Geographically Weighted Quantile Regression for Assessing the Spatial Variations of the High-Risk Diarrhea on Children Under Five in Bandung, Indonesia

Wara Alfa Syukrilla[1, a)]Yudhie Andriyana[2, b)],Anneleen Verhasselt[3, c)],

[1]*Universitas Islam Negeri Syarif Hidayatullah Jakarta, Tangerang Selatan 15412, Indonesia*
[2]*Universitas Padjadjaran, Sumedang 45361, Indonesia*
[3]*Universiteit Hasselt, Hasselt 3590, Belgium*

a) Corresponding author: wara.alfa@uinjkt.ac.id
[b)]y.andriyana@unpad.ac.id
[c)]anneleen.verhasselt@uhasselt.be

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Abstract. We investigate the impact of the percentage of clean water access, the percentage of handwashing habit, and the toilet category factors on the upper quantile of toddlers' diarrhea risks in Bandung city, Indonesia using Geographically Weighted Quantile Regression model. We analyzed $n = 30$ districts in Bandung, applying Geographically Weighted Quantile Regression with the predictors are the percentage of clean water access, hand washing habit, and toilet category. We focus on the 75[th] percentile ($\tau = 0.75$). Breusch-Pagan test was used to detect the spatial heterogeneity. The optimum bandwidth was selected using cross-validation. The results shows that the significance, strength, and direction of the relationship between diarrhea and its risk factors are found to depend on the location. At the upper quantile $\tau = 0.75$, the district named Panyileukan district is predicted to have the highest diarrhea risk. In this district, all of the three predictors are significantly affecting the toddlers' diarrhea risk with the variable of percentage of houses practicing hand washing habit is observed to reduce diarrhea risk the most. In conclusion, clean water access, handwashing habits, and toilet category are the potential risk factors of high-risk childhood diarrhea. The significance, strength, and direction of the effect varies between districts. This method is powerful as it would allow the decision maker to handle the diarrhea problem aptly based

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on which predictor has substantial effect at a specific district of interest. And it can be used to investigate the effect of various intervention strategies, and effectively allocate the limited available resources according to which locations are the most important.

INTRODUCTION

Most people think that diarrhea is not a serious situation since almost everyone experienced diarrhea at least once in a lifetime and usually, one recover within one or two days. Although diarrhea is a treatable and preventable disease, it is the leading killer of toddlers worldwide [1]. UNICEF has recorded that every day, around 2,000 children in the world die before the age of 5 due to diarrhea [2]. Diarrhea highly infects children living in low- and middle-income countries, including Indonesia which is one of the top 15 countries with the highest contribution to the world's children death due to pneumonia and diarrhea [3,4]. Besides threating the life of toddlers, repeated and frequent diarrhea occurrence could degrade children's growth and cognitive development, as well as increase their vulnerability to other infectious diseases[5]

Most diarrhea is caused by bacteria which easily found in contaminated water or soil. The ease of bacteria transmission through water and soil makes diarrhea could spread from one district to the neighboring districts. Several past studies show that there is spatial dependency in childhood diarrhea occurrence [6–8]. Ignoring spatial effect when actually spatial dependency exists will lead to bias and inefficiency in the estimates [9]. The commonly used spatial approach assumes that the effect of predictors on the response is the same everywhere within the study region, which is called spatial stationarity [10]. However, this approach is not always sufficient to describe the actual variation in reality. The effect of one predictor might depend on location such that a predictor can be essential at one location but not at the other location. When the configuration within the data cannot be explained using a single "global" spatial model, a varying coefficient spatial model called Geographically Weighted Regression (GWR) model should be considered [11]. The use of locally spatial analysis, such as GWR, gives the opportunity to detect where the key areas across the large study areas are and detailed information on how interventions affect the hotspot areas of the disease.

Past studies have utilized GWR for considering the spatially varying relationship when analyzing diarrhea and its risk factors [12–14]. However, GWR concentrates on modeling the mean of the response. While, it can be happened that the upper or lower part of the response responds the predictors differently from the middle part. Our study is more interested in analyzing the upper quantile rather than middle or lower quantile of the response distribution because assessing the risk factors of high-risk diarrhea is more essential in the effort of reducing diarrhea issue. Therefore, this study uses a quantile regression scheme (introduced by [15]) that is combined with Geographically Weighted Regression resulting in the so-called Geographically Weighted Quantile Regression (GWQR).

Several studies took advantage of quantile regression for exploring the association of several risk factors by subgroups of their response distribution [16,17]. Furthermore, quantile regression is robust to outliers which overcome

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the drawback of ordinary GWR that is not robust to outliers [18]. In the situation when the response distribution is skewed, the mean-based regression will likely under/overestimate the effect of predictors on the tail probability of the response, but not with the quantile regression since it is less sensitive to the tail behavior of the response distribution [19].

GWQR method accounts for spatial heterogeneity of the response distribution at the same time. In this study, we aim to investigate the impact of the selected factors on the 0.75 quantile of toddlers' diarrhea risks in Bandung, Indonesia using Geographically Weighted Quantile Regression model.

DATA AND METHODS

Data

West Java province has the highest diarrhea infection in Indonesia [20] and its capital, Bandung, is one of the top 5 cities in West Java province with the highest diarrhea incidence [21]. Therefore, Bandung needs serious control and treatment to reduce diarrhea occurrence. This study focuses on the diarrhea cases in children under five in Bandung city, Indonesia. Bandung has 30 districts with the geographical maps presented in Figure 1.

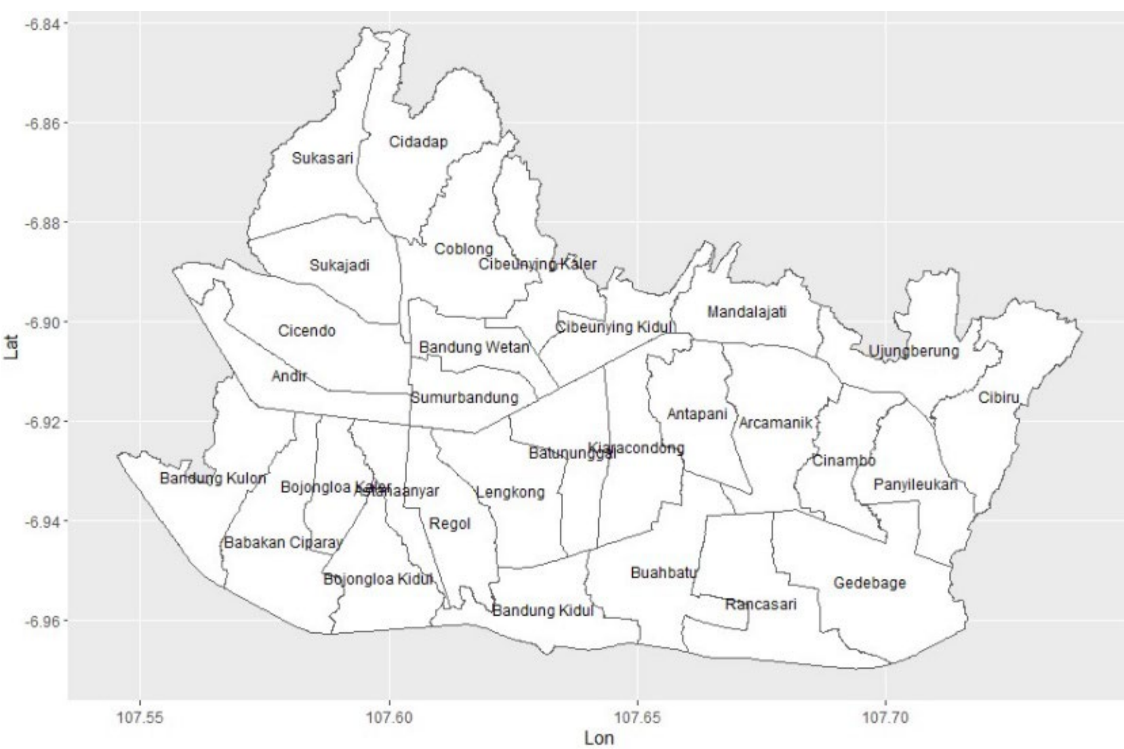

Figure 1. Maps of 30 districts in Bandung city, Indonesia

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Raw data for the response variable were generated from the Bandung Department of Health, Indonesia and contains information of the number of toddler's diarrhea occurrences in 2015 at n = 30 districts of Bandung city together with the number of toddlers in each district. The response of interest, namely diarrhea risk, was calculated from the number of diarrhea occurrences per district divided by the number of toddlers within that district then multiplied by 100, hence it is ranged from 0 to 100. The derived response data are available on request to the corresponding author.

The three predictors used in this study are believed to be associated with diarrhea infection based on the diarrhea bulletin from [22]) and the WASH (water, sanitation, and hygiene) campaign from the United Nations [23]. These three predictors have a range of 0-100 and are obtained from the Bandung Department of Health. The first predictor (X_1) is the percentage of households that use clean water for their daily activities in every district, the second predictor (X_2) is the percentage of households in every district that practicing hand washing habit in their daily activities, and the third predictor is the percentage of houses in every district that have toilets fulfilling the healthy toilet criteria by Indonesian Ministry of Health [24].

Statistical Analysis

In this section, we present a brief description about GWQR. For more details about GWQR regression coefficients, its standard error, and the evaluation of spatial non-stationarity, the reader is referred to [25]. In the classical Geographically Weighted Regression (GWR), we consider the model

$$Y = \boldsymbol{X}^{\intercal}\boldsymbol{\beta}(u, v) + \varepsilon, \tag{1}$$

where Y is the response, $\boldsymbol{X} = (1, X_1, \dots, X_p)$ is the vector of the predictors with a constant 1 for intercept, $\boldsymbol{\beta}(u, v) = (\beta_0(u, v) + \ldots + \beta_p(u, v))^{\intercal}$represents the regression coefficients that are estimated for location with geographical coordinate (u, v), u stands for latitude and v stands for longitude, and ε is a random error term that is normally distributed with mean zero and common variance σ^2. Hence $E(Y|\boldsymbol{X}, u, v) = \boldsymbol{X}^{\intercal}\boldsymbol{\beta}(u, v)$. While in the quantile regression (QR) scheme, it is the τth quantile of ε given X, u, v is equal to zero ($Q_{\varepsilon}(\tau|\boldsymbol{X}, u, v) = 0$) since there is no distributional assumption regarding the error term ε. Hence, $Q_Y(\tau|\boldsymbol{X}, u, v) = \boldsymbol{X}^{\intercal}\boldsymbol{\beta}^{\tau}(u, v)$ [26].

This study uses GWQR, which is the combination of GWR and QR. The parameters of GWQR are estimated by minimizing the following weighted quantile loss function[25]

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$$\sum_{i=1}^{n} \rho_\tau [Y_i - \boldsymbol{X}_i^\intercal \boldsymbol{\beta}(u_0, v_0)] K\left(\frac{d_{i0}}{h}\right), \quad (2)$$

where $\rho_\tau(e)$ is a V-shaped piecewise linear check-function that assign weight τ to the positive residuals and assign weight $(\tau - 1)$ to negative residuals. $K\left(\frac{d_{i0}}{h}\right)$is the spatial weight. $\boldsymbol{X}_i^\intercal = (1, X_{1i}, \dots, X_{pi})$ and $i = 1, \dots, n$ is the index for n independent observations. The vector of parameter $\boldsymbol{\beta}(u_0, v_0)$ is the regression coefficients at the location coordinates (u_0, v_0). The equation Eq. 2 does not have explicit form hence it is solved using linear programming [26,27].

We conducted the spatial analysis using GWQR model at the district level at the upper quantile since we are interested in the association at high diarrhea risk. There is no theoretical cut off for diarrhea risk which classifies the risk of diarrhea to be high, hence in this paper we use conventional cut off i.e. high risk of diarrhea is 75th percentile ($\tau = 0.75$).

Initial step before applying GWQR model is to check the presence of outliers and spatial heterogeneity. For checking the spatial heterogeneity, we used the Breusch-Pagan test [28]. Breusch-Pagan Test with p-value smaller than 0.05 indicates that we can reject null hypothesis (variance of the errors from a spatial regression is dependent on the values of the predictors) and conclude that there is spatial heterogeneity in the study area which strengthen our motivation to use GWQR model.

The next step is to generate spatial weight. The spatial weight assigned to each observation i is determined based on a kernel method. A kernel function $K(.)$ involves distance (d_{i0}) and bandwidth parameter (h). The distance (d_{i0}) is the distance between the ith observation with coordinate $(u_i, v_i)$and the regression point (u_0, v_0) measured using the Euclidean distance. A smaller distance from the regression point (u_0, v_0) will result in a higher weight than those with greater distance. The bandwidth parameter ($h \geq 0$) is a measure of distance-decay in the weighting process as well as a controller of the smoothness of the resultant coefficients.

This study uses a bi-square kernel with adaptive bandwidth where the kernel size will be big/small following the density of observations at a region. According to [10], any choice of kernel gives relatively the same results, but different bandwidth will raise different results. Thus, selecting optimal bandwidth is necessary. In this paper, Leave One Out Cross Validation (CV) criteria will be used in selecting the optimum bandwidth. The bandwidth with the smallest CV score will be chosen. All of the analyses were done in R software.

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RESULTS

Exploratory Data Analysis

We present a boxmap in Figure 2 which is a box plot of map data. Boxmap helps to indicate if outliers are present in the response in geographical map visualization. Figure 2 shows that there is no outlier in the response.

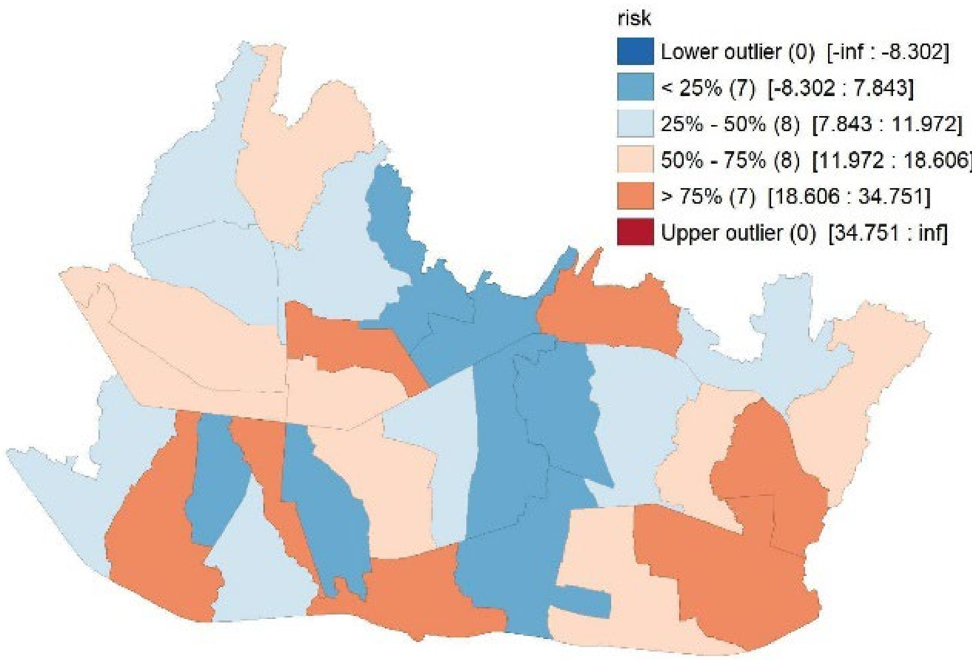

Figure 2. Boxmap of the observed diarrhea risk

The histogram of the response in Figure 3 shows that the diarrhea risk is asymmetrically distributed. The skewed pattern of the response is suitable to be handled with a quantile regression scheme since quantile regression has no assumption for the distribution of the response. While if the skewed pattern of the response is handled using mean-based regression, it could cause violation of regression assumption.

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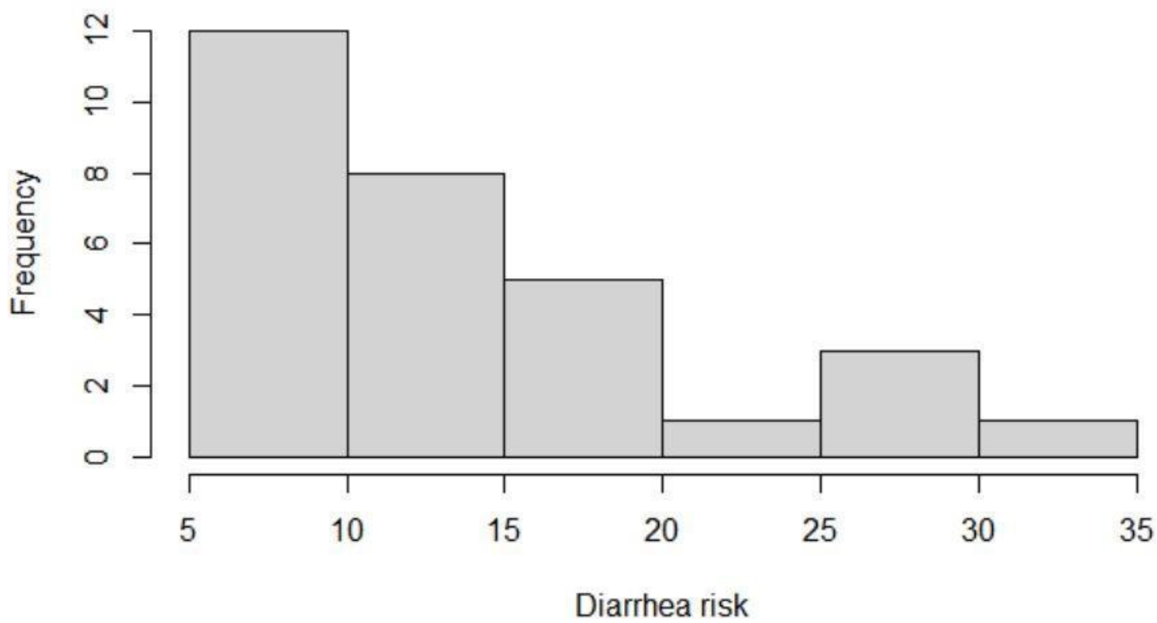

Figure 3. Histogram of the observed diarrhea risk

A test for spatial heterogeneity was performed using Breusch-Pagan test after taking spatial effect into account. The Breusch Pagan p-value is equal to 0.043 (significant at $\alpha = 0.05$) which means that spatial heterogeneity is present in the data. This is an indication that the relationship between covariates and the response seems to vary over space and the use of locally varying spatial models such as Geographically Weighted model would be logical to be used.

Figure 4 shows the scatter plots of response at the Y-axis and predictor at the X-axis. Each point represents the risk value of each district. The variability seems to increase as the predictors' values increase since all three scatter plots show more points at the higher values of predictors than the smaller values of predictors.

For the plot at the left, that is the plot of X_1 (the percentage of houses with clean water access), almost all of the points are located at the rate of 99-100 %, although the diarrhea risk varies from 5 to 32 percent. A similar case happens with the plot of X_2 at the middle (the percentage of houses practicing hand washing habits). The majority of the districts have a percentage of houses with hand washing habits above 90% even though the diarrhea risk is spread widely from low to high. The third predictor on the right seems to have a larger variability than the previous 2 predictors since the points spread from low to high values of the X_3 (the percentage of houses with healthy toilets status). Further, it was observed that there was one point (one district) which has low values for percentage of clean water, hand washing habits, and healthy toilets, but it has low value of diarrhea risk.

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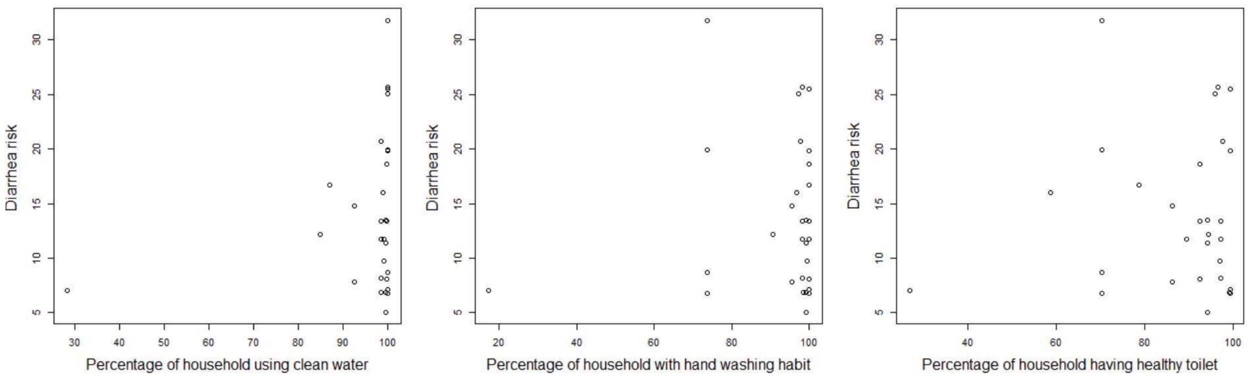

Figure 4. Scatter plot of predictors (left to the right: X_1-X_3) against the response

Results of Geographically Weighted Quantile Regression

GWQR bi-square kernel using the adaptive bandwidth approach found that the optimal bandwidth obtained from cross-validation is $h = 28$ for the 0.75th quantile.

Figure 5 illustrates the map of diarrhea risk predictions from GWQR model based on the 0.75 quantile. It shows that there are two districts at the eastern part of the map with very dark color. It means that these districts are predicted to have the highest diarrhea risk of all districts at the upper percentile, which amounted to greater than 30 percent. In these 2 districts, 25 out of 100 children under five have a risk of diarrhea of 30 percent or more. These districts might require serious attention from the health institute regarding the diarrhea issue.

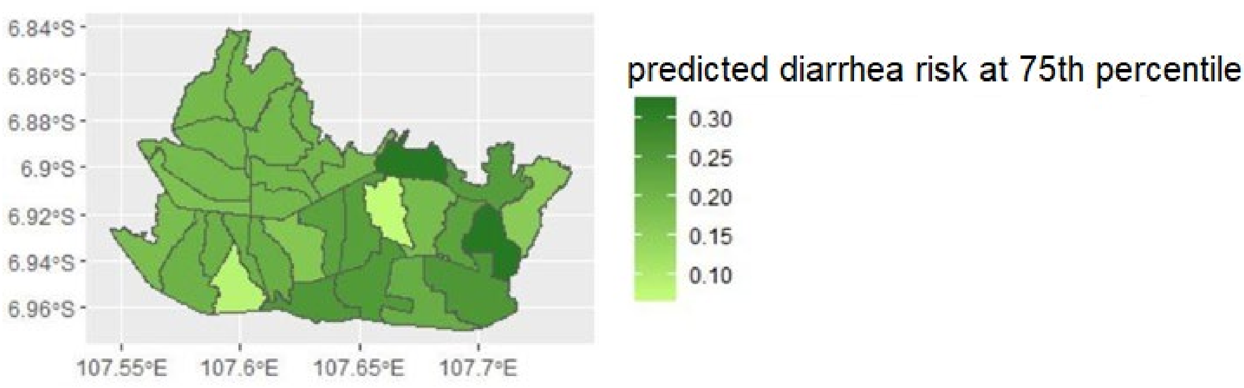

Figure 5. GWQR predictions

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The map of the GWQR parameter estimates and its significance evaluated at different quantiles are presented at Figure 6, 7, and 8. The darker the color indicates the larger positive effect of a covariate on the response, while the lighter the color indicates the smaller positive effect of a covariate or a negative effect of the predictor. Locations with white color are the areas in which the effect of the predictor is not significant at 5% significance level.

Figure 6 illustrates how the percentage of houses that use clean water (X_1) is associated with the diarrhea risk. At the 75th percentile, there is a negative effect of the percentage of clean water towards the diarrhea risk at the western part of the map, indicating that the higher percentage of houses that use clean water for daily activities, the lower toddlers' diarrhea risk. However, this effect is not significant in one district. In addition, although the percentage of houses with clean water is statistically significant affecting the diarrhea risk in almost all districts, the magnitude of the effect varies between locations. Its effect gets larger as we move from the west to the east areas of Bandung. These results illustrate how spatial non-stationarity exists in the data, where the effect of a predictor depends on where it is evaluated.

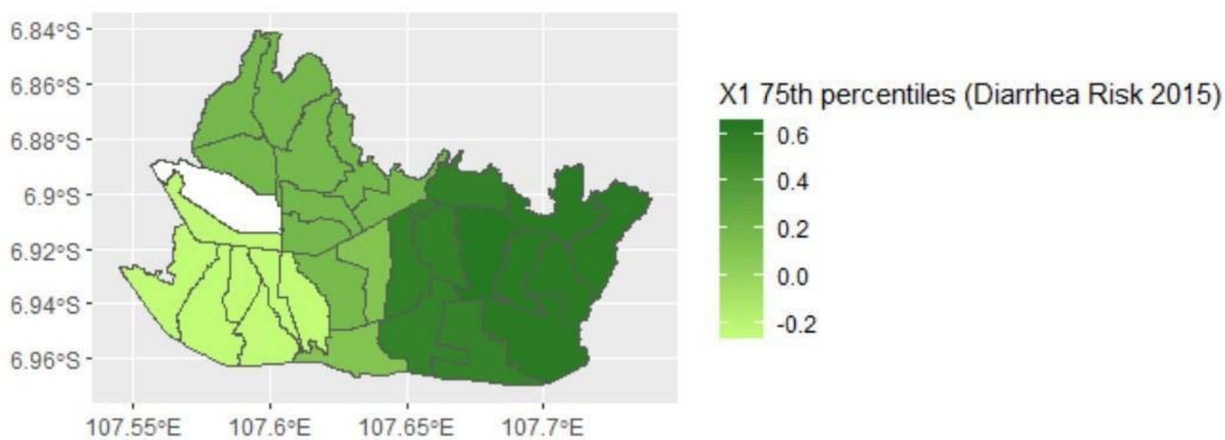

Figure 6. Maps of GWQR $\tau = 0.75$ Estimates for X_1 (Percentage of Houses with Clean Water Usage) significant at $\alpha = 5\%$

Figure 7 illustrates the geographical map of parameter estimates' significance for the percentage of houses that practiced hand washing habits (X_2) evaluated at the 0.75th quantile. At the 75th percentile, the percentage of houses that practiced hand washing habits is proven to be an important predictor in reducing the high risk of toddlers' diarrhea at half of Bandung area from the center to the east side of Bandung. However, this predictor was observed to have a non-significant effect at the other half of Bandung area. These results are valuable as it helps the decision makers to efficiently identify which districts will experience a decreasing diarrhea risk when the government promotes policy or campaign related to handwashing habits.

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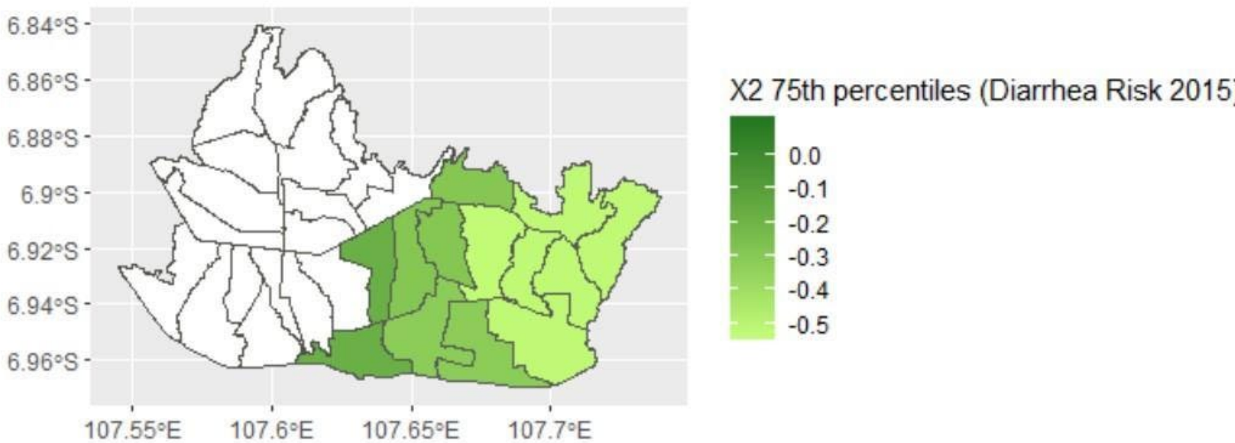

Figure 7. Maps of GWQR $\tau = 0.75$ Estimates for X_2 (Percentage of houses practicing hand washing habit) significant at $\alpha = 5\%$

Figure 8 shows the geographical map of GWQR coefficients for the percentage of houses with healthy toilets status (X_3) significant at a 5% significance level. At the 75th percentile, the percentage of houses with healthy toilets is proven to be an important predictor on the toddlers' diarrhea risk at both western and eastern part of Bandung city, but not important at the middle part of Bandung. Again, this illustrates that the effect of predictors can be different between locations, both in the significance and magnitude.

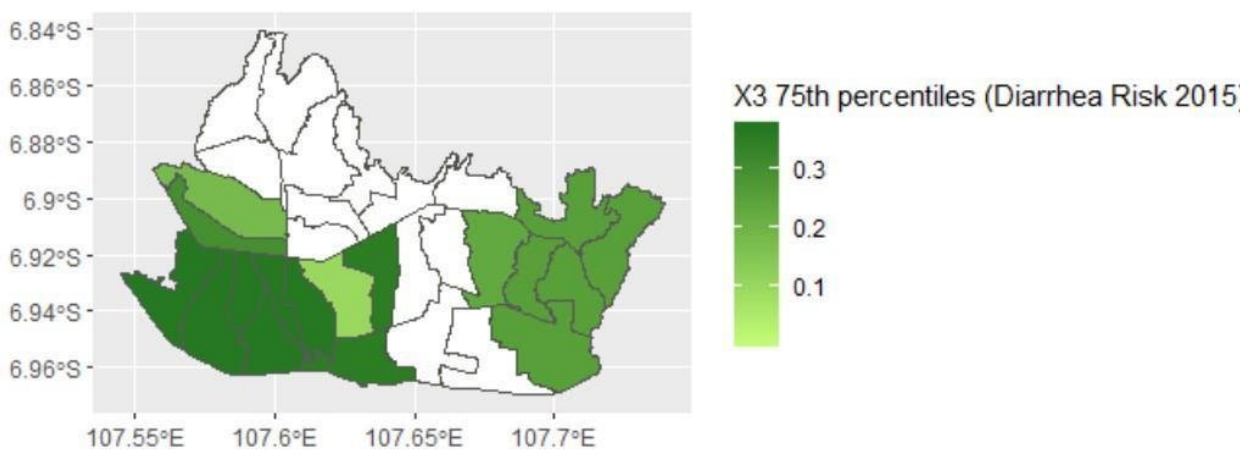

Figure 8. Maps of GWQR $\tau = 0.75$ Estimates for X_3 (Percentage of Houses with Healthy Toilet) significant at $\alpha = 5\%$

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DISCUSSION

The use of quantile regression scheme is beneficial over the mean-based model in that it can handle the skewed data in this study which might have violated assumptions in mean-based regression models. It also allows us to characterize the impact of predictors on subgroups of response distribution using all of the available data. This study employed Geographically Weighted Quantile Regression (GWQR) model to answer the research questions in the study: how is the relationship between the selected predictors and the diarrhea risk for children under 5 years old at various spatial location, evaluated at the upper quantile ($\tau = 0.75$) of the diarrhea risk distribution. This method is powerful as it can reflect spatial variation of targeted childhood high risk diarrhea and identify the important risk factors at every district especially in Bandung where the water access and sanitation are varying between districts.

In Bandung, many houses subscribe to water service from the Municipal Water Corporation but many others rely on water from the well. For houses that subscribed to water service from the Municipal Water Corporation, the water distribution service is grouped into three sub-regions, so does the water pipeline systems. The variation in water access over districts in Bandung leads to a non-stationary risk of diarrhea. Furthermore, Bandung city has not reached 100% ODF (Open Defecation Free) status yet because there are houses that do not have a septic tank for their toilets [29][29]. They flowed the feces disposal to the river or practiced open defecation. This fact might suggest that those areas with the geographical location near the river or the feces disposal point seem to be at a higher risk of soil and underground water contamination, leading to non-stationary diarrhea risk across districts.

Our results show that the location that is predicted to have the highest diarrhea risk in Bandung is the district at the coordinate (6.93° S, 107.7° E) named Panyileukan district. Using GWQR we can identify toddlers' diarrhea determinants locally for every district differently. As an example, let us compare two districts namely Panyileukan and Antapani districts, where the former is the district that predicts the highest diarrhea risk while the later predicts the smallest diarrhea risk at the 75th percentile of the response distribution. In the Panyileukan district, the covariate X_3 or the percentage of houses with healthy toilets is considered as an important predictor as its effect is significant in this district. On the other hand, in Antapani district, the predictor X_3 was observed to have no effect. Looking at the X_2 predictor, although its effect is significant at both locations, X_2 is predicted to have a bigger reduction on diarrhea risks compared to it in the Antapani district.

The results show some coefficients show a negative relationship between predictors and the response while some others show a positive relationship. The positive coefficients seem contradictory to the intuition since we do not expect that an increase in the percentage of houses with clean water access, healthy toilets, and hand washing habits, would increase the toddlers' diarrhea risk. Looking at the scatter plot of the data (Figure 4), the values of diarrhea risk (Y) varies between districts from small to high values but the predictors have high percentage of houses with clean water,

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hand washing habit, and healthy toilet at the majority of the districts regardless the level of diarrhea risk. The percentage reaches above 98% for X_1 and X_2 at almost all districts including districts with very high diarrhea risk. In addition, there seems a trend between X_3 and Y where the response increases as X_3 increases. Furthermore, there is one district with a low percentage in all predictors but has low diarrhea risk. These situations cause the model to tend to predict a positive linear association between predictors and the response.

In addition, there might be another relevant risk factor of childhood diarrhea which is not included in the analysis such as what stated by [30] that a nutrition deficiency due to non-optimal breastfeeding or due to low economic prosperity. Optimal breastfeeding is believed to build babies' immunity that will help toddlers to fight against diarrhea bacteria. However, many parents underestimate the importance of breastfeeding including young mothers with low education [30]. These rationales might be the contributing reasons of why some coefficients have inappropriate signs. Future studies that investigate diarrhea for toddlers are recommended to include other risk factors of toddlers' diarrhea such as breastfeeding information and mothers' educational status [31].

CONCLUSION

In conclusion, clean water access, handwashing habits, and toilet category are the potential risk factors of high risk childhood diarrhea. The significance, strength, and direction of the effect varies between districts. The estimation of GWQR at the 75th percentile predicts the district with highest risk is the one at the coordinate (6.93° S, 107.7° E) namely Panyileukan district. In this district, all of the three predictors significantly affect the toddlers' diarrhea risk but the variable percentage of houses practicing hand washing habit (X_2) is observed to reduce diarrhea risk the most. This information is valuable and would allow the decision maker to handle the diarrhea problem aptly based on which predictor has substantial effect at a specific district of interest. At an expanded level, GWQR can be used to investigate the effect of various intervention strategies, and effectively allocate the limited available resources according to which locations are most important. This can also be applied to other cities in Indonesia and other high burden countries to reduce the world diarrhea number, and a large number of toddlers' lives would be saved.

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