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ESTIMATING GEOGRAPHICALLY WEIGHTED NEGATIVE BINOMIAL REGRESSION (GWNBR) MODEL AND MAPPING SPATIAL PATTERNS ON ANEMIA DATA IN INDONESIA

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ABSTRACT: Geographically Weighted Negative Binomial Regression (GWNBR) is a spatial regression approach designed to account for spatial heterogeneity by incorporating geographic coordinates (latitude and longitude) as spatial weights while simultaneously addressing overdispersion in count data. The empirical application in this study utilized data on anemia cases among women of childbearing age (WCA) across 33 provinces in Indonesia. The GWNBR model was employed to estimate local regression parameters and examine the spatial variation in regression coefficients. The analysis revealed that at least one explanatory variable significantly influenced the response variable in each province. In the central and eastern regions of Indonesia, the number of anemia cases per 100 WCA increased proportionally with increases in the number of WCA affected by pneumonia, malaria, and hepatitis. In contrast, western Indonesia exhibited distinct spatial patterns, where anemia cases per 100 WCA were positively associated with the number of WCA residing in rural areas (particularly in Java and Kalimantan), the number of WCA affected

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by acute respiratory infections (ARI) in Sumatra and Kalimantan, and the number of WCA diagnosed with tuberculosis.

Keywords: *Negative binomial regression, Geographically Weighted Negative Binomial Regression (GWNBR), anemia, Women of Childbearing Age (WCA*

1. INTRODUCTION

Negative binomial regression is a statistical model commonly employed for count response variables, particularly when the data exhibit overdispersion. In this model, the response variable is assumed to follow a negative binomial distribution, whose probability function can be derived from a Poisson–Gamma mixture distribution. Similar to Poisson regression, negative binomial regression is used to examine the relationship between a count response variable and one or more explanatory variables. However, unlike Poisson regression, the negative binomial model is more flexible because it does not require the equality of the mean and variance.

A previous study [1] demonstrated that Poisson regression modeling encountered an overdispersion problem. Consequently, the negative binomial regression model was identified as the most appropriate approach, revealing that the proportion of the male population significantly affected the number of leprosy cases in West Java in 2019.

Spatial data consist of observations that include not only information on the variables of interest but also the geographic coordinates of the locations where the data were collected. One important issue in spatial data analysis is the potential presence of spatial heterogeneity, which arises when the characteristics of observations vary across locations. Spatial heterogeneity implies that observational data are location dependent, causing the effects of explanatory variables on the response variable to differ from one location to another. As a result, the application of global linear regression models may be inappropriate, as it can lead to biased parameter estimates.

To address spatial heterogeneity, geographically weighted regression (GWR) can be employed. According to [2], GWR is a local regression technique that allows regression relationships to vary across geographic locations. In GWR, a spatial weighting matrix, W(i), is incorporated, where the weights are determined by the proximity between locations. These weights represent the relative influence of neighboring observations,

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under the assumption that geographically closer observations exert a stronger influence than observations located farther apart [3].

For count data exhibiting overdispersion and spatial dependence, Geographically Weighted Negative Binomial Regression (GWNBR) can be utilized. GWNBR, first introduced by Ricardo and Carvalho in 2013, extends the negative binomial regression model by incorporating spatial weighting based on the latitude and longitude coordinates of observation points while simultaneously accounting for overdispersion [4]. Negative binomial regression modeling for spatial data is particularly important because spatial heterogeneity may cause regression parameter estimates to vary across observation locations, resulting in location-specific or local parameter estimates.

This study applies the GWNBR model to empirical data on anemia cases among women of childbearing age (WCA) in Indonesia. Anemia is a condition characterized by hemoglobin levels below the normal threshold for an individual. It remains a major nutritional health problem in Indonesia and is most prevalent among women of childbearing age and children. Despite various health interventions, the prevalence of anemia remains relatively high and continues to persist over time.

2. RESEARCH METHODS

2.1 Data Sources and Research Variables

This study utilized secondary data obtained from the 2013 Indonesian Basic Health Research (Riskesdas) biomedical survey and supporting data retrieved from the Statistics Indonesia (BPS) database for 2013. The study area comprised 33 provinces in Indonesia, which served as the spatial units of analysis. The response variable and explanatory variables were selected based on their potential association with anemia among women of childbearing age (WCA). The number of WCA samples in each province is presented in Table 1.

Table 1. Total WCA Samples in Each Province

Province	Total	Province	Total	Province	Total
Aceh	115	West Java	1,623	East Kalimantan	158
North Sumatra	425	Central Java	1,468	North Sulawesi	109
West Sumatra	197	Special Region of Yogyakarta	218	Central Sulawesi	152

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Riau	120	East Java	1,311	South Sulawesi	301
Jambi	122	Banten	668	Southeast Sulawesi	20
South Sumatra	373	Bali	190	Gorontalo	41
Bengkulu	50	West Nusa Tenggara	397	West Sulawesi	53
Lampung	346	East Nusa Tenggara	171	Maluku	83
Bangka Belitung Islands	19	West Kalimantan	156	North Maluku	47
Riau Islands	79	Central Kalimantan	34	West Papua	68
Jakarta Special Capital Region	73	South Kalimantan	157	Papua	119

The research variables used are as follows:

Table 2. Research Variables

Variables	Information
Y_1	Number of WCA affected by anemia per 100 WCA in each province in Indonesia
X_1	Number of WCA living in rural areas per 100 WCA
X_2	Number of WCA affected by pneumonia per 100 WCA
X_3	Number of WCA affected by ARI per 100 WCA
X_4	Number of WCA affected by malaria per 100 WCA
X_5	Number of WCA affected by TB per 100 WCA
X_6	Number of WCA affected by hepatitis per 100 WCA
X_7	Percentage of districts/cities that have PHBS (Perilaku Hidup Bersih dan Sehat/Clean and Healthy Living Behavior) policies

The primary analytical method employed in this study was Geographically Weighted Negative Binomial Regression (GWNBR). The model was used to estimate location-specific regression parameters and to identify the spatial distribution of the regression coefficients for each explanatory variable. The analysis was conducted using R software version 4.1.3.

The analytical procedures consisted of the following steps:

1. Describing the characteristics of anemia among WCA in each province using descriptive statistical analysis.

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2. Examining multicollinearity among explanatory variables using correlation analysis and the Variance Inflation Factor (VIF).
3. Testing for spatial heterogeneity.
4. Constructing the GWNBR model through the following procedures:
    - determining the geographic coordinates (latitude and longitude) of each province;
    - calculating the Euclidean distance between observation locations;
    - selecting the optimal bandwidth by minimizing the cross-validation (CV) criterion;
    - constructing the spatial weighting matrix using the Adaptive Bisquare Kernel function;
    - performing simultaneous significance testing of the GWNBR model parameters; and
    - interpreting the local regression coefficients and mapping their spatial distribution to identify factors associated with anemia among WCA across Indonesia.

2.2 Multicollinearity

Multicollinearity refers to the existence of a strong linear relationship among explanatory variables. When explanatory variables are highly correlated, their individual effects become difficult to distinguish, resulting in unstable, inefficient, and potentially biased estimates of the regression coefficients. Multicollinearity was evaluated using the **Variance Inflation Factor (VIF)**, which is defined as [5]

$$VIF(X_i) = \frac{1}{(1-R_i^2)} \tag{1}$$

where

$i = 1,2,3, \dots, n$

R_i^2 = i-th coefficient of determination (square of the correlation coefficient)

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High multicollinearity can be indicated by the high value of VIF obtained. If the VIF value is not more than 10, the conclusion is that there are no cases of multicollinearity [6].

2.3. Negative Binomial Regression

Negative binomial regression is a mixed model of Poisson and Gamma, which is one solution for overcoming the problem of overdispersion in Poisson regression [7]. The negative binomial probability function can be stated as follows:

$$f(y,\mu,\theta) = \frac{\Gamma\left(y+\frac{1}{\theta}\right)}{\Gamma\left(\frac{1}{\theta}\right)y!}\left(\frac{1}{1+\theta\mu}\right)^{1/\theta}\left(\frac{\theta\mu}{1+\theta\mu}\right)^{y} \quad , y = 0, 1, 2, \ldots \tag{2}$$

The negative binomial regression model equation can be written as follows:

$$y_i = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi}) \tag{3}$$

The Maximum Likelihood Estimation (MLE) method with Newton Raphson iteration is also used in estimating negative binomial regression model parameters. The function likelihood of the Poisson regression model is formulated as follows:

$$L(\beta,\theta) = \prod_{i=1}^{n}\left(\prod_{r=0}^{y_i-1}(r+\theta^{-1})\right)\frac{1}{(y_i!)}\left(\frac{1}{1+\theta\mu_i}\right)^{1/\theta}\left(\frac{\theta\mu_i}{1+\theta\mu_i}\right)^{y_i} \tag{4}$$

Simultaneously test the significance of the negative binomial regression model using the Maximum Likelihood Ratio Test (MLRT) with the following hypothesis [8]:

$H_0: \beta_1 = \beta_2 = \cdots = \beta_p = 0$

$H_1: there\ is\ at\ least\ one\ \beta_k \neq 0, i = 1, 2, \ldots., n; k = 0,1,2, \ldots, p$

Test statistics:

$$D(\hat{\beta}) = -2ln\left(\frac{L(\hat{\omega})}{L(\hat{\Omega})}\right) \tag{5}$$

The rejection area is rejected H_0 if $D(\hat{\beta}) > \chi^2_{p(a)}$ or p-value $< \alpha$.

Furthermore, the partial test of the negative binomial regression model with the following hypothesis:

$H_0: \beta_k = 0$ (The effect of the *k-th* is not significant)

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$H_1: \beta_k \neq 0, k = 1, 2, \ldots, p$ (The effect of the *k-th* is significant)

Test statistics:

$$W = \frac{\hat{\beta}_k}{se(\hat{\beta}_k)} \quad (6)$$

The rejection area is rejected H_0 if $W \text{ or } t - value > t_{(n-k,\alpha/2)}$ or p-value $< \alpha$, which means the k-th independent variable has an effect on the dependent variable.

2.4. Spatial Heterogeneity Test

Spatial heterogeneity testing is used to see the characteristics at an observation location. One of the impacts arising from the emergence of spatial heterogeneity is that the regression parameters vary spatially, or spatial nonstationarity in the regression parameters. The spatial heterogeneity test can be tested using the Breusch Pagan test statistic with the hypothesis [9]:

$H_0: \sigma^2(u_i, v_i) = \cdots = \sigma^2(u_n, v_n) = \sigma^2$ (The variance between locations is the same / there is no spatial heterogeneity)

$H_1: there\ is\ at\ least\ one\ \sigma^2(u_n, v_n) \neq \sigma^2$ (The variance between locations is different / there is spatial heterogeneity)

BP test statistics are:

$$BP = \left(\frac{1}{2}\right) f^T Z(Z^T Z)^{-1} Z^T f \sim \chi^2_{(k)} \quad (7)$$

The rejection area is rejected $\boldsymbol{H_0}$ if $\boldsymbol{BP} > \boldsymbol{\chi^2_{(\alpha,k)}}$ or p-value $< \boldsymbol{\alpha}$, which means that the variance between locations is different / there is spatial heterogeneity.

2.5. Geographically Weighted Regression (GWR)

Geographically Weighted Regression (GWR) extends classical regression by allowing regression coefficients to vary across geographic locations. Unlike global regression models, GWR estimates a separate set of regression parameters for each observation location using spatial weighting, thereby capturing spatial heterogeneity [2]. The spatial weights reflect the influence of neighboring observations, assuming that geographically closer locations exert a stronger influence than more distant locations [3].

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Spatial weights are determined from the distances between observation locations, which are calculated using the Euclidean distance:

$$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2} \qquad (8)$$

where $u_i$and $v_i$denote the latitude and longitude coordinates of the i-th observation, respectively.

Among several spatial weighting schemes, the Adaptive Bisquare Kernel is commonly used. The corresponding weight function is defined as [2]

$$w_j(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h_{i(q)}}\right)^2\right)^2, & d_{ij} < h_i, \\ 0, & d_{ij} \geq h_i, \end{cases} \qquad (9)$$

where $h_{i(q)}$denotes the adaptive bandwidth at the i-th location, corresponding to the distance to its q-th nearest neighbor.

The bandwidth is a key parameter because it determines the spatial scale of the local estimation. A small bandwidth produces highly localized parameter estimates that depend primarily on nearby observations, whereas a large bandwidth yields smoother estimates that increasingly resemble those of a global regression model [2].

2.6. Geographically Weighted Negative Binomial Regression (GWNBR)

Geographically Weighted Negative Binomial Regression (GWNBR) extends negative binomial regression by incorporating spatially varying coefficients. The model is particularly suitable for overdispersed count data exhibiting spatial heterogeneity, as it produces location-specific parameter estimates [4,10].

The GWNBR model is expressed as

$Y_i \sim BN(\mu_i, \theta_i),$

With

$$\mu_i = \exp\left(\sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik}\right), \qquad (10)$$

or equivalently,

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$$Y_i \sim BN\left[\exp\left(\sum_{k=1}^{p}\beta_k(u_i,v_i)x_{ik}\right),\theta_i(u_i,v_i)\right].$$

where

- Y_i denotes the response variable at the i-th location;
- x_{ik} is the value of the k-th explanatory variable at location (u_i, v_i);
- $\beta_k(u_i,v_i)$ is the location-specific regression coefficient; and
- (u_i, v_i) represents the latitude and longitude coordinates of the i-th observation.

The model parameters are estimated using the Maximum Likelihood Estimation (MLE) method through the Newton–Raphson iterative algorithm [10].

Simultaneous Significance Test

The overall significance of the GWNBR model is evaluated using the Maximum Likelihood Ratio Test (MLRT) with the hypotheses

$H_0: \beta_1(u_i,v_i) = \cdots = \beta_p(u_i,v_i) = 0,$

$H_1:$at least one $\beta_k(u_i,v_i) \neq 0.$

The test statistic is

$$D(\hat{\beta}) = -2\ln\left[\frac{L(\widehat{\omega})}{L(\widehat{\Omega})}\right] = 2\left[\ln L(\widehat{\Omega}) - \ln L(\widehat{\omega})\right].$$

The null hypothesis is rejected when

$$D(\hat{\beta}) > \chi^2_{p,\alpha}$$

or when the p-value is less than α.

Partial Significance Test

The significance of individual local regression coefficients is assessed using the hypotheses

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

$H_1: \beta_k(u_i,v_i) \neq 0, k = 1, \dots, p.$

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The Wald statistic is

$$W = \frac{\hat{\beta}_k(u_i, v_i)}{SE\left[\hat{\beta}_k(u_i, v_i)\right]}.$$

The null hypothesis is rejected when

$$| W | > z_{\alpha/2}$$

or when the corresponding p-value is less than α, indicating that the explanatory variable has a significant local effect on the response variable.

2.7. Anemia

Anemia is a condition characterized by hemoglobin concentrations below the normal physiological threshold. It remains a major global public health problem, affecting approximately 1.62 billion people worldwide, many of whom are unaware of their condition [11]. The prevalence of anemia is estimated at 9% in developed countries and 43% in developing countries, contributing annually to more than 115,000 maternal deaths and 591,000 prenatal deaths worldwide [12].

In Indonesia, anemia is one of the most prevalent nutritional disorders, particularly among women of childbearing age (WCA) and children. It ranks among the leading health problems affecting these populations. According to national estimates, anemia affects approximately 47% of children, 42% of pregnant women, and 30% of non-pregnant women aged 15–49 years. Riskesdas data indicate that the prevalence of anemia increased from 37.1% in 2013 to 48.9% in 2018. In response, the World Health Organization (WHO) has set a target of reducing anemia among WCA by 50% by 2025 [13].

Despite interventions such as iron (Fe) supplementation, anemia remains highly prevalent. The condition increases the risk of maternal mortality, low birth weight, prematurity, miscarriage, congenital abnormalities, and maternal and neonatal infections [14,15]. Chronic anemia also reduces work productivity, impairs cognitive performance, increases susceptibility to infectious diseases, and imposes substantial economic and social burdens.

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Because anemia often develops gradually and presents with mild or nonspecific symptoms, it frequently receives insufficient public health attention. Nevertheless, it is recognized as the second leading cause of disability worldwide and an important indicator of population health and socioeconomic well-being [16]. Consequently, identifying the determinants of anemia, particularly among WCA in Indonesia, is essential for developing effective prevention and intervention strategies.

Women of childbearing age are especially vulnerable to iron-deficiency anemia because of menstruation, pregnancy, inadequate dietary iron intake, and parasitic infections. The etiology of anemia involves complex interactions among biological, socioeconomic, environmental, and behavioral factors [17].

Infectious diseases, including tuberculosis, malaria, and helminthiasis, are well-established causes of anemia, particularly in endemic regions, as they promote hemolysis and impair erythropoiesis [18,19]. Other chronic diseases, such as pneumonia, acute respiratory infection (ARI), chronic kidney disease, and cancer, are also associated with anemia by suppressing red blood cell production, shortening erythrocyte lifespan, and reducing nutritional intake [20].

Socioeconomic and environmental conditions also play important roles in anemia occurrence. Previous studies have reported that geographic disparities influence anemia prevalence [16]. Differences have been observed between rural and urban populations, with Riskesdas 2013 reporting a higher prevalence of anemia among pregnant women in rural areas (37.8%) than in urban areas (36.4%) [21,22]. Inadequate nutrition, poor sanitation, and unhealthy living environments are additional risk factors closely associated with household Clean and Healthy Living Behavior (PHBS) indicators [23]. These findings suggest that anemia is influenced by multiple spatially varying determinants, supporting the application of spatial regression models such as GWNBR.

3. RESULTS AND DISCUSSION

3.1 Data Exploration of WCA Affected by Anemia in Indonesia

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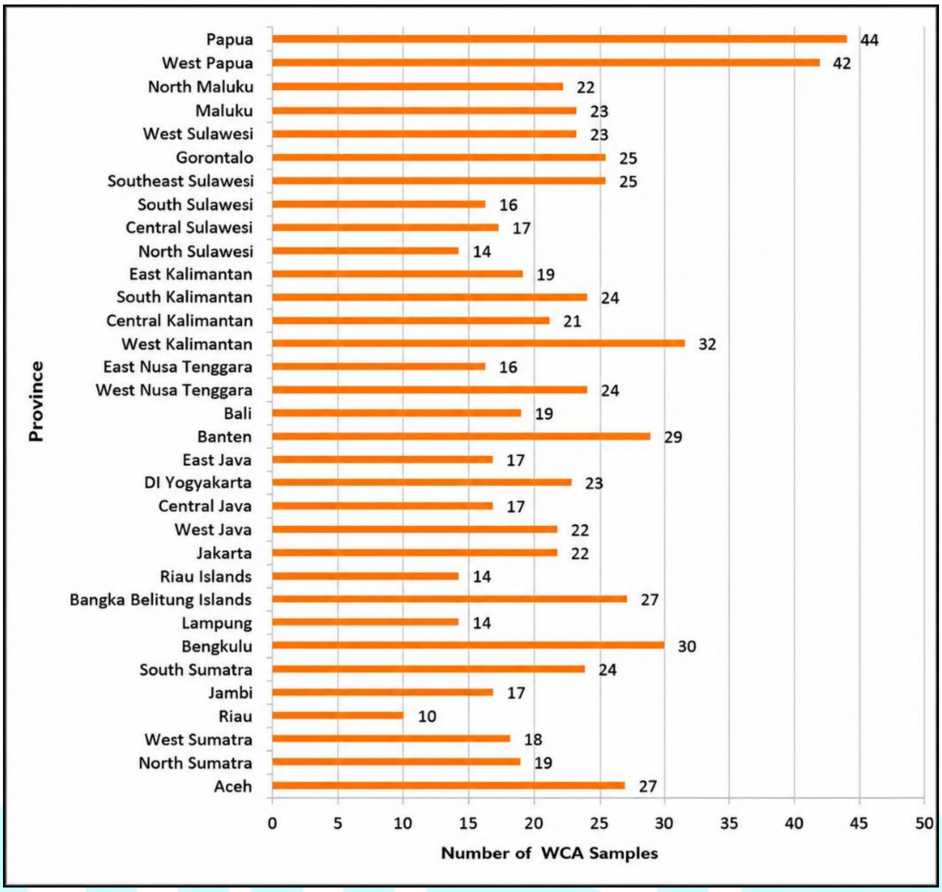

Figure 1. The number of cases of anemia in WCA per 100 population

Figure 1 illustrates the distribution of anemia cases among women of childbearing age (WCA) per 100 population across the 33 provinces of Indonesia. Considerable variation is observed among provinces, indicating potential geographic differences in the prevalence of anemia. Papua Province recorded the highest prevalence, with approximately 44 anemia cases per 100 WCA, followed by West Papua Province with about 42 cases per 100 WCA. These findings indicate that nearly one-half of the WCA population in both provinces suffers from anemia. In contrast, Riau Province exhibited the lowest prevalence, with only 10 anemia cases per 100 WCA. Overall, the average prevalence of anemia among WCA across all provinces was 22.3 cases per 100 population, with a standard deviation of 7.35, suggesting substantial variability in anemia prevalence among provinces. This spatial variation indicates that local demographic, environmental, socioeconomic, and health-related factors may contribute differently to anemia incidence across Indonesia.

3.2. Multicollinearity

Before fitting the regression model, a multicollinearity test was performed to assess whether strong linear relationships existed among the explanatory variables. High

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multicollinearity may result in unstable parameter estimates, inflated standard errors, and difficulties in interpreting the individual effects of explanatory variables. In this study, multicollinearity was evaluated using the Variance Inflation Factor (VIF). According to the commonly accepted criterion, a VIF value less than 10 indicates that multicollinearity is not a serious concern [7]:

Table 3. *VIF value.*

Variable	X_1	X_2	X_3	X_4	X_5	X_6	X_7
VIF	1.44	1.46	1.64	1.80	2.00	1.52	1.30

As shown in Table 3, all explanatory variables have VIF values ranging from 1.30 to 2.00, which are well below the threshold value of 10. These results indicate that no substantial multicollinearity exists among the explanatory variables. Consequently, each variable contributes independent information to the model, and all variables can be retained for subsequent GWNBR analysis.

3.3. Spatial Heterogeneity Test

Spatial heterogeneity refers to the presence of differences in data characteristics or relationships across geographic locations. Detecting spatial heterogeneity is important because it indicates whether the relationship between the response and explanatory variables varies spatially. If spatial heterogeneity exists, a global regression model may produce biased or inefficient parameter estimates, making local regression models, such as GWNBR, more appropriate.

The presence of spatial heterogeneity was examined using the Glejser test, with the following hypotheses:

$$H_0: \sigma^2(u_1, v_1) = \cdots = \sigma^2(u_n, v_n) = \sigma^2,$$

indicating homogeneous variance (no spatial heterogeneity), and

$$H_1\text{:at least one } \sigma^2(u_i, v_i) \neq \sigma^2,$$

indicating heterogeneous variance (spatial heterogeneity).

The Glejser test produced a p-value of 7.671×10^{-8}. At the 5% significance level, this p-value is substantially smaller than 0.05; therefore, the null hypothesis is rejected. This

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result provides strong statistical evidence that the variance differs significantly across observation locations, confirming the presence of spatial heterogeneity among the provinces. Consequently, the use of a geographically weighted modeling approach, such as GWNBR, is justified because it allows regression coefficients to vary spatially.

3.4. GWNBR Modeling

3.4.1. GWNBR Model Parameter Testing

The significance of the GWNBR model parameters was evaluated using both simultaneous and partial hypothesis tests. The simultaneous test determines whether the explanatory variables jointly have a significant effect on the response variable.

The hypotheses are

$$H_0: \beta_1(u_i, v_i) = \beta_2(u_i, v_i) = \cdots = \beta_p(u_i, v_i) = 0,$$

H_1:at least one $\beta_k(u_i, v_i) \neq 0$.

The simultaneous significance test was conducted using the Maximum Likelihood Ratio Test (MLRT). The analysis performed in R software produced a model deviance statistic of 30.2772. At the 5% significance level, the critical chi-square value with seven degrees of freedom is

$$\chi^2_{(7,0.05)} = 14.0671.$$

Because the calculated deviance statistic (30.2772) is greater than the critical chi-square value (14.0671), the null hypothesis is rejected. This result indicates that the explanatory variables are jointly significant and that at least one explanatory variable has a statistically significant effect on the number of anemia cases among women of childbearing age. Therefore, the GWNBR model provides a statistically significant framework for explaining the spatial variation in anemia prevalence across the provinces of Indonesia.

3.1.1 GWNBR Model Coefficient Mapping

Based on the parameter estimation results of the GWNBR method, the regression coefficient for the number of WCA living in rural areas is generally positive and there are negative regression coefficients in several provinces. Western and eastern parts of

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Indonesia tend to have positive coefficients, which means that for every increase of 1 WCA living in rural areas per 100 WCA, the number of anemic WCA per 100 WCA increases to $\exp(0.0000205 \leq \beta_1 \leq 0.00095) =$ 1.00002 to 1.001 times from the previous assumption other variables constant.

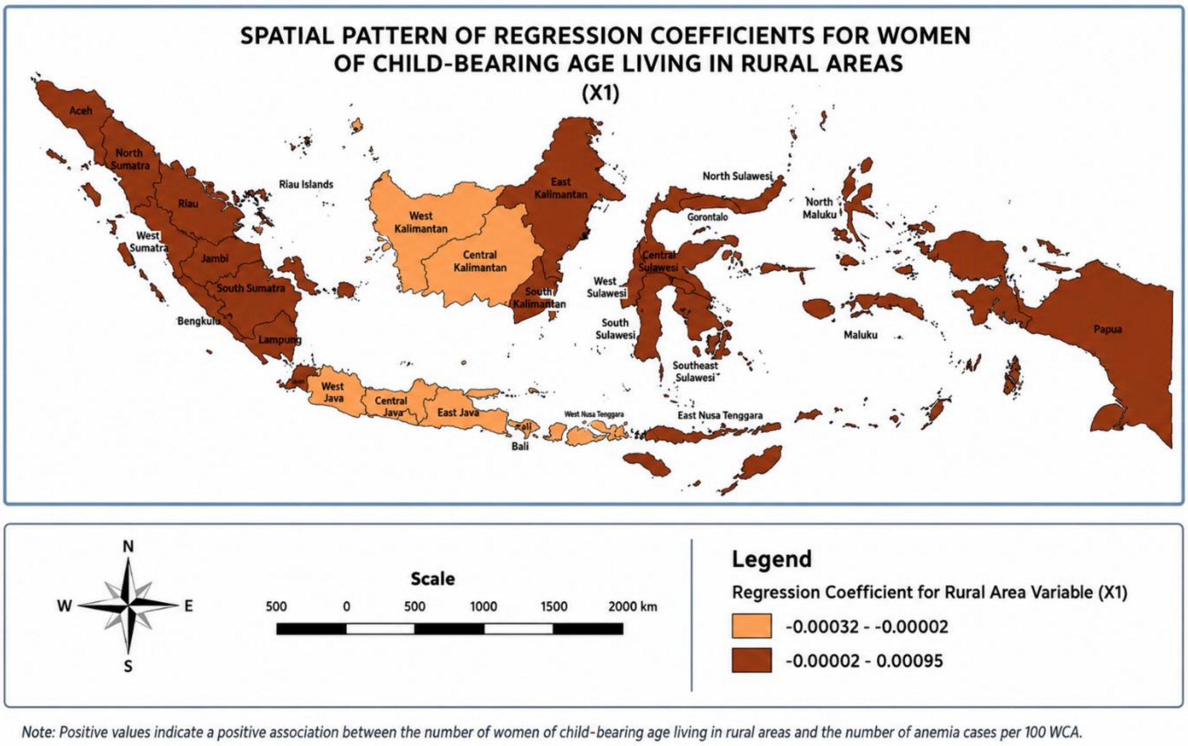

Figure 2. The spatial pattern of the regression coefficient X_1

Figure 2 presents the spatial distribution of the estimated local regression coefficients for the variable representing the number of women of childbearing age (WCA) living in rural areas (X_1) obtained from the Geographically Weighted Negative Binomial Regression (GWNBR) model. Unlike global regression models, GWNBR estimates location-specific coefficients, allowing the relationship between rural residence and anemia prevalence to vary across provinces. The figure therefore illustrates the spatial heterogeneity in the effect of rural residence on anemia among WCA in Indonesia.

The estimated regression coefficients range from −0.00032 to 0.00095. Most provinces exhibit positive regression coefficients, whereas only a few provinces show negative coefficients. The positive coefficients are predominantly observed in western Indonesia (including most provinces in Sumatra), eastern Indonesia (Papua, Maluku, and most provinces in Sulawesi), and parts of Kalimantan. In contrast, negative coefficients are

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primarily found in Java, Bali, West Kalimantan, and Central Kalimantan, indicating regional differences in the influence of rural residence on anemia prevalence.

For provinces with positive coefficients, an increase of one WCA living in rural areas per 100 WCA is associated with an increase in the expected number of anemia cases, assuming all other explanatory variables remain constant. Based on the estimated coefficients, the incidence rate ratio (IRR) ranges from

$$\exp(0.0000205 \leq \beta_1 \leq 0.00095) = 1.00002 \text{ to } 1.001.$$

This indicates that every additional WCA residing in a rural area increases the expected number of anemia cases by approximately 0.002% to 0.10%, although the magnitude of the effect differs across provinces.

The strongest positive associations are observed in Papua, West Papua, Maluku, North Maluku, Sulawesi, East Kalimantan, South Kalimantan, and several provinces in Sumatra, suggesting that rural residence is an important determinant of anemia in these regions. The stronger effects may reflect limited access to healthcare facilities, inadequate nutritional intake, lower socioeconomic conditions, poorer sanitation, and reduced availability of maternal health services in rural communities. These factors have been widely recognized as contributing to the higher burden of anemia among women of childbearing age.

Conversely, several provinces in Java, Bali, West Kalimantan, and Central Kalimantan exhibit negative regression coefficients. Although the estimated effects are relatively small, these coefficients suggest that, after controlling for the other explanatory variables in the model, an increase in the proportion of WCA living in rural areas is associated with a slight decrease in the expected number of anemia cases. This finding may indicate that rural residence is not the primary determinant of anemia in these provinces. Instead, other factors included in the model, such as infectious diseases, health policies, or socioeconomic conditions, may play a more dominant role. Furthermore, provinces in Java generally have better healthcare infrastructure, higher accessibility to maternal and child health services, and more comprehensive nutritional intervention programs, which may reduce the disparity in anemia prevalence between rural and urban populations.

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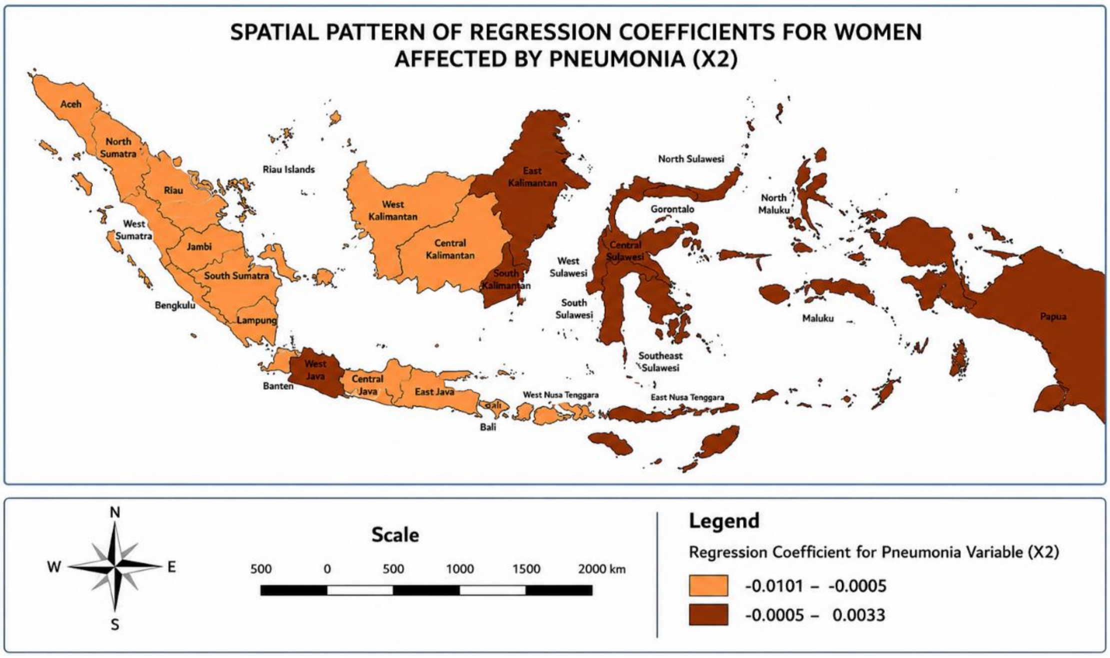
Overall, Figure 2 demonstrates that the effect of rural residence on anemia among WCA is spatially heterogeneous across Indonesia. The variation in both the magnitude and direction of the local regression coefficients confirms that the relationship between rural residence and anemia is location dependent rather than spatially homogeneous. These findings justify the application of the GWNBR model, which accounts for spatial heterogeneity by estimating province-specific regression coefficients. From a policy perspective, the results suggest that strategies to reduce anemia among WCA should be tailored to regional characteristics, with greater emphasis on improving healthcare accessibility, nutrition programs, sanitation, and disease prevention in rural areas where the positive association is strongest.



Note: Positive values indicate a positive association between the number of women affected by pneumonia and the number of anemia cases per 100 WCA.

Figure 3. The spatial pattern of the regression coefficient X_2

Figure 3 illustrates the spatial distribution of the local regression coefficients for the number of women of childbearing age (WCA) affected by pneumonia (X_2) estimated using the Geographically Weighted Negative Binomial Regression (GWNBR) model. The figure demonstrates that the effect of pneumonia on anemia among WCA is not spatially uniform across Indonesia. Instead, the magnitude and direction of the relationship vary considerably between provinces, confirming the existence of spatial heterogeneity and supporting the use of the GWNBR model.

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The estimated regression coefficients range from −0.0101 to 0.0033. Provinces are classified into two groups according to the sign of their local regression coefficients. Most provinces in western Indonesia, including Sumatra, Java, Bali, and large parts of Kalimantan, exhibit negative regression coefficients. In contrast, provinces in eastern Indonesia, including East Kalimantan, South Kalimantan, Sulawesi, Maluku, North Maluku, Papua, and West Papua, generally display positive regression coefficients.

For provinces with positive regression coefficients, an increase in the number of WCA affected by pneumonia is associated with an increase in the expected number of anemia cases after adjusting for the other explanatory variables in the model. Based on the estimated coefficients, the incidence rate ratio (IRR) is

$$\exp(0.0000494 \leq \beta_2 \leq 0.0033) = 1.000049 \text{ to } 1.0033.$$

This indicates that, holding all other variables constant, every additional woman of childbearing age diagnosed with pneumonia per 100 WCA increases the expected number of anemia cases by approximately 0.005% to 0.33%, depending on the province. Although the estimated effects are relatively small, the consistently positive coefficients across eastern Indonesia indicate that pneumonia contributes to an increased risk of anemia in these regions.

The strongest positive effects are observed in Papua, West Papua, Maluku, North Maluku, Sulawesi, East Kalimantan, and South Kalimantan. These findings suggest that pneumonia may be an important determinant of anemia among WCA in eastern Indonesia. The stronger association may reflect limited access to healthcare services, delayed diagnosis and treatment of respiratory infections, poorer nutritional status, and higher burdens of infectious diseases. Pneumonia can contribute to anemia through chronic inflammation, impaired iron metabolism, reduced erythropoiesis, and decreased nutritional intake during illness, all of which may reduce hemoglobin concentrations.

Conversely, western Indonesia, including most provinces in Sumatra, Java, Bali, and parts of Kalimantan, exhibits negative regression coefficients. These coefficients indicate that, after controlling for the other explanatory variables, an increase in pneumonia cases is associated with a slight reduction in the expected number of anemia cases. However, the magnitude of these negative coefficients is relatively small and should not be interpreted as

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indicating that pneumonia protects against anemia. Rather, they suggest that pneumonia is not the dominant factor explaining spatial variation in anemia in these provinces. Other variables included in the GWNBR model, such as rural residence, malaria, tuberculosis, hepatitis, socioeconomic conditions, and public health interventions, may have a stronger influence on anemia prevalence. In addition, western Indonesia generally has better healthcare infrastructure, broader immunization coverage, improved nutritional programs, and greater access to medical treatment, which may weaken the association between pneumonia and anemia.

Overall, Figure 3 reveals a clear east–west spatial contrast in the relationship between pneumonia and anemia among women of childbearing age in Indonesia. Positive coefficients are concentrated in eastern Indonesia, whereas negative coefficients are more common in western Indonesia. This spatial variation demonstrates that the impact of pneumonia on anemia is geographically dependent rather than constant across the country. The results further confirm the presence of spatial non-stationarity, indicating that the relationship between pneumonia and anemia differs by province. Consequently, geographically weighted models such as GWNBR provide a more appropriate analytical framework than conventional global regression models for identifying local risk factors.

From a public health perspective, these findings suggest that anemia prevention strategies should incorporate region-specific approaches. In eastern Indonesia, strengthening pneumonia prevention through improved vaccination coverage, early diagnosis, prompt treatment, nutritional supplementation, and enhanced access to healthcare services may help reduce the burden of anemia among women of childbearing age. In contrast, intervention strategies in western Indonesia should focus more on other locally significant determinants of anemia, as pneumonia appears to play a relatively smaller role in these provinces. Such geographically targeted interventions are expected to improve the effectiveness of national anemia control programs.

The regression coefficient on the variable number of ARI cases in WCA is more negative in several provinces. Meanwhile, the positive regression coefficient was only in 12 provinces, namely Riau, West Kalimantan, South Kalimantan, Central Kalimantan, Jambi, Bengkulu, DKI Jakarta, South Sumatra, Riau Islands, Banten, Bangka Belitung, and Lampung. This means that for every increase of 1 WCA affected by ISPA per 100 WCA,

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the number of WCA who are anemic per 100 WCA in the province increases to $\exp(0.0000125 \leq \beta_3 \leq 0.0017)$ =1.000013 to 1.0017 times from before assuming other variables are constant. Whereas the malaria variable also tends to have a negative regression coefficient so that for every increase of 1 WCA affected by malaria per 100 WCA, the number of WCA who are anemic per 100 WCA in the province decreases to $\exp(-0.0101 \leq \beta_4 \leq -0.0003)$ =0.98995 to 0.9997 times the previous time assuming other variables are constant.

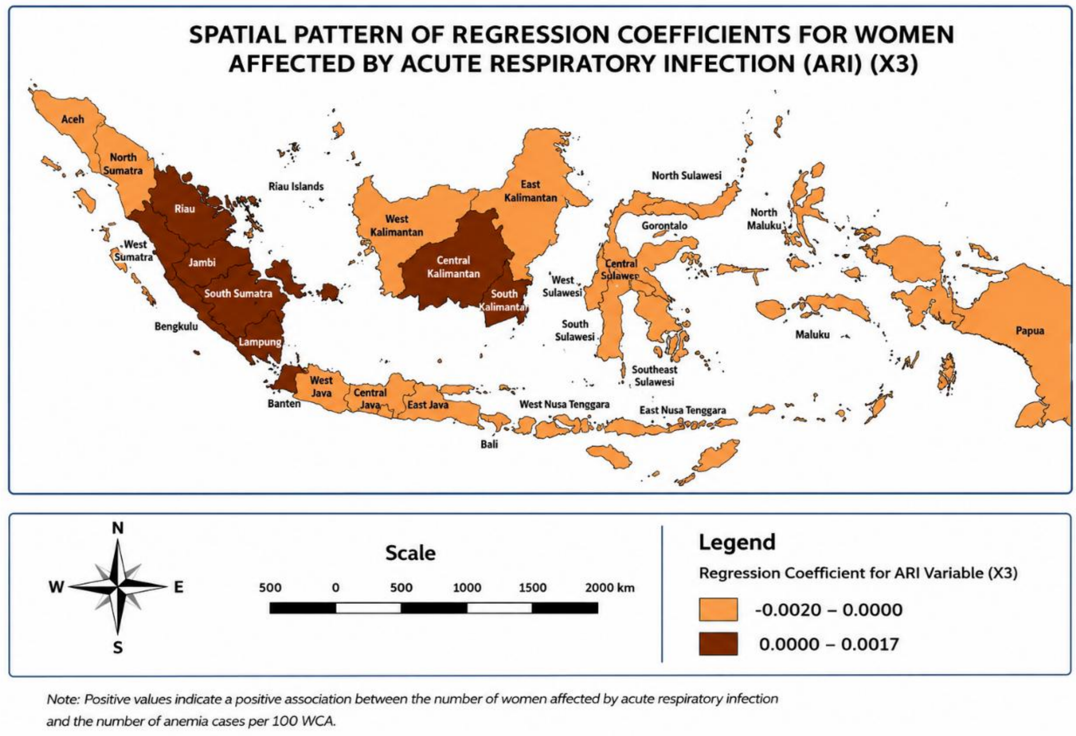

Figure 4. The spatial pattern of the regression coefficient $\boldsymbol{X_3}$

Figure 4 illustrates the spatial distribution of the local regression coefficients for the number of women of childbearing age (WCA) affected by acute respiratory infection (ARI) (X_3) estimated using the Geographically Weighted Negative Binomial Regression (GWNBR) model. The map demonstrates that the relationship between ARI and anemia among WCA varies geographically across Indonesia, indicating that the effect of ARI is not spatially homogeneous. This variation in local regression coefficients confirms the presence of spatial non-stationarity, supporting the use of GWNBR rather than a conventional global regression model.

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The estimated regression coefficients range from −0.0020 to 0.0017. Based on the map, positive regression coefficients are concentrated primarily in Sumatra, particularly in Riau, Jambi, South Sumatra, Bengkulu, and Lampung, as well as West Kalimantan, Central Kalimantan, and South Kalimantan. In contrast, negative regression coefficients are observed in most provinces of Java, Bali, Nusa Tenggara, Sulawesi, Maluku, Papua, and East Kalimantan, indicating regional differences in the effect of ARI on anemia among women of childbearing age.

For provinces with positive regression coefficients, an increase in the number of WCA affected by ARI is associated with an increase in the expected number of anemia cases after controlling for the other explanatory variables included in the GWNBR model. Based on the estimated coefficients, the corresponding incidence rate ratio (IRR) is

$$\exp(0.0000 \leq \beta_3 \leq 0.0017) = 1.0000 \text{ to } 1.0017.$$

This result indicates that, assuming all other variables remain constant, each additional WCA diagnosed with ARI per 100 WCA increases the expected number of anemia cases by approximately 0.00% to 0.17%, depending on the province. Although the magnitude of the effect is relatively small, the positive coefficients suggest that ARI contributes to an increased risk of anemia in these regions.

The positive association between ARI and anemia is biologically plausible because respiratory infections trigger inflammatory responses that interfere with iron metabolism and suppress erythropoiesis. During infection, inflammatory cytokines increase the production of hepcidin, which inhibits intestinal iron absorption and reduces the availability of iron for hemoglobin synthesis. Furthermore, recurrent respiratory infections may reduce appetite and nutritional intake, thereby increasing the risk of iron deficiency and anemia among women of childbearing age. These mechanisms may explain why the effect of ARI is more pronounced in several provinces of Sumatra and Kalimantan.

Conversely, provinces with negative regression coefficients, including most of Java, Bali, Nusa Tenggara, Sulawesi, Maluku, Papua, and East Kalimantan, exhibit an inverse relationship between ARI and anemia after adjustment for the other explanatory variables. The negative coefficients do not imply that ARI protects against anemia. Instead, they indicate that ARI is not the dominant factor influencing the spatial distribution of anemia in

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these provinces. Other explanatory variables included in the GWNBR model, such as malaria, tuberculosis, hepatitis, rural residence, and socioeconomic conditions, may contribute more substantially to variations in anemia prevalence. In addition, provinces with better healthcare systems, improved nutritional status, and greater access to diagnosis and treatment may experience a weaker association between ARI and anemia.

Overall, Figure 4 demonstrates substantial geographic variation in the influence of ARI on anemia among women of childbearing age. Positive associations are primarily observed in Sumatra and Kalimantan, whereas negative associations dominate Java and eastern Indonesia. These findings indicate that the contribution of ARI to anemia differs across provinces and highlight the importance of considering local characteristics when developing public health interventions. Consequently, strategies to reduce anemia should integrate ARI prevention and management in provinces where the positive association is strongest, while in other provinces greater emphasis may be placed on addressing more influential determinants of anemia. Such geographically targeted interventions are expected to improve the effectiveness of anemia prevention and control programs in Indonesia.

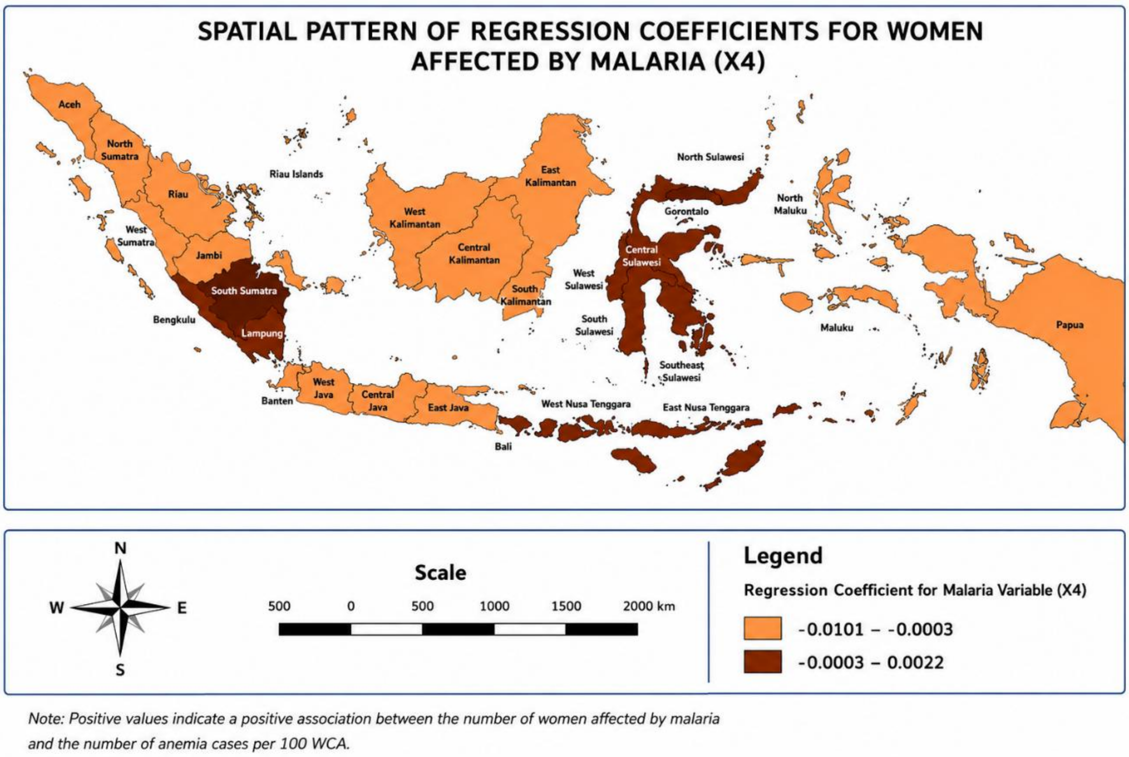

Figure 5. The spatial pattern of the regression coefficient X_4

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Figure 5 presents the spatial distribution of the local regression coefficients for the number of women of childbearing age (WCA) affected by malaria (X_4) estimated using the Geographically Weighted Negative Binomial Regression (GWNBR) model. The map illustrates that the relationship between malaria and anemia varies substantially across provinces, indicating that the influence of malaria on anemia is spatially heterogeneous rather than constant throughout Indonesia. This spatial variability supports the application of the GWNBR model, which allows regression coefficients to differ by geographic location.

The estimated local regression coefficients range from −0.0101 to 0.0022. Two distinct spatial patterns are observed. Positive regression coefficients are concentrated in South Sumatra, most provinces on Sulawesi Island, and several provinces in Nusa Tenggara, whereas negative regression coefficients dominate Sumatra (except South Sumatra), Java, Bali, Kalimantan, Maluku, Papua, and West Papua.

For provinces with positive regression coefficients, an increase in the number of WCA affected by malaria is associated with an increase in the expected number of anemia cases after controlling for the other explanatory variables in the model. Based on the estimated regression coefficients, the corresponding incidence rate ratio (IRR) is

$$\exp(0.0003 \leq \beta_4 \leq 0.0022) = 1.0003 \text{ to } 1.0022.$$

This result indicates that, assuming all other variables remain constant, every additional WCA diagnosed with malaria per 100 WCA increases the expected number of anemia cases by approximately 0.03% to 0.22%, depending on the province. Although the estimated increase is relatively modest, the consistently positive coefficients in these regions suggest that malaria contributes significantly to the occurrence of anemia among women of childbearing age.

The strongest positive associations are observed in South Sumatra, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, North Sulawesi, and several provinces in Nusa Tenggara. These findings are consistent with the biological mechanism of malaria, whereby *Plasmodium* infection destroys infected erythrocytes and accelerates the removal of both infected and uninfected red blood cells. In addition, malaria suppresses

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erythropoiesis through inflammatory responses, resulting in reduced hemoglobin concentrations and an increased risk of anemia. In regions where malaria transmission remains relatively high, recurrent infections may substantially contribute to the burden of anemia among women of childbearing age.

Conversely, most provinces in Java, Bali, Kalimantan, Papua, Maluku, and much of Sumatra exhibit negative regression coefficients. These coefficients indicate that, after accounting for the effects of the other explanatory variables, malaria is not positively associated with anemia in these provinces. The negative coefficients should not be interpreted as suggesting that malaria reduces the risk of anemia. Instead, they indicate that malaria is not the predominant factor explaining the spatial variation in anemia prevalence in these areas. Other explanatory variables included in the GWNBR model, such as rural residence, pneumonia, acute respiratory infection (ARI), tuberculosis, hepatitis, socioeconomic conditions, nutritional status, and public health interventions, may have a greater influence on anemia prevalence.

The observed spatial differences may also reflect regional variations in malaria endemicity, healthcare accessibility, malaria control programs, environmental conditions, and population immunity. Provinces with effective malaria surveillance, early diagnosis, prompt antimalarial treatment, and vector-control programs may experience a weaker relationship between malaria and anemia than provinces where malaria transmission remains more persistent.

Overall, Figure 5 demonstrates that the association between malaria and anemia among women of childbearing age is location dependent, with clear geographic differences in both the magnitude and direction of the regression coefficients. Positive associations are concentrated primarily in Sulawesi, South Sumatra, and parts of Nusa Tenggara, whereas negative associations dominate much of western Indonesia, Kalimantan, Maluku, and Papua. These findings confirm the presence of spatial non-stationarity and highlight the importance of using geographically weighted regression models to capture local variations in disease risk. From a public health perspective, the results suggest that malaria prevention and control should be prioritized in provinces where malaria exhibits a positive association with anemia, while anemia reduction strategies in other provinces should focus

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on more influential local determinants. Such region-specific interventions are expected to improve the effectiveness of anemia prevention and control programs across Indonesia.

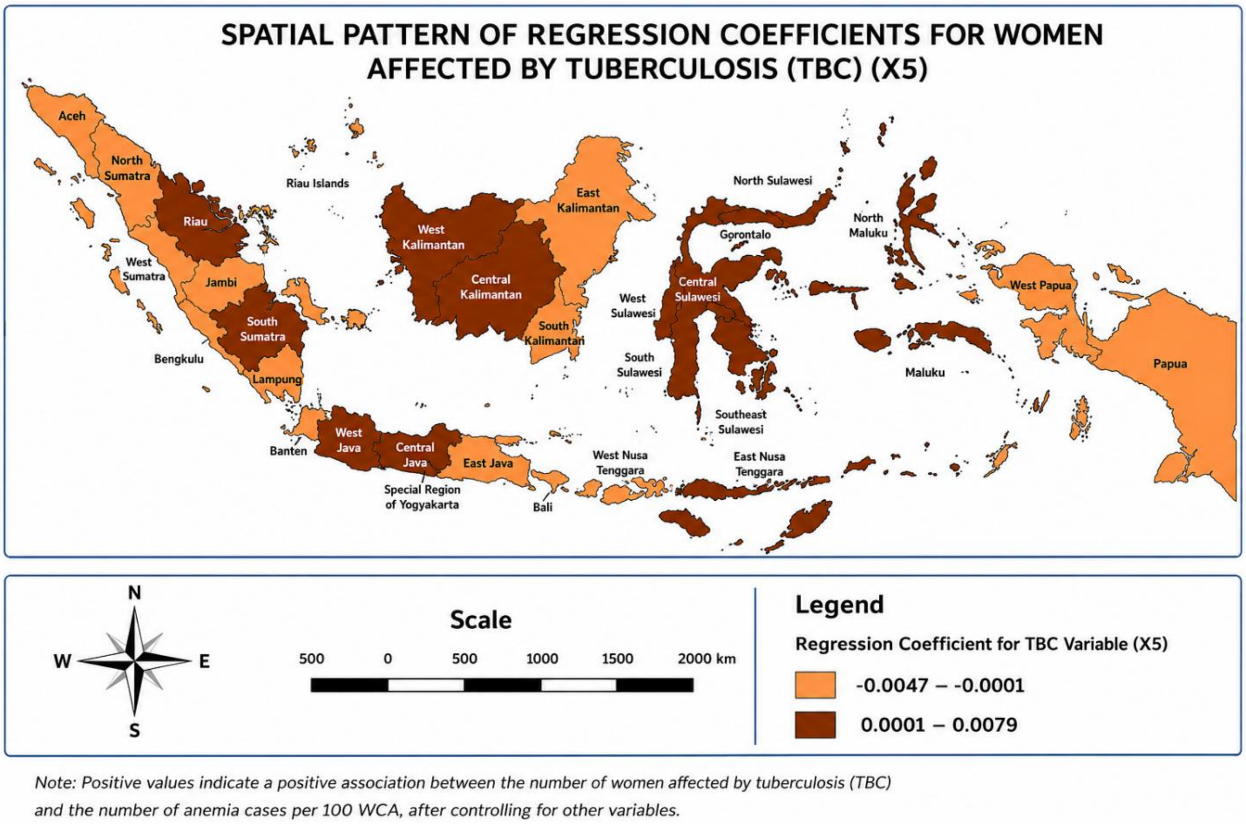

Figure 6. The spatial pattern of the regression coefficient X_5

Based on Figure 6, the regression coefficient for the tuberculosis (TBC) variable (X5) varies spatially across Indonesian provinces, with coefficients ranging from **−0.0047 to 0.0079**. The interpretation can be written as follows:

For provinces with **positive regression coefficients**, an increase in the number of women of childbearing age (WCA) affected by tuberculosis (TBC) is associated with an increase in the expected number of anemia cases after controlling for the other explanatory variables in the model. Based on the estimated regression coefficients, the corresponding incidence rate ratio (IRR) is

$$\exp(0.0001 \leq \beta_5 \leq 0.0079) = 1.0001 \text{ to } 1.0079.$$

This result indicates that, assuming all other variables remain constant, every additional WCA diagnosed with tuberculosis per 100 WCA increases the expected number of anemia

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cases by approximately 0.01% to 0.79%, depending on the province. Although the estimated increase is relatively small, the consistently positive coefficients observed in these provinces suggest that tuberculosis is an important contributing factor to anemia among women of childbearing age.

In contrast, provinces with negative regression coefficients ($\beta_5 = -0.0047$ to -0.0001) have IRRs ranging from

$$\exp(-0.0047 \leq \beta_5 \leq -0.0001) = 0.9953 \text{ to } 0.9999.$$

This implies that, after adjusting for other explanatory variables, an additional WCA affected by tuberculosis is associated with an expected **0.01% to 0.47% decrease** in anemia cases in these provinces. The negative association may reflect regional heterogeneity, differences in healthcare access, tuberculosis detection and treatment programs, nutritional status, or the influence of other unobserved factors that modify the relationship between tuberculosis and anemia.

Based on Figure 6, the provinces can be grouped into two categories according to the sign of the regression coefficient for the tuberculosis (TBC) variable (X5). This spatial variation indicates that the effect of tuberculosis on anemia among women of childbearing age (WCA) differs across Indonesia.

Provinces with Positive Regression Coefficients ($\beta > 0$)

These provinces include Riau, South Sumatra, Lampung, West Java, Central Java, West Kalimantan, Central Kalimantan, South Sulawesi, Central Sulawesi, Southeast Sulawesi, Gorontalo, North Sulawesi, East Nusa Tenggara (NTT), North Maluku, Maluku, and several other eastern provinces shown in dark brown on the map.

For these provinces, tuberculosis is positively associated with anemia after adjusting for all other explanatory variables in the model. The estimated regression coefficients range from 0.0001 to 0.0079, corresponding to an incidence rate ratio (IRR) of

$$\exp(0.0001 \leq \beta_5 \leq 0.0079) = 1.0001 \text{ to } 1.0079.$$

This means that, holding all other variables constant, every additional woman of

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childbearing age diagnosed with tuberculosis per 100 WCA increases the expected number of anemia cases by approximately 0.01% to 0.79%, depending on the province.

The largest positive coefficients are observed primarily in Central Kalimantan, West Kalimantan, South Sulawesi, Central Sulawesi, Southeast Sulawesi, North Sulawesi, North Maluku, and East Nusa Tenggara, indicating that tuberculosis has a relatively stronger association with anemia in these provinces. These stronger effects may be explained by higher TB prevalence, nutritional deficiencies, delayed diagnosis, limited access to healthcare services, or socioeconomic conditions that increase the likelihood of anemia among women with tuberculosis.

In contrast, provinces with smaller positive coefficients, such as Riau, Lampung, West Java, and Central Java, still exhibit a positive association, but the magnitude of the effect is relatively weaker. Although the increase in anemia risk per additional TB case is modest, the consistent positive relationship suggests that tuberculosis remains an important predictor of anemia in these provinces.

Provinces with Negative Regression Coefficients ($\beta < 0$)

The provinces shaded in light orange, including Aceh, North Sumatra, West Sumatra, Bengkulu, Jambi, East Kalimantan, South Kalimantan, East Java, West Nusa Tenggara (NTB), Bali, Papua, West Papua, and several surrounding provinces, exhibit negative regression coefficients, ranging from −0.0047 to −0.0001.

The corresponding incidence rate ratio is

$$\exp(-0.0047 \leq \beta_5 \leq -0.0001) = 0.9953 \text{ to } 0.9999.$$

This indicates that, after controlling for all other explanatory variables, each additional WCA diagnosed with tuberculosis is associated with an expected decrease of approximately 0.01% to 0.47% in anemia cases, depending on the province.

The negative association should not be interpreted as tuberculosis protecting against anemia. Rather, it reflects the complex spatial heterogeneity captured by the geographically weighted regression model. In these provinces, the relationship between tuberculosis and

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anemia may be overshadowed by stronger determinants such as maternal nutritional status, iron deficiency, malaria, socioeconomic conditions, sanitation, healthcare accessibility, or effective tuberculosis control programs. Consequently, tuberculosis contributes relatively less to explaining spatial variation in anemia after these other factors are taken into account.

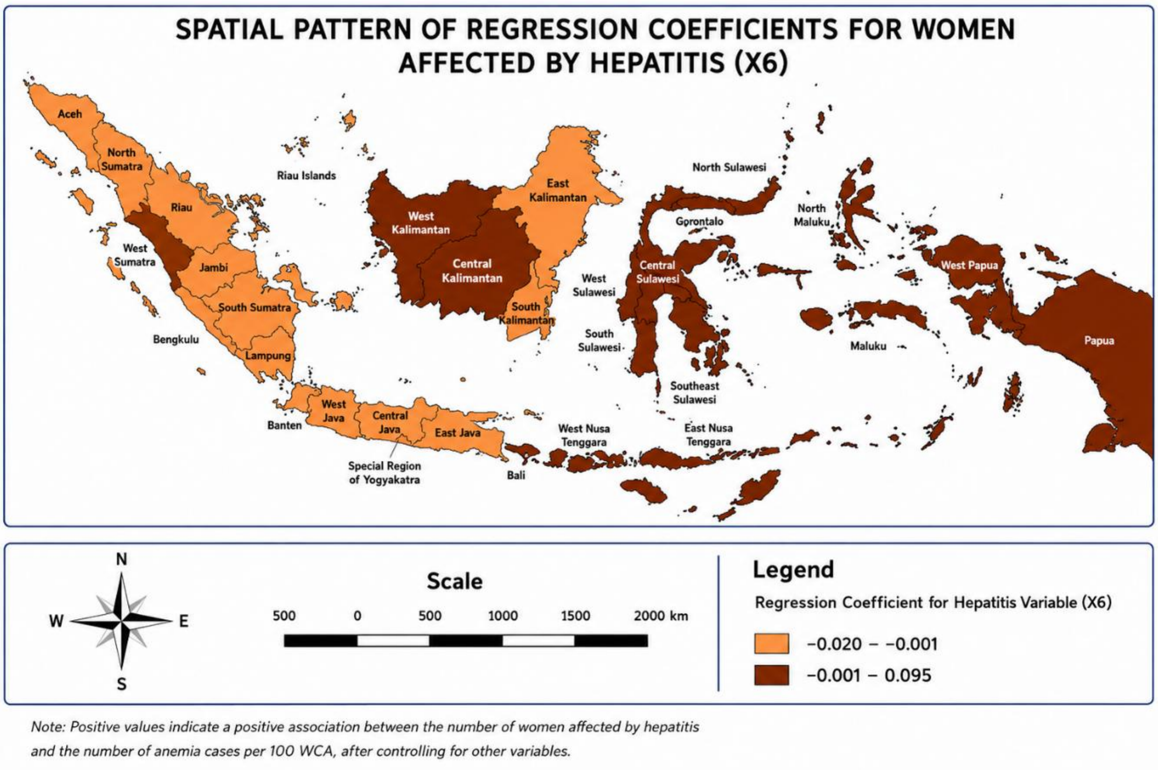

Figure 7. The spatial pattern of the regression coefficient X_6

Figure 7 illustrates the spatial distribution of the local regression coefficients for the hepatitis variable (X6) obtained from the geographically weighted count regression model. The estimated coefficients range from −0.020 to 0.095, indicating substantial spatial heterogeneity in the relationship between hepatitis and anemia among women of childbearing age (WCA) across Indonesian provinces.

Provinces with Positive Regression Coefficients ($\beta > 0$)

The provinces shaded in dark brown exhibit positive regression coefficients, including West Kalimantan, Central Kalimantan, South Kalimantan, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, North Sulawesi, North Maluku, Maluku, East Nusa Tenggara (NTT), West Papua, Papua, and several surrounding provinces.

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For these provinces, hepatitis is positively associated with anemia after controlling for the effects of all other explanatory variables in the model. The estimated regression coefficients range from 0.001 to 0.095, corresponding to an incidence rate ratio (IRR) of

$\exp(0.001 \leq \beta_6 \leq 0.095) = 1.001 \text{ to } 1.100.$

This result indicates that, assuming all other variables remain constant, every additional woman of childbearing age diagnosed with hepatitis per 100 WCA increases the expected number of anemia cases by approximately 0.1% to 10.0%, depending on the province.

The strongest positive effects are observed mainly in Papua, West Papua, Central Kalimantan, West Kalimantan, Central Sulawesi, South Sulawesi, Southeast Sulawesi, North Sulawesi, North Maluku, Maluku, and East Nusa Tenggara. In these provinces, hepatitis appears to contribute substantially to the spatial variation in anemia prevalence.

This stronger association may reflect a combination of factors, including chronic liver disease resulting from hepatitis infection, impaired iron metabolism, chronic inflammation, nutritional deficiencies, limited healthcare access, delayed diagnosis, and disparities in hepatitis prevention and treatment services.

The biological relationship is also plausible because chronic hepatitis may reduce erythropoietin production, impair iron homeostasis, and cause persistent inflammation, all of which increase the risk of anemia. Therefore, in provinces with large positive coefficients, integrated strategies combining hepatitis prevention, early diagnosis, nutritional interventions, and anemia screening among women of childbearing age may substantially reduce the burden of anemia.

Provinces with Negative Regression Coefficients ($\beta < 0$)

The provinces shown in light orange, including Aceh, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, Banten, West Java, Central Java, East Java, East Kalimantan, and Bali, exhibit negative regression coefficients, ranging from −0.020 to −0.001.

The corresponding incidence rate ratio is

$\exp(-0.020 \leq \beta_6 \leq -0.001) = 0.980 \text{ to } 0.999.$

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This indicates that, after adjusting for the other explanatory variables, each additional WCA diagnosed with hepatitis is associated with an expected decrease of approximately 0.1% to 2.0% in anemia cases, depending on the province.

However, this negative association does not imply that hepatitis protects against anemia. Instead, it reflects the spatially varying nature of the geographically weighted regression model, in which the local effect of hepatitis is estimated after accounting for other important predictors. In these provinces, anemia may be more strongly influenced by factors such as nutritional status, iron deficiency, tuberculosis, malaria, socioeconomic conditions, maternal health services, sanitation, or healthcare accessibility. Consequently, hepatitis contributes relatively little to explaining local anemia variation once these factors are included in the model.

Moreover, provinces in western Indonesia generally have more developed healthcare infrastructure, higher hepatitis vaccination coverage, earlier disease detection, and better management of chronic liver disease. These conditions may weaken the observed association between hepatitis and anemia compared with provinces where access to healthcare remains more limited.

Overall, Figure 7 demonstrates a clear east–west spatial pattern in the relationship between hepatitis and anemia among women of childbearing age. Positive and relatively stronger regression coefficients predominate in eastern Indonesia, particularly Kalimantan, Sulawesi, Maluku, Nusa Tenggara, Papua, and West Papua, whereas negative coefficients are concentrated in western Indonesia, especially Sumatra, Java, Bali, and parts of Kalimantan.

These findings indicate that the contribution of hepatitis to anemia is not spatially uniform across Indonesia. Instead, its impact varies considerably according to regional epidemiological characteristics, healthcare availability, nutritional conditions, and socioeconomic factors. Therefore, interventions aimed at reducing anemia should adopt geographically targeted strategies. In provinces with strong positive coefficients, strengthening hepatitis prevention programs, expanding vaccination coverage, improving early diagnosis and treatment, and integrating hepatitis management with maternal

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nutrition and anemia control programs may yield greater public health benefits than implementing a uniform national intervention strategy.

The regression coefficient with the variable percentage of districts/cities that have PHBS policies is positive for almost all provinces in Indonesia except for the Riau Islands and the Bangka Belitung Islands. That is, for every 1% increase in regencies/cities that have PHBS policies, the number of WCA who are anemic per 100 WCA increases to $\exp(0.000074 \le \beta_7 \le 0.0187) =$ 1.000074 to 1.0189 times from before assuming other variables are constant. This result is unrealistic, where an increase in PHBS should be able to reduce the number of cases of anemia in WCA; this is caused by factors that are not involved in the calculation, so it does not support reducing the number of cases of anemia (Figure 8)

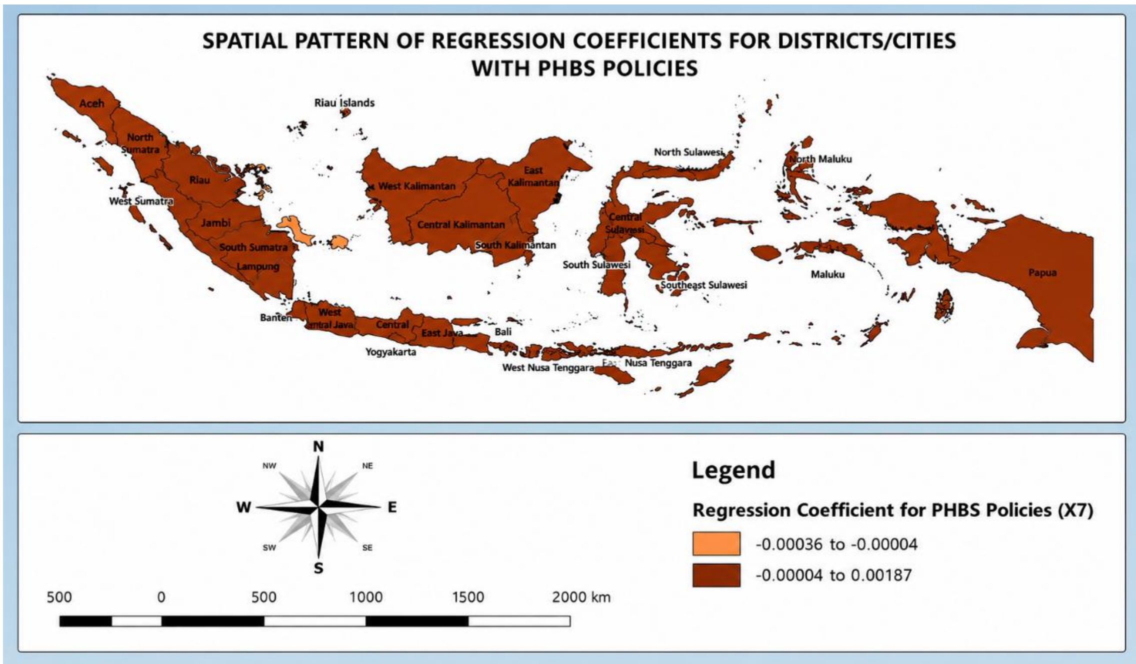

Figure 8. The spatial pattern of the regression coefficient X_7

4 CONCLUSIONS

Based on the results of the study, it is concluded that at least there is one explanatory variable in a province that has a significant effect on the response variable. Central and eastern Indonesia experienced an increase in anemia cases per 100 WCA to $\exp(\beta_k)$times the previous, with every rise of 1 WCA affected by pneumonia, malaria, and hepatitis. The western part of Indonesia tends to experience more cases of anemia in WCA per 100 WCA

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to $\exp(\beta_k)$times than before with every increase of 1 WCA living in rural areas (Java Island and Kalimantan), 1 WCA affected by ISPA (Sumatra and Kalimantan), as well as 1 WCA affected by tuberculosis. Meanwhile, the percentage of regencies/cities that have PHBS policies is positive for almost all provinces in Indonesia except for the Riau Islands and the Bangka Belitung Islands. This result is unrealistic, where an increase in PHBS should be able to reduce the number of cases of anemia in WCA; this is caused by factors that are not involved in the calculation, so it does not support reducing the number of cases of anemia.

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