UNVEILING SPATIAL DISPARITIES: EXPLORING HIGH-RISK DIARRHEA AMONG CHILDREN UNDER FIVE USING GEOGRAPHICALLY WEIGHTED QUANTILE REGRESSION

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Abstrak

Penelitian ini menyelidiki pengaruh persentase akses air bersih, persentase kebiasaan mencuci tangan, dan kategorisasi toilet sehat pada kuantil atas risiko diare balita di Kota Bandung, Indonesia, menggunakan model Geographically Weighted Quantile Regression pada persentil ke-75 ($\tau = 0{,}75$). Bandwidth optimal dipilih menggunakan validasi silang. Hasil penelitian menunjukkan bahwa signifikansi, kekuatan, dan arah hubungan antara diare dan faktor risikonya tergantung pada lokasinya. Pada kuantil atas $\tau = 0{,}75$ Kecamatan Panyileukan diprediksi memiliki risiko diare tertinggi. Di kabupaten ini, ketiga prediktor berpengaruh signifikan terhadap risiko diare pada balita, dengan variabel persentase rumah yang mempraktikkan kebiasaan cuci tangan adalah variabel paling besar pengaruhnya dalam menurunkan risiko diare. Kesimpulannya, akses air bersih, kebiasaan cuci tangan, dan kategori toilet merupakan faktor risiko potensial terjadinya diare pada anak risiko tinggi. Metode GWQR memungkinkan pembuat keputusan untuk menangani masalah diare dengan tepat berdasarkan prediktor mana yang memiliki pengaruh besar pada daerah tertentu yang diminati. Selain itu, GWQR dapat digunakan untuk menyelidiki efek dari berbagai strategi intervensi dan secara efektif mengalokasikan sumber daya terbatas yang tersedia sesuai lokasi yang paling membutuhkannya.

Kata Kunci: Geographically Weighted Quantile Regression, balita, diare

Abstract

We investigate the impact of the percentage of clean water access, the percentage of handwashing habits, and the toilet category factors on the upper quantile of toddlers' diarrhea risks in Bandung City, Indonesia, using the Geographically Weighted Quantile Regression model on the 75th percentile ($\tau=0.75$). The optimum bandwidth was selected using cross-validation. The results show that the significance, strength, and direction of the relationship between diarrhea and its risk factors depend on the location. At the upper quantile $\tau = 0.75$, the Panyileukan district is predicted to have the highest diarrhea risk. In this district, all three predictors significantly affect the toddlers' diarrhea risk, with the variable of the percentage of houses practicing hand washing habits observed to reduce diarrhea risk the most. In conclusion, clean water access, handwashing habits, and toilet category are the potential risk factors for high-risk childhood diarrhea. This method is powerful as it would allow the decision-maker to handle the diarrhea problem aptly by focusing on the predictor that has a significant impact on a particular 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 the most important locations.

***Keywords**: Geographically Weighted Quantile Regression, toddlers, diarrhea*

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 recovers within one or two days. Although diarrhea is a treatable and preventable disease, it is the leading killer of toddlers worldwide (UNICEF, 2018). UNICEF has recorded that every day, around 2,000 children in the world die before the age of 5 due to diarrhea (Centers for Diseases Control and Prevention (CDC), 2018). Children residing in low- and middle-income countries, such as Indonesia - ranked among the top 15 countries with the highest number of child deaths caused by pneumonia and diarrhea worldwide - are particularly vulnerable to contracting diarrhea (International Vaccine Access Center (IVAC) and Johns Hopkins Bloomberg School of Public Health, 2018, 2020). Besides threatening 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 (Liu et al., 2012).

Several past studies show that there is spatial dependency in childhood diarrhea occurrence (Kandala et al., 2007; Azage et al., 2015; Bogale et al., 2017). Most diarrhea is caused by infectious bacteria which easily found in contaminated water or soil. When individuals in a particular area become infected with the disease, they have the potential to pass it on to people in neighboring regions through direct or indirect contact, polluted water sources, or communal facilities. The ease of bacteria transmission through water and soil makes diarrheacould spread from one district to the neighboring districts.

In addition, diarrheal diseases are frequently linked to inadequate sanitation, polluted water sources, and suboptimal hygiene practices (Yilgwan and Okolo, 2012). Shared environmental conditions among neighboring areas can amplify the likelihood of diarrhea outbreaks (Alexander et al., 2018). For instance, the absence of clean water and proper sanitation facilities in one area not only elevates the risk of diarrhea within that area but also poses a heightened threat to nearby regions. Due to these spatial dependencies and influences, it is crucial to incorporate spatial effects into disease modeling studies.

If spatial effects is not accounted for, it can result in biased and inefficient estimates (Stakhovych et al., 2012). Typically, the spatial approach used assumes spatial stationarity, meaning that the impact of predictors on the response is consistent throughout the study area (Fotheringham et al., 2003). However, this approach may not always be adequate to represent the true variation in real-life situations. This is because the influence of a particular predictor can be location-dependent, meaning that it may be significant in one area but not in another. In cases where the data cannot be fully explained by a single "global" spatial model, it is necessary to consider a Geographically Weighted Regression (GWR) model, which incorporates varying coefficients based on location (Brunsdon et al., 1996). 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 (Khoirunnisa et al., 2019; Dunn et al., 2020; Carrel et al., 2011). 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 research utilizes a method called Geographically Weighted Quantile Regression (GWQR), which combines Geographically Weighted Regression and a quantile regression scheme developed by Koenker and Bassett in 1978 (Koenker and Bassett, 1978).

Several studies took advantage of quantile regression for exploring the association of several risk factors by subgroups of their response distribution (Beyerlein et al., 2010; Hu et al., 2021). Furthermore, quantile regression is robust to outliers which overcome the drawback of ordinary GWR that is not robust to outliers (Andriyana et al., 2014). In If the response distribution is skewed, a regression based on the mean may give an incorrect estimate of the impact of predictors on the tail probability of the response. However, quantile regression is less affected by the tail behavior of the response distribution, so it is less likely to over or underestimate the effect of predictors (Alsayed et al., 2020).

The GWQR method takes into consideration both the spatial variability and the distributional differences of the response. 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.

METHODOLOGY

1. Reference Review

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 (Chen et al., 2012). In the classical Geographically Weighted Regression (GWR), we consider the model

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

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. $\boldsymbol{\beta}(u,v) = (\beta_0(u,v) + \dots + \beta_p(u,v))^\intercal$ denotes the regression coefficients that are computed for a particular location identified by its geographical coordinates (u,v). In this study, the geographical coordinates (u,v) identify the locations of various subdistricts within Bandung city. For each set of coordinates (u,v) used in this study, u and v correspond to the latitude and the longitude of the center point of each subdistrict in Bandung city. Additionally, there is a random error term ε, which follows a normal distribution with a mean of zero and a common variance of 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, $Q_Y(\tau|\boldsymbol{X},u,v) = \boldsymbol{X}^\intercal \boldsymbol{\beta}^\tau(u,v)$ (Koenker, 2005).

This study uses GWQR, which is the combination of GWR and QR. The GWQR's parameters are estimated through the process of minimizing the weighted quantile loss function given below (Chen et al., 2012)

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

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 (Chen and Wei, 2005; Koenker, 2005).

2. Analysis Method

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 specific theoretical limit for the level of diarrhea risk at which it can be considered 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, where the spatial heterogeneity detection can be done using the Breusch-Pagan Test (‘Afifah et al., 2017; Fitriani and Jaya, 2020; Octavianty et al., 2017; Rahayu et al., 2023; Hothorn et al., 2017). A Breusch-Pagan Test result with a p-value below 0.05 signifies the presence of spatial heterogeneity in the study area, meaning that a predictor's effect varies across locations and the use of the global spatial

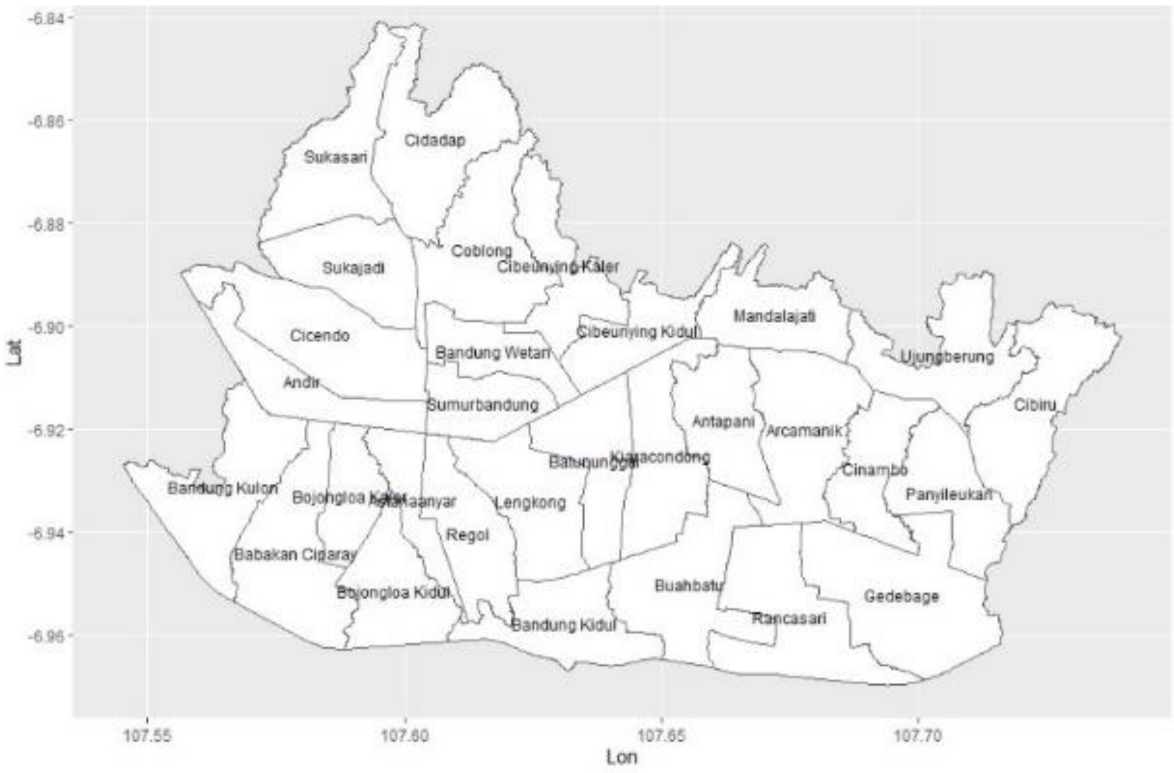

Figure 1. Maps of 30 districts in Bandung city, Indonesia

regression model is insufficient, highlighting the need for a geographically weighted regression model.

The next step is to generate spatial weight. To allocate a spatial weight to each observation, a kernel method is used, which employs a kernel function $K(.)$ that considers two factors: the distance (d_{i0}) between the coordinates of the ith observation (u_i, v_i) and the regression point (u_0, v_0), measured using Euclidean distance, and a bandwidth parameter (h). The closer an observation is to the regression point (u_0, v_0), the greater weight it will be assigned, while those further away will have a lower weight. The bandwidth parameter $(h \geq 0)$ determines the degree of distance-decay in the weighting process and to adjust the smoothness of the resulting 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. The bi-square kernel was preferred due to its robustness in handling data with outliers and non-normal characteristics, such as skewness. Given that our diarrhea occurrence dataset exhibits skewness, the bi-square kernel was deemed suitable for mitigating the influence of outliers and providing reliable density estimates in the presence of non-well-behaved data distributions. Fotheringham et al. (2003) suggested that different kernels produce similar results, but varying bandwidths can lead to different outcomes. Therefore, it is crucial to choose the appropriate bandwidth. The paper uses the Leave One Out Cross Validation (CV) criteria to determine the best bandwidth, where the bandwidth with the lowest CV score will be selected. All of the analyses were done in R software version 4.0.0. The GWQR analysis in this thesis utilized a modified version of GWmodel package sourced from Khaeri (2018).

Data and Variables

According to the Indonesian Ministry of Health (2017) the West Java province has the highest incidence of diarrhea in Indonesia, and among the top five cities in the province with the highest incidence of diarrhea is Bandung, the provincial capital (West Java Department of Health, 2017). As a result, serious measures need to be taken in Bandung to control and treat diarrhea in order to reduce its 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.

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 by dividing the number of cases of diarrhea in each district by the number of toddlers in that district, and then multiplying the result by 100. This calculation produces a range of values between 0 and 100. The derived response data are available on request to the corresponding author.

The three predictors used in this study are thought to be linked with the occurrence of diarrhea infection, according to the diarrhea bulletin released by the Indonesian Ministry of Health (2011) and the United Nations' WASH (water, sanitation, and hygiene) campaign (UNICEF, 2019). 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 in each district that utilize clean water for their everyday tasks, 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 (Indonesian Ministry of Health, 2014).

RESULTS

Exploratory Data Analysis

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

The histogram of the response variable in Figure 3 reveals that the distribution of diarrhea risk is not symmetrical. The skewed pattern of the response is suitable to be handled with a quantile regression scheme since quantile regression does not make any assumptions about the distribution of the response variable. While if the skewed pattern of the response is handled using mean-based regression, it could cause violation of regression assumption.

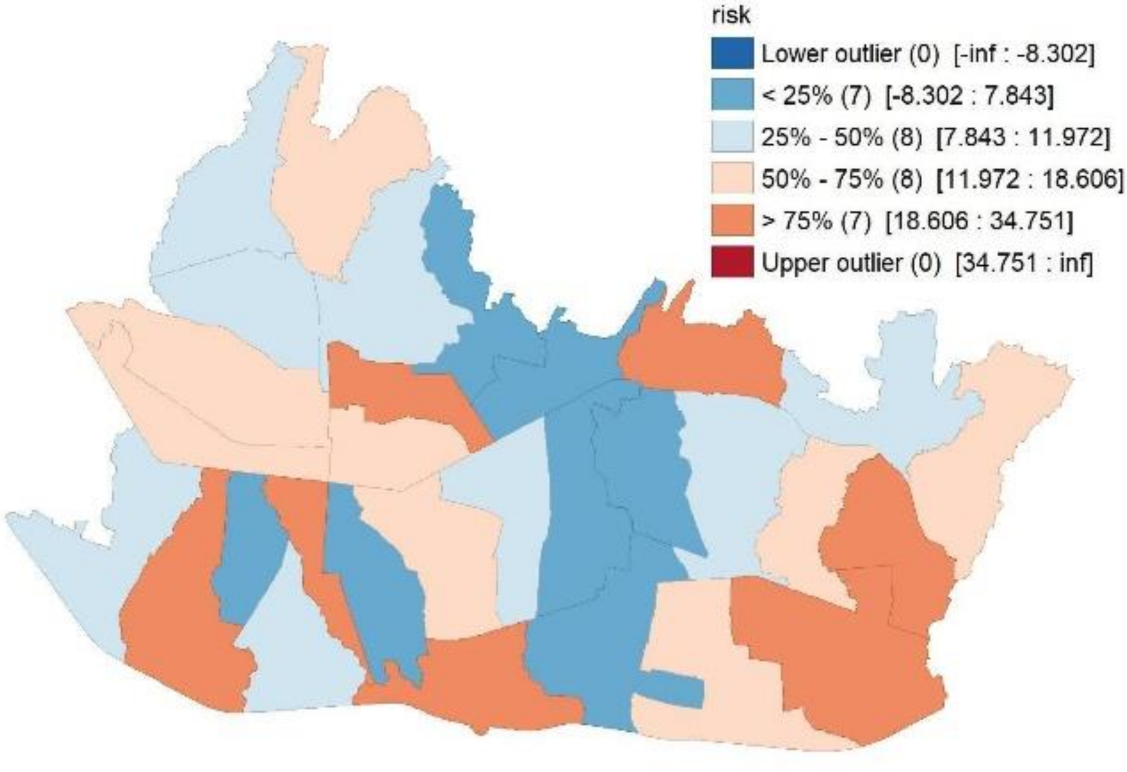

Figure 2. Boxmap of the observed diarrhea risk

After considering the spatial effect, the Breusch-Pagan test was conducted to examine spatial heterogeneity. The test yielded a p-value of 0.043, which is significant at a level of $\alpha = 0.05$, indicating that there is spatial heterogeneity in the data. This suggests that the association between the predictors and the response variable varies across space and that utilizing locally varying spatial models such as the Geographically Weighted model would be appropriate

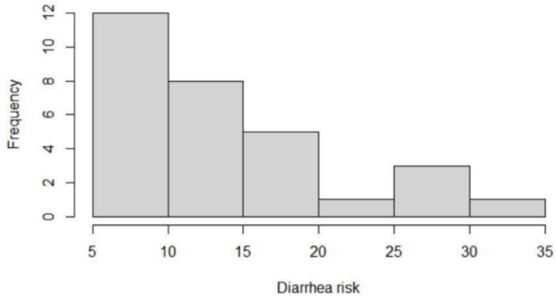

Figure 3. Histogram of the observed diarrhea risk

Displayed in Figure 4 are the scatter plots of the response at the Y-axis and the predictor at the X-axis. Each point represents the risk value of each district. It can be observed that the amount of variability tends to increase with higher values of the predictor variable, as evidenced by the greater distribution of data points at higher predictor values in all three scatter plots.

Regarding the left graph representing X_1 (the percentage of houses with clean water access), the majority of the data points are concentrated at a range of 99 to 100 percent. However, the prevalence of diarrhea ranges from 5 to 32 percent despite this high proportion of houses with clean water access. An alike case happens with the plot of X_2 at the middle (the percentage of houses practicing hand washing habits). Although the risk of diarrhea spans a wide range from low to high, most districts have a percentage of houses with hand washing habits exceeding 90%. The scatterplot for the third predictor on the right displays a greater range of variability than the previous two predictors, as indicated by the spread of points across a range of low to high values for X_3 (the percentage of houses with healthy toilets status). Additionally, it was noted that one district has low values for clean water percentage, hand washing habits, and healthy toilets, yet the risk of diarrhea in that district is also low.

Results of Geographically Weighted Quantile Regression

The adaptive bandwidth method was used with the GWQR bi-square kernel, and it was discovered through cross-validation that the best bandwidth for the 0.75th quantile is $h = 28$.

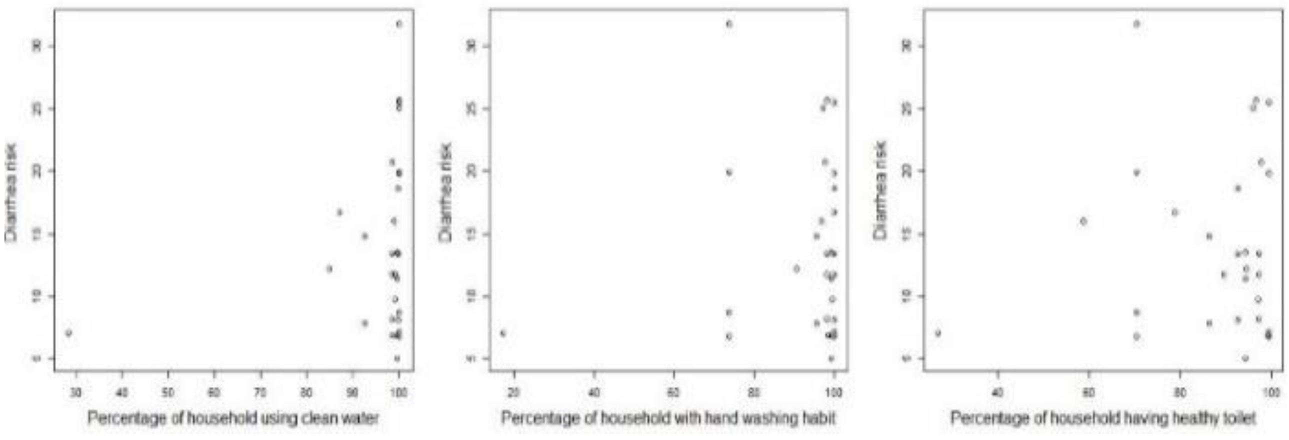

Figure 4. Scatter plot of predictors (left to the right: X1-X3) against the response

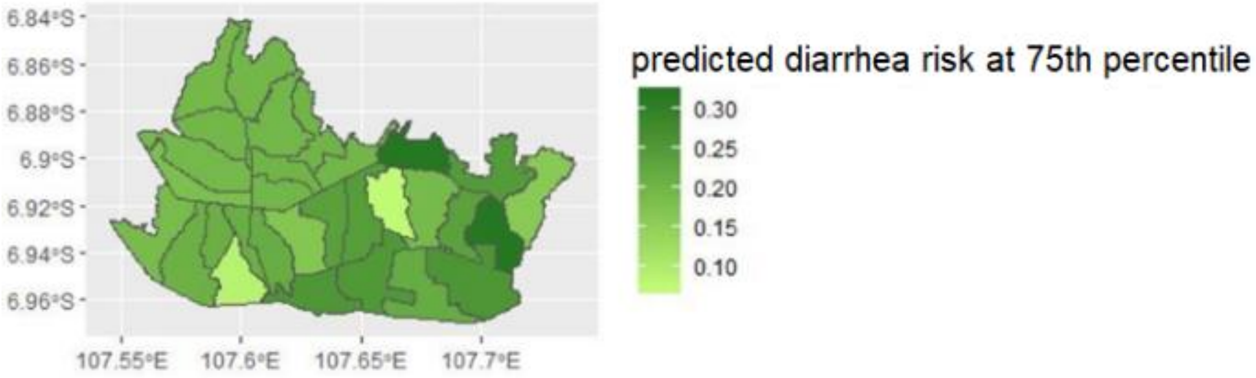

Figure 5. GWQR predictions for diarrhea risk at the 75th percentile

Figure 5 illustrates the map of diarrhea risk predictions from GWQR model based on the 0.75 quantile. The darker colors in the eastern part of the map signify two specific districts that have been identified as having the highest probability of experiencing diarrhea. This is in comparison to all other districts in the upper percentile, with a diarrhea risk of over 30%. In these two districts, 25 out of every 100 children under the age of five are estimated to have a 30% or greater risk of contracting diarrhea. As a result, it is recommended that the health authorities give particular attention to the issue of diarrhea in these districts.

Figure 6, 7, and 8 display the maps for the GWQR parameter estimates and their corresponding significance tests at the upper quantiles ($\tau = 0.75$). The degree of darkness in the color on the maps represents the magnitude of the positive impact of a covariate on the response variable. Conversely, lighter shades suggest that the effect of a predictor is either slightly positive or negative. The areas on the maps that are colored white are locations where the predictor's effect is not significant at a 5% level of significance.

The association between the percentage of houses that use clean water (X_1) and diarrhea risk is depicted in Figure 6. The western section of the map shows a negative effect of the percentage of clean water on diarrhea risk at the 75th percentile, 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. Furthermore, while the impact of the percentage of houses with clean water (X_1) on the incidence of diarrhea is statistically significant in nearly all districts, the extent of this impact differs across various 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.

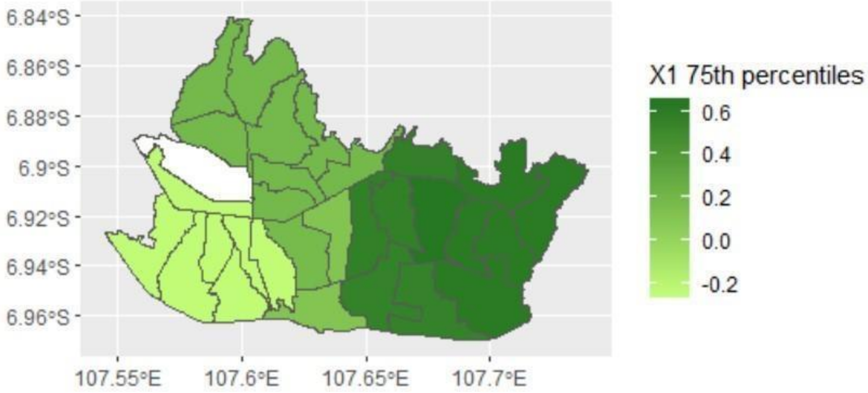

Figure 6. Maps of GWQR $\tau = 0.75$ Estimates for X_1 (Percentage of Houses with Clean Water Usage) and its significance at $\alpha = 0.05$

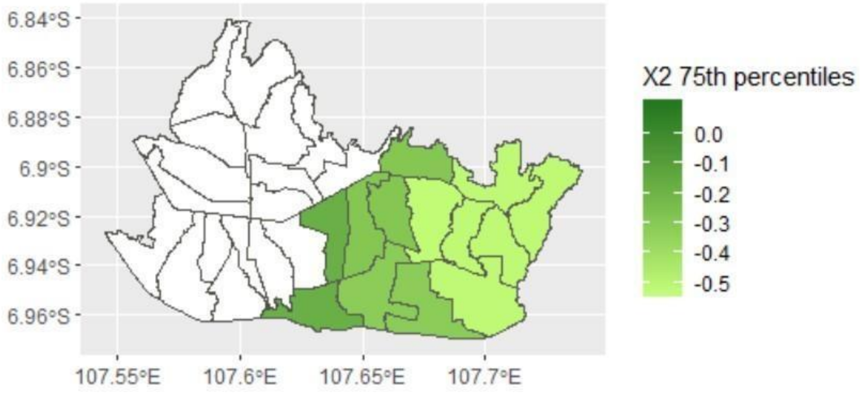

Figure 7. Maps of GWQR $\tau = 0.75$ Estimates for X_2 (Percentage of houses practicing hand washing habit) evaluated at the 5% significant level

The map shown in Figure 7 displays the significance of parameter estimates for the percentage of houses that practiced hand washing habits (X2) for all districts at the 0.75th quantile level. At the 75th percentile, the percentage of houses that practiced hand washing habits is a significant factor in reducing the likelihood of toddlers in the eastern half of Bandung developing diarrhea. 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.

Figure 8 illustrates the geographic distribution of GWQR coefficients for X_3, which represents the percentage of houses with healthy toilets status significant at a 5% significance level. The study found that the percentage of houses with healthy toilets (X_3) is a significant predictor of the risk of toddlers developing diarrhea in both the western and eastern regions of Bandung when at the 75th percentile. However, it is not a significant predictor in the central part of the city. Again, this illustrates that the effect of predictors can be different between locations, both in the significance and magnitude.

All three predictors were found to have significant influences on toddlers' diarrhea in the following districts: Gede Bage, Ujung Berung, Cinambo, Batu Nunggal, Bandung Kidul, Cibiru, Panyileukan, and Arcamanik. These districts are mostly located in the eastern area of Bandung city maps picture.

There was no location where no significant predictor variables influenced the diarrhea events. At least one predictor significantly influences diarrhea risks in Bandung districts. For example, diarrhea risks in the Cicendo district were influenced by X_3 (Percentage of Houses with Healthy Toilet). Diarrhea events at the following locations were influenced by only X_1 (Percentage of Houses with Clean Water Usage): Sukajadi, Cidadap,

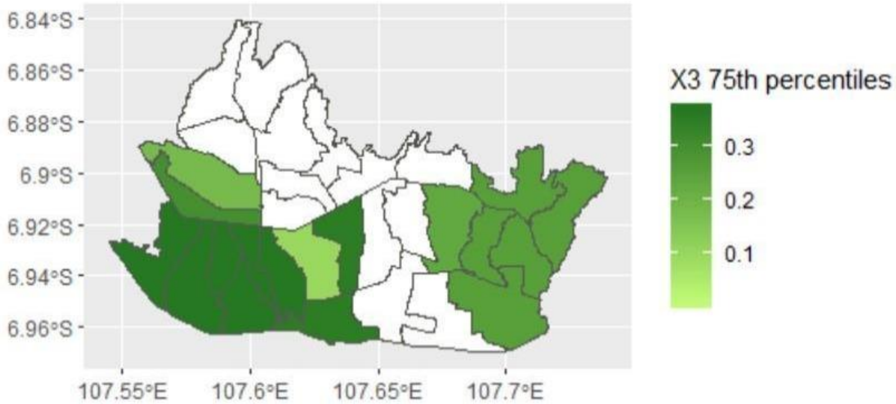

Figure 8. Maps of GWQR $\tau = 0.75$ Estimates for X_3 (Percentage of Houses with Healthy Toilet) significant at $\alpha = 5\%$

Coblong, Bandung Wetan, Sumur Bandung, Cibeunying Kidul, Cibeunying Kaler, Sukasari.

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. In this research, the Geographically Weighted Quantile Regression (GWQR) model was utilized to address the research questions regarding the association between selected predictors and the risk of diarrhea in children under the age of 5 in various spatial locations. The evaluation was done 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.

A lot of households in Bandung obtain their water supply either from the Municipal Water Corporation or from wells. The Municipal Water Corporation divides its water distribution service and pipeline systems into three sub-regions for those subscribed to it. Unequal access to water across different districts of Bandung poses a varying risk of diarrhea. Additionally, there are still some households without septic tanks for their toilets in Bandung, which prevents the city from achieving complete ODF status (Bandung Public Relations, 2020). They flowed the feces disposal to the river or practiced open defecation. The evidence could imply that regions situated close to rivers or where waste is disposed are more susceptible to soil and groundwater pollution, resulting in an unstable diarrhea risk in various 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 findings indicate that certain coefficients exhibit a negative association between the predictors and the response, while others indicate a positive association. The positive coefficients may appear counterintuitive because it is not anticipated that an increase in the proportion of households with access to clean water, hygienic toilets, and handwashing practices would amplify the risk of diarrhea in young children. After examining the scatter plot in Figure 4, it can be observed that the diarrhea risk values (Y) vary across districts, ranging from low to high values. However, the predictors, such as the percentage of households with clean water access, handwashing habits, and healthy toilets, have high percentages across most districts, irrespective of the level of diarrhea risk. The percentages of X1 and X2, in particular, exceed 98% in almost all districts, even those with a very high risk of diarrhea. Furthermore, a correlation seems to exist between X3 and Y, with the response increasing as X3 increases. Additionally, there is one district with low percentages in all predictors but still has a low diarrhea risk. These patterns cause the model to predict a positive linear relationship between the predictors and the response.

In addition, since the number of data used in this study is 30 and the weighting function is adaptive, thus less data was used to model a regression point than 30. This limitation of the study might contribute to the counterintuitive positive associations between predictors and response in some locations. Therefore, future studies are suggested to use a larger number of data points or opt for another kernel choice when modeling using GWQR.

CONCLUSIONS

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 important and would enable the decision-maker to effectively address the issue of diarrhea by identifying which predictor has a significant impact on a particular district of concern. 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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