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A COMPARATIVE STUDY OF GWR, HLM, AND HGWR FOR MODELING CHILDHOOD STUNTING IN INDONESIA

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Abstract: Childhood stunting is an important biological and public health problem in Indonesia, with far-reaching consequences for cognitive development, disease risk and economic productivity. The prevalence of stunting shows considerable spatial and contextual differences, which are influenced by local socioeconomic and environmental conditions. We compare three regression models, Geographically Weighted Regression (GWR), Hierarchical Linear Model (HLM), and Hierarchical Geographically Weighted Regression (HGWR), to represent this complexity with the observations of 514 districts nested in 34 provinces in Indonesia. The outcome variable is the prevalence of stunting (%), with district-level predictors of poverty rate, education, sanitation, immunisation, and access to clean water and province-level predictors of HDI, health budget per capita, and prevalence of malnutrition. All Models capture Different dimensions of structure: GWR for spatial non-stationarity, HLM for hierarchical nesting, and HGWR for both. Model assessment was based on AIC, RMSE and adj. R^2 values. The best model for overall goodness of fit was HGWR (AIC = 3196.563; RMSE = 5.159; Adjusted R^2 = 65.73%), in which it showed high performance to model spatially-structured and hierarchically-nested health themes. This research highlights the value of spatial-hierarchical models and encourages support for the soundness of HGWR as an effective paradigm to support targeted public health interventions in geospatial epidemiology.

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1. INTRODUCTION

In Indonesia, stunting is still a significant public health issue, and its prevalence, as well as differences across regions are still relatively high [1], [2]. It is related to socioeconomic, environmental, and healthcare access differences [2]. Nationally, to the best of the spatial analysis, the stunting prevalence was found in 54.9% of the districts or cities with a higher prevalence than the national average, with the prevalence of stunting being significantly high or low clustered spatially/geo-spatially (spatial autocorrelation between adjacent areas) [1], [3]. Stunting has been reported to be mainly influenced by nutrition, diarrhea, dependency ratio and hygiene [4], [5]. On the other hand, interventions to reduce stunting risk have been verified, such as antenatal care and sanitation improvement(intervention) [2]. Geographic and socioeconomic disparities are particularly pronounced, with an increased prevalence of stunting mortality observed in the Papua region and in low-income districts compared with more developed regions like Java [6]. Thus, to tackle stunting in Indonesia, we need an exhaustive multisectoral approach, addressing health, socioeconomic, and environmental factors aligned with the Sustainable Development Goals (SDGs) for 2030.

Previous studies have extensively employed advanced statistical modeling to gain better insights into the determinants of stunting and the need for effective policy interventions. Such methods are intended to relax the assumptions of traditional regression models in terms of accommodating spatial heterogeneity and hierarchical data structures. Bayesian spatial models have been used to explore undernutrition in African countries [7], while structured additive quantile regression models were more appropriate for childhood stunting data from Malawi [8]. Bayesian geo-statistical models in Ethiopia successfully identified areas of high stunting prevalence by accounting for spatial dependency [9]. In Indonesia, the model with locally compensated ridge-geographically (LCR-GWR) performed significantly better in solving multicollinearity problems in spatial data [10]. These researchers stress the critical importance of spatial modeling in analyzing complex patterns and risk factors associated with stunting.

However, most previously proposed models have targeted spatial heterogeneity or hierarchical data structure independent of each other. Recent works seek to integrate these two

facets to enhance model accuracy and interpretability. [11] proposed the Hierarchical data structure and spatially Varying Coefficient approach (HLM-GWR) to investigate real estate prices in Wuhan. The model outperformed conventional GWR and HLM models regarding bandwidth optimization and coefficient estimation. Following this work, [12], [13] presented a Hierarchical Geographically Weighted Regression (HGWR) model that integrates fixed effects, random effects, and spatially varying coefficients into one framework. Its performance surpasses standard HLM and GWR in simulation studies and real-world data. In Indonesia, [14] used HGWR to analyze poverty rates and reported an R-squared of 0.8004, with HGWR significantly outperforming HLM and GWR. The model also showed pronounced local effects, especially in eastern Indonesia.
In addition, multilevel regression modeling is well-known in many fields due to the nested data structure, especially in education in Indonesia. [15], for example, used a two-level multilevel regression model where the mean scores of national examinations were nested, and schools (level-1) were nested in the districts/cities (level-2). Their research showed that multilevel approaches can account for contextual impacts at higher-level units (e.g., local government policy and resources), profoundly affecting educational achievement. These results provide additional evidence for the applicability of multilevel modeling approaches, such as hierarchical linear modeling (HLM) and hierarchical geographically weighted regression (HGWR), in hierarchical and spatially structured data.

This study employs various socioeconomic, health, and environmental indicators to model stunting prevalence in Indonesia, aiming to capture its determinants' complexity comprehensively. The dependent variable is stunting prevalence (%). In contrast, the independent variables include poverty rate (%), average years of schooling (years), complete basic immunization coverage (%), access to improved sanitation facilities (%), and access to safe drinking water (%). In addition, macro-level variables such as the Human Development Index (HDI), provincial health budget per capita (IDR), and the prevalence of malnutrition at the provincial level (%) are incorporated to capture broader structural and policy-related factors affecting stunting. The above variables are selected according to their importance in previous studies and availability in national data sources. The input of district-level and province-level variables also mirrors the hierarchical structure of our data, where districts/cities are nested within provinces. The nested structure will allow more complex spatial and hierarchical analyses to be carried out to explore the predictors of stunting prevalence in Indonesia. Despite the development of various advanced models in the literature, a comprehensive comparison of GWR, HLM, and HGWR models in stunting prevalence in

Indonesia has not yet been conducted. Such a comparison is essential for identifying the most suitable modeling approach that captures both spatial heterogeneity and hierarchical data structures, thereby providing methodological insights and supporting evidence-based policymaking to address stunting in Indonesia.

2. DATA AND METHODS

2.1 Data

The data for this study were obtained from official Indonesian government sources for the year 2022. The dataset encompasses all 34 provinces and 514 districts/cities, encompassing the country's inherent diversity in geography, socioeconomics, and health-related conditions. 2022 was chosen because it offers the most recent and complete national data set of stunting prevalence-related factors. Because stunting is a multidimensional public health problem, this study included various district/city-level indicators covering socioeconomic status, education, health services, and environmental conditions. Province-level variables were also included to reflect wider structural factors and policy dimensions, such as human growth, health expenditures, and malnutrition. The link between both levels of variables is in accordance with the data hierarchical structure, in which districts/cities are nested within provinces. Multi-level data are utilized to examine the predictors of stunting prevalence in Indonesia thoroughly. Data were obtained from the Central Bureau of Statistics (BPS) and the Ministry of Health. All variables were chosen to be relevant to previous literature and ensure reliable data availability at the national level. Table 1 presents a detailed description of every variable applied in this study.

Table 1. Description of Variables Used in the Study

No.	Variable	Data Level	Source	Description
1	Stunting Prevalence	District	Ministry of Health	Proportion of children under five who are stunted based on height-for-age.
2	Poverty Rate	District	BPS	Proportion of population living below the poverty line.
3	Average Years of Schooling	District	BPS	Mean number of completed years of formal education in the population.
4	Complete Basic Immunization Coverage	District	Ministry of Health	Coverage rate of children receiving all basic immunizations.

No.	Variable	Data Level	Source	Description
5	Access to Improved Sanitation Facilities	District	BPS	Households with access to proper sanitation facilities.
6	Access to Safe Drinking Water	District	BPS	Households with access to improved water sources.
7	Human Development Index	Province	BPS	Composite index of life expectancy, education, and income.
8	Provincial Health Budget per Capita	Province	BPS	Total health budget allocation divided by the provincial population.
9	Prevalence of Malnutrition	Province	Ministry of Health	Proportion of population (or children) suffering from undernutrition.

The selection of variables was based on their relevance in previous literature and their availability in national datasets. The inclusion of district-level and province-level indicators reflects the hierarchical structure of the data, where districts/cities are nested within provinces.

2.2 Research Design

This study is a descriptive comparative cross-sectional spatial and multilevel modeling research type. A research framework was developed to examine the determinants of stunting prevalences across districts and cities in Indonesia with respect to spatial heterogeneity and a hierarchical data structure. The research process unfolded in four main stages:

2.2.1 Descriptive analysis

Descriptive analysis was conducted to explore the distribution of stunting prevalence and its related variables across districts and provinces in Indonesia.

2.2.2 Spatial Analysis

The second stage was a spatial analysis that aimed to determine the presence of spatial autocorrelation in stunting prevalence by districts and cities. To determine whether the spatial distribution of stunting prevalence showed clustering patterns, we used the global index of spatial association, the Global Moran's I statistic [16]. The mathematical formulation of Global Moran's I is as follows:

$$I = \frac{n}{W} \times \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{1}$$

where: n : number of spatial units (districts/cities);

x_i : value of the variable at location i;

$\bar{x}$: mean of the variable;

w_{ij} : spatial weight between location i and j;

W : sum of all spatial weights.

A significant positive Moran's I value indicates clustering of high or low stunting prevalence in neighboring areas, supporting the use of spatial modeling.

2.2.3 Model Development

This stage consisted of building and using three sophisticated regression models to assess the association between stunting prevalence and its predictor variables, specifically:

a. Geographically Weighted Regression (GWR)

Geographically weighted regression (GWR) is a local spatial regression method proposed by [17] that enables model coefficients to vary over space. The broad mathematical formulation is as such:

$$y_i = \beta_0(u_i, v_i) + \sum_{p=1}^{P} \beta_p(u_i, v_i) x_{ip} + \varepsilon_i \tag{2}$$

where: y_i : dependent variable at location i;

x_{ip} : independent variable k at location i;

(u_i, v_i) : spatial coordinates

$\beta_p(u_i, v_i)$: local regression coefficient at location (u_i, v_i);

ε_i : error term.

GWR is appropriate for detecting localized relationships between stunting and its predictors.

b. Hierarchical Linear Model (HLM)

HLM (or hierarchical linear modeling) allows the analysis of this nested data structure by modeling both within- and between-group variation [18]. Level-1 units are districts/cities, while level-2 units are provinces in this study. The two-level HLM can be represented as:

Level 1 (district/city):

$$y_{ij} = \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} x_{pij} + \varepsilon_{ij} \tag{3}$$

Level 2 (province):

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} z_{qj} + u_{0j}; \qquad \beta_{pj} = \gamma_{p0} + u_{pj} \tag{4}$$

where: y_{ij} : outcome for unit i in group j;

x_{pij} : level-1 predictors;

z_{qj} : level-2 predictors;

ε_{ij} : level-1 residuals (error term);

$u_{0j}; u_{pj}$: level-2 random effects.

HLM is used to determine contextual province influences on district-level outcomes.

c. Hierarchical Geographically Weighted Regression (HGWR)

HGWR employs a hybrid method that combines GWR and HLM to obtain spatially varying coefficients within a hierarchical data structure [11]. It captures local and contextual influence at the same time. The model is formulated as:

Level 1 (district/city):

$$y_{ij} = \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} x_{pij} + \varepsilon_{ij} \tag{5}$$

Level 2 (province):

$$\beta_{0j} = \gamma_{00}(u_i, v_i) + \sum_{q=1}^{Q} \gamma_{0q}(u_i, v_i) z_{qj} + u_{0j}; \quad \beta_{pj} = \gamma_{p0} + u_{pj} \tag{6}$$

This model can identify spatial patterns and cross-level interactions that drive stunting specifically.

2.2.4 Model Evaluation

The model performance was evaluated and compared using three main statistical indicators:

a. Akaike Information Criterion (AIC)

AIC is a measure of model fit that penalizes model complexity [19]:

$$AIC = -2\ln(L) + 2p \tag{7}$$

where: L : maximum likelihood of the model;

p : number of estimated parameters.

Lower AIC values indicate better model performance.

b. Root Mean Square Error (RMSE)

RMSE measures the average magnitude of the model prediction error [20]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

Lower RMSE values indicate higher model accuracy.

c. Adjusted R-squared

Adjusted R^2 evaluates the goodness of fit while adjusting for the number of predictors used in the model [21]:

$$R_{adj}^2 = 1 - \left(\frac{(1-R^2)(n-1)}{n-p-1}\right) \tag{9}$$

Higher R_{adj}^2 values indicate better model fit with adjustment for model complexity.

3. MAIN RESULTS

3.1 Descriptive Analysis

Figure 1 shows the spatial distribution of stunting prevalence across regions/cities in Indonesia. The map illustrates substantial geographical variation, with higher prevalence predominantly observed in eastern Indonesia, including Papua, West Papua, East Nusa Tenggara, and several districts in Maluku. Most Java, Sumatra, and Bali regions recorded lower stunting prevalence, particularly in urban and developed areas. The spatial pattern suggests the emergence of regional inequality in stunting prevalence, which may align with previous studies mentioning the stable health development gaps between Indonesia's western and eastern regions.

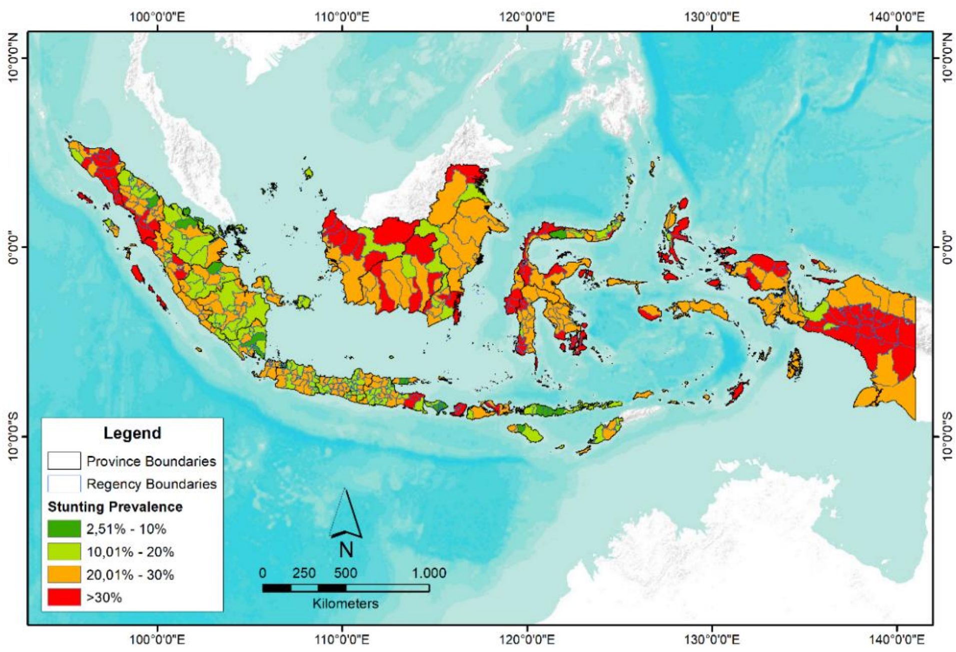

Figure 1. Map of Stunting Prevalence in Regency/City of Indonesia.

Figure 2 presents the boxplot of stunting prevalence for each province. Eastern provinces in Indonesia, e.g. Papua, West Papua, and East Nusa Tenggara, have relatively high median values and a wider range of stunting prevalence than others. The medians for Java, Bali, and Sumatra provinces are comparatively lower and have the narrowest interquartile ranges. In addition, several provinces show the presence of extreme outliers, indicating districts or cities with exceptionally high or low stunting prevalence within the same province. This suggests that localized conditions within provinces also play an important role in determining stunting prevalence.

Overall, the descriptive analysis confirms that stunting prevalence in Indonesia is not evenly distributed, exhibiting strong geographical variation and heterogeneity both between and within provinces. These findings justify the need for spatial and multilevel modeling approaches to further investigate the determinants of stunting prevalence.

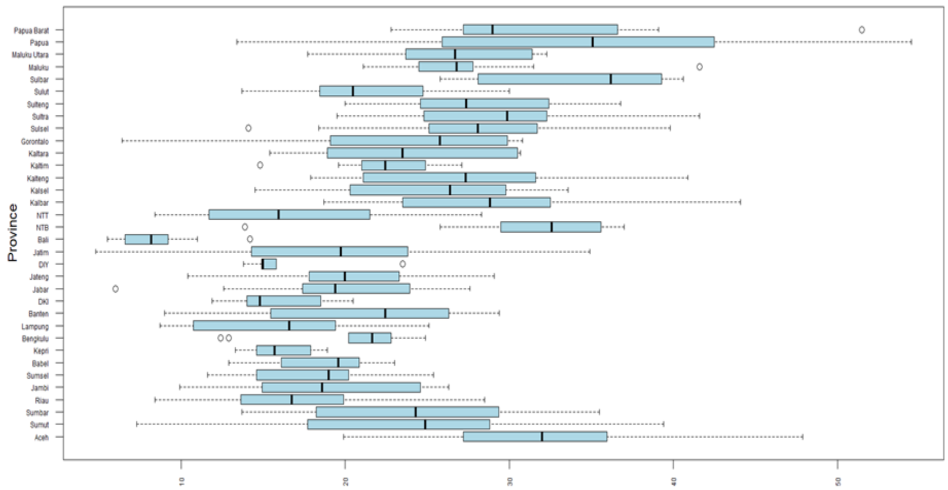

Figure 2. Boxplot of Stunting Prevalence by Province.

3.2 Spatial Analysis

Global Moran's I was calculated to verify spatial dependency in the distribution of stunting prevalence. The locality value was calculated as a final step, producing a value of 0.378 ($p < 0.01$), showing significant positive spatial autocorrelation. This means that districts, where a high percentage of people are stunted, are likely to be surrounded by districts where a high rate of neighbors are stunted, and the same is true for places with low stunting prevalence. In addition to spatial dependence, descriptive findings—including the thematic map and boxplot analysis—suggest the presence of spatial heterogeneity. The strength and direction of associations between predictors (e.g., poverty rate, access to sanitation) and stunting prevalence appeared to vary across regions. For example, eastern provinces exhibited higher stunting rates and stronger associations between key predictors and outcomes. This non-uniformity implies that a single global model may not sufficiently capture localized influence patterns. Therefore, spatial models that allow for location-specific relationships, such as GWR and HGWR, must account for both spatial autocorrelation and spatial heterogeneity in the data.

3.3 Model Development and Comparison

The relationship between the predicted effects and the prevalence of stunting was evaluated using three regression models (Geographically Weighted Regression (GWR), Hierarchical Linear Model (HLM), and Hierarchical GWR (HGWR). These several different models can be seen as summarizing the structure of the data from various angles, enabling a more complete understanding of the spatial and contextual influences of observation.

a. Geographical Weighted Regression (GWR)

The GWR model yielded spatially varying coefficients that allowed the estimation of localized effects for each predictor. For example, the impact of the poverty rate on the prevalence of stunting varied from 0.12 to 0.61 across districts. The most significant impacts were found in eastern regions such as Papua and East Nusa Tenggara, while weaker impacts were found in more developed regions such as Java and Bali. This variation shows evidence of spatial heterogeneity that global models assuming constant relationships cannot account for.

b. Hierarchical Linear Model (HLM)

HLM was used with province-level (level-2) and district-level (level-1) effects where the hierarchically nested data structure was accounted for. The Intraclass Correlation Coefficient (ICC) was estimated to be 19.8%, suggesting that a significant amount of variance in stunting prevalence could be explained at the provincial level. The poverty in this model was a fixed effect with a coefficient of 0.38 ($p < 0.01$), indicating an increase in stunting as well as higher district-level poverty. However, this model assumes spatial stationarity and fails to account for variations in predictor effects in different locations.

c. Hierarchical Geographically Weighted Regression (HGWR)

Using a unified model, the HGWR model simultaneously included spatial heterogeneity and hierarchical structure. In HGWR, local coefficients for the poverty rate varied from 0.18 to 0.67, with the effect remaining statistically significant in ~ 78% of districts. The model also preserved province-specific effects, indicating that both local and contextual factors play an important role in the prevalence of stunting. As such, HGWR offers the most nuanced interpretation of spatially varying and contextually dependent relationships, making it the most appropriate model for public health investigations conducted within complex geographical contexts such as Indonesia.

3.4 Model Evaluation

With more than one model, as is the case here, we can calculate measures for their prediction capabilities. The Akaike information criterion (AIC), root mean square error (RMSE), and adjusted R-squared (R^2_{adj}) were calculated to assess and compare the predictive performance of the three models. The summary of the findings is displayed in Table 2.

Table 2. Model Performance Comparison

Model	AIC	RMSE	Adjusted R^2
GWR	3291.909	5.476	63.98%
HLM	3329.741	5.675	62.57%
HGWR	3196.563	5.159	65.73%

Among the three models, the HGWR model fitted better than the GWR and HLM. It had the smallest AIC value and, thus, the best trade-off between goodness-of-fit and model complexity. HGWR provided the most accurate predictions with the lowest RMSE value. At the same time, its highest adjusted R-squared indicates an increased explanation of variance in stunting prevalence compared to the total number predicted. These results demonstrate that modeling both spatial heterogeneity and hierarchical structure significantly improves model performance in geographically structured health outcomes.

3.5 Discussion

Geographically adaptive modeling is essential for mapping the spatial heterogeneity of stunting in Indonesia. In several large islands, spatial autocorrelation was detected among districts, showing that stunting was non-randomly distributed [1], [22]. Hotspots were located in 133 districts on four major islands [22]. Stunting prevalence is influenced by many factors, such as sanitation, antenatal care, poverty, immunization, and child nutrition [1], [23]. Bayesian spatial models, particularly the localized Conditional Autoregressive model, were further proved as a good descriptor of stunting risk and its determinants [24]. Results showed that poverty and low birth weight are risk factors for stunting, while dietary diversity is protective. According to the mapping of stunting risk, the highest was in Sulawesi Barat and the lowest in DKI Jakarta [24].

This study builds upon these insights by highlighting the significance of spatial and contextual considerations when interpreting the stunting landscape of the Indonesian. The strong spatial autocorrelation from Moran's I indicate that stunting's distribution is heterogeneous and clustered, particularly in eastern Indonesia, where a high prevalence remains. The evidence of spatial heterogeneity, descriptively and from model fitting, provides additional support for using geographically adaptive modeling techniques, such as geographically weighted regression (GWR) and heterogeneous GWR (HGWR), that can better account for complex spatially varying determinants. Although GWR could capture local variation, it could not model province-level context. HLM also addressed the hierarchical structure yet assumed spatial stationarity. On the other hand, HGWR integrates both techniques, incorporating the most flexible and nuanced modeling of the underlying dynamics. For this reason, its higher performance indicates that place-based and context-aware interventions are required in high-risk areas such as Papua, Maluku, and East Nusa Tenggara.

From a policy perspective, these results imply that interventions to reduce stunting should go beyond one-size-fits-all, national-level approaches. Instead, they need to adopt geographically targeted, context-sensitive approaches. Such tailored interventions, which are supported by provincial policy and infrastructure, may be more effective in addressing both local and systemic drivers of stunting.

4. CONCLUSIONS

This study aimed to assess the performance of Geographically Weighted Regression (GWR), Hierarchical Linear Model (HLM), and Hierarchical Geographically Weighted Regression (HGWR) for modeling stunting in Indonesia. By assessing spatial and hierarchical aspects, this study identified spatial clusters in stunting prevalence with contextual conditions at multiple levels that influence stunting prevalence. The findings confirmed that the GWR approach had considerable merit in analyzing local variations; by contrast, it neglected hierarchical effects, whilst the hierarchical linear model (HLM) modeling tackled contextual variations across provinces without considering spatial heterogeneity. HGWR, a combination of both approaches, was the strongest model, providing the best AIC, RMSE, and adjusted R-squared. Consequently, the results prove that spatial heterogeneity and hierarchical structure must be integrated when modeling geographically distributed public health phenomena like stunting.

From a policy perspective, the findings call for geographically targeted and context-sensitive strategies. Unidirectional areas with high stunting prevalence, e.g., certain eastern provinces in

Indonesia) need to be dedicated or targeted to national intervention, with strong provincial governance and resource allocation. In future studies, model accuracy could be improved by adding other temporal dimensions to the data and other structural determinant factors like maternal education, availability of health services, and food security.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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