77% from 11 neighborhood sub-districts that are Kuatnana, Oenino, East Amanuban, Fatukopa, North Amanatun, Fautmolo, Noebana, Southern Amanatun, Santian and Boking. Likewise, the yellow and green zones of each sub-district had an influence due to neighborhood.

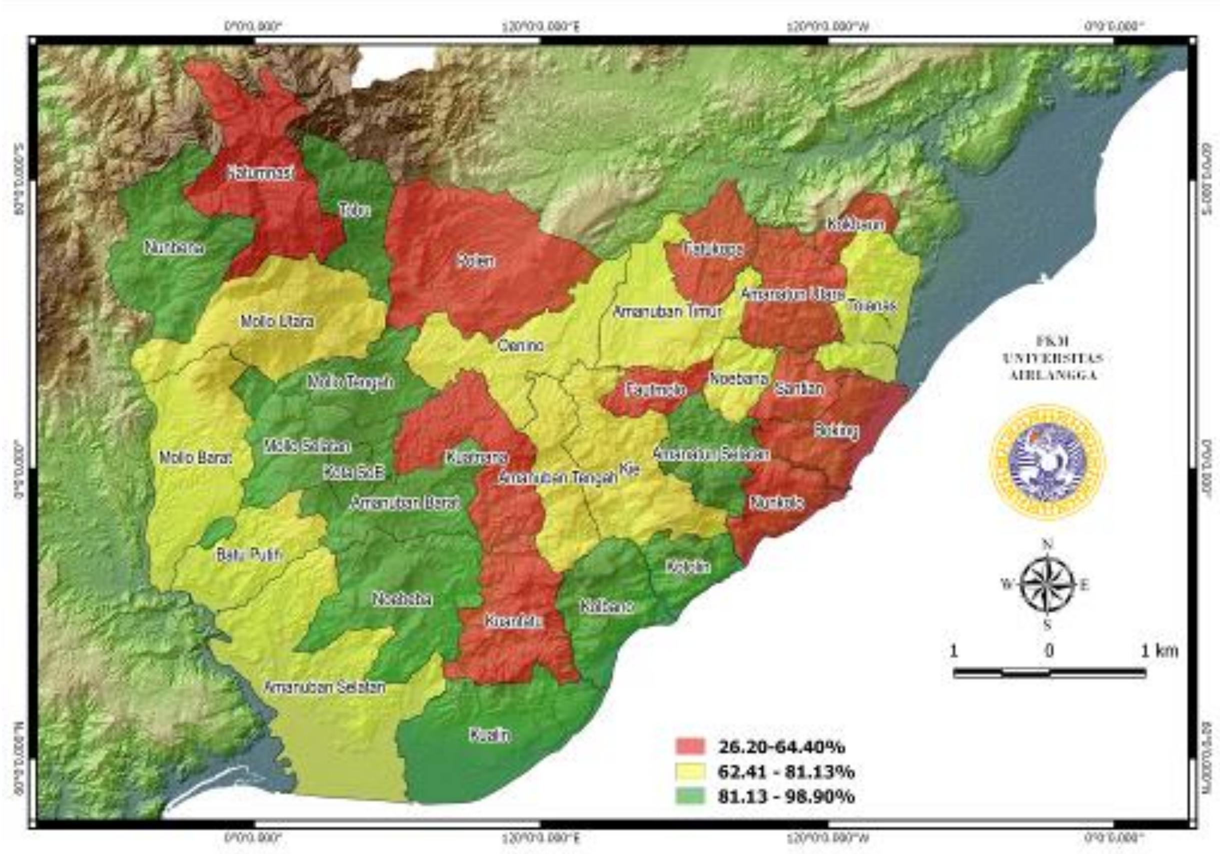

Figure 4. Thematic Map of the percentage pregnant gets fe tablets distribution

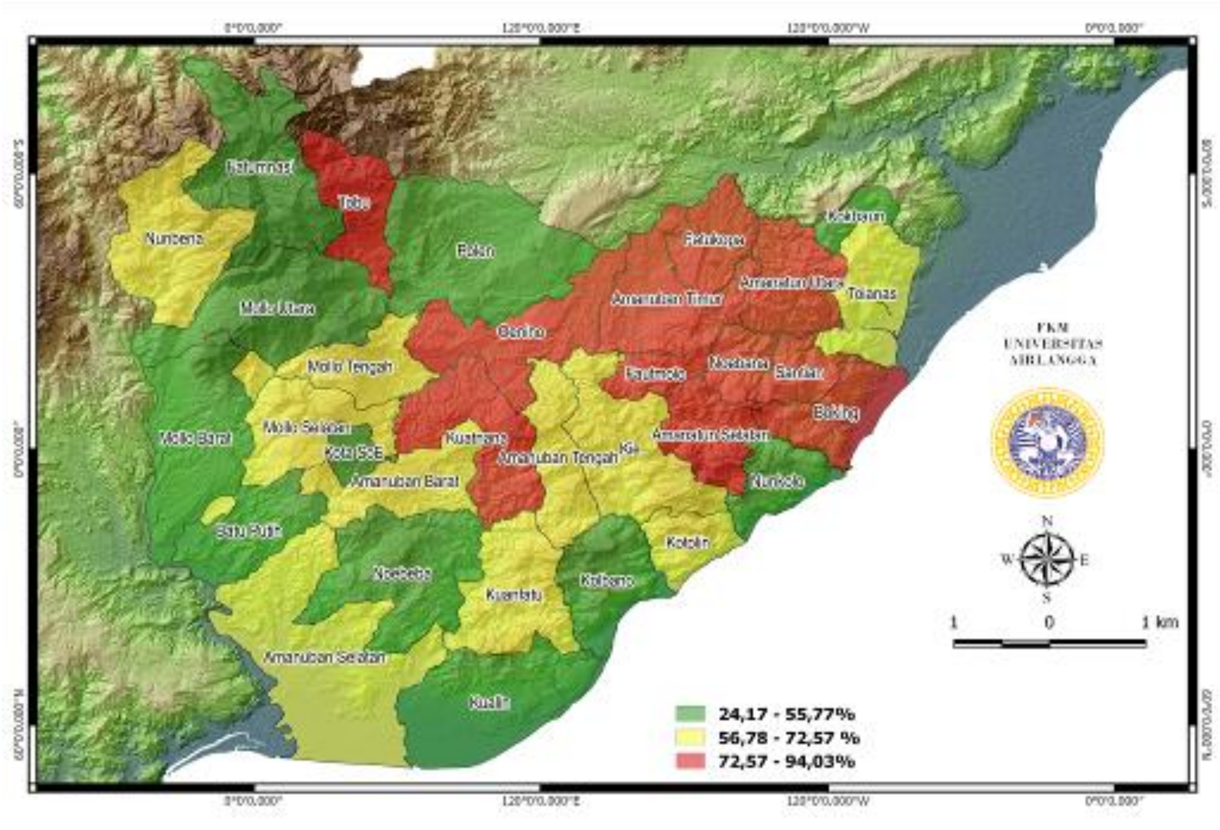

Figure 5. Thematic map of the percentage poor pre prosperous family distribution

Variables Predictors Multicolinearity Detection

Multicolinearity detection on predictor variables using Variance Inflation Factor (VIF) value

Table 1. VIF value between predictor variables

No	Predictor variable	VIF
1	Percentage of first-time neonatal visits (KN1) (X1)	1,052
2	Percentage of neonatal visits 3 times (Completed KN) (X2)	1,056
3	Percentage of pregnant get Fe tablet (X3)	1,053
4	The percentage of poor pre prosperous family (X4)	1,046

The VIF value of each predictor variable <10 indicated that the absence of a multicolinearity case among the predictor variables, thus the predictor variables were not correlated.

Table 2. AIC value of Adaptive Gaussian Kernel Wighting Function

No	Predictor variable	AIC value	Best bandwidth
1	Adaptive Bisquare Kernel	42,492958	32,000
2	Adaptive Gaussian Kernel	44.327890	31,000

Table 2 shows the AIC value of modeling of the Adaptive Bisquare Kernel weighting function l less than the adaptive Gaussian Kernel. The smaller the AIC value of a model, then better the model was formed, the smallest AIC value of 42,492958 in the adaptive Gaussian Kernel weighting function. The optimum bandwidth value is 32,000, which means there are 32 significant neighbors had spatial relationships in a region. The adaptive bisquare Gaussian Kernel weighing function then was used to perform the estimation process to analyze each sub district location (*ui, vi*), i = 1, 2, 3, ..., 32.

Parameter Ejection Model GWLR with Adaptive Weighing Function Bisquare Gaussian Kernel

Table 3. Estimation of global model parameter with Adaptive Bisquare Kernel Weighted Function

Variable	Parameter	Estimation	Standard Error	Z (Est/SE)
Intercept	β_0	0,941086	0,441471	2,131703*
X1	β_1	0,427695	0,405293	1,055274
X2	β_2	-0,294211	0,424029	-0,693848
X3	β_3	-0,184757	0,444051	-0,416071
X4	β4	-0,892506	0,518313	-1,721944*

*) Parameters that influential significant on α = 10% (Ztable = 1.64)

Table 3 showed significant parameters of β0 and β4 so that the global GWLR model for infant mortality rate in South Central Timor Regency was formulated as follows:

$$\hat{\pi}(\mathrm{x}) = \frac{\exp(0{,}941086 - 0{,}892506\mathrm{X}_4)}{1 + \exp(0{,}941086 - 0{,}892506\mathrm{X}_4)}$$

Or its logit transformation model was

$$\mathrm{g}(\mathrm{x}) = 0{,}941086 - 0{,}892506\mathrm{X}_4$$

The model provides information that the significant variables affecting infant mortality rate in South Central Timor Regency was the percentage of poor pre prosperous family (X4). Global model testing results obtained X4 significant, so it needs to do partial testing. Partial parameter test to determine the X4 predictor variable affecting infant mortality rate in South Central Timor District in each sub-district (*ui, vi*), the hypothesis form as follows:

H0: βi (ui, vi) = 0, (The parameter of βi had no significant effect on i location)
H1: βi (ui, vi) ≠ 0, (The parameters of βi had significant effect on i location)

Table 4. GWLR model with Adaptive Weighting Function Bisquare Kernel in each sub-district

No	Sub-district	β_o	β_4	T	GWLR Model
1.	Mollo Utara	1,568421	-1,939565	-1,906846*	$g(x) = 1{,}568421 - 1{,}939565X_4$
2.	Tobu	1,697587	-2,365938	-1,956991*	$g(x) = 1{,}697587 - 2.365938X_4$
3.	Fatumnasi	1,657304	-2,278198	-2,278198*	$g(x) = 1{,}657304 - 2{,}278198X_4$
4.	Nunbena	1,660958	-2,092516	-1,827952*	$g(x) = 1{,}660958 - 2{,}092516X_4$
5.	South Mollo	1,516956	-1,103989	-1,446581	-
6.	Central Mollo	1,624722	-1,182293	-1,425538	-
7.	West Mollo	1,624722	-1,182293	-1,425538	-
8.	Polen	1,720239	-1,821684	-1,982971*	$g(x) = 1{,}72039 - 1{,}821684X_4$
9.	Kota SoE	1,448534	-1,140706	-1,528359	
10.	West Amanuban	1,327806	-1,066745	-1,553021	
11.	Kuatnana	1,3478	-1,400024	-1,834505*	$g(x) = 1{,}3478 - 1{,}400024X_4$
12.	Batuputih	1,628531	-0,744493	-1,048349	-
13.	South Amanuban	1,50223	-0,412658	-0,647961	-
14.	Noebeba	1,294569	-0,523464	-0,877496	-
15.	Kuanfatu	1,090872	-0,261027	-0,479629	-
16.	Kualin	1,163209	0,003812	0,006651	-
17.	Central Amanuban	1,376401	-1,394877	-1,826082*	$g(x) = 1{,}376401 - 1{,}394877X_4$
18.	Oenino	1,706916	-1,873804	-1,960746*	$g(x) = 1{,}706916 - 1{,}873804X_4$
19.	Kolbano	0,916496	-0,234792	-0,456523	-
20.	Eaast Amanuban	1,481671	-1,364694	-1,864357*	$g(x) = 1{,}481671 - 1{,}364694X_4$
21.	Fatukopa	1,627277	-1,491971	-1,886823*	$g(x) = 1{,}627277 - 1{,}491971X_4$
22.	Fautmolo	1,291758	-1,1203	-1,718848*	$g(x) = 1{,}291758 - 1{,}1203X_4$
23.	KiE	1,154627	-0,9415	-1,556318	-
24.	Kotolin	0,901028	-0,451634	-0,885701	-
25.	South Amanatun	1,137436	-0,887726	-1,499847	-
26	Nunkolo	1,140465	-0,780596	-1,332794	-
27.	Boking	1,221148	-0,87206	-1,415976	-
28.	Santian	1,296447	-1,007526	-1,562947	-
29.	Noebana	1,336608	-1,101369	-1,665215	-
30.	North Amanatun	1,463154	-1,230734	-1,726461*	$g(x) = 1{,}463154 - 1{,}230734X_4$
31.	Kokbaun	1,575214	-1,343348	-1,766294*	$g(x) = 1{,}575214 - 1{,}343348X_4$
32.	Toianas	1,424332	-1,123418	-1,609606	-

*) Parameter that had a significant value on α = 10% ($t_{0,1;27)}$ = 1,70329)

Table 4 shows the β4 parameters that affect each sub district location in South Central Timor Regency. The results of the $|t_{hitung}|$ values on the predictor variable X_4, shown in table 4 using α = 10%, then the value (t0,1,27) = 1.70329, The decision taken was reject Ho when $|t_{hitung}|$ >, obtained parameters that significantly affect the sub-district is β4. The model, if it was assumed to decreased one percent of poor pre prosperous family (X4), then as big as β4 reduces infant mortality rate in each sub-district.

DISCUSSION

The best weights that had the smallest AIC value, the results showed that from the four Kernel weighted functions it was found that the AIC value of the adaptive bisquare Kernel weighting function is 42.492958 smaller than the AIC value of the adaptive Kernel weighting function. The adaptive Kernel function assigns different bandwidth values to each observation location. This was due to the ability of adaptive Kernel functions that could be adapted to the conditions of observation points. This function would had a large bandwidth value when the data at that location was rare, (Chasco, et al. 2008). In the adaptive Kernel function, the points of observation locations were dispersed densely around the location of the observation then the bandwidth obtained was relatively narrow. Otherwise, if the points of observation location had a distance relative far from the point of location of the observation to the bandwidth would be gained wider (Dwinata, 2012).

Significant predictor variable modeling results were poor pre prosperous family (X4) affecting infant mortality rate in South Central Timor Regency. The study results of UNICEF (2012) stated that the child mortality rate was related to poverty. Children in the poorest households generally had double child mortality rates more than in the wealthiest family. This was because richer households had more access to quality health and social services, better health practices and generally higher levels of education. The child mortality rate in urban poor areas was much higher than the average of child mortality rate in urban areas. Higher infant mortality was caused by diseases and associated conditions with excessive population density, as well as poor quality of clean water and poor sanitation. The results of infant mortality study in Donggala Central Sulawesi stated that infant mortality from big families generally tend to lack adequate health care, especially for poor children. Likewise, children born of unwanted pregnancies had a higher risk of death than children with a planned pregnancy. The socioeconomic characteristics of households were related to infant mortality, due to the better quality of household economy, the infant mortality rate was smaller, the social and behavioral characteristics of pregnant were related to the infant mortality rate, as the greater the level of mother's awareness of health behavior during Pregnant and childbirth, then the infant mortality rate was getting smaller. Result of Cahyono A D et.al (2015) research obtained poverty was positive and significant impact on infant mortality rate in Jember, poverty in the community would be the main cause of infant mortality rate.

CONCLUSION

The results of the analysis and discussion that had been described, so the conclusion were : (1) Predictor variables X1 - X4 in the red, yellow and green zones illustrated the distribution of predictor variables that had a tendency between neighborhood sub districts influence each other on observation data. (2) The AIC value of GWLR modeling of adaptive bisquare Kernel weighting function was smaller than the adaptive Kernel weighting function, the smaller AIC value of a model, then better the model formed in infant mortality rate, (3) The best GWLR spatial modeling in infant mortality rate in South Central Timor Regency were adaptive bisquare Kernel weighting function (4) GWLR global model parameters with adaptive bisquare Kernel weighting function obtained by equation $g(x) = 0{,}941086 - 0{,}892506X_4$ whereas the local model parameter of GWLR with the adaptive bisquare Kernel only in 13 sub-districts was obtained $g(x) = \beta_4 - \beta_4 X_4$.

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