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Geographic Modeling on The Infant Mortality Rate In West Java

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Abstract. In geographic modeling, global models such as ordinary linear regression (OLR) model theoretically it provides quite reliable local information if there is not any spatial diversity by region. In other words, OLR model cannot describe the relations between variables in heterogeneous difference of each region. This study will consider a model that will be used to estimate or predict the infant mortality rate in the several regencies / cities in West Java Province. Because the response variable observed in this study is count data which is assumed Poisson distributed, geographically weighted Poisson regression model (GWPR) is used. A better model is used to analyze the data of infant deaths in each regency / city in West Java based on the AIC value, GWPR model has the smallest value (compared to Poisson regression model), in which there is an interesting and important difference from each regency/city about the factors that significantly influence the Infant Mortality rate in each region.

Keywords: geographically weighted Poisson regression, Poisson regression, Infant Mortality Rate.

Introduction

Infant mortality rate (IMR) is one of the important indicators to determine public health level. A successful health development plays an important role in improving the quality of human resources of one country. Health development is aimed to achieve international commitments which are outlined in the Millennium Development Goals (MDGs). One of the MDGs points is to reduce child mortality. For the last decades Infant mortality rate tends to decline and the health level has improved, this is indicated by the increasing life expectancy of the population. Based on the results of the SP in 1980, infant mortality rate (IMR) in West Java was 134 per 1,000 live births, meaning on average for 1,000 live births, 134 babies were presumed to die.

This condition reflects the degree of public health was still low at that time. The government made some efforts to improve the health level such as providing community health centers for much easier access to have health services and giving health education by child center and health staff . These efforts were able to decrease the infant and maternal rate. In 2003, the Infant Mortal Rate of West Java declined to 42.50 per 1,000 live births or an average of for every 1,000 live births, only 42 babies died and in 2004 dropped to just 41.72 per 1,000 births.

Some research suggests that the high rate of infant mortality is not simply due to a medical problem, but also very fundamental non-medical problems (basic and large), such as lack of health infrastructures, people live in a remote area where it is difficult to access health centers, lack of a midwife, low economy level and human error such as the mothers factor. Indonesia Demographic and Health Survey in 2002 to 2003 collected various information. One of which is the infant mortality which is classified by socio-economic characteristics and biodemografic.

The socio-economic variable includes housing, education, and wealth quintile index. Biodemografic variable includes maternal age, parity and birth interval. Some other variables that affect infant mortality

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include infant weight at birth, antenatal care and birth attendants, as well as complications during childbirth.

High Infant mortality rate cannot be ignored because child survival determines the quality of human resources in the future. Therefore an intervention to decrease infant mortality race is needed. An effective intervention can be done if the significant factors that affect infant mortality can be recognized. Basically, identifying these factors can be done through *ordinary linear regression* (OLR).

Ordinary Linear regression analysis based on the assumptions that must be fulfilled, for example, the assumption about the residues that must be normally distributed and independent, and has homogeneous variances. In social research, especially the data which is obtained through a survey such as data on infant mortality often provides a response variable that is spatial-non stationary, which depends on the region or area observed. In the regional-based modeling, theoretically global model provide quite reliable local information if there is no spatial diversity by region. In other words, OLR model can describe the relations among variables in homogenous diversities between the regions.

The consequences of any violation to these assumptions are on the value of standard error estimator parameter. If the standard error estimator of this parameter is used to calculate the confidence /trust interval and to conduct statistical hypothesis testing, it will obtain a very small average. This will result in a very short confidence interval and the hypothesis testing will reject null hypothesis. In other words, in conducting an analysis of this case, this will enlarge the wrong type I, which means that the opportunity to reject the null hypothesis that should be accepted becomes bigger.

Based on this, it is necessary to find a model that has the right statistics solution in determining the functional relationship between responses and the number of predictor variables, where the response variable is dependent and there is spatial diversity between regions.

Indonesia has implemented a model that considers the spatial diversity between regions. One of them is implemented by Jajang,et al (2013) who implemented spatial panel statistics model to analyze data about the poverty in Indonesia. Meanwhile, Hajarisman, *et al* (2013) used Bayes Poisson model of a two-level hierarchical to predict infant mortality rate. In that study, the unit of observation is the level of regencies in Bojonegoro, East Java Province.

This study considerd several models that will be used to estimate or predict infant mortality rate in some regencies/ cities in West Java Province. There are three models that will be studied in this research which is a regression model by taking into account spatial effects. Because the observed response variable is in discrete data which is assumed to have Poisson distribution, then these models are *geographically weighted Poisson regression* models (GWPR).

Based on the results obtained from these models, they are then analyzed to determine a model that has the highest degree of matching (according to relevant various statistical measures), in order to obtain valid information about the factors that affect infant mortality in West Java province.

The objective of this study is to provide an alternative for the observers and users of statistics who are interested in the application of spatial statistics modeling. In particular, there are two main objectives to be achieved from this study namely: choosing the right model to analyze relations between response variable and one or more predictor variables where there are problems of spatial diversity by region; and to identify factors that significantly affect infant mortality rate in West Java Province based on geographic modeling.

This study needs to be conducted considering the regression modeling which is widely used today are still using ordinary linear regression model that ignores the effects of inter-regional spatial diversity. If the classical model is applied universally in all regions, then the form of the relations becomes invalid. This will lead to a wrong conclusion about the phenomenon that is being studied.

The results of the study of regional development - based model will be applied to predict the factors that significantly affect the infant mortality rate in West Java province. The high Infant Mortality Rate in West Java Province cannot be ignored because child survival determines the quality of human resources in the future. An intervention is necessary to decrease infant immortal rate.

An effective intervention can be made if significant factors that affect infant mortality are recognized. Therefore, the findings of this study can be used by local governments to determine more targeted policies, especially the policies that relate to the development of health sector.

The concept of Infant Mortality

The Strategic Plans of the Government of West Java in 2008-2013 stated that the main strategy to improve the quality of Human Resources (HR) is by professionally improving education and health managed through life cycle approach and professional empowerment. Health development is intended to improve people's health by reducing mortality, especially infant mortality rate, maternal mortality rate and toddler mortality rate. In addition, there should be some efforts to improve the quality of environmental health and community healthy behavior.

There are some interesting indicators such as infant mortality, morbidity and nutrition issue. The degree of people's health is affected by several factors such as culture, lifestyle, education, welfare, and others. Cultural factor is related to people's habits in general, for example; people build house next to their animal cage , people do not throw trash to the right place, and people use river/ sewer water as the source of clean water.

Meanwhile, lifestyle involves mass behavioral changes due to the influence of new values that are considered to be modern such as smoking, drinking, eating fast food. In fact, those habits are not healthy and bring disease. The low level of public education makes it difficult for people to access health facilities, and fulfill nutrition needed.

Some indicators that reflect the level of people's health is infant mortality rate (IMR), crude death rate (CDR), nutritional condition, and life expectancy. The number of these indicators is closely related to the education level of the family, especially the mother, healthy behavior, hygiene, and environmental health and the availability health care facilities.

In addition to those factors, the level of IMR is also influenced by the time of delivery, breast-feeding and food, as well as immunization. Therefore, the duration of breastfeeding and complete vaccinations need to be considered.

To monitor the results of human development, high infant mortality rate reflects a lot of things. The low level of the use of health care, malnutrition, environmental contamination and lack of education of the mother are the factors which influence IMR. Therefore, the effort to reduce IMR is by improving education for women. Patrilineal culture, which prioritize the education of boys over of the girls is adopted by most of society, is expected to be eliminated. Thus the gap of human resources quality between women and men is not too far.

The infant mortality rate in West Java over the past decades tends to decline and the health of people gets improved indicated by the increasing life expectancy of the population. Based on the results of SP in 1980, infant mortality rate (IMR) in West Java was 134 per 1,000 live births. This means that in every 1,000 live births, there were 134 babies that died. This number reflects the low level of people's health. Since some attempts to improve people's health level, such as an easier access for people to have health services in hospitals and health care centers and education program on the health of kids and maternal hospitals and health care staff, infant and maternal mortality rate has decreased. In 2003, the IMR in West Java was 42.50 per 1,000 live births or, on average 42 babies died in every 1,000 births and in 2004 the rate dropped to just 41.72 per 1,000 births.

In terms of gender, the attainment of female infant mortality rate is relatively better than that of males. The data shows that in 2004, female IMR was 40.44 per 1,000 births which is relatively lower than male IMR which was at 45.12 per 1,000 live births.

Viewed from the perspective of human development, the efforts to improve health status through a decline of infant mortality rates requires the effort in considering the ideas about ways to intervene problems of health, especially the health of mothers, infants and children, and specifically focusing on rural areas . The health service coverage in West Java has not been optimal because West Java is a large province .Therefore; main priority of health service is in the areas where the IMR is quite high such as north coast and southern West Java.

Based on the data, in 2004 the

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IMR of those areas is high, such as in Karawang regency which IMR is 55.70 per 1.000 live births, and followed by Cirebon (54.46 per 1,000 live births), Indramayu (53.89), Majalengka (48.50) and Bekasi (46.61). Meanwhile, in the southern regions of West Java, The IMR with high infant mortality rate are Garut (53.79 per 1,000 live births) , and Tasikmalaya (48.75) and Cianjur regency (50.87).

The high rate of infant and child mortality cannot be ignored because child survival determines the quality of human resources in the future. Therefore, a proper intervention to decrease mortality rate is necessary. Effective intervention can happen if the significant factors that affect child mortality are found.

Various empirical studies that have been done regarding infant mortality rate show that the factors that affect child survival are not only health sectors such as numbers of health care, midwife, and health infrastructure but also non-health factors such as the education level of the parents and household income.

Infant Mortality Rate (IMR) is the number of infants who died while being younger than one year old per 1,000 live births in a year. Furthermore, IMR is calculated using this formula:

$$AKB = \frac{Y_{0-<1\text{year old}}}{\sum live\ birth} \times 1000$$

Where: $Y_{0-<year}$ is the Number of Infant mortality (aged younger than 1 year) in a certain year in a certain area. Σ is the number of live births in a given year in a given area.

Geographically Weighted Poisson Regression Model

To identify the factors that significantly affect the infant mortality rate, some previous studies used ordinary linear regression (OLR). OLR method is based on ordinary least squares method to estimate the parameters of the model. According to Montgomery and Peck (1992), there are three main problems in the least squares analysis.

The three problems are related to the failure to meet basic assumptions, namely: normality, homogeneous variance and mutually error-free. The other issues that also arise are outlier's data that has a potential to be influential data, specification improprieties of functional form of the model, as well as a strong dependence between multicollinearities.

However, in a geographic modeling, global models such as OLR method theoretically can provide reliable local information if there is no spatial diversity between the regions. In other words, OLR model can recognize the relations between variables when the observation between regions tends to be homogeneous, which mean that the measurement of the shape of the relationship does not depend on the region.

This condition is also referred to as spatial stationary (Fotheringham et al., 2002). In the study of social science and public health, such as the study of infant mortality, in general the objects of the study (e.g., provincial or regency / city) are not stationary. Therefore, OLR model is applied universally in all regions, this kind of relationship becomes invalid because it ignores the spatial diversity.

To overcome these problems, there are statistical models that accommodate spatial diversity between regions using spatial statistic. One of the approaches that can be used to create a spatial non stationary model is *geographically weighted regression,* GWR) which was first introduced by Brunsdon et al. (1996, 1999). This model is an extension of the weighted regression model where the weights used in the GWR is based on the relative position or distance between regions (Leung et al., 2000). In GWR model, the local parameters are estimated by setting a greater weight on the adjacent observation compared with a greater distance, so local parameters tend to vary by regions (Jetz et al., 2005).

By using GWR model, each region will have its own estimate model. GWR model is already widely applied to areas such as the socio-economic and demographic, as indicated by Propastin et al. (2006), Pavlyule (2009), and Shariff, et al. (2010).

The general form of GWR model is:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \qquad \dots (1)$$

Indicates *the location of the observation the i- times* in geographical space, *is the number of parameter of the i- times observations.* Different from OLR model, the parameter estimator vary by region. Therefore, this model is very useful to show the local parameter estimator (Mennis, 2006). Estimator of is *obtained through weighted least squares method.*

GWR model which has been discussed in the previous section is a regional-based model for data or a response variable which is continuous, especially following the normal distribution. GWR model is then developed for data with response variable in discrete data, especially in the form of *count data.*

Discrete data in the form of count data is generally assumed to follow Poisson distribution, so the model that can be used to model the count data is geographically *Weighted Poisson Regression* (GWPR) model. GWPR model makes a local model parameters estimator for each point or location where the data is collected.

GWPR model can be written as follows in equation

$$\mu_i = \exp\left(x_i^T \beta(U_i)\right) \quad \text{... (2)}$$

In which

$$x_i = \left(1 \quad x_{1i} x_{2i} \ldots x_{pi}\right)^T$$

$$\beta(U_i) = \left(\beta_0(U_i)\beta_1(U_i) \quad \beta_2(U_i) \ldots \beta_p(U_i)\right)^T$$

$U_i = (u_i, v_i)$ = *(The coordinates (latitude, longitude) the i-location*

The estimation of GWPR model parameter can be done using method of *maximum likelihood estimation* (MLE). Parameter estimator is obtained by maximizing its log-likelihood function by decline it on k, then the result is null.

The equation is an implicit equation and therefore, to solve the problems, a numerical iterative procedure is used. Numerical iterative procedure uses iteratively reweighted least Square (IRWLS) method. GWPR model parameter estimator model is as follows:

$$\beta^{(m+1)}(U_i) = \left(X^T W(U_i)^{(m)} A(U_i)^{(m)} X\right)^{-1} \left(X^T W(U_i)^{(m)} A(U_i)^{(m)} z(u_i)^{(m)}\right) \quad \text{... (3)}$$

in which:
X: matrix predictor, denoted as follows:

$$\begin{bmatrix} 1 & x_{1,1} \ldots & x_{k,1} \\ 1 & x_{1,2} \ldots & x_{k,2} \\ 1 & x_{1,n} \ldots & x_{k,n} \end{bmatrix}$$

$W(U_i)$: *Weighted matrix, denoted as follows:*

$W(U_i)$ = diag $[w_{i1} w_{i2} \ldots w_{in}]$

$A(U_i)^{(m)}$:*Weighted Variance matrix that is associated with Fisher scoring* for each location- i, denoted as follows:

$$\mathrm{A}(U_i) = \mathrm{diag}\left[\hat{y}_i\left(\beta^{(m)}(U_i)\right)\hat{y}_2\left(\beta^{(m)}(U_i) \ldots \hat{y}_n\left(\beta^{(m)}(U_i)\right)\right]\right.$$

And (u_i) *: adjusted vector* of response variables, defined as follows:

$$z^{(m)}(U_i) = \left(z_1^{(m)}(U_i), z_2^{(m)}(U_i), \ldots, z_n^{(m)}(U_i)\right)^t$$

$$z_j^{(m)}(U_i) = \left\{\left(\frac{y_i - \hat{y}_i\beta^{(m)}(U_i)}{\hat{y}_i\beta^{(m)}(U_i)}\right) + X_i^T\hat{\beta}_{(m)}(U_i)\right\}$$

$$z_j^{(m)}(U_i) = \left\{\left(\frac{y_i - \hat{y}_i\beta^{(m)}(U_i)}{\hat{y}_i\beta^{(m)}(U_i)}\right) + \left(\beta_0^{(m)}(U_i) + \sum_k^K \beta_k^{(m)}(U_i)x_{k,j}\right)\right\}$$

$$z_j^{(m)}(U_i) = \left\{\eta_j\beta^{(m)}(U_i) + \left(\frac{y_i - \hat{y}_i\beta^{(m)}(U_i)}{\hat{y}_i\beta^{(m)}(U_i)}\right)\right\}$$

The testing of the model feasibility that is obtained from parameter estimation, carried out using the method of Maximum Likelihood Ratio Test (MLRT) by testing the following hypothesis:

$H_0 : \beta_k(u_i, v_i) = \beta_k, k=1,2,\ldots,p$: *(There was no significant difference between the Poisson regression model and GWPR)*

Against

H_1 : *At least one* $\beta_k(u_i, v_i)$ *related to the location* (u_i, v_i)*(there is a significant difference between Poisson regression model and GWPR).*

$$D(\hat{\beta}) = -2ln\left(\frac{L(\hat{\omega})}{L(\Omega)}\right) \quad \text{... (4)}$$

$D(\beta)$ *Also called likelihood ratio statistic, in which this statistic is an approach ofdistribution with degree of freedom* ($n - k - 1$) in a model, that is being observed, is true, $D(\beta)$ and is *also called the likelihood ratio statistic. Conformance testing of GWPR Poisson regression model is indicated by model A with a degree of freedom* d and *GWPR model is indicated with model B with degrees of freedom* d, *therefore:*

$$F_{calculate} = \frac{Deviance\ Model\ B/\ \mathrm{d}f_A}{Deviance\ Model\ B/\ \mathrm{d}f_B} \quad \text{....(5)}$$

The testing criteria is rejecting H_0 if $F_{calculate} > F_{(\alpha;\ df_A;\ df_B)}$

Model parameter testing is conducted by testing the parameter partially. This testing is conducted to see which parameters that significantly affect the response variable.

The hypothesis is as follows:

$$H_0: \beta_k(u_i, v_i) = 0$$

$$H_1: \beta_k(u_i, v_i) \neq 0; k = 1,2,\ldots,p$$

Test statistic can be used in hypothesis testing as follows:

$$t = \frac{\widehat{\beta}_k(u_i)}{Se(\widehat{\beta}_k(u_i))} \quad \text{... (6)}$$

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The testing criteria is rejecting H_0 *if*

$|t_{calculate}| > t_{\frac{\alpha}{2}; \mathrm{n-(p+1)}} \ldots$

In the spatial analysis, parameter estimation on one point (u_i, v_i), will be more influenced by the nearest spots to the location (u_i, v_i) than to the farther points. Therefore, *the selection of spatial weighting that is used in estimating the parameters in the equation becomes very important. A weight used is the kernel function as defined below:*

$$w_j(u_i, v_i) = \begin{Bmatrix} \left(1 - \left({}^{d_{ij}}/_{G}\right)^2\right)^2, for\ d_{ij} \leq G; \\ 0\ , for\ d_{ij} > G \end{Bmatrix} \quad \ldots (7)$$

Furthermore, to get the best model, a number of models must be evaluated. The method that is used to select the optimum bandwidth and the best model for GWPR use *AIC (Akaike's Information Criterion).*

The best model to analyze the number of infant deaths in East Java Province is the model with the smallest *AIC* value.

AIC = D (G) + 2K (G) ... (8

where D (G) = $(,\sum_i^N (y_i \log \hat{y}_i(\beta(u_i)), G)/y_i + \ (y_i - \hat{y}_i(u_i), G))$ *and* K (G) = the number of parameters in the model with the *bandwidth* (G).

Research materials

Materials or data that are used for this study is secondary data, where the source of the data used in this study is data taken from a survey that was by the Central Bureau of Statistics (BPS). This included the Socio-Economic Survey National (SUSENAS) and Indonesia Demographic and Health Surveys (IDHS).

The main points or components of information that can be extracted from the data taken from *SUSENAS* in 2007 are: Main description of Household; Information about Household Members; Mortality Since year 2004; Individual information About Toddler Health; Education; Employment; Fertility and family planning; Housing; Household expenditure; other Socio-Economic information and Technology and Information.

The data from SDKI is specifically designed to collect various information about birth rate, mortality rate, prevalence of family planning and health, especially reproductive health. The general objective of organizing the SDKI is to collect information about mother and children health and information regarding to reproduction health, family family planning prevalence, knowledge about AIDS and IMS and vaccination prevalence.

According to the type of data or information that had been collected, the questionnaire that was used included questionnaires for, household data collection of household and a questionnaire for individual data collection.

Research variables

A number of variables that will be used in this study are the variables that are considered to affect the infant mortality rate. The observed response variable is BM variable, i.e. the number of infant deaths (aged younger than 1 year old) in a specific year in a specific region (regency or city). The LH variable is a variable which expresses the number of live births in a specific year in a specific area. Then, there are 10 predictor variables that will be observed in this study, all of which are presented in Table 1.

Table 1
Variables and Definitions

NAKES	=	The percentage of baby-labors that are not helped by a health care staff is the percentage of laboring mothers in a certain area and certain time. Health care service that is provided by professional staff, midwife – assistants, specialists, doctors, midwives, and nurses.
KN1	=	The percentage of mothers who do not check their infants in health care. A number of infants who are younger than one year old (29 days-11 months) to have health service
MSKN	=	Percentage of people who live under poverty
ASI	=	Percentage of infants who do not receive exclusive breast-feeding. Exclusive breast feeding is where infants only receive breast feeding as the only food source until they are six months old.
RIST	=	Percentage of risti pregnant women, Risti pregnant woman is an abnormal pregnancy that causes pain and death to the mother and the infant.
POSY	=	Percentage of availability ratio of mother and child health care on number of population.

RSHT	=	Percentage of unhealthy house. A healthy house requires a clean toilet, a good trash system, clean water, pollution–waste system, good air ventilation system, a balance between the size of the house and people, and the floor of the house is tiled.
PEND	=	The last education level of the mothers (counted in years of education level).

K1	=	Percentage of pregnant women who do not come to health care to receive health service from professionals (gynecologists, general practicioners,midwives and nurses) during their pregnancy.
RTKS	=	Ratio of professionals and public health staff to the number of population.

Table 2
Population Statistic of West Java

Number.	**Regencies/ Cities**	Area Km^2	Districts.	Number of Population	Population Density	Number of live births	Number of infant mortality
1	BOGOR Regency	26,639	40	4,316,236	1.620	88.633	174
2	SUKABUMI Regency	412,799	47	2,258,253	547	49.220	109
3	CIANJUR Regency	350,249	30	2,149,121	614	45.874	189
4	BANDUNG Regency	163,937	30	3,038,038	1.853	67.541	114
5	GARUT Regency	306,688	42	2,429,167	792	35.629	312
6	TASIKMALAYA Regency	256,335	39	1,792,092	699	33.318	340
7	CIAMIS Regency	255,909	36	1,586,076	620	28.158	347
8	KUNINGAN Regency	116,826	32	1,140,777	976	55.434	107
9	CIREBON Regency	99,036	40	2,162,644	2.184	41.684	413
10	MAJALENGKA Regency	120,424	23	1,204,379	1.000	19.274	345
11	SUMEDANG Regency	152,221	26	1,112,336	731	18.592	134
12	INDRAMAYU Regency	20,403	31	1,795,372	880	29.359	328
13	SUBANG Regency	205,176	22	1,459,077	711	29.003	170
14	PURWAKARTA Regency	97,172	17	798.272	822	18.299	86
15	KARAWANG Regency	175,327	30	2,073,356	1.183	50.049	196
16	BEKASI Regency	127,388	23	2,032,008	1.595	52.223	190
17	BANDUNG BARAT Regency	130,577	15	1,493,225	1.144		
18	BOGOR	11,869	6	866.034	7.297	19.335	28
19	SUKABUMI	4,981	7	300.694	6.037	6.659	39
20	BANDUNG	1,681	30	2,364,312	14.065	36.122	134
21	CIREBON	3,736	5	290.450	7.774	5.372	85
22	BEKASI	21,049	12	2,084,831	9.905	38.578	89
23	DEPOK	21,224	6	1,412,772	6.656	27.131	115
24	CIMAHI	4,026	3	518.985	12.891	9.729	60
25	TASIKMALAYA	17,779	8	624.478	3.512	13.100	104
26	BANJAR	11,431	4	180.744	1.581	4.165	69
WEST JAVA		35,533.89	604	41,483,729	1.167	822.481	4.277

Region or area of research is regencies / cities in West Java province which covers 25 regencies / cities. Therefore, the data used is SUSENAS in 2007 and SDKI in 2010. Bandung Barat regency is not the object of this study.

The list of regencies / cities that become the objects of this study in conjunction with demographic data (such an area, the number

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of regencies, population, population density, the number of live births, as well as the number of infant mortality rate) in West Java presented in Table 2.

The Results of Global Exchange Model

The first stage in this research is to model the data using ordinary Poisson regression model. The purpose of the modeling is to see the global effects of the factors that affect infant mortality rate in regencies / cities in West Java. The global effect is referred to the effects that do not include geographic local effect.

The result of Poisson regression modeling is presented in Table 3 which shows that from 10 pieces of observed variables there are six variables that significantly affect the infant mortality rate in West Java. This is indicated by p-value based on chi-square statistic Wald which is less than 0.05. These six variables are the percentage of mothers who do not take their infants to health care.

The number of infants (younger than one year old) (29 days-11 months) to get the service (KN1), the percentage of poor people (MSKN), the percentage of infants who are not exclusively breastfaed (ASI), the percentage ratio of availability POSYANDU (health care) to the population (posy), the percentage of unhealthy house (RSHT), and the percentage of pregnant women who do not visit health care to receive health service from professionals during their pregnancy (K1).

Meanwhile the other four variables, such as the percentage of births which are not helped by skilled health staff, percentage of high-risk pregnant women, which is a high-risk pregnant women pregnant with deviations from normal circumstances that directly cause illness and death for both mother and baby. (RISTI), Education last taken by the mother (PEND), as well as the ratio of the availability of health professionals and community health workers to population (RTKS), are variables that are not statistically significant in affecting the infant mortality rate in West Java.

The Results of Local Effect Model

It is assumed that the number of infant deaths in s / cities in West Java is count data that follows Poisson distribution. Thus, the next step is to model the data using a GWPR model. The steps in building this model is by selecting an optimum bandwidth (G), determining load matrix, parameter estimation and hypothesis testing. By using the AIC criterion, the optimum bandwidth is the *nearest neighbor* (*q*) = 33. For each central location, the optimum bandwidth value will be different depending on the Euclidean distance to the nearest neighbor (q) 33.

The central location that has a wider geographical area, the bandwidth is bigger because the Euclidean distance to the nearest neighbors (*q*)-33rd is bigger. The estimation of GWPR model parameters is obtained by incorporating spatial weighting in its calculation using the method of *iteratively reweighted least squares* (IRWLS).

Table 4 shows the results of GWPR modeling, especially those regarding the

Table 3
The results of The Modeling of The Effects of Global Through Poisson Regression model

Parameters	Estimator	Standard Deviation	95 % Confidence Interval		Wald Chi-Square	p-value
Intersep	-11.3594	0.6094	12.5538	-10.1651	347.49	<.0001
NAKES	0.0790	0.1000	-0.1171	0.275	0.62	0.4299
KN1	0.0424	0.0081	0.0265	0.0583	27.32	<.0001
MSKN	0.0449	0.0104	0.0246	0.0652	18.74	<.0001
ASI	0.0402	0.0085	0.0236	0.0569	22.37	<.0001
RISTI	-0.0615	0.0344	-0.1289	0.0059	3.2	0.0736
POSY	0.0103	0.0035	0.0034	0.0172	8.65	0.0033
RSHT	0.014	0.0042	0.0057	0.0222	10.93	0.0009
PEND	-0.0042	0.0048	-0.0137	0.0052	0.77	0.3816
K1	0.2317	0.0837	0.0677	0.3957	7.67	0.0056
RTKS	0.0043	0.0047	-0.0049	0.0135	0.85	0.3572

Table 4
Summary of Parameter Estimation Statistics of GWPR Model

Parameter	Average	STANDARD Deviation	Estimator		Range
			Max	Min	
Intersep	2.8472	0.1271	3.0826	2.7374	0.3452
NAKES	0.146	0.0804	0.1301	-0.22	0.3501
KN1	0.294	0.3573	0.2921	-0.678	0.9704
MSKN	0.049	0.2542	0.3914	-0.391	0.7825
ASI	0.287	0.0783	-0.164	-0.467	0.3031
RISTI	0.1472	0.105	0.3178	0.011	0.3068
POSY	0.261	0.124	0.4629	-0.028	0.4911
RSHT	0.0282	0.1123	0.3088	-0.135	0.4437
PEND	-0.748	-0.034	-0.278	0.164	-0.4420
K1	0.349	0.5581	0.2141	0.1007	0.1130
RTKS	0.0262	0.0825	0.0456	0.0117	0.0339

value of the biggest and smallest estimator in each regency/ city that is observed simultaneously with average value, standard deviation, maximum and minimum value for each estimator in each regency / city, as well as the range.

The next stage is conducting statistical testing to see whether there is difference between parameters of GWPR model with the parameters of the global models obtained by Poisson regression. The hypothesis is formulated as follows:

$$H_0: \beta_k(u_i, v_i) = \beta_k, \text{ for } k = 1, 2, \ldots, p$$

$$H_1: \beta_k(u_i, v_i) \neq \beta_k, \text{ for } k = 1, 2, \ldots, p$$

In case, a *parameter -k* for GWPR model and *are a parameter of Poisson regression model. Test statistic that is used for this test is F-test statistic in which the ratio between deviance values obtained from the Poisson regression model with the values obtained from the GWPR model deviance, the results of which are summarized in Table* 5.

Based on the results of summary of deviance value and statistics F in Table 4 , the deviance value of Poisson regression model and GWPR model is 425.1266 and 398.3365 each, and each has degrees of freedom 14 and 10, thus resulting F value at 1.0672 .

By using a significance level at 0.05 , the value of $F_{(0:05;\ 14,\ 10)}$ = 2.60. Therefore the value of F = 1.0672 is smaller than $F_{(0:05;\ 14,\ 10)}$ = 2.60, it can be said that based on the data, there is not enough evidence to suggest there is a difference between the parameters of Poisson regression model and GWPR model.

The next step is conducting model parameter testing partially to see the factors that affect infant mortality rate in each regency or city in West java.

Although the results of significance testing of the parameters for the Poisson regression model shows that there are only six (out of ten variables observed) that are statistically significant on the number of infants death , but in GWPR modeling purpose, all variables that are observed are analyzed.

For example, the first location, Bogor, is tested and the variables that will be tested are NAKES variable (variable for the percentage of births that are helped by non-health personnel), the testing hypothesis is as follows:

Table 5
Summary of deviance value and F-test

Model	Deviance	db	Deviance/db	F
Poisson Regression	425.1266	14	30.3662	1.0672
GWPR	398.3365	10	28.4526	

H0: $\beta_{(NAKES)}(u_1, v_1) = 0$ against H1: $\beta_{(NAKES)}(u_1, v_1) \neq 0$

Null hypothesis means that parameter is a parameter that related with NAKES variable which is an insignificant parameter on IMR of Bogor*. The Hypotheses is tested using T-test statistic,* which is based on the calculations, the *T-value* = 1.5408. If the value is compared with the value of T, the significance level is 5% and the degree of freedom db = 14, then we obtain $T_{(0.025,\ 14)}$ = 2.145. The result of statistics hypotheses testing is not significant because *T* = 1.5408 < $T_{(0.025,\ 14)}$ = 2.145. This shows that the variable of health workers is not a variable or factors that influence the number of infant mortality in Bogor.

The results also mean that NAKES variable is not necessarily a variable that statistically influence Infant Mortality rate in other cities/ regencies in West Java.

The other result is, for example, to test the significance of ASI (breast-feeding) factors or variables (variables of infants that do not receive exclusive breast feeding) is still in Bogor. Based on the calculation, the value of T is 10.2599, where the value of T is bigger than the value of $T_{(0025,\ 14)}$ = 2.145, so that null hypothesis is rejected. This means that ASI is a variable or factor that influence Infant mortality rate in Bogor.

However, these results cannot necessarily be applied in other locations in West Java Province. The significance variables in each regency / city are shown in Table 6.

Based on the information summarized in Table 6, each regency/ city has different factors that affect infant mortality rate. One interesting thing here is ASI variable occurs in all locations. This means that exclusive breastfeeding (ASI) is an important factor in reducing infant mortality rate in West Java. This means that ASI variables are variables or factors that influence the number of infant deaths in Bogor.

Another interesting variable is PEND Variable (variable of the mothers education). Edu variable is a factor that influences infant mortality rate in most places (the cities of Bogor, Sukabumi, Cirebon, Cimahi, Tasikmalaya, Banjar and Purwakarta) in West Java.

The comparison between Poisson regression model and GWPR model is made to determine which better model can be applied for infant mortality case in West Java. The Criteria of the fit of model used is made by comparing the value of AIC (Akaike's *Information Criterion*) on both models. The

Table 6
Influencing factors in each regency /city

<table>
<tr><th>Number</th><th>Regencies/Cities</th><th>Significance Variable</th><th>Number</th><th>Regencies/Cities</th><th>Significance Variable</th></tr>
<tr><td rowspan="3">A</td><td>BOGOR Regency</td><td rowspan="3">ASI
MSKN
K1
RSHT</td><td rowspan="6">C</td><td>CIAMIS Regency</td><td rowspan="6">NAKES
RISTI
ASI
K1
RSHT</td></tr>
<tr><td>TASIKMALAYA Regency</td><td>KUNINGAN Regency</td></tr>
<tr><td>SUBANG Regency</td><td>MAJALENGKA Regency</td></tr>
<tr><td rowspan="7">B</td><td>PURWAKARTA Regency</td><td rowspan="7">(SI
K1
KN1
PEND</td><td>SUMEDANG Regency</td></tr>
<tr><td>BOGOR</td><td>INDRAMAYU Regency</td></tr>
<tr><td>SUKABUMI</td><td>DEPOK</td></tr>
<tr><td>CIREBON</td><td rowspan="9">D</td><td>SUKABUMI Regency</td><td rowspan="9">ASI
POSY
NAKES
MSKN</td></tr>
<tr><td>CIMAHI</td><td>CIANJUR Regency</td></tr>
<tr><td>TASIKMALAYA</td><td>BANDUNG Regency</td></tr>
<tr><td>BANJAR</td><td>GARUT Regency</td></tr>
<tr><td colspan="3" rowspan="5">KARAWANG Regency
BEKASI
BANDUNG
BEKASI</td><td>CIREBON Regency</td></tr>
<tr><td></td></tr>
<tr><td></td></tr>
<tr><td></td></tr>
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</table>

Table 7
The result of the calculation of AIC and Deviance

Model	Deviance	AIC
Poisson Regression	425.1266	436.1266
GWPR	398.3365	409.3365

best model is the model with the smallest AIC value. The result of AIC calculation for both of these models is presented in Table 7.

The best model shown in Table 7 is GWPR model which has the smallest AIC value GWPR. Therefore, GWPR model is better to use for analyzing infant mortality rate in West Java than Poisson regression (which the parameter has similar value in each research location)

Conclusions

The development of community health status can be seen from the numbers of deaths in society from time to time. In addition, deaths can also be used as an indicator in assessing the success of health care and other health development programs. The mortality rate can be calculated by conducting various surveys and research.

To monitor the result of human development, high infant mortality rate reflects a lot of things. The low level of people who access health care, malnutrition, environmental contamination and lack of education of the mothers are all factors which influence IMR.

Therefore, some efforts to reduce IMR are by giving more education for women. Patrilineal culture, which prioritizes the education of males over that of females, which was adopted by most of society is expected to be eliminated. Thus, the gap of human resources quality between women and men will not be too big.

This study has demonstrated the application of regional- based model, a model that considers local effects of the location / area observed, in this case is the regencies/ cities in West Java. GWPR model is a local form of Poisson regression where the observed location is assumed with Poisson distributing data. The estimation of GWPR model parameter uses MLE method and solved by Newton-Raphson iteration.

The equation Testing of Poisson regression and GWPR models is approached by F-distribution, while the partial test of the model parameters using Z-test. The selection for the best model in GWPR uses AIC.

Several conclusions can be drawn with respect to the identification of factors that affect infant mortality level of s / cities in West Java Province as follows:; (1) a better model that can be used to analyze the data of infant mortality rate in each / city in the West Java based on the smallest value of AIC is GWPR models (compared with Poisson regression model); (2) There is different information that is interesting and important from each regency / city in West Java about the factors that significantly influence the number of infant mortality rate. The Factors that significantly influence the number of infant mortality rate in all regencies /cities in East Java are the percentage of infants who do not receive an exclusive breastfeeding. Exclusive breastfeeding is breastfeeding the baby without giving the infants any food and other drinks until the infants reach 6 months old (ASI variable); And (3) Variable for maternal education (PEND) is a factor that influences the number of infant mortality rate in most cities in West Java.

Geographic modeling with GWPR model better uses semi parametric approach through the use of several fixed variables in each location and there are local or different variables for each location of research. Therefore, the interpretation of parameter estimator will become easier and the model becomes simpler, it can describes the conditions of each local area.

On the other hand, the samples that are used for sub-s in order to have better a spatial analysis. The variables that are used should include the elements of local social culture to obtain a final result that can explain the local conditions of the area.

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