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Modelling Acute Malnutrition in Ethiopia: A Bayesian Distributional Regression Approach

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Abstract

Child wasting, a severe form of acute malnutrition remains a pressing public health concern in Ethiopia. This study aimed to identify key determinants influencing child wasting, measured through Weight-for-Height Z-scores (WHZ), and to explore spatial variations using a Bayesian Distributional Regression (BDR) framework. By analyzing data from the 2019 Ethiopian Demographic and Health Survey (EDHS), the study examined the complex relationships between socio-economic, demographic, and geographical factors affecting WHZ. Unlike traditional regression approaches that focus solely on mean effects, BDR enabled a comprehensive assessment of the full distribution of WHZ, offering deeper insights into nutritional disparities.

The results indicated notable regional differences in WHZ, with the Somali region showing the lowest values. BDR analysis highlighted maternal education and household wealth as crucial factors positively influencing mean WHZ. Conversely, child age and malaria incidence were negatively associated with WHZ, indicating their detrimental effects on child nutrition. Environmental factors also played a role, as higher mean temperatures were linked to lower WHZ and increased variability. Further, the sigma model indicated that maternal education and moderate household wealth contributed to reducing WHZ variability, suggesting their stabilizing effects on child nutrition outcomes. Additionally, non-linear relationships were observed in the effects of child age, mean temperature, precipitation, and population density, emphasizing the complexity of these interactions. Model fit diagnostics confirmed the reliability of the analysis.

The study underscores the multifaceted nature of child wasting in Ethiopia, driven by socio-economic, health, and environmental determinants. Addressing these factors through targeted interventions is essential to enhance child nutritional outcomes. Future research should focus on understanding causal pathways and evaluating the effectiveness of proposed interventions to ensure sustainable solutions for combating child malnutrition.

Keywords: Child wasting; Ethiopia; Bayesian distributional regression; Prior distribution; posterior distribution; Statistical inference.

Introduction

Malnutrition remains a critical global challenge, particularly under-nutrition, which significantly impacts child health and development. This form of malnutrition arises from inadequate intake of essential nutrients and poses severe risks, especially to young children. According to the World

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Health Organization [1], approximately 7.7% of children under five about 52 million are affected by wasting, with 17 million experiencing severe acute malnutrition. Childhood malnutrition assessment primarily utilizes anthropometric measurements. Stunting, reflecting chronic malnutrition and assessed by height-for-age. Wasting, indicative of acute malnutrition, is assessed by weight-for-height. Weight-for-age provides a general indicator of both malnutrition conditions. This critical health issue disproportionately affects low- and middle-income countries, where malnutrition contributes to nearly 45% of under-five child mortality [1, 2]. Acute malnutrition, particularly in the form of wasting, represents a critical public health challenge in Ethiopia. Recent estimates indicate that a substantial proportion of children under five are affected by this condition, which can have severe implications for their health and development [2]. Several studies conducted in Ethiopia have identified various determinants linked to malnutrition, particularly wasting, highlighting the need for effective strategies to combat this issue. Socioeconomic factors play a significant role; for instance, [3] found that a mother's level of education is crucial, with higher education levels associated with lower rates of malnutrition. Similarly, [4] emphasized the impact of household income, noting that families with greater financial resources have better access to nutritious food and healthcare. [5] further reinforced this by indicating that household wealth is a strong predictor of child nutrition. Environmental and health factors also contribute significantly; access to safe drinking water is critical, as demonstrated by [6], who found that it correlates with a reduced risk of malnutrition. Additionally, the relationship between aridity and nutritional status is non-linear, with increasing aridity impacting food availability and child nutrition [6]. Drought severity complicates this further, leading to increased malnutrition rates during severe drought conditions, indicating a threshold effect [7].

Temperature is another critical environmental factor with complex links to malnutrition. Studies have shown that increased temperatures can negatively impact crop yields, leading to reduced food availability and nutritional deficiencies [8]. Malaria incidence is also closely related to temperature, particularly in countries like Ethiopia. Higher temperatures can expand the habitat and breeding grounds of malaria-carrying mosquitoes, leading to a rise in malaria cases [9]. Malaria infection is a significant contributor to malnutrition in children as it causes fever, loss of appetite, and impaired nutrient absorption, further exacerbating the risk of wasting and other forms of under-nutrition [10]. The interplay between temperature, malaria, and malnutrition creates a complex challenge for child health, especially in tropical and subtropical regions. Child-specific factors, including age, are crucial, as younger children are at a higher risk of wasting [11]. Maternal Body Mass Index (BMI) also plays a significant role; while a higher BMI generally correlates with better nutritional outcomes for children, this relationship may plateau or reverse at extreme values, indicating potential health risks for both mother and child [4]. Breastfeeding practices demonstrate non-linearity as well; exclusive breastfeeding for the first six months is beneficial, but the positive effects may not continue to increase linearly with the introduction of complementary foods [11]. Furthermore, maternal age has been linked to child nutrition outcomes [12], and differences in malnutrition rates between male and female children have been noted by [13]. These findings underscore the multifaceted nature of malnutrition and the necessity for comprehensive strategies to address its determinants in Ethiopia. Exploring non-linear effects related to child age, maternal BMI, and geographical factors is crucial for developing a robust model of acute malnutrition, providing deeper insights into the complex interplay of various determinants affecting child nutrition. While numerous studies have explored the determinants of wasting, many have relied on traditional statistical modeling techniques, such as linear regression and generalized linear models. These approaches often focus on average effects and may overlook the complex, non-linear relationships that exist between socio-economic factors and malnutrition outcomes [14, 15].

One major limitation of these traditional methods is their emphasis on the mean response, which can obscure critical insights into the distribution of malnutrition, particularly when extreme values are of interest [16]. Additionally, many of these models assume a normal distribution for the response variable, a premise that is frequently violated in malnutrition research, where distributions are often skewed [17]. To overcome these limitations, this study proposes employing a Bayesian distributional regression approach. This innovative methodology provides several advantages, including the ability to model the entire distribution of the response variable, thus offering insights into both the mean and the variability of wasting [18]. Furthermore, by incorporating spatial covariates, the analysis aims to capture the spatial patterns of malnutrition that may not be fully explained by socio-economic factors alone [19]. In this study, we aim to identify the key determinants of wasting in Ethiopia, quantify the impact of these determinants on the distribution of wasting, and explore spatial variations in malnutrition patterns. Ultimately, the findings will inform targeted interventions designed to address malnutrition at the regional level, contributing to improved health outcomes for vulnerable populations.

Data and Methodology

Data and Study Design

This study uses data from the 2019 Ethiopian Demographic and Health Survey (EDHS), a nationally representative survey

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providing detailed information on household demographics and health. The EDHS covers key areas such as fertility, family planning, child mortality, child nutritional status, maternal and child health service utilization, and knowledge of HIV/AIDS and STIs. The survey employed a stratified two-stage cluster sampling design across Ethiopia's 9 regions and 2 city administrations. In the first stage, clusters were selected; in the second, households within these clusters were selected. Clusters were stratified by rural/urban residence and district (Woreda). Woredas are subdivided into Kebeles, which are further divided into census enumeration areas (EAs). Spatial information, including latitude and longitude coordinates, is available for selected enumeration areas, enabling analysis of geographic variations in health outcomes. This rigorous sampling methodology ensures the representativeness of the findings for Ethiopia [20].

Variable of the study

The outcome variable for this study is the weight-for-height z-score (wasting), specifically measured through the indicator of wasting, and obtained from the Ethiopian Demographic and Health Surveys conducted 2019. The covariates were selected based on their potential connection with the outcome variable, drawing on insights from previous research [3, 5, 6, 8, 1, 11, 13]. This approach ensures that the chosen variables are relevant and meaningful in understanding the factors influencing malnutrition, particularly wasting. The predictor variables included in this investigation are classified into socio-economic, demographic, health, and as well as geographical covariates. The description and measurements of these variables are presented in Table 1. Geospatial covariate data were sourced from multiple platforms. Climatic data, including temperature and precipitation, were obtained from the WorldClim website [21]. Information on distance to the nearest cities and healthcare facilities was acquired from the Malaria Atlas Project (MAP) [22]. Additionally, population density data were retrieved from WorldPop [23]. Geographic factors such as the Average Aridity Index and Drought Severity Index were obtained from WorldClim and Palmer Drought Severity Index (PDSI) respectively. Covariates were selected based on their potential association with malnutrition outcomes, as demonstrated in previous literature, and the availability of high-resolution, countrywide data.

Table 1: Description of study variables included in the Models.

	Variable	**Description**	**Measurements**
Response variable	Wasting	Weight-for-height z-score below -2 SD from the mean (WHO standards), indicating acute under-nutrition.	Z-score < -2 indicates wasting; Z-score ≥ -2 indicates normal weight-for-height
Linear covariate	Child's Sex (ref.= Female)	Gender of the child	- Sex (ref.= Female) Male
	Maternal Education	Educational level of the mother, influencing health-seeking behaviors and nutritional practices.	- no education(ref) - Primary - Secondar Higher
	Household Wealth Index	Measure of overall economic status, impacting access to resources.	- Poorest—ref - Poorer - Middle - Richer Richest
	Access to Clean Water and Sanitation	Availability of clean water and proper sanitation facilities, critical for preventing illness.	- Improved(ref) Unimprove
Non-linear covariate	Child's Age	Age of the child, reflecting different nutritional needs during growth phases.	Child's age from 0–59 months
	Maternal Body Mass Index (BMI)	Nutritional status of the mother, which can affect her children's health outcomes.	As a ration weight/ $(height)^2$
	Precipitation	Climate variable affecting agricultural productivity and food availability.	Mean precipitation
	Temperature	Climate variable that influences food security and health outcomes.	**Mean Temperature**
	Malaria Incidence	Prevalence of malaria, which can adversely affect child health and nutrition.	Malaria Prevalence
	Population Density	Concentration of people in a given area, influencing competition for resources and healthcare access.	Population density
Spatial	Region	Region (State where mothers live)	Categories (1, 2, . . ., 11)

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Methodology

To investigate the intricate relationships between socio-economic, demographic, and geographical covariates and anthropometric outcomes, we employed the Bayesian Distributional Regression (BDR) framework. BDR offers a powerful statistical approach that surpasses traditional regression methods by modeling the entire distribution of the response variable not just its mean. This allows for a comprehensive understanding of how covariates influence various aspects of the outcome distribution, such as its mean, variance, skewness, and kurtosis [24].

BDR allows for a flexible approach in capturing various covariate effects [25, 26]:

- Linear effects: Direct, proportional relationships between covariates and the response distribution.
- Non-linear effects: Complex, non-linear associations between covariates and the response distribution, captured through smooth functions (e.g., splines).
- Spatial effects: Spatial autocorrelation in the response distribution, accounting for geographical clustering or dependencies.
- Varying effects: Heterogeneous effects of covariates across different subpopulations or regions.

By modeling the full distribution, BDR provides a nuanced understanding of the impact of covariates on anthropometric outcomes. In this study, we focused on Weight-for-height z-scores, but BDR's ability to analyze the entire distribution extends beyond the conditional mean. This allows us to directly capture potential heterogeneity in the effects of socio-economic, demographic, and geographical factors across different levels of the anthropometric measure [27].

Bayesian Distributional Regression

Bayesian Distributional Regression (BDR) is a sophisticated statistical framework that not only estimates the conditional mean of the response variable but also models its entire distribution. This is particularly advantageous when analyzing anthropometric measures like Weight-for-Height z-scores, allowing for a more comprehensive understanding of the data's underlying structure [28]. In BDR, the initial step involves specifying the distributional form of the response. For this study, we assume a Gaussian (normal) distribution for the Weight-for-Height z-scores. This assumption enables us to model both the conditional mean (μ) and the conditional variance (σ²) of the response variable.

The response distribution parameters, μ and σ, are linked to a structured additive predictor, which incorporates various covariates and their effects. We denote the number of children as n (where i = 1,2,…,n) and the location of the primary sampling unit as S (where s = 1,…,S).

The structured additive predictor for the mean (μ_i) can be expressed as:

$$g(\mu_i) = f_1(X_{1i}) + f_2(X_{2i}) + \cdots + f_p(X_{pi}) + f_{spat}(S) + \boldsymbol{X}^T\boldsymbol{\beta} \quad (1)$$

Where:

- $g(\mu_i)$: Link function for the mean, typically the identity function for Gaussian responses.
- $f_j(X_{ji})$: Smooth functions representing non-linear effects of covariates X_j.
- $\boldsymbol{X}^T\boldsymbol{\beta}$: Represents the fixed effect associated with the primary sampling unit S.
- $f_{spat}(S)$: Spatial effect

Similarly, the structured additive predictor for the variance, we can specify:

$$h(\sigma_i) = h_1(Z_{1i}) + h_2(Z_{2i}) + \cdots + h_p(Z_{pi}) + f_{spat}(S) + \boldsymbol{\delta}_s \quad (2)$$

where:

$h(\sigma_i)$: Link function for the variance, often using the log link.

- $h_j(Z_{ji})$: Functions representing the effects of other covariates Z_j.
- $\boldsymbol{\delta}_s$: The variability associated with the primary sampling unit S.

Combining the specifications for the mean and variance, the full BDR model can be represented as follows:

$$Y_i \sim N(\mu_i, {\sigma_i}^2) \quad (3)$$

where μ_i and ${\sigma_i}^2$ are modeled as described in equations (1) and (2), respectively.

By simultaneously modeling both the mean and variance, BDR provides a comprehensive analysis of how socio-economic, demographic, and geographical factors influence not only the average Weight-for-Height z-score but also its variability. This dual modeling enhances our understanding of the distributional characteristics of anthropometric data, revealing potential heterogeneity in effects across different groups and contexts [29].

Prior assumptions:

For the fixed effects parameters, non-informative or diffuse priors are typically employed, such as $\beta_p \sim (0, \sigma^2{}_\beta)$ with a large variance $\sigma^2{}_\beta$. This reflects a lack of strong prior beliefs, allowing the data to predominantly inform the estimates [18]. By using a diffuse prior $p(\boldsymbol{\beta}) \propto const$, the model remains flexible, enabling it to adapt effectively to the underlying data without imposing undue constraints on the parameter estimates [30]. For the coefficients associated with the non-linear effects (f_j), Bayesian P-splines are commonly used [31]. These splines leverage B-spline basis functions to capture complex relationships in the data. The prior for the

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coefficients is specified as:

$$p\left(\boldsymbol{\beta}_j \middle| \tau_j\right) \propto \frac{1}{2\tau_j}\boldsymbol{\beta}'_j K_j \boldsymbol{\beta}_j \tag{4}$$

Here, K_j serves as a penalty matrix that promotes smoothness by penalizing abrupt changes in the spline coefficients, effectively implementing a random walk prior. This structure encourages neighboring coefficients to remain close to one another, thus preventing overfitting and ensuring continuity in the estimated functions. The precision parameter τ_j controls the degree of smoothness. A weakly informative Gamma prior is typically assigned to the precision parameter τ_j:

$$\tau_j \sim Gamma(a_j, b_j) \tag{5}$$

with small values for the shape (a_j) and rate (b_j) parameters (e.g., 0.01). This choice allows the data to significantly influence the smoothness of the functions while incorporating some prior knowledge. Overall, this prior formulation strikes an essential balance between flexibility and regularization, leading to stable and interpretable estimates of the non-linear relationships in the model [32].

In the context of Bayesian Distributional Regression (BDR), spatial effects are introduced to account for the correlation between observations located in connected geographical regions. We denote the index s as representing the location or site within these regions, which are labeled consecutively. A common assumption is that neighboring sites share more similarities than arbitrary sites, necessitating the definition of a neighborhood for each site s. Typically, two sites s and s' are considered neighbors if they share a common boundary. The prior for the spatial effect β_s at site s is modeled using a spatial smoothness prior, which takes the form:

$$\boldsymbol{\beta}_s \,|\boldsymbol{\beta}_{s'}, s \neq s', \tau_j^2 \sim N\left(\frac{1}{N_s}\sum_{s' \in D_s} \beta_{s'}, \frac{\tau_j^2}{N_s}\right) \tag{6}$$

Here, N_s represents the number of adjacent sites, and D_s denotes the set of neighbors for site s. This formulation allows the conditional mean of β_s to be an unweighted average of the function evaluations at neighboring sites. This prior can be interpreted as a direct generalization of a first-order random walk to two dimensions, which is referred to as a Markov random field (MRF) [33, 30].

Bayesian Inference for Distributional Regression

In Bayesian Distributional Regression (BDR), the inference process centers around the posterior distribution. This distribution synthesizes information from prior distributions, which represent our initial beliefs about the parameters, and the likelihood of the observed data, which quantifies how well the model explains the data [18]. The steps involved in deriving the posterior and making subsequent inferences are outlined below.

The likelihood function for Weight-for-Height z-scores, assuming a Gaussian distribution, is given by:

$$p(y_i|\mu_i, \sigma_i^2) = \prod_i p(Y_i|\mu_i, \sigma_i^2) = \prod_i \frac{1}{\sqrt{2\pi\sigma_i^2}} exp\left(-\frac{(y_i - \mu_i)^2}{2\sigma_i^2}\right) \tag{7}$$

Where:

- Y_i represents the Weight-for-Height z-score for the $i-th$ child.
- μ_i is the mean for the $i-th$ child, modeled by the structured additive predictor.
- σ_i^2 is the variance for the $i-th$ child, also modeled by a structured additive predictor.
- X includes socio-economic, demographic, and geographical covariates.
- $\beta, f, \gamma, and\ v$ denote, the fixed effects, smooth functions, spatial effects, and variance parameters, respectively.

The priors for the fixed effects, non-linear effects and spatial effects are specified as in equation (4, 5, 6). Then the **posterior distribution** of the model parameters is expressed by Bayes' theorem by combining the likelihood and the priors, we have:

$$P(\mu, \sigma^2, \beta, f, \gamma, v|Y, X) \propto P(Y|\mu, \sigma^2, \beta, f, \gamma, v) * P(\beta) * P(f) * P(\gamma) * P(v) \tag{8}$$

Due to the often intricate forms of the likelihood and prior distributions in BDR models, direct analytical computation of the posterior distribution is typically infeasible [34].

Markov Chain Monte Carlo (MCMC) Methods

To overcome the challenges of direct posterior computation, **Markov Chain Monte Carlo (MCMC) techniques** are employed to obtain samples from the posterior distribution [35]. Methods such as **Gibbs sampling** or **Metropolis-Hastings** iteratively draw samples from the full conditional distributions of each parameter. Once the posterior distribution is established, inferences about the effects of covariates on the mean and variance of Weight-for-Height z-scores can be drawn. This includes estimating the magnitude and direction of covariate effects, identifying significant predictors for both the mean and variance, visualizing non-linear relationships between covariates and the response, and mapping spatial patterns within the data.

Model selection

Selecting the most suitable statistical model from a set of candidates is a critical step in any data analysis, and within the gamlss framework in R, several tools are available to facilitate this process [29]. Among the most commonly used are the Deviance, the Akaike Information Criterion (AIC), and Schwarz's Bayesian Criterion (SBC), also known as the Bayesian Information Criterion (BIC). The deviance serves as a measure of how well a model fits the observed data, quantifying the discrepancy between the fitted model and a

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perfect fit. A smaller deviance generally suggests a better fit. For nested models, where one model is a specific instance of another, the difference in their deviances can be formally tested using a likelihood ratio test to determine if the increased complexity of the larger model is statistically justified [36].

Mathematically, the deviance (D) is often expressed as:

$$D = -2\left[L(\hat{\boldsymbol{\theta}}|y) - L(\hat{\boldsymbol{\theta}}_{sat}|y)\right] \tag{9}$$

where, $L(\hat{\theta}|y)$ is the log-likelihood of the fitted model with parameter estimates $\hat{\theta}$ given the data y and $L(\hat{\theta}_{sat}|y)$ is the log-likelihood of the saturated model.

To account for model complexity and avoid overfitting, information criteria like the AIC and SBC are employed. The AIC estimates the relative information loss when a particular model is used to approximate the true underlying process, balancing the model's goodness of fit with the number of parameters it estimates [37]. Models with lower AIC values are generally preferred. Similarly, the SBC also aims to strike a balance between fit and complexity but imposes a larger penalty for the number of parameters, particularly with larger datasets [38]. Consequently, the SBC tends to favor simpler models and is often used when the goal is to identify the model with the highest posterior probability of being the true model. The formulas for Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) are expressed as follows:

$$AIC = -2L(\hat{\boldsymbol{\theta}}|y) + 2k \tag{10}$$

$$SBC = -2L(\hat{\boldsymbol{\theta}}|y) + \log(n)\,k \tag{11}$$

where, $L(\hat{\boldsymbol{\theta}}|y)$ is the log-likelihood of the fitted model, k is the number of estimated parameters in the model and n is the number of observations in the data.

Model Diagnosis

Model diagnosis in the Generalized Additive Models for Location, Scale and Shape (GAMLSS) framework relies heavily on the analysis of residuals. The gamlss package in R employs normalized (or randomized, for discrete responses) quantile residuals, which, under correct model specification, are expected to follow a standard normal distribution [39].

Key diagnostic measures and plots include:

- **Residual Mean and Variance:** The mean and variance of the quantile residuals should be approximately 0 and 1, respectively.
- **Skewness and Kurtosis:** These statistics quantify the symmetry and tail heaviness of the residual distribution. Departures from zero skewness and a kurtosis of 3 indicate deviations from normality.
- **Quantile-Quantile (Q-Q) Plots:** These plots visually assess the agreement between the empirical distribution of the residuals and the theoretical normal distribution. The Filliben correlation coefficient measures the linearity of the Q-Q plot, with values close to 1 indicating a good fit.
- **Residual Plots:** Plotting residuals against fitted values and covariates can reveal patterns indicative of model misspecification, such as non-constant variance or non-linear relationships.

By examining these diagnostics, researchers can evaluate the adequacy of the chosen distributional family and the functional forms of the predictors in a GAMLSS model [29].

Results

This study investigates the socio-economic, demographic, and environmental determinants of Weight-for-Height Z-Scores (WHZ) using Bayesian Distributional Regression. We employ the Bayesian Generalized Additive Models for Location, Scale, and Shape (GAMLSS) framework, implemented with the gamlss package in R 4.3.2, to model both the mean and dispersion of WHZ. This Bayesian approach enhances the precision of estimates and accounts for population heterogeneity. Markov Chain Monte Carlo (MCMC) methods are used to estimate the conditional meaning and variance, and flexible smoothing functions capture complex relationships. Model performance is evaluated using diagnostics and fit criteria, including the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC).

Exploratory data analysis of Factors Influencing the Weight-for-Height Z-Scores

Figure 1 presents a compelling visualization of the regional disparities in mean Weight-for-Height Z-scores (WHZ) across Ethiopia, revealing significant variations in child wasting. Notably, the Somali region exhibits the lowest mean WHZ, substantially below all other regions, indicating a severe and alarming prevalence of acute malnutrition. This stark contrast underscores the urgent need for targeted interventions in this area. The Gambella and Afar regions also display concerningly low mean WHZ values, suggesting that these areas are home to particularly vulnerable populations requiring targeted nutritional support.

In contrast, Addis Ababa, the capital city, demonstrates the highest means of WHZ, potentially reflecting better access to healthcare, nutrition services, and higher socioeconomic status when compared to other regions. The remaining regions, including Benishangul-Gumuz, Amhara, Tigray, Dire Dawa, SNNPR, Harari, and Oromia, exhibit moderate levels of wasting, with mean WHZ values falling between these extremes.

These findings highlight the critical need for region-specific strategies to address malnutrition, considering the unique challenges and contexts of each area. Furthermore,

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while this exploratory analysis provides a valuable overview, a deeper investigation into the underlying causes of these disparities, such as socioeconomic factors, access to resources, and environmental conditions, is crucial for developing effective interventions and improving child nutritional outcomes across Ethiopia.

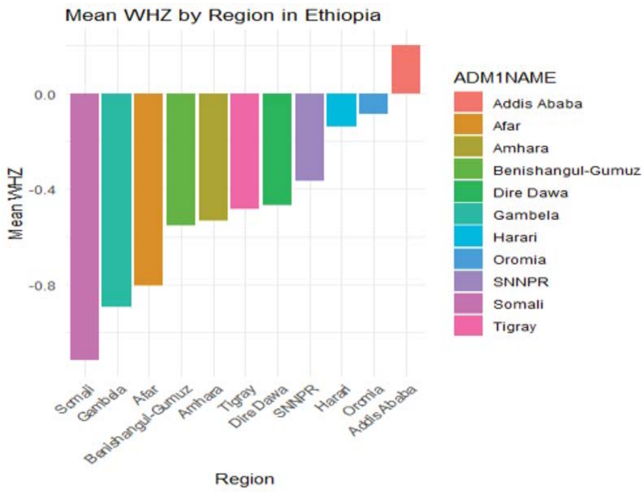

Figure 1: Regional Variation in Child Wasting (WHZ) in Ethiopia

Figure 2 presents a compelling spatial visualization of child wasting across Ethiopia, where Weight-for-Height Z-scores (WHZ) is used to illustrate regional disparities. The map effectively demonstrates a clear spatial gradient, where darker blue hues indicate regions with lower WHZ values and consequently, higher levels of wasting; lighter shades, transitioning to yellow, signify regions with higher WHZ values and lower wasting. Notably, the southern and eastern regions of Ethiopia are predominantly shaded in darker blue, signaling a higher prevalence and severity of child wasting within these areas. This finding is particularly consistent with the previous bar chart (Figure 1), which identified the Somali region, located in the east, as having the lowest mean WHZ.

Conversely, the central and northern regions exhibit lighter shades, suggesting comparatively better nutritional outcomes for children. The presence of a grey area in the northwest denotes a region where data were not collected, emphasizing a limitation in complete national coverage. Overall, this spatial representation underscores the critical need for targeted interventions, particularly in the southern and eastern regions, to address the geographically clustered nature of child wasting in Ethiopia and highlights the importance of considering regional factors when developing public health strategies.

The histogram presented in Figure 3, provides a visual representation of the distribution of Weight-for-height z-scores (WHZ), a crucial metric for assessing child wasting, within the dataset. The histogram demonstrates a roughly symmetrical, bell-shaped distribution centered around zero.

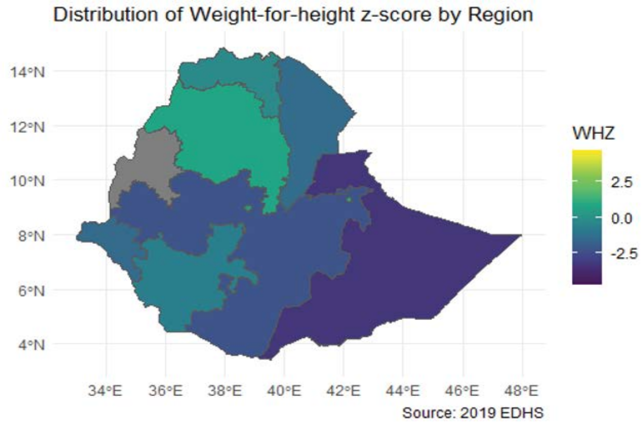

Figure 2: Spatial Distribution of Child Wasting (WHZ) Across Ethiopian Regions

The distribution shows a slight positive skew, with a longer tail extending towards the negative z-scores, implying a higher prevalence of children with lower WHZ (potential wasting) compared to those with higher WHZ (potential overweight). The superimposed red curve, representing the density estimate, closely follows the shape of the histogram, reinforcing the visual assessment of the distribution's central tendency and spread. Overall, the histogram suggests a distribution that is approximately normal, with a slight skew towards lower WHZ values, highlighting the presence of children with potential wasting within the studied population.

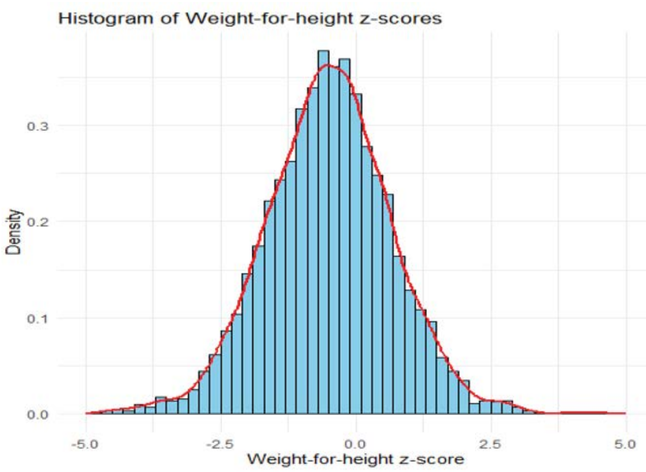

Figure 3: WHZ Distribution: A Near-Normal Curve

Model comparison

The results presented in Table 2 highlight the importance of incorporating relevant predictors to enhance the model's ability to explain variations in Weight-for-Height Z-scores (WHZ). The null model (Model 1), lacking any predictors, exhibits the poorest fit with the highest Global Deviance (15012.66), AIC (15016.66), and SBC (15029.6). This underscores the necessity of considering influencing factors when modeling WHZ. Model 2, which includes the mean

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sub model (ημ) but does not explicitly model dispersion, significantly improves fit, reducing Global Deviance to 14154.67 and AIC to 14222.68, suggesting that accounting for mean effects enhances the model's ability to capture variations in WHZ. Model 3, which incorporates both mean and dispersion sub models (ημ and σ), achieves the best fit, with the lowest Global Deviance (13864.56), AIC (13996.56), and SBC (14423.71). This indicates that modeling both the mean WHZ and its variability provides a more precise representation of nutritional disparities. The inclusion of dispersion effects allows the model to account for heterogeneity in WHZ scores across the population, highlighting differences in nutritional stability rather than just central tendencies. Therefore, Model 3 is the preferred model as it provides the most comprehensive and accurate representation of both central tendencies and the spread of Weight-for-Height Z-scores.

Table 2: Model Fit Comparison Using Deviance, AIC, and SBC

Model	Global Deviance	AIC	SBC
Model 1(null model)	15012.66	15016.66	15029.6
Model 2 Mean model (ημ) (Does *not* include a dispersion (sigma) model)	14154.67	14222.68	14442.73
Model 3 Mean model (ημ) and dispersion (sigma) model)	13864.56	13996.56	14423.71

Factors Influencing the Mean Weight-for-Height Z-Scores (μ)

The Generalized Additive Model for Location, Scale, and Shape (GAMLSS), employing a normal distribution, revealed significant relationships between various socio-economic, demographic, and environmental factors and child Weight-for-Height Z-scores (WHZ), a key indicator of wasting. The results, summarized in Table 3, highlight several crucial determinants of child nutritional status as described below. The model intercept (-0.493) is statistically significant and serves as the predicted baseline value of the outcome variable before accounting for covariates.

Maternal Education: Children whose mothers had secondary (edu_sec) or higher education (edu_high) exhibited significantly higher WHZ compared to those with uneducated mothers. Specifically, having a mother with secondary education led to an average increase of 0.140 in WHZ (95% CI: 0.022, 0.259), while having a mother with higher education resulted in an average increase of 0.166 in WHZ (95% CI: 0.023, 0.309). This underscores the protective role of maternal education in improving child nutritional outcomes.

Household Wealth: Economic status significantly impacted WHZ. Children from wealthier households demonstrated substantially higher WHZ. Compared to the poorest wealth quintile, children from middle-income (wealth_mid), rich (wealth_rich), and richest (wealth_richest) households had significantly higher average WHZ. For example, children in the richest households had an average WHZ increase of 0.233 (95% CI: 0.122, 0.345). This emphasizes the critical role of economic resources in mitigating child wasting.

Child Age (cs(C_age)): Child age showed a negative relationship with WHZ, indicating that younger children are more vulnerable to wasting. The smooth term "cs(C_age)" suggests a non-linear relationship, with a notable decrease in WHZ observed in younger age groups. For each unit increase in the smooth term related to age, WHZ decreased by approximately 0.006 (95% CI: -0.008, -0.004).

Malaria Incidence (cs(Malaria_Incidence_2020)): Areas with higher malaria incidence were associated with significantly lower WHZ. Specifically, for each unit increase in the smooth term related to malaria incidence, WHZ decreased by 0.746 (95% CI: -1.19, -0.302). This highlights the detrimental impact of malaria on child nutritional status.

Population Density (cs (UN_Population_Density_2020)): Higher population density was positively associated with WHZ. Specifically, for each unit increase in the smooth term related to population density, WHZ increased by 0.038 (95% CI: 0.010, 0.067). This suggests that greater population density may correlate with improved access to healthcare and resources, potentially benefiting child nutrition.

Mean Temperature (cs (Mean_Temperature_2020)): Elevated mean temperatures were linked to lower WHZ. For each unit increase in the smooth term related to mean temperature, WHZ decreased by 0.062 (95% CI: -0.077, -0.047). This suggests that environmental factors like temperature may negatively impact child nutrition, possibly through effects on food security and disease prevalence.

Water Source (water source): While the estimate for water source was negative, it was not statistically significant (95% CI: -0.076, 0.060), suggesting that access to clean water, as represented by this variable, did not significantly affect WHZ in this model.

The analysis highlights the pivotal roles of maternal education, household wealth, child age, malaria incidence, population density, and environmental factors in shaping child nutritional outcomes in Ethiopia.

Factors Influencing the Variability of Weight-for-Height Z-Scores (σ)

Beyond the meaning, the analysis explored factors influencing the variability (σ) of weight-for-height z-scores. The sigma (σ) model, presented in Table 4, examines the

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Table 3: Mean Effects on WHZ

	Parameter	Estimate	Std.Error	95% CI
	(Intercept)*	-0.493	0.017	(-0.526, -0.46)
Linear effect	Child’s Sex (ref.= Female)	-	-	-
	Male	0.057	0.038	(-0.016, 0.132)
	Mother's education (ref = No edu.)	-	-	-
	Primary	0.054	0.036	(-0.016, 0.124)
	Secondary*	0.140	0.060	(0.022, 0.259)
	Higher*	0.166	0.073	(0.023, 0.309)
	Wealth Index (ref=Poorest)	-	-	-
	Poorer	0.062	0.049	(-0.034, 0.157)
	Middle*	0.109	0.051	(0.009, 0.209)
	Rich*	0.236	0.056	(0.126, 0.347)
	Richest*	0.233	0.057	(0.122, 0.345)
	Water source (ref=Improved)	-	-	-
	Unimproved	-0.008	0.035	(-0.076, 0.060)
Non-linear effect	Child age cs(C_age)*	-0.006	0.001	(-0.008, -0.004)
	Maternal Body Mass Index (BMI)*	0.000	0.000	(0.000, 0.000)
	cs(Malaria Incidence)*	-0.746	0.226	(-1.19, -0.302)
	cs(Precipitation)	-0.000	0.001	(-0.002, 0.001)
	cs(Population Density)*	0.038	0.014	(0.010, 0.067)
	cs(Mean Temperature)*	-0.062	0.008	(-0.077, -0.047)

The reference category is denoted as ref. The significant categories are indicated by ∗, identified by the non-inclusion of zero in the confidence interval (95%CI).

factors influencing the variability or spread of Weight-for-Height Z-scores (WHZ), providing insights into the consistency of child nutritional status across different population groups. The **sigma coefficients** in this model provide insights into the factors influencing the variability of **Weight-for-Height Z-Scores (WHZ)** among children. The **intercept (0.152, 95% CI: 0.132–0.172)** represents the baseline level of WHZ dispersion, suggesting moderate variability across the population.

Maternal Education: Higher levels of maternal education were associated with a significant reduction in the variability of WHZ. Specifically, having primary (edu_pri) or higher education (edu_high) significantly decreased the spread of WHZ. Children of mothers with primary education showed a decrease in WHZ variability by 0.073 (95% CI: -0.121, -0.025), and those with higher education showed a decrease by 0.122 (95% CI: -0.224, -0.021). This suggests that educated mothers provide more consistent care and nutritional practices, leading to more uniform WHZ outcomes among their children.

Household Wealth: The middle wealth quintile (wealth_mid) was associated with a significant decrease in WHZ variability, with a reduction of 0.101 (95% CI: -0.172, -0.029). This indicates that children from middle-income households exhibit more consistent nutritional status compared to those from poorer or richer households, suggesting a stabilizing effect of moderate wealth.

Child Age (cs(C_age)): Child age displayed a significant negative relationship with WHZ variability. For each unit increase in the smooth term related to age, the variability of WHZ decreased by 0.006 (95% CI: -0.007, -0.005). This implies that younger children exhibit higher variability in WHZ, suggesting that their nutritional status is more heterogeneous and potentially more sensitive to environmental and caregiving variations.

Malaria Incidence (cs (Malaria_Incidence_2020)): Higher malaria incidence was associated with a significant decrease in WHZ variability, with a reduction of 0.539 (95% CI: -0.849, -0.228). This suggests that malaria-prone areas exhibit less variability in WHZ, potentially indicating a uniformly negative impact on child nutritional status.

Population Density (cs (UN_Population_Density_2020)): Higher population density was associated with an increase in WHZ variability. For each unit increase in the smooth term related to population density, the variability of WHZ increased by 0.035 (95% CI: 0.015, 0.054). This suggests that densely populated areas exhibit more fluctuations in WHZ, possibly due to diverse socio-economic and environmental conditions.

Mean Temperature (cs (Mean_Temperature_2020)): Higher mean temperatures were associated with an increase in WHZ variability. For each unit increase in the smooth term related to mean temperature, the variability of WHZ increased by 0.018 (95% CI: 0.008, 0.028). This indicates that areas

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with higher temperatures exhibit more heterogeneous WHZ outcomes, potentially due to varied impacts of climate on food security and health.

In summary, the sigma model highlights that maternal education and moderate household wealth are crucial for reducing the variability of WHZ, leading to more consistent nutritional outcomes. Child age, malaria incidence, population density, and mean temperature significantly influence the spread of WHZ.

Table 4: Dispersion (variance) Effects on Weight-for-Height Z-Scores (WHZ)

Parameter	Estimate	Std.Error	95% CI
(Intercept)*	0.152	0.01	(0.132, 0.172)
Child's Sex (ref.= Female)	-	-	-
Male	0.222	0.027	(-0.031, 0.075)
Mother's education (ref=No edu.)	-	-	-
Primary	-0.073	0.025	(-0.121, -0.025)
Secondary*	-0.059	0.041	(-0.140, 0.020)
Higher*	-0.122	0.052	(-0.224, -0.021)
Wealth Index (ref=Poorest)	-	-	-
Poorer	0.012	0.033	(-0.052, 0.076)
Middle*	-0.101	0.036	(-0.172, -0.029)
Rich*	0.013	0.039	(-0.062, 0.089)
Richest*	-0.015	0.038	(-0.090, 0.061)
Water source (ref=Improved)	-	-	-
Unimproved	-0.034	0.023	(-0.080, 0.011)
Child age cs(C_age)*	-0.006	0.001	(-0.007, -0.005)
Maternal Body Mass Index cs(BMI)	0.000	0.000	(-0.000, 0.000)
cs(Malaria_ Incidence_2020)*	-0.539	0.158	(-0.849, -0.228)
cs(Precipitation_2020)	-0.000	0.000	(-0.001, 0.001)
cs(UN_Population_ Density_2020)*	0.035	0.010	(0.015, 0.054)
cs(Mean_ Temperature_2020)*	0.018	0.005	(0.008, 0.028)

The reference category is denoted as ref. The significant categories are indicated by ∗, identified by the non-inclusion of zero in the confidence interval (95%CI).

Non- linear effects

Figure 4 reveals nuanced non-linear effects of key predictors on child malnutrition, as indicated by the Weight-for-Height Z-scores (WHZ). Notably, younger children exhibit a steeper decline in mean WHZ, suggesting increased vulnerability to stunting or wasting during early developmental stages. Conversely, areas with elevated mean temperatures demonstrate a negative association with WHZ, potentially reflecting climate-related impacts on food security and health. Precipitation displays a complex, non-linear relationship with WHZ, hinting at a potential optimal range for child nutritional outcomes. Interestingly, higher population density correlates with improved WHZ, possibly due to enhanced access to essential services.

In summary, these plots suggest that child age, mean temperature, precipitation, and population density all have non-linear effects on the mean of WHZ, highlighting the complexity of factors influencing child malnutrition.

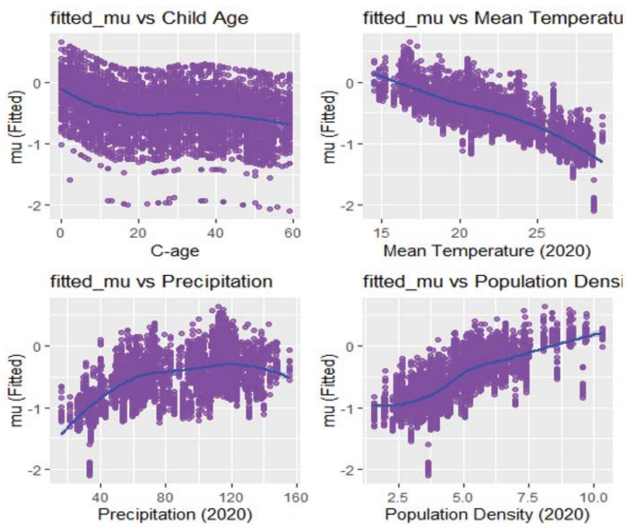

Figure 4: Non-Linear Effects on Child WHZ

Figure 5 shows that the variability in child malnutrition, as reflected by the fitted sigma of WHZ scores, is significantly influenced by non-linear relationships with key environmental and demographic factors. Notably, child age exhibits a profound inverse association with sigma, indicating a heightened heterogeneity in WHZ among younger children, potentially stemming from diverse developmental trajectories. While mean temperature and precipitation display subtler, yet discernible, impacts on WHZ variability, population density demonstrates a complex U-shaped relationship, suggesting that both sparse and moderately populated regions experience greater variability compared to densely populated areas. These findings underscore the necessity for nuanced, context-specific interventions that account for the diverse factors contributing to the spread of malnutrition within a population.

Spatial Effects on Mean and Variance of Weight-for-Height Z-scores

The spatial GAMLSS model presented in Table 5 reveals substantial regional disparities in Weight-for-Height Z-scores (WHZ) across Ethiopia, highlighting geographic influences on child nutritional status. The intercept (0.19996) represents the baseline WHZ for the reference region (Addis Ababa), with several regions showing significantly lower average

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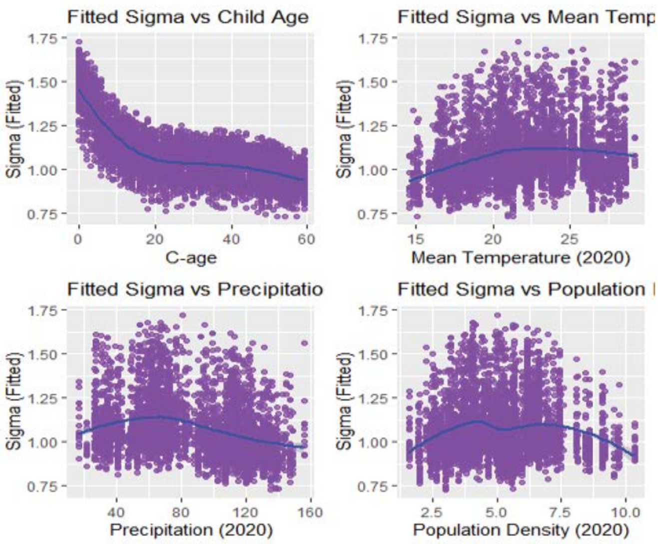

Figure 5: Effects of non-linear Predictors on WHZ Standard Deviation (Sigma)

WHZ scores. Specifically, Afar, Amhara, Benishangul-Gumuz, Dire Dawa, Gambela, Harari, Oromia, SNNPR, Somali, and Tigray exhibit statistically significant negative effects. Among them, Somali (-1.31841) records the largest decline, indicating severe nutritional challenges compared to the reference region. These pronounced regional variations emphasize the spatial heterogeneity of child malnutrition in Ethiopia, reinforcing the need for localized nutrition programs and targeted policy interventions.

Beyond regional differences in mean WHZ, the model also assesses WHZ variability, capturing disparities within each area. The intercept (0.012125) for the variance equation represents the baseline log standard deviation of WHZ. Several regions show higher dispersion in WHZ, with Afar (0.146681), Oromia (0.117233), SNNPR (0.118879), and Somali (0.168380) demonstrating statistically significant increases in variance. This indicates that, beyond lower average nutritional scores, these regions experience greater inequality in child nutrition, with wider disparities in WHZ outcomes.

Table 5: Spatial Effects on Mean and Variance of WHZ

Region	Mean Estimate	Mean Std. Error	Mean 95% CI	Variance (σ) Estimate	Variance Std. Error	Variance (σ) 95% CI
Intercept	0.200	0.063	(0.076, 0.323)	0.012	0.044	(-0.074, 0.099)
Afar	-1.006	0.080	(-1.162, -0.851)	0.147	0.053	(0.043, 0.250)
Amhara	-0.731	0.080	(-0.888, -0.574)	0.054	0.055	(-0.054, 0.161)
Benishangul-Gumuz	-0.754	0.079	(-0.909, -0.598)	-0.002	0.055	(-0.110, 0.107)
Dire Dawa	-0.669	0.084	(-0.834, -0.505)	0.041	0.058	(-0.072, 0.154)
Gambela	-1.092	0.091	(-1.270, -0.915)	0.067	0.061	(-0.053, 0.187)
Harari	-0.339	0.084	(-0.504, -0.174)	0.094	0.057	(-0.017, 0.205)
Oromia	-0.288	0.077	(-0.439, -0.137)	0.117	0.052	(0.015, 0.219)
SNNPR	-0.565	0.084	(-0.731, -0.400)	0.119	0.056	(0.009, 0.228)
Somali	-1.318	0.083	(-1.481, -1.156)	0.168	0.054	(0.062, 0.275)
Tigray	-0.686	0.083	(-0.848, -0.524)	0.092	0.056	(-0.017, 0.201)

The significant categories are identified by the non-inclusion of zero in the confidence interval (95%CI).

Model diagnosis

Figure 6, combined with the quantile residual summary presented in Table 6, indicate a reasonably well-fitting model. The scatterplots of residuals against fitted values and index show random distribution, suggesting sound linearity and independence. The near-zero mean and unit variance of the residuals, alongside a high Filliben correlation coefficient (0.999), confirm a strong fit. The density and Q-Q plots presented in Figure 6 depict a near-normal distribution, with slight tail deviations. The skewness and kurtosis coefficient shown in Table 6 are close to ideal values, further validating the fit. The model's overall adequacy is supported, allowing for reliable inference with potential refinement through robust methods.

Table 6: Summary of the Quantile Residuals

Statistic	Value
mean of Quantile Residuals	0.0005920541
Variance of Quantile Residuals	1.000209
Coefficient of Skewness	-0.02080211
Coefficient of Kurtosis	3.427885
Filliben Correlation Coefficient	0.9990684

Discussion

This study employed Bayesian Distributional Regression (BDR) to provide a comprehensive analysis of the factors influencing child wasting in Ethiopia, using data from the 2019 EDHS. The BDR framework, by modeling the full

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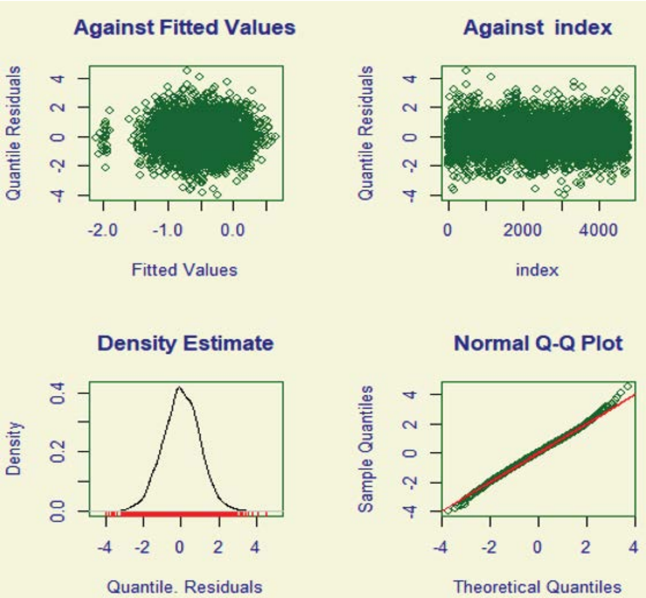

Figure 6: Quantile Residual Plots and Summary Statistics

distribution of Weight-for-Height Z-scores (WHZ), offered insights beyond traditional mean-focused regression, revealing complex relationships between socio-economic, demographic, and geographical covariates and child nutritional status.

The exploratory data analysis revealed significant regional disparities in WHZ, with the Somali region exhibiting alarmingly low mean WHZ, highlighting the urgent need for targeted interventions. These findings are consistent with previous studies that have emphasized the geographical clustering of malnutrition in Ethiopia [6]. The spatial visualization further emphasized this, highlighting the southern and eastern regions as areas of heightened vulnerability.

The BDR analysis identified several key determinants of WHZ. Notably, maternal education and household wealth emerged as strong predictors of improved child nutritional status. These results align with previous research indicating the protective role of socio-economic factors in mitigating child wasting [3, 4]. The significant negative association between child age and WHZ underscores the vulnerability of younger children, consistent with findings by [11].

Moreover, the study revealed the detrimental impact of malaria incidence on WHZ, highlighting the need for integrated health interventions. These findings align with previous research that highlights malaria infection as a major factor contributing to childhood malnutrition. By inducing fever, diminishing appetite, and disrupting nutrient absorption, malaria exacerbates the risk of wasting and other forms of under-nutrition, reinforcing the need for comprehensive health strategies [10]. Environmental factors, especially mean temperature, were found to have a significant impact on WHZ. Higher temperatures were linked to lower mean WHZ and greater variability, potentially indicating climate-related effects on food security and health. This study aligns with previous research highlighting temperature as a crucial environmental determinant with intricate connections to malnutrition. Research has demonstrated that rising temperatures can adversely affect crop yields, reduce food availability and increasing nutritional deficiencies [8].

The analysis of the sigma model, which examined the variability of WHZ, provided further insights into the consistency of child nutritional status. Maternal education and moderate household wealth were found to reduce WHZ variability, suggesting more equitable nutritional outcomes in these groups. Child age, malaria incidence, population density, and mean temperature significantly influenced the spread of WHZ, emphasizing the need for nuanced, context-specific interventions.

Conclusion

This study investigated the multifaceted determinants of child wasting in Ethiopia using a Bayesian Distributional Regression (BDR) approach on data from the 2019 Ethiopian Demographic and Health Survey (EDHS). Moving beyond traditional mean-focused analyses, BDR allowed for a detailed examination of how socio-economic, demographic, and geographical factors influence the entire distribution of Weight-for-Height Z-scores (WHZ). The analysis revealed significant regional disparities in WHZ, with the Somali region exhibiting the highest levels of wasting. Key determinants of improved child nutritional status included maternal education and household wealth, while younger child age and higher malaria incidence were associated with increased wasting. Additionally, higher mean temperatures were found to negatively impact WHZ. These results underscore the complex interplay of factors contributing to child malnutrition in Ethiopia and highlight the need for targeted, region-specific interventions that integrate socio-economic development, health initiatives, and climate change mitigation strategies to effectively address this critical public health issue.

Authors' Contributions

FGH: Conceptualization, Methodology, Investigation, Software, Data curation, Formal analysis, Visualization, Write draft and final manuscript.

BGA: Supervision, Methodology, Formal analysis, Editing draft and final manuscript.

All authors have read and approved the final manuscript.

Availability of Data and Materials

The data we used for this analysis are publicly available through the MEASURE DHS initiative, which you can find

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at *www.measuredhs.com*. The dataset can be accessed and downloaded freely after describing the study's goals

Declarations

Ethics approval and consent to participate

Not applicable.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. World Health Organization (WHO). Global Nutrition Report 2017: Nourishing the SDGs (2017).
2. World Health Organization (WHO). World Health Statistics 2021: Monitoring Health for the SDGs (2021).
3. Tadesse A W, Siraj E S, and Negeri E E. Determinants of child malnutrition in Ethiopia: Evidence from the 2016 Ethiopian Demographic and Health Survey. BMC Public Health 20 (2020): 1-10.
4. Abebe Y, Sommerfelt H, and номад S W. Household wealth and maternal education as determinants of child nutritional status in Ethiopia. Maternal & Child Nutrition 15 (2019): 12652.
5. Berhe K K, Gebremichael T G, Gidey K, et al. Household wealth index and its association with child undernutrition in Ethiopia: Evidence from the 2016 Ethiopian Demographic and Health Survey. BMC Pediatrics 20 (2020): 1-9.
6. Anley M, and Gebremedhin S. Access to safe drinking water and its association with child malnutrition in Ethiopia: Evidence from the 2016 EDHS. Journal of Water and Health 19 (2021): 1-12.
7. G. T. M. A, Smith J, Johnson L, et al. Drought and child malnutrition in Ethiopia: A threshold effect analysis. Environmental Research Letters 15 (2020): 124001.
8. Wheeler T, and von Braun J. Climate change impacts on global food security. Science 341 (2013): 508-513.
9. Grover S, Ebi K L, and Hales S. The influence of climate change on vector-borne infectious diseases. Annual Review of Public Health 33 (2012): 69-82.
10. Gebresilassie A, Ali A, annd Awel H. Temperature and malaria incidence in Ethiopia: A time-series analysis. Malaria Journal 18 (2019): 1-12.
11. Tamiru D, Abebe Y, Tesfaye R, et al. Age and child malnutrition: A study of wasting in Ethiopia. Nutrients 14 (2022): 1000.
12. Melaku T, Desta A, Teshome A, et al. Maternal age and child nutrition outcomes in Ethiopia: A cross-sectional study. BMC Nutrition 5 (2019): 1-9.
13. Assefa N, and Demissie T. Gender differences in child malnutrition in Ethiopia: Evidence from the 2016 EDHS. BMC Public Health 19 (2019): 1-10.
14. Baird S J, Ferreira F H G, Özler B, et al. The impact of cash transfers on child nutrition in low-income countries: A systematic review. Journal of Development Studies 52 (2016): 1131-1146.
15. Ghosh-Jerath S, Singh A, and Kumar P. Non-linear relationships between socio-economic factors and malnutrition outcomes: Evidence from India. Public Health Nutrition 20 (2017): 1825-1834.
16. Hollander M, Wolfe D A, and Chicken E. Nonparametric statistical methods. John Wiley & Sons (2014).
17. Kirkpatrick S I, Lachat C, and Moubarac J C. Skewed distributions of dietary intake data: Implications for nutrition research and policy. American Journal of Clinical Nutrition 110 (2019): 1-3.
18. Gelman A, Carlin J B, Stern H S, et al. Bayesian data analysis. CRC press (2013).
19. Kearney J M, McCarthy S N, and McGowan L. Spatial patterns of malnutrition in children: A global perspective. Global Health Action 11 (2018): 1-10.
20. Central Statistical Agency (CSA), ICF. Ethiopia Demographic and Health Survey 2019. Addis Ababa: CSA and ICF (2019).
21. WorldClim. WorldClim: Global climate data (2023).
22. Malaria Atlas Project (MAP). Malaria Atlas Project data (2023).
23. WorldPop. WorldPop: High-resolution population data (2023).
24. Klein N, Kneib T, Lang S, et al. Bayesian distributional regression: A flexible framework for modeling complex data. Statistical Modelling 15 (2015): 421-445.
25. Fahrmeir L, and Lang S. Bayesian regression analysis. In Handbook of Statistics Elsevier 21 (2001): 1-30.
26. Rue H and Held L. Gaussian Markov Random Fields: Theory and Applications. CRC Press (2005).
27. Klein N, Kneib T, Lang S, et al. Bayesian methods for health data analysis: A review. International Journal of Statistics in Medical Research 2 (2013): 1-19.
28. Czado C, Delwarde A, and Klein N. Bayesian modeling and inference for life sciences. Springer Science & Business Media (2012).
29. Rigby R A, and Stasinopoulos D M. Generalized additive models for location, scale and shape. Journal of the Royal Statistical Society: Series C (Applied Statistics) 54 (2005): 507-554.

Habtewold FG and Arero BG., J Psychiatry Psychiatric Disord 2025
DOI:10.26502/jppd.2572-519X0265

30. Lang S, and Brezger A. Bayesian P-spline regression models. Journal of Computational and Graphical Statistics 13 (2004): 183-212.

31. Eilers P H C, and Marx B D. Flexible smoothing with B-splines and penalties. Statistical Science 11(1996): 89-121.

32. Fahrmeir L, Kneib T, Lang S, et al. Regression: Models, methods and applications. Springer Science & Business Media (2010).

33. Besag J. Spatial interaction and the statistical analysis of lattice systems. Journal of the Royal Statistical Society. Series B (Methodological) 36 (1974): 192-236.

34. Congdon P. Applied Bayesian Modelling. John Wiley & Sons (2015).

35. Robert C P, Casella G. Monte Carlo statistical methods. Springer Science & Business Media (2004).

36. Dobson A J, Barnett A G. An introduction to generalized linear models (4th ed.). CRC Press (2018).

37. Akaike H. A new look at the statistical model identification. IEEE Transactions on Automatic Control 19 (1974): 716-723.

38. Schwarz G. Estimating the dimension of a model. The Annals of Statistics 6 (1978): 461-464.

39. Dunn P K, Smyth G K. Randomized quantile residuals. Journal of Computational and Graphical Statistics 5 (1996): 236-244.