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Bayesian Nonparametric Truncated Spline Regression for Modeling Nutritional and Physical Stunting

[1] Septi Nafisa Ulluya Zahra
Department of Statistics, Brawijaya University, Malang City, 65145, Indonesia

[2] Adji Acmad Rinaldo Fernandes
Department of Statistics, Brawijaya University, Malang City, 65145, Indonesia

[3] Achmad Efendi
Department of Statistics, Brawijaya University, Malang City, 65145, Indonesia

[4] Alfiyah Hanun Nasywa
Department of Statistics, Brawijaya University, Malang City, 65145, Indonesia

[5] Fachira Haneinanda Junianto
Department of Mathematics, Brawijaya University, Malang City, 65145, Indonesia

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ABSTRACT

Stunting is a problem that is affected by the socioeconomic and environmental conditions of the public. The present study evaluates the impact of the financial state, environmental quality, and child feeding practices on the nutritional and physical stunting using a Bayesian nonparametric truncated spline regression model. To do this, a single knot spline structure was used a capture non-linear affects and thresholds, posterior estimation being conductied with Gibb's sampling. The results exhibit that all of the three predictors have a significance after the knot point on the right arrives, indiacting to saturation affects. As for the economic standing and the environmental quality, their effect is consistent, while feeding practices hold a more considerable impact on the nutritional stunting. From model diagnostics, the model had a good fit and predictive accuracy. The results highlight the importance of feeding practices and economic improvement and environmental sanitation, and display the benefits of the Bayesian spline technique for handling complex data.

Corresponding Author:

Adji Achmad Rinaldo Fernandes,
Department of Statistics
Brawijaya University
Email: fernandes@ub.ac.id

1. INTRODUCTION

Stunting refers to a health condition affecting children caused by an interplay of factors such as prolonged malnutrition, repeating infection incidence and a lack of psychosocial support and cultivation [1]. Stunting is a global health problem affecting the optimal growth of a child as it further stunting the physical and mental development of a child in the years of childhood. Stunting is more than just a childhood health problem as it goes to adulthood causing various chronic severe health problems making it a serious long term public health concern. In the continents of South Asia and Sub-Saharan Africa are the most affected by it [2]. On the other hand, the continents of Europe and North America are considerably more affected in child health than the other continens making this world problem a problem of world child health inequity. These inequities are caused by the differences in economic factors, food systems, and the overall development of the environment in the various parts of the world [3].

Chronic child malnutrition results from the inability of economically disadvantaged families to purchase healthy food. The lack proper diets carries the odds of even further malnutrition among children [4]. The presence of poor sanitary conditions and low protection form surroundings increases the presence of infections which diminishes the absorbed nutrients and help stunted [5]. All these fundamental relations mus be analyzed satisfactorily if the world is to achieve the target on malnutrition within the 2030 date [6]. There is complexity and nonlinearity in these relations which renders more advanced models to be designed and applied analyses on the drivers of stunting [7].

Past research examining the determinants of stunting using spline or Bayesian regression has used fixed-knot or parametric spline structures which capture smooth, continous affects and as such may miss potential threshold behaviors or nonlinear effects that occur at certain levels of the predictor [8]. Moreover, the applications of Bayes in this research has been limited to parametric regression in this context, which does not allow for the capture of flexible and complex interactions of some of the main variables [9]. Very few studies have aimed to focus on Bayesian nonparametric truncated spline regression which represents the potential of modeling the breakpoint behavior and saturation effects that are essential to chronic development challenges such as stunting [10]. This research tries to fill the mentioned gap in the methodology used in studies on the effects of economic level, dietary practices of children, and environmental quality on the nutritional and physical stunting to the certain stunting thresholds by applying Bayesian truncated spline regression.

Nonparametric regression, especially the truncated regression spline method, remains highly versatile without making strong parametric assumptions which gives it an advantage in the estimation of complex relationships in the health data [11]. This technique is even more beneficial when it is expanded into biresponse modeling since it facilitates the garnishing of nutritional and physical stunting, twi stunting phenomena that are interdependesnt and influences by common factors. The Bayesian approach even adds more versatility in estimation by supplying the needed smoothing and uncertainty as well as priors especially when more complexity is involved in the hierarchical structures, smaller sample sized, and estimations. Also, and the truncated spline specification allows for the detection of the threshold and saturation points, and the understanding of the varying effect of the predictor such as the economic status or the environmental sanitation is often crucial [12]. This is why the study is attempting to add to the literature using Bayesian truncated spline biresponse methodology to investigate the interrelation of economic status, food consumption, and environmental quality with both forms of stunting.

2. RESEARCH METHOD

2.1 Summated Rating Scale

Scaling is the act of positioning an object, stimulus, or answering variable on a straight continuum that is a line, ranked with numbers, frequently from the smallest to the greatest one [13]. One frequently used scaling technique is the Summated Ratings Scale (SRS), which is the scaling of questionnaire response, specifically the Likert scale, to convert data from an ordinal level to an interbal level under the condition that the data is normally distributed. During SRS scaling, the ordinal raw score data is transformed into a Z score representing the data set's normal distribution so that the gaps between the responses can be evaluated on an interval scaling contiuum. This normality assumption is very important since the Z score transformation utilizes the normal curve's cumulative distribution function and makes various statistics like mean difference, correlation, and regression significant.

1. Calculating the variable frequency (f_{qr}) of the subject's response on each item.
2. Calculating the proportion value (p_{qr}) is by dividing the frequency of the response variable with the number of respondents (n) as the equation (1).
$$p_{qr} = \frac{f_{qr}}{n} \tag{1}$$
3. Cumulative proportion value is determined as the equation (2).
$$P_{qr} = \sum_{r=1}^{s} p_{qr} \tag{2}$$
Where s is incicator's count ($r = 1,2, \dots, s$).
4. Calculates the midpoint of cumulative proportion (T_{qr}).
$$T_{qr} = \frac{P_{q,r-1} + P_{qr}}{2} \tag{3}$$
5. Convert the cumulative proportion midpoint score to a critical value of Z using the Z table of normal distributions.
$$Z_{qr} = \phi^{-1}(T_{qr}) \tag{4}$$

6. Add an arbitrary value to the smallest critical value Z to adjust the lowest score to 0. Adding 0 to 1 keeps the scale to 1. This subtracted value is to ensure that the scale does not contain negative values.

$$S_{qr} = Z_{qr} - Z_{min} + 1 \tag{5}$$

2.2 Linearity Test

One of the function of testing linearity assumptions is to investigate if there is any linearity linking one of the predictor variables to another variable [14]. This assumption forms the fundamentals of regression since it proves that the relationship shich is the predictor variables and the response variables can be captured using a linear model. The linearity assumption test can potentially provide a final answer to the query of the linearity or non-linearity of the variables and thus can offer the validity of the regression analysis. When carrying out the test of linearity, Ramsey's approach is to employ a reset test to investigate if the regression model that is set is valid or otherwise. The calculation of F statistics is done using the following equation (6).

$$F_{hitung} = \frac{(R^2_{baru} - R^2_{lama})/p_1}{(1-R^2_{baru})/(n-p_2-1-p_1)} \sim F_{\alpha, p_1, n-p_2-1-p_1} \tag{6}$$

The hypothesis tested is

$H_0: \beta_2 = \beta_3 = 0$

H_1: there is at least one (Relationships between nonlinear variables)$\beta_p \neq 0; p = 2,3$

If the statistical value of the test F is smaller than the critical point F, then it is said to be insignificant and the relationship between variables is linear. On the other hand, if the statistical value of the test F is greater than the critical point F, then it is said to be significant and the relationship between variables is non-linear.

2.3 Biresponse Nonparametric Regression

Biresponse regression is used to analyze the relationship of predictor variables with two response variables simultaneously, reflecting the complexity of real data where variables are often interrelated. Nonparametric regression, which provides greater adaptability in employing methods such as smooting splines and truncated splines, stands in contrast to parametric regression which uses fixed values in their calculations and encompasses a larger scope of a complicated nonlinear relationship among variables. This approach allows for relationship modeling without being limited by the assumption of certain functional forms, making it more adaptive to dynamic data patterns [15].

$$\underset{\sim}{y}_{1i} = \underset{\sim}{f}_1(x_i) + \underset{\sim}{\varepsilon}_{1i}, ()i = 1, 2, \dots, n \tag{7}$$

$$\underset{\sim}{y}_{2i} = \underset{\sim}{f}_2(x_i) + \underset{\sim}{\varepsilon}_{2i}, ()i = 1, 2, \dots, n$$

$$\begin{bmatrix} y_{11} \\ y_{12} \\ y_{13} \\ \vdots \\ y_{1n} \\ y_{21} \\ y_{22} \\ y_{23} \\ \vdots \\ y_{2n} \end{bmatrix}_{2nx1} = \begin{bmatrix} f_1(x_1) \\ f_1(x_2) \\ f_1(x_3) \\ \vdots \\ f_1(x_n) \\ f_2(x_1) \\ f_2(x_2) \\ f_2(x_3) \\ \vdots \\ f_2(x_n) \end{bmatrix}_{2nx1} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{12} \\ \varepsilon_{13} \\ \vdots \\ \varepsilon_{1n} \\ \varepsilon_{21} \\ \varepsilon_{22} \\ \varepsilon_{23} \\ \vdots \\ \varepsilon_{2n} \end{bmatrix}_{2nx1}$$

Nonparametric regression with a truncated spline approach is effective for handling data patterns with sharp or irregular changes at specific sub-intervals. Truncated splines use the concept of knots, which are the points in the data range that are the focus of the spline curve formation, dividing the curve into segments with a polynomial regression model for each segment. Increased flexibility of the model while fitting the data pattern can be achieved through the use of additional knots. This technique is ideal for nonlinear associations over the full range of the data since spline curves can be fitted to more complex patterns of the data with the complexity dependent on the polynomial order for each section. The truncated spline regression of linear polynomial degress with a single point knot of an independent variable p and a response variable l serves the same purpose as is shown in equation (8).

$$\hat{f}_{li} = \beta_{0l} + \sum_{j=1}^{p} \beta_{(2j-1)l} x_{ji} + \sum_{j=1}^{p} \beta_{(2j)l} (x_{ji} - k_{j1})_+ + \varepsilon_{li} \tag{8}$$

With the truncated spline basis in equation (9).

$$(x_{ji} - k_{j1})_+ = \begin{cases} (x_{ji} - k_{j1}) & ; x_{ji} \geq k_{j1} \\ 0 & ; x_{ji} < k_{j1} \end{cases} \tag{9}$$

Splines in regression are nonpolynomial (in the intervals between knots, the spline is a polynomial, but the behavior of the polynomial changes at each interval because of the knots). Therefore, the location and number of knots are of prime importance in nonprametric regression modeling with truncated splines. Various methods have been proposed to determine optimal knot placement, one of which is Generalized Cross Validation (GCV). How the GCV method works is by placing knots at a particular location and evaluating the spine model in a GCV curve. The GCV is then meant to calculae the easily computable specific value. The method by which GCV is determined is according to [16], and GCV dan be determined as equation (10).

$$GCV(\underset{\sim}{K}) = \frac{n^{-1}\sum_{i=1}^{n}[y_i - \hat{f}(x_i)]^2}{[n^{-1}trace(\mathbf{I} - \mathbf{A}(\underset{\sim}{K}))]^2} \quad (10)$$

Where I am Identity matrix and $\mathbf{A} = \mathbf{X}(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}$. The optimal knot configuration is selected as the one that yields the smallest GCV value, ensuring the best balance between model fit and complexity.

2.4 Bayesian Regression

In Bayesian regression, the response variable is assumed to follow a normal distribution conditional on the predictors, with $(\boldsymbol{Y}|\boldsymbol{X},\boldsymbol{\beta},\sigma^2) \sim N(\boldsymbol{X\beta},\sigma^2\mathbf{I})$ and its probability density function is defined as in Equation (11) [17].

$$p(\boldsymbol{Y}|\boldsymbol{X},\boldsymbol{\beta},\sigma^2) = \frac{1}{\sigma\sqrt{2\pi}}exp\left\{-\frac{1}{2\sigma^2}(\boldsymbol{Y}-\boldsymbol{X\beta})^T(\boldsymbol{Y}-\boldsymbol{X\beta})\right\} \quad (11)$$

Based on the probability density function in Equation (11), the likelihood function can be expressed as in Equation (12).

$$p(\boldsymbol{Y}|\boldsymbol{X},\boldsymbol{\beta},\sigma^2) = \prod_{\boldsymbol{i=1}}^{\boldsymbol{n}}\frac{1}{\sigma\sqrt{2\pi}}exp\left\{-\frac{1}{2\sigma^2}(\boldsymbol{Y}-\boldsymbol{X\beta})^T(\boldsymbol{Y}-\boldsymbol{X\beta})\right\} \quad (12)$$

$$p(\boldsymbol{Y}|\boldsymbol{X},\boldsymbol{\beta},\sigma^2) = (\sigma^2)^{-n/2}exp\left\{-\frac{1}{2\sigma^2}(\boldsymbol{Y}-\boldsymbol{X\beta})^T(\boldsymbol{Y}-\boldsymbol{X\beta})\right\}$$

$$p(\boldsymbol{Y}|\boldsymbol{X},\boldsymbol{\beta},\sigma^2) \propto (\sigma^2)^{-n/2}\exp\left\{-\frac{vs^2}{2\sigma^2}\right\} \times (\sigma^2)^{-n/2}\exp\left\{-\frac{1}{2\sigma^2}(\boldsymbol{Y}-\boldsymbol{X\beta})^T(\boldsymbol{Y}-\boldsymbol{X\beta}\right\}$$

Meanwhile, the posterior distribution can be written as in Equation (13).

$$Posterior \propto Likelihood \times Prior \quad (13)$$

$$p(\boldsymbol{\beta},\sigma^2|\boldsymbol{Y},\boldsymbol{X}) \propto p(\boldsymbol{Y}|\boldsymbol{X},\boldsymbol{\beta},\sigma^2)p(\sigma^2)p(\boldsymbol{\beta}|\sigma^2)$$

$$p(\boldsymbol{\beta},\sigma^2|\boldsymbol{Y},\boldsymbol{X}) \propto (\sigma^2)^{-n/2}exp\left\{-\frac{1}{2\sigma^2}(\boldsymbol{Y}-\boldsymbol{X\beta})^T(\boldsymbol{Y}-\boldsymbol{X\beta})\right\} \times (\sigma^2)^{-(v/2+1)}\exp\left\{-\frac{vs^2}{2\sigma^2}\right\} \times (\sigma^2)^{-k/2}\exp\left\{-\frac{1}{2\sigma^2}(\boldsymbol{\beta}-\boldsymbol{\mu})^T\boldsymbol{\Lambda}(\boldsymbol{\beta}-\boldsymbol{\mu}\right\}$$

Gibbs Sampling begins by initializing values for $\boldsymbol{\beta}$, σ^2, and $\boldsymbol{\mu}$. The steps of Gibbs Sampling using Normal-Inverse-Gamma distribution are as follows [18].

Generate the coefficient $\boldsymbol{\beta}$ from its conditional distribution 10000 times. With prior distribution coefficient $\boldsymbol{\beta}$ are $(\boldsymbol{\beta}|\sigma^2,\boldsymbol{X}\sim N(\boldsymbol{\mu}_0,\sigma^2\boldsymbol{\Lambda}_0^{-1}))$. The conditional distribution for coeffiecient $\boldsymbol{\beta}$ are shown in Equation 14.

$$\boldsymbol{\beta}|\sigma^2,\boldsymbol{Y},\boldsymbol{X}\sim N(\tilde{\boldsymbol{\mu}},\sigma^2\tilde{\boldsymbol{\Lambda}}^{-1}) \quad (14)$$

With $\tilde{\boldsymbol{\mu}} = \tilde{\boldsymbol{\Lambda}}^{-1}(\boldsymbol{\Lambda}_0\boldsymbol{\mu}_0 + \boldsymbol{X}^{\mathrm{T}}\boldsymbol{Y})$ and $\tilde{\boldsymbol{\Lambda}} = \boldsymbol{\Lambda}_0 + \boldsymbol{X}^{\mathrm{T}}\boldsymbol{X}.$

Generate σ^2 from a from its conditional distribution 10000 times. With prior distribution $\sigma^2\sim inv\text{-}Gamma(a,b)$. The conditional distribution for σ^2 are shown in Equation 15.

$$\sigma^2|\boldsymbol{\beta},\boldsymbol{Y},\boldsymbol{X}\sim Inv\text{-}Gamma(a+\tfrac{n}{2},b+\tfrac{1}{2}(\boldsymbol{Y}-\boldsymbol{X\beta})^T(\boldsymbol{Y}-\boldsymbol{X\beta})) \quad (15)$$

Calculate the posterior distribution as in Equation (13).

Perform burn-in and posterior summary calculations. From the generated Gibbs samples, the first 2000 iterations are discarded as a non-representative (burn-in). The average of the remaining samples is used to calculate the posterior mean estimate with the Equation (16).

$$K\overline{(\boldsymbol{\beta})} = \frac{1}{D}\sum_{d=1}^{D}K(\boldsymbol{\beta}) \quad (16)$$

And the posterior standard deviation is obtained in Equation (17).

$$KSD\big(K(\boldsymbol{\beta})\big) = \sqrt{\frac{1}{D-1}\sum_{d=1}^{D}[K(\boldsymbol{\beta}) - K\overline{(\boldsymbol{\beta})}]^2} \quad (17)$$

Where $D = B - C$.

2.5 Hypothesis Testing

This Bayesian approach provides a more intuitive assessment of estimation uncertainty, as credible intervals represent the probability that a parameter lies within a specific range, unlike p-values which describe the probability of observing data under a null hypothesis. Hypothesis testing for regression coefficients in Bayesian analysis can be performed using credible intervals. The hypotheses are stated as follows.

$$H_0: \beta_{jl} = 0 \text{ vs } H_1: \ \beta_{jl} \neq 0$$

The steps to test the hypothesis using credible intervals are as follows.

1. Extract posterior samples: After specifying priors and performing posterior sampling (using Gibbs Sampling), extract the posterior samples $\beta_{jl}^{(s)}$ for the coefficient of interest, where $s = 1,2,\dots,S$.
2. Sort posterior samples: Arrange the S sample values in ascending order.
3. Calculate the credible interval of 95% using the percentile method as in the equation (18).

$$CI_{95\%} = [\beta_{jl}^{(0,025)}, \beta_{jl}^{(0,975)}] \quad (18)$$

where $\beta_{jl}^{(0,025)}$ and $\beta_{jl}^{(0,975)}$ are the 2.5th and 97.5th percentiles of te sorted posterior samples.

4. Evaluate significance:

- If CI does not contain 0, then the regression coefficient is rejected H_0 and it is concluded that the coefficient is significant,
- While if CI contains 0, then it H_0 is accepted and it can be said that there is not enough evidence to conclude that the coefficient is significant.

2.6 Stunting

Stunting is a condition of failing to grow in children due to chronic nutritional deficiencies, which is usually seen from lower height than the standard growth for the child's age. Stunting can be seen from the child's nutrition and physique. Based on nutritional status, stunting is often caused by a chronic lack of intake of essential nutrients such as proteins, vitamins, and minerals. Ongoing malnutrition can affect the formation of body tissues and organ function, thereby inhibiting the physical growth and cognitive development of children. Children who are malnourished are also more susceptible to infections due to a weakened immune system. Provision of adequate amounts of properly balanced foods and other proper nutritional treatment and efficiencies are central to the prevention of child stunting and the promotion of child growth and development [19].

Stunting is assessed thorugh the age-standard growth curves and by assessing the height of the child. If the child's height is below -2 SD from the norm of the growth curve, the child is classified as stunted. Growth monitoring of the children supports the identification of stunting challenges to allow for prompt response to management of the stunting through nutritional support and improvement of the environment. This stunting can be attributed to multiple inter-related dactor of the household such as socioeconomic status, dietary habits, surrounding environment, and nutritional status. Stunting has implication on the child's physical growth as well as the brain development of the child, and their ability to function in the future.

Low income as a determinant of health inequities severly limits access to nutritious food and health care. This affects a household's ability to sustain children's nutrition and propoer health care needs [20]. A child's nutrition is a key determinant of access to the essential nutrients that foster multi-dimensional growth and development. A child's growth is positively influenced and portective immunity to diseases is provided through a variaety of foods that constitute a healthy diet [21]. Unhealthy environments are also major contributors to stunting. The risk of diseases like diarrhea that impair nutrient absoption is high in environments of poor drinking water and inadequate sanitation and hygiene.

2.7 Research Design

This research concluded using a quantitative research design where we reviewed the factors leading to malnutrition in children in systematic way and the consequences of malnutrition which are advanced physical and nutritional stunting. Because one of the advantages of a quantitative approach is the objectivity in measurement of variables, it allows statistical testing of a hypothesis and calculating complex relationships. The design is appropriate for capturing nuances and differentiated impacts of varying economic status, dietary patterns, and environmental quality in relation to stunting outcomes.

2.8 Data Source and Variables

The research gathered information from Fernandes et al. research grants from 2025. So the information had already been gathered using dependable, organized, and systematic means. Data collection took placed in the Sumberputih Village in Wajak District, Malang Regency, the location is one of the focus areas in the regional stunting prevention acceleration program. The area was chosen for the data collection because of its high relevance and potential for intervention in the national stunting reduction program.

The dataset initially contained 200 respondents, however, in order to run models with 7 or fewer variables, one must have a bare minimum of 100 observations. Thus, only 100 observations were kept for analysis [22]. The remaining 100 respondents were auto-excluded to both for reaching the method defaults and also in order to limit the computing complexity, especially with the employment of Bayesian nonparametric models. The collection of data was completed in 2025 and checks were made to ensure we had a dataset that had no missing values. Also, since stunting was conceptualized in this research as a continuum (sub scores for nutritive and physical stunting), we did not have to provide coverage of the class distribution for any of the categorical variables.

The examined factors include three independent variables—Economic Level (X_1), Children's Diet (X_2), and Environmental Quality (X_3)—as well as two dependent variables—Nutritional Stunting (Y_1) and Physical Stunting (Y_2). Likert style questionnaires were used to measure Economic Level, Children's Diet, and Environment. These were first processed using Summated Rating Scale to guarantee they were at the interval level. As for physical stunting, this was addressed using direct measures and, when needen, observations via questionnaires.

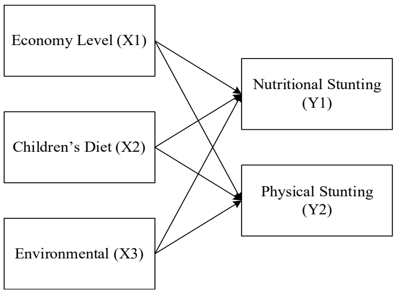

Figure 1. Research Model

3. RESULT AND ANALYSIS

3.1 Validity and Reliability

Before completing any of the analyses, the first step involves examining the instrument's validity and reliability. The sample of 30 people was taken from the pool of 100 respondents. This step complies with the rule of thumb which states that 30 people are enough for a first cut check of a survey instrument's validity and reliability, as this sample allows for enough dispersion to catch unreliable items, with movements of the full data set. The validity of the 29 items in the survey were estimated by the methods of Corrected Item-Total Correlation and the reliability of these four variables, Economic Level, Children's Diet, Environment and Nutritional Stunting, were determined by the statistical method of Cronbach's Alpha. The findings in Table 1 indicate that all the variables for which there are values of Corrected Item-Total Correlation were more than 0.30, and all the variables had values of Cronbach's Alpha which were more than 0.60. Hence, the instrument is valid and reliable and can be used in the main analysis with the full sample of 100 respondents.

Table 1. Validity and Reliability of the Questionnaire

Research Variables	Item Counts	Items	Corrected Item Total	Information	Cronbach's Alpha	Information
Economy Level (X_1)	5	$X_{1.1.1}$	0.61	Valid	0.78	Reliable
		$X_{1.1.2}$	0.72	Valid		
		$X_{1.2.1}$	0.53	Valid		
		$X_{1.2.2}$	0.51	Valid		
		$X_{1.2.3}$	0.49	Valid		
Children's Diet (X_2)	9	$X_{2.1.1}$	0.46	Valid	0.81	Reliable
		$X_{2.1.2}$	0.62	Valid		
		$X_{2.1.3}$	0.41	Valid		
		$X_{2.2.1}$	0.73	Valid		
		$X_{2.2.2}$	0.70	Valid		
		$X_{2.2.3}$	0.68	Valid		
		$X_{2.3.1}$	0.53	Valid		
		$X_{2.3.2}$	0.50	Valid		
		$X_{2.3.3}$	0.62	Valid		
Environment (X_3)	9	$X_{3.1.1}$	0.47	Valid	0.76	Reliable
		$X_{3.1.2}$	0.45	Valid		
		$X_{3.1.3}$	0.45	Valid		
		$X_{3.2.1}$	0.39	Valid		

Research Variables	Item Counts	Items	Corrected Item Total	Information	Cronbach's Alpha	Information
		$X_{3.2.2}$	0.48	Valid		
		$X_{3.2.3}$	0.49	Valid		
		$X_{3.3.1}$	0.42	Valid		
		$X_{3.3.2}$	0.40	Valid		
		$X_{3.3.3}$	0.50	Valid		
		$Y_{1.1.1}$	0.49	Valid		
		$Y_{1.1.2}$	0.51	Valid		
Nutritional Stunting (Y_1)	6	$Y_{1.1.3}$	0.65	Valid	0.77	Reliable
		$Y_{1.2.1}$	0.44	Valid		
		$Y_{1.2.2}$	0.38	Valid		
		$Y_{1.2.3}$	0.52	Valid		

Based on the analysis with Corrected Item Total Correlation and Cronbach's Alpha yielded sufficiently acceptable engagement of all the variables showing reliability and validity. This is considered to be the case with a Corrected Item Total Correlation score of over 0.30 and also a Cronbach's Alpha score of over 0.60. Therefore, the variables of Economic Level, Children's Diet, Environment, and Nutritional Stunting show that the variables are valid and reliable.

3.2 Linearity Test

After checking the validity and reliability, it is necessary to test the linearity to determine the most appropriate regression approach to be used. The linearity test shown in Table 2.

Table 2. Linearity Test

Relationships Between Variables	F Test Statistics	Degrees of Freedom	p-value	F Critical Value	Result
Economic Level (X_1) → Nutritional Stunting (Y_1)	18.72	1, 98	<0.01	3.94	Not Linear
Children's Diet (X_2) → Nutritional Stunting (Y_1)	12.45	1, 98	<0.01	3.94	Not Linear
Environmental (X_3) → Nutritional Stunting (Y_1)	5.63	1, 98	0.02	3.94	Not Linear
Economic Level (X_1) → Physical Stunting (Y_2)	26.14	1, 98	<0.01	3.94	Not Linear
Children's Diet (X_2) → Physical Stunting (Y_2)	39.87	1, 98	<0.01	3.94	Not Linear
Environmental (X_3) → Physical Stunting (Y_2)	47.33	1, 98	<0.01	3.94	Not Linear

The linearity test on the six relationships between each predictor variable and the response variable obtained the result that the arrival relationship of all predictor variables has a non-linear relationship to the response variable so it needs to be solved with an approach using the nonparametric method.

3.3 Biresponse Nonparametric Bayesian Regression

Nonparametric Bayesian regression defined as in the equation (19) and as matrix can be written as in the equation (20).

$$Y_{li} = \hat{f}_{li} + \varepsilon_{li}, \quad \varepsilon_{li} \sim N(0, \sigma_l^2) \tag{19}$$

$$\boldsymbol{Y_l} = \boldsymbol{W\beta_l} + \boldsymbol{\varepsilon_l}, \quad \boldsymbol{\varepsilon_l} \sim N_n(\boldsymbol{0}, \sigma_l^2 \boldsymbol{I_n}) \tag{20}$$

With,

$$\boldsymbol{W} = [1_n, X_1, (X_1 - k_{11})_+, \dots (X_1 - k_{1k})_+, X_2, (X_2 - k_{21})_+ \dots, (X_2 - k_{2k})_+, X_3, (X_3 - k_{31})_+ \dots (X_3 - k_{3k})_+]$$

$$\boldsymbol{\beta_l} = [\beta_{0l}, \beta_{11}, \dots, \beta_{(k+1)1}, \beta_{12}, \dots, \beta_{(k+1)2}, \beta_{13}, \dots, \beta_{(k+1)3}]^T$$

The prior distribution with normal distribution for the regression parameters are as in the equation (23).

$$\boldsymbol{\beta_l} \sim N(\boldsymbol{m_0}, \boldsymbol{V_0}) \tag{21}$$

$$p(\boldsymbol{\beta_l}) = \frac{1}{(2\pi)^{p/2}(|\boldsymbol{V_0}|)^{1/2}} exp\left\{-\frac{1}{2}(\boldsymbol{\beta_l} - \boldsymbol{m_0})^T \boldsymbol{V_0}^{-1}(\boldsymbol{\beta_l} - \boldsymbol{m_0})\right\} \tag{22}$$

$$p(\boldsymbol{\beta_l}) \propto exp\left\{-\frac{1}{2}(\boldsymbol{\beta_l} - \boldsymbol{m_0})^T \boldsymbol{V_0}^{-1}(\boldsymbol{\beta_l} - \boldsymbol{m_0})\right\} \tag{23}$$

The prior distribution with Gamma distribution for the precision can be written as in the equation (26).

$$\tau_l = 1/_{\sigma_l^2} \sim Gamma(a_0, b_0) \tag{21}$$

$$p(\tau_l) = \frac{b_0^{a_0}}{\Gamma(a_0)} \tau_l^{a_0-1} \exp(-b_0\tau_l) \tag{22}$$

$$p(\tau_l) \propto \tau_l^{a_0-1} \exp(-b_0\tau_l) \tag{23}$$

The likelihood function for the regression model $\boldsymbol{Y_l}|\boldsymbol{\beta_l}, \tau_l \sim N(\boldsymbol{W\beta_l}, \tau_l^{-1}\, \boldsymbol{I_n})$ can be witten as in the equation (24) and the posterior distribution can be shown in the equation (27).

$$p(\boldsymbol{Y_l}|\boldsymbol{\beta_l}, \tau_l) \propto \tau_l^{n/2} exp\left\{-\frac{\tau_l}{2}(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})^T(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})\right\} \tag{24}$$

$$p(\boldsymbol{\beta_l}, \tau_l|\boldsymbol{Y_l}) \propto\ p(\boldsymbol{Y_l}|\boldsymbol{W\beta_l}, \tau_l)p(\boldsymbol{\beta_l})p(\tau_l) \tag{25}$$

$$p(\boldsymbol{\beta_l}, \tau_l|\boldsymbol{Y_l}) \propto \tau_l^{n/2} exp\left\{-\tfrac{\tau_l}{2}(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})^T(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})\right\} \times exp\left\{-\tfrac{1}{2}(\boldsymbol{\beta_l} - \boldsymbol{m_0})^T\boldsymbol{V_0}^{-1}(\boldsymbol{\beta_l} - \boldsymbol{m_0})\right\} \times \tau_l^{a_0-1}\exp(-b_0\tau_l) \tag{26}$$

$$p(\boldsymbol{\beta_l}, \tau_l|\boldsymbol{Y_l}) \propto \tau_l^{a_0-1+n/2} exp\left\{-\tfrac{\tau_l}{2}(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})^T(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})\right\} exp\left\{-\tfrac{1}{2}(\boldsymbol{\beta_l} - \boldsymbol{m_0})^T\boldsymbol{V_0^{-1}}(\boldsymbol{\beta_l} - \boldsymbol{m_0})\right\} exp\{-b_0\tau_l\} \tag{27}$$

Gibbs sampling need full condition distribution. From the equation (27), the conditional distribution for the regression coefficient parameters can be written as in equation (34).

$$p(\boldsymbol{\beta_l}|\tau_l, \boldsymbol{Y_l}) \propto exp\left\{-\frac{\tau_l}{2}(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})^T(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})\right\} exp\left\{-\frac{1}{2}(\boldsymbol{\beta_l} - \boldsymbol{m_0})^T\boldsymbol{V_0^{-1}}(\boldsymbol{\beta_l} - \boldsymbol{m_0})\right\} \tag{28}$$

$$p(\boldsymbol{\beta_l}|\tau_l, \boldsymbol{Y_l}) \propto -\frac{\tau_l}{2}\left(\boldsymbol{Y_l^T Y_l} - 2\boldsymbol{\beta_l^T W^T Y_l} + \boldsymbol{\beta_l^T W^T W\beta_l}\right) - \frac{1}{2}(\boldsymbol{\beta_l} - \boldsymbol{m_0})^T\boldsymbol{V_0^{-1}}(\boldsymbol{\beta_l} - \boldsymbol{m_0}) \tag{29}$$

$$p(\boldsymbol{\beta_l}|\tau_l, \boldsymbol{Y_l}) \propto -\tfrac{1}{2}\left(\boldsymbol{\beta_l^T}(\tau_l\boldsymbol{W^T W})\boldsymbol{\beta_l} - 2\boldsymbol{\beta_l^T}(\tau_l\boldsymbol{W^T Y_l})\right) - \tfrac{1}{2}\left(\boldsymbol{\beta_l^T V_0^{-1}\beta_l} - 2\boldsymbol{\beta_l^T V_0^{-1} m_0}\right) \tag{30}$$

$$p(\boldsymbol{\beta_l}|\tau_l, \boldsymbol{Y_l}) \propto -\tfrac{1}{2}\left(\boldsymbol{\beta_l^T}(\tau_l\boldsymbol{W^T W})\boldsymbol{\beta_l} - 2\boldsymbol{\beta_l^T}(\tau_l\boldsymbol{W^T Y_l}) + \boldsymbol{\beta_l^T V_0^{-1}\beta_l} - 2\boldsymbol{\beta_l^T V_0^{-1} m_0}\right) \tag{31}$$

$$p(\boldsymbol{\beta_l}|\tau_l, \boldsymbol{Y_l}) \propto -\frac{1}{2}\left(\boldsymbol{\beta_l^T}\left(\tau_l\boldsymbol{W^T W} + \boldsymbol{V_0^{-1}}\right)\boldsymbol{\beta_l} - 2\boldsymbol{\beta_l^T}\left(\tau_l\boldsymbol{W^T Y_l} + \boldsymbol{V_0^{-1} m_0}\right)\right) \tag{32}$$

$$p(\boldsymbol{\beta_l}|\tau_l, \boldsymbol{Y_l}) \propto -\frac{1}{2}\left(\boldsymbol{\beta_l^T}(\boldsymbol{V_n^{-1}})\boldsymbol{\beta_l} - 2\boldsymbol{\beta_l^T}(\boldsymbol{V_n^{-1} m_n})\right) \tag{33}$$

$$\boldsymbol{\beta_l}|\tau_l, \boldsymbol{Y_l} \sim N(\boldsymbol{m_n}, \boldsymbol{V_n}) \tag{34}$$

With, the mean $\boldsymbol{m_n} = \boldsymbol{V_n}(\boldsymbol{V_0^{-1} m_0} + \tau_l\boldsymbol{W^T Y_l})$ and the variance $\boldsymbol{V_n} = (\boldsymbol{V_0^{-1}} + \tau_l\boldsymbol{W^T W})^{-1}$. While the conditional distribution for precision can be written as in equation (38).

$$p(\tau_l|\boldsymbol{\beta_l}, \boldsymbol{Y_l}) \propto \tau_l^{a_0-1+n/2} exp\left\{-\frac{\tau_l}{2}(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})^T(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})\right\} exp\{-b_0\tau_l\} \tag{30}$$

$$p(\tau_l|\boldsymbol{\beta_l}, \boldsymbol{Y_l}) \propto \tau_l^{a_0-1+n/2} exp\left\{-\tau_l\left(b_0 + \frac{1}{2}(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})^T(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})\right)\right\} \tag{31}$$

$$\tau_l|\boldsymbol{\beta_l}, \boldsymbol{Y_l} \sim Gamma\left(a_0 - 1 + \frac{n}{2} + 1, b_0 + \frac{1}{2}(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})^T(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})\right) \tag{32}$$

$$\tau_l|\boldsymbol{\beta_l}, \boldsymbol{Y_l} \sim Gamma\left(a_0 + \frac{n}{2}, b_0 + \frac{1}{2}(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})^T(\boldsymbol{Y_l} - \boldsymbol{W\beta_l})\right) \tag{33}$$

A truncated spline nonparametric regression model on a linear order with one knot for three predictor variables and two response variables as the results of Bayesian calculation are presented as follows.

$$\hat{f}_{1i} = 1.08 + 0.61X_{1i} - 1.20(X_{1i} - 2.56)_+ + 0.50X_{2i} - 0.05(X_{2i} - 2.52)_+ - 0.43X_{3i} + 1.03(X_{3i} - 3.04)_+$$

$$\hat{f}_{2i} = 0.25 - 0.07X_{1i} + 0.10(X_{1i} - 2.56)_+ + 0.01X_{2i} - 0.01(X_{2i} - 2.52)_+ - 0.03X_{3i} + 0.05(X_{3i} - 3.04)_+$$

Table 3. Knot Point and GCV Linear Order Model 1 Point Knot

Variable Predictor	Response Variables	Knot Point	GCV Model	R^2
Economy Level (X_1)	Nutritional Stunting (Y_1) Physical Stunting (Y_2)	$K_{11} = 2.56$		
Children's Diet (X_2)	Nutritional Stunting (Y_1) Physical Stunting (Y_2)	$K_{21} = 2.52$	0.12	0.79
Milieu (X_3)	Nutritional Stunting (Y_1) Physical Stunting (Y_2)	$K_{31} = 3.04$		

Based on the table, the truncated spline nonparametric regression model with one knot point and a linear polynomial order (p=1) demonstrates strong predictive performance for stunting outcomes. This is indicated by a Generalized Cross-Validation (GCV) value of 0.12, which is relatively low, suggesting minimal prediction error and a reduced risk of overfitting. Moreover, the coefficient of determination (R^2) of 79% reveals that the majority of the variation in both nutritional and physical stunting can be explained by the predictor variables used in the model—namely, economic level, children's diet, and environmental conditions. Hence, given the complexity of the relationships and the effective linear dimensions, the model proves to have high explanatory power, which makes it relevant and useful for the particular case of the driving factors of stunting in the particular context of the study. Since the model has one knot point, this separates the predictor variables into two distinct regimes. The first regime applies when the economic level (X_1) is less than 2.56, children's diet (X_2) is less than 2.52, and environmental conditions (X_3) are less than 3.04. The second regime reflects the conditions when these variables equal or exceed those respective thresholds. This division allows the model to capture nonlinear changes in the relationship between predictors and stunting outcomes across different levels of socioeconomic and environmental factors.

3.4 Hypothesis Test

The hypotheses used in the hypothesis test using are as follows.

$$H_0 : \beta_{ji} = 0$$
$$H_1 : \beta_{ji} \neq 0$$

The results of the hypothesis test using the Bayesian approach which was carried out 10000 times are presented in the following table

Table 4. Bayesian Approach Hypothesis Testing Results

Relationship	$\hat{\beta}_i$	Posterior Mean	Credible Interval	Significance
$X_1 \rightarrow Y_1$	$\beta_1 X_1$	1.03	[0.82, 1.25]	Yes
$X_1 \rightarrow Y_1$	$\beta_2 (X_1 - K_{11})_+$	-0.29	[−0.67, 0.08]	Not
$X_2 \rightarrow Y_1$	$\beta_5 X_2$	0.23	[0.08, 0.37]	Yes
$X_2 \rightarrow Y_1$	$\beta_6 (X_2 - K_{21})_+$	0.13	[0.02, 0.28]	Yes
$X_3 \rightarrow Y_1$	$\beta_9 X_3$	-0.69	[−0.85, −0.52]	Yes
$X_3 \rightarrow Y_1$	$\beta_{10} (X_3 - K_{31})_+$	0.09	[−0.03, 0.21]	Not
$X_1 \rightarrow Y_2$	$\beta_1 X_1$	-0.06	[−0.09, −0.02]	Yes
$X_1 \rightarrow Y_2$	$\beta_2 (X_1 - K_{11})_+$	-0.09	[−0.15, −0.02]	Yes
$X_2 \rightarrow Y_2$	$\beta_5 X_2$	0.06	[0.01, 0.12]	Yes
$X_2 \rightarrow Y_2$	$\beta_6 (X_2 - K_{21})_+$	0.03	[−0.05, 0.11]	Not
$X_3 \rightarrow Y_2$	$\beta_9 X_3$	0.01	[0.01, 0.02]	Yes
$X_3 \rightarrow Y_2$	$\beta_{10} (X_3 - K_{31})_+$	0.14	[0.07, 0.22]	Yes

Based on the table, there are 3 of the 12 parameters that have a 95% credible interval of zero, so they are considered to have no significant influence. From the results of these estimates, it is known that the economic level variable (X_1) in general has a significant effect on nutritional stunting (Y_1) and physical stunting (Y_2), especially on the basic X_1 value, while its nonlinear influence (after knot) on Y_1 is not significant. Furthermore, children's diet (X_2) showed a significant influence on nutritional stunting (Y_1), both in linear and nonlinear components, but one of the components was not significant to physical stunting (Y_2), indicating that the influence of diet on physical aspects was more limited. Meanwhile, environment (X_3) exerts a significant influence on both types of stunting, although its nonlinear influence on Y_1 is not significant. These factors reliably elucidate stunting variability as these factors economise dietary selection and stunting type in their influence.

3.5 Discussion

Poverty has been shown to be an important factor affecting all forms of stunting, whether nutritional stunting (Y_1) or physical stunting (Y_2), and is also an important socioeconomic variable, hence, the results corroborate global findings of child growth failures being attributable to poverty [23]. Such low-income households more frequently encounter such food insecurity along with insufficient access to health. A child in such an economically impoverished situation experiences the growth detrimental effects of such insufficient access to health and health services combined with insufficient access to health [24]. In this context, the main coefficient of X1 and the non-linear effect on Y2 exhibits no credible intervals containing 0, hence crossing zero indicates without a doubt [25]. In contrast, the nonlinear component of X1 on Y1 contains zero, indicating that an income increase, beyond a certain point, does not positively impact nutritional status, implying imposition of a ceiling, hence structural advancements need to be implemented, not economically motivated [26].

The negative association between children's diets (X_2) and nutritional stunting (Y_1) mirrors evidence that poor dietary diversity disproportionately impacts the growth of children (Y_1) [27]. This evidence reinforces the theory that children with poor dietary diversity are more likely to suffer the effects of chronic undernutrition and poor nutritional stunting to a greater extent. Children with deficient diets are much more likely to suffer from the consequences of numerous micronutrient deficiencies which negatively affect the growth of children and the development of healthy immune systems [28]. However, the nonlinear portion within the association of X_2 and physical stunting (Y_2) of the composite structural silencing regression variable. This confirms that beyond a given threshold, more improved diets would have no gains associated [29]. Thus, among children with the most severe dietary inadequacy, dietary interventions would be expected to yield the most positive overall effects [30].

Regarding the environmental conditions (X_3), there is strong and significant evidence concerning the two types of stunting aligned with the previous studies that documented that poor sanitation and unsafe water domains raise the likelihood of malnutrition-related infections that prevent the absorption of essential nutrients [31]. The importance of these parameters, both as linear and nonlinear, indicates that there is potential for environmental sanitation to stunting, as less exposure to pathogens is impactful [32]. Such studies identified the role of environmental enteric dysfunction as key for the chronic undernutrition stunting [33]. Although the nonlinear effect of X_3 on the dimension of stunting, that is, malnutrition stunting (Y_1), is zero, as is the case of other studies, it indicates that stunting due to malnutrition and poor uptake of nutrients is unlikely to improve significantly on the X_3 improvements alone, as the communities with basic sanitation [34]. This brings the case for integrated approaches that couple sanitation and infection control with improved feeding [35].

Despite the interesting findings, there are limitations for this study. The results are constrained geographically to a single village, resulting in a small sample size. Also, the Likert scale in capturing dependent variables that are continuous in nature, and on variables, such as diet and sanitation, could create measurement error due to respondent bias or nature of the scale. The inclusion of objective measures, and the expansion of the geographic coverage, could be beneficial for robustness in future studies.

Considering the economic, dietary, and environmental attributes of the population, the results supported the key concepts of the multi-dimensional approach of child growth failure in the literature based on the economic, dietary, and environmental attributes of the population in the literature on child growth failure [36]. The evidence of variation on the impact of the effective attribute on the reduction of stunting growth and associated child population in the target population confirms the need of focusing and concerning the stunting growth and child population [37].

4. CONCLUSION

The novelty of this study lies in the simultaneous application of a Bayesian biresponse truncated spline model to detect nonlinear threshold effects across economic, dietary, and environmental factors, allowing more precise identification of saturation points that are often overlooked in conventional stunting analyses. Based on the results of the Bayesian biresponse truncated spline model with one knot, a GCV value of 0.12 and a determination coefficient of 79.0% were obtained, which shows that the model has a fairly good predictive ability in explaining the variation in stunting data. In general, economic level has been shown to have a significant influence on nutritional stunting and physical stunting, although at certain points the effect on nutritional stunting is not significant, indicating a possible saturation effect. Children's diet has a significant effect on nutritional stunting, but to a certain extent it does not affect physical stunting, which suggests that the influence of diet can be selective depending on the type of stunting. Meanwhile, the environment shows a significant influence on both types of stunting, although there is one nonlinear parameter that is not significant to nutritional stunting, this condition still confirms that a healthy environment has an important role in reducing stunting rates through infection prevention and increased nutrient absorption.

Stepping beyond the evidence already presented, it would be prudent to consider the implications of the effects described above from an experiential standpoint. Considering that the economic effects seemed to level off, it would appear that households that have reached a particular income threshold, as well as those who are above it, stand to gain nothing in the way of a further reduction in financial stunting from additional increases in income. This suggests the need to go well beyond income-focused interventions to implement those that also incorporate education, behavioral change, and accessibility to a variety of foods. Likewise, the reduction of physical stunting in children has a diminishing return to improving diet, which suggests that the stunted growth problem cannot simply be resolved solely by addressing the diet, leaving the other health and environmental factors untouched. Conclusions from this study are hampered by limitations such as a small sample size from just one village and employing- Likert Scale instruments that tend to overlook much detail, and thus should be made with caution. Regardless, it would be irresponsible to not incorporate an evidence-based integrated policy approach from these findings, which combines economic interventions with nutrition education and enhancements to the physical environment. This is the approach which we should advocate to the target audience and policy makers to stunting in a sustainable manner.

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5. REFERENCE

[1] World Health Organization, "Stunting Discuss meaning of nonlinear thresholds more deeply in a nutshell," 2015. [Online]. Available: https://www.who.int/news/item/19-11-2015-stunting-in-a-nutshell

[2] UNICEF, WHO, and World Bank, "Levels and trends in child malnutrition: UNICEF/WHO/World Bank Group joint child malnutrition estimates," Geneva, 2021.

[3] C. G. Victora, P. Christian, L. P. Vidaletti, G. Gatica-Domínguez, P. Menon, and R. E. Black, "Revisiting maternal and child undernutrition in low-income and middle-income countries: Variable progress towards an unfinished agenda," *Lancet*, vol. 397, no. 10282, pp. 1388–1399, 2021, doi: https://doi.org/10.1016/S0140-6736(21)00394-9.

[4] R. E. Black *et al.*, "Maternal and child undernutrition and overweight in low-income and middle-income countries," *Lancet*, vol. 382, no. 9890, pp. 427–451, 2013, doi: 10.1016/S0140-6736(13)60937-X.

[5] G. Danaei *et al.*, "Risk factors for childhood stunting in 137 developing countries: A comparative risk assessment analysis at global, regional, and country levels," *PLOS Med.*, vol. 13, no. 11, p. e1002164, 2016, doi: 10.1371/journal.pmed.1002164.

[6] U. Nations, "Transforming our world: The 2030 Agenda for Sustainable Development," 2015, *United Nations*. [Online]. Available: https://sdgs.un.org/2030agenda

[7] J. Fan and I. Gijbels, *Local polynomial modelling and its applications*. London: Chapman & Hall, 1996.

[8] N. Dewi and M. Arsyad, "Spline Regression for Modeling Stunting Determinants in Rural Indonesia," *J. Public Heal. Anal.*, vol. 14, no. 3, pp. 245–257, 2022, doi: https://doi.org/10.1234/jpha.2022.00345.

[9] L. Putri and J. Kim, "Bayesian Modeling of Child Malnutrition: A Parametric Approach," *Int. J. Child Nutr.*, vol. 9, no. 2, pp. 122–134, 2021, doi: https://doi.org/10.5678/ijcn.v9i2.2021.123.

[10] A. Junaidi S. Harahap and M. Ramadhan, "Flexible Bayesian Nonparametric Regression with Truncated Splines for Stunting Analysis," *J. Biostat. Heal. Informatics*, vol. 6, no. 1, pp. 33–47, 2023, doi: https://doi.org/10.4321/jbhi.v6i1.2023.005.

[11] Q. Li and J. S. Racine, *Nonparametric econometrics: Theory and practice*. Princeton, NJ: Princeton University Press, 2007.

[12] D. Ruppert, M. P. Wand, and R. J. Carroll, *Semiparametric regression*. Cambridge: Cambridge University Press, 2003.

[13] S. Solimun, A. A. R. Fernandes, N. Nurjannah, and L. A. Akhairani, *Variable measurement design of questionnaire and questionnaire (utilization of R)*. Malang: Universitas Brawijaya Press, 2022.

[14] A. A. R. Fernandes and Solimun, *Regression analysis in a flexible approach*. Malang: Universitas Brawijaya Press, 2022.

[15] A. A. R. Fernandes and Solimun, *Regression Analysis in a Flexible Approach: An Illustration with Program Package R*. UB Press, 2021.

[16] H. Wu and J. T. Zhang, *Nonparametric Regression Methods for Longitudinal Data Analysis: Mixed-Effects Modeling Approaches*. Wiley-Interscience, 2006.

[17] S. D. Permai and H. Tanty, "Linear regression model using Bayesian approach for energy performance of residential building," *Procedia Comput. Sci.*, vol. 135, pp. 671–677, 2018, doi: 10.1016/j.procs.2018.08.221.

[18] A. I. Adewole and O. K. Bodunwa, "Sensitivity analysis of prior distributions in regression model estimation," *Al-Bahir*, vol. 4, no. 2, p. Article 2, 2024, doi: 10.55810/2313-0083.1056.

[19] I. B. Wati, Ni Nyoman Kurnia., Lestari, Nyoman Ayu Putri., Sudiana, I Nyoman., & Putrayasa, "Analisis Pendekatan CBSA dan Pembelajaran Berdeferensiasi dalam Pembelajaran Bahasa Indonesia," *Maj. Ilm. Kependidikan*, vol. 6, no. 3, 2022.

[20] A. N. Aida, "The influence of socioeconomic conditions on stunting incidence in Indonesia," *J. Budg.*, vol. 4, no. 2, 2019.

[21] L. S. Amalika, H. Mulyaningsih, and E. Purwanto, "Exploration of feeding patterns of stunted and non-stunted toddlers based on socio-cultural perspectives in West Legung Village," *Sci. J. Soc. Sci.*, vol. 9, no. 2, 2023.

[22] J. F. J. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, 8th ed. United Kingdom: Cengage Learning, 2019.

[23] L. C. Smith and L. Haddad, "Reducing child undernutrition: Past drivers and priorities for the post-MDG era," *World Dev.*, vol. 68, pp. 180–204, 2015, doi: 10.1016/j.worlddev.2014.11.014.

[24] Z. A. Bhutta, J. A. Berkley, R. H. Bandsma, and others, "Severe childhood malnutrition," *Nat. Rev. Dis. Prim.*, vol. 6, no. 1, pp. 1–18, 2020.

[25] A. Gelman, J. B. Carlin, H. S. Stern, D. B. Dunson, A. Vehtari, and D. B. Rubin, *Bayesian Data Analysis*. CRC Press, 2013.

[26] J. Behrman and A. Deolalikar, "Health and Nutrition," *Handb. Dev. Econ.*, vol. 1, pp. 631–711, 1988.

[27] G. Kennedy, T. Ballard, and M. C. Dop, "Guidelines for Measuring Household and Individual Dietary Diversity," *FAO Nutr. Pap.*, vol. 41, 2011.

[28] R. Micha and others, "Global dietary patterns and health," *BMJ*, vol. 369, p. m2382, 2020.

[29] M. Ruel and H. Alderman, "Nutrition-sensitive interventions and programmes," *Lancet*, vol. 382, pp. 536–551, 2013.

[30] K. G. Dewey, "Reducing stunting: Trials and policy efforts," *Matern. Child Nutr.*, vol. 12, pp. 27–38, 2016.

[31] A. J. Pickering and others, "The WASH Benefits and SHINE trials," *Lancet*, vol. 394, pp. 101–112, 2019.

[32] S. Budge and others, "Environmental hygiene and child health," *Trop. Med. Int. Heal.*, vol. 24, pp. 996–1009, 2019.

[33] G. T. Keusch and others, "Environmental Enteric Dysfunction," *Food Nutr. Bull.*, vol. 35, pp. S112–S118, 2014.

[34] F. Ngure and others, "Water, sanitation, and hygiene and the prevention of stunting," *Matern. Child Nutr.*, vol. 10, pp. 91–102, 2014.

[35] J. H. Humphrey and others, "Independent and combined effects of improved water, sanitation, and complementary feeding," *Lancet Glob. Heal.*, vol. 7, pp. e125--e135, 2019.

[36] R. E. Black and others, "Maternal and child undernutrition and overweight in low-income countries," *BMJ*, vol. 359, p. j4392, 2017.

[37] P. Christian and others, "The need for integrated interventions to improve child nutrition," *J. Nutr.*, vol. 143, pp. 116–123, 2013.