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Analysis of social and economic factors influencing overweight and obesity among women of childbearing age in Nigeria: A GAMLSS approach

Omolola Olubukola Fadugba [a,*], Ezra Gayawan [a], Osafu Augustine Egbon [b]

[a] Department of Statistics, Federal University of Technology Akure, Nigeria
[b] Institute of Mathematical and Computer Sciences, Universidade de São Paulo, São Carlos, Brazil

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ABSTRACT

The rising prevalence of overweight and obesity among women of reproductive age presents significant public health challenges, particularly in low and middle income countries. Utilizing data from the 2018 Nigeria Demographic and Health Survey (NDHS), this research employed a Generalized Additive Model for Location, Scale, and Shape (GAMLSS) alongside with reparameterized Marshall–Olkin distribution within the quantile regression framework to analyze the relationships between the response variable Body Mass Index (BMI) and various predictor. The findings reveal that higher levels of education, wealth, employment status, and advancing age are significant predictors influencing BMI, while urban residence did not show a consistent effect. Access to improved water, sanitation, and electricity was associated with a lower risk of obesity. Additionally, media exposure, particularly television was strongly linked to higher BMI, indicating potential behavioral and lifestyle choice. The integration of spatial analysis reveals substantial regional disparities in overweight and obesity prevalence. These findings underscore the pivotal role of public health policies in mitigating socioeconomic disparities and regional variations, thereby guiding the development of more targeted and effective obesity prevention strategies among women of reproductive age in Nigeria.

Introduction

Overweight and obesity are among the major public health burdens faced by both developed and developing countries [1,2]. Obesity is characterized by the excessive storage of fat in the body resulting from an individual's inability to properly expend the energy consumed [3]. The validity of using Body Mass Index (BMI) as a measure of overweight and obesity in accordance with the standard established by the World Health Organization (WHO) was explored by Karchynskaya (2020). BMI is estimated by dividing a person's weight in kilograms by the square of their height in meters. Overweight is classified as having BMI $> 25\,\text{kg/m}^2$ while obesity is characterized by BMI exceeding $> 30\,\text{kg/m}^2$ [4]. According to the 2021 Global Nutrition Report, approximately 2.2 billion adults worldwide are burdened with overweight and obesity. Among this vast population, 772 million are classified as obese, with women of reproductive age accounting for about 40.8 percent of those affected [5,6].

Overweight and obesity among women of childbearing age are driven by different factors. Fabunmi et al. [7] highlighted that these conditions result from an imbalance between energy intake and expenditure where excess caloric intake is not efficiently metabolized into usable energy. Several factors contribute to this energy imbalance among them are modifications in dietary

* Corresponding author.
E-mail address: fadugbaoo@futa.edu.ng (O.O. Fadugba).

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habits, sedentary lifestyle, excessive alcohol consumption, and smoking [8]. Other factors include environmental conditions [9], social dynamics [10], demographic characteristics [11], and cultural influences [12]. Studies have shown that overweight and obesity in women of childbearing age are closely associated with a heightened risk of infertility and hormonal imbalances [13], breast cancer [14,15], coronary heart disease [16], and various pregnancy-related complications such as type II diabetes mellitus, hypertension, hemorrhage, and eclampsia [17,18], as well as metabolic disorders. The World Health Organization (WHO) has classified being overweight and obese as the fifth probable cause of death globally [19]. The prevalence of overweight and obesity has exhibited a consistent upward trend globally over the past four decades and this trend is mirrored in African nations like Nigeria where similar increases have been observed compared to those witnessed in developed countries posing a critical public health challenge [20].

Numerous researchers have demonstrated the efficacy of various modeling techniques in epidemiological studies. Manickam et al. [21] used fractional-order mathematical models to capture intricate disease dynamics and provide deeper insights into progression patterns and control strategies. Malar et al. [22] explored the modeling of disease epidemics using the Caputo–Fabrizio fractional derivative and emphasized the significance of this mathematical approach. Onyeji and Sanusi [23], Chukwuonye et al. [24] used statistical modeling techniques to analyze and address the complexities of overweight and obesity among women of reproductive age in Nigeria. Among these modeling methodologies, linear regression is recognized as one of the most widely used tools and has been applied to examine the influence of covariates and spatial variability [25–28]. It assumes that covariate effects and regression coefficients remain constant across the entire population. However, these approaches exhibit limitations in accurately capturing variable relationships particularly in distribution's extreme upper and lower tails. Additionally, linear regression assumes that the error term follows a normal distribution. When this assumption is violated, such as in datasets with heavy tails or outliers, the resulting estimates become less robust and efficient

Due to the limitations of mean regression, there has been an increasing interest in exploring quantile regression [29]. Originally introduced by [30], quantile regression is a statistical technique used to estimate the conditional quantile of a response variable (Y) given a set of covariates (X), offering a more flexible and comprehensive analysis of data distribution. It is widely recognized for its robustness against outliers and provides a detailed exploration of how different covariates influence the entire conditional distribution of the response variable [31]. The method has been widely employed in overweight and obesity research by numerous Scholars. Lee et al. [32] examined the impact of various determinants of overweight and obesity among Paraguayan adults using quantile regression. Ouyang et al. [33] applied quantile regression to examine shifts in adult BMI distributions, highlighting how various predictors influenced BMI quantiles over time. Oyedapo-Ishola et al. [34] employed quantile regression techniques to analyze BMI determinants and provides comprehensive insights into their effects across different segments of the distribution among women of reproductive age in Nigeria. A study by [35] examined various distributions within the framework of parametric quantile regression models. These distributions demonstrated superior capability in capturing data characteristics such as skewness and kurtosis, a crucial factors in the analysis of health metrics and economic data, where a coherent progression of quantile estimates are essential for accurate interpretation. Enhancing distributions flexibility to accommodate a broader range of shapes and characteristics is vital for diverse applications. Marshall and Olkin [36] proposed an approach for incorporating additional parameters into an existing distributions, thereby improving their adaptability to complex data structures. These parameters facilitate a more nuanced representation of data characteristics thereby enhancing model performance and interpretability. Additionally, it broadens the scope of the models making them more adaptable to diverse data structures.

Understanding the geographical patterns of overweight and obesity among women of reproductive age is essential for developing targeted intervention strategies that increase the awareness of associated risk factors [37]. Few studies have addressed spatial dependency when evaluating the prevalence and risk factors of overweight and obesity among women of childbearing age in Nigeria. Ezenweke et al. [38] employed a structured Geo-additive semi-parametric binary logistic regression model to examined the association between risk factors of overweight and obesity, incorporating spatial effects at the state level to account for geographic disparities. However, this approach lack flexibility because the model conferred a high level of complexity which complicates the interpretation of results and limits its uses in guiding public health interventions. Moreover, the reliability of these models depends on the validity of assumptions regarding spatial effects, which affect the result significantly. Cortés et al. [39] introduced an innovative family of quantile regression models that leverage on reparameterized Marshall-Olkin distribution within the location-scale family. This framework increases the model flexibility, making it well-suited for analyzing slightly asymmetric response variables and enabling the joint modeling of quantile, scale, and asymmetry parameters which is useful for studying non-homogeneous populations. However, this approach does not account for spatial dimension in data that are from different geographical dimensions, which is crucial for capturing the spatial heterogeneity and improving the modeling and predictions of regional variations. Identifying spatial patterns and trends is crucial for informed decisions-making, this can reveal spatial auto-correlation in situations where nearby locations exhibit similar values that traditional models may overlook. Furthermore, incorporating spatial dimension significantly enhances the robustness and reliability of statistical models by accounting for geographic influences that are frequently overlooked. This study aims to extend the existing quantile regression framework by integrating spatial dimension, thereby enhancing the model's applicability to datasets with spatially correlated observations. The integration of spatial component captures and analyses spatial heterogeneity, offering a comprehensive understanding of the underlying patterns in the data. Additionally, the study will embeds spatial dimension within the quantile regression model to achieve more accurate and insightful analyses, leveraging on the strengths of both spatial statistics and quantile regression.

Methods

Data

The data used in this study were obtained from the Demographic and Health Survey (DHS), a reputable provider of reliable population-level data funded by the United States Agency for International Development (USAID). The 2018 Nigeria Demographic and Health Survey (NDHS) provides a comprehensive national assessment,delivering up-to-date information on key demographic and health indicators through a rigorously designed questionnaire. To ensure precise and representative data, the survey employed a stratified two-stage cluster sampling method. This approach involved dividing each state and the Federal Capital Territory (FCT) into urban and rural strata, with Enumeration Areas (EAs) serving as the primary sampling units in the first stage. In each of the 1389 selected EAs, a comprehensive household listing was conducted, from which approximately 30 households per cluster were systematically selected. This methodology resulted in interviews with 41,821 women aged 15–49. The eligibility criteria include both permanent residents and visitors who had stayed in the selected households the night before.

The Household Questionnaire was used to collect data on the characteristics of dwelling units and to record the height and weight of women from which BMI was estimated. The socio-demographic variables considered in the study include the type of place of residence, highest educational attainment, household drinking water source (classified as being protected or not protected), type of household toilet facilities (categorized as improved or non-improved), access to electricity, and exposure to mass media defined as whether a woman read a newspaper or magazine, listens to radio or watches television at least ones a week. Additional variables include women employment status and household wealth index.

Statistical method

Quantile regression

In a linear regression model, the conditional mean of the dependent variable y_i is expressed as a linear function of covariates x_i :

$$E(y_i|x_i) = x_i^T \beta \tag{1}$$

The study presents a statistical framework that models the conditional mean of the response variable while examining the effects of covariates across different quantiles of the response distribution. Research conducted by Koenker [40] introduced quantile regression as a method for modeling the distribution of the response variable, thereby establishing relationships between its quantiles and predictor variables to produce reliable results across various applications. This approach allows detailed analysis of how different predictors influence multiple points within the response distribution. A study by Park et al. [41] further demonstrated that assessing the effects covariates at various points within the response distribution reveals complex relationships inherent in the data while enhancing model flexibility. Quantile regression accommodates diverse data structures, enabling the joint estimation of quantile distributions and capturing complexities that the standard mean-based approaches may be overlook as investigated by Park et al. [42]. As shown by Li [43], quantile regression is particularly valuable for handling outliers, making it a crucial technique for analyzing data characterized by skewed distributions. Akrami et al. [44] emphasized that estimated conditional quantiles establish a direct relationship with the response variable, revealing the heterogeneous effects of predictors across the distribution. Arnroth and Vegelius [45] demonstrated the model's effectiveness in capturing distributions characterized by asymmetry, scale, and variability particularly when the response variable exhibits skewness. In this study, the quantile parameter u_q represents the specific quantiles associated with overweight and obesity calculated at ($\tau = 0.69$) and ($\tau = 0.75$) respectively using quantile regression techniques, incorporating additional parameters such as scale σ and asymmetry α, which are essential for capturing variability and skewness thereby enabling a comprehensive analysis of distributional changes across different quantiles.

For each quantile (τ), where τ is a probability between 0 and 1 representing the quantile of interest, the conditional quantile (τ) of the response variable y_i is modeled as a non-linear function of the covariates and expressed as

$$Q_y(\tau|x_i, Spatial) = x_i^T \beta(\tau) + f(Spatial, \tau) \tag{2}$$

Where $\beta(\tau)$ represents the quantile-specific coefficients that vary with the quantile τ to be estimated, and $f(Spatial, \tau)$ denotes a nonlinear spatial component that captures variability influenced by geographical location or region. Numerous researchers among them are [46–48] have explored the application of quantile regression to assess the effects of covariates at various points within the response distribution, providing deeper insights into its shape and tail behavior. To improve model flexibility, embedding the Marshall–Olkin distribution within the quantile regression framework enhances the distribution of the response variable across different quantiles, facilitating the effective modeling of asymmetric and heavy-tailed data. This approach offers a comprehensive framework for capturing the complexities inherent in skewed distributions, thereby addressing the limitations of conventional methodologies.

MarshallOlkin distribution

Marshall and Olkin [36] introduced a widely used technique that enhances the flexibility of statistical distribution within the location-scale family by incorporating additional parameters into an existing distribution, allowing greater flexibility in modeling complex data structures. The Marshall–Olkin (MO) family of distributions studied by Naz et al. [49], Sastry [50] extends the original distribution by integrating additional parameters that significantly enhance the model flexibility. This extension not only enables a more accurate representation of complex data behaviors in real-world applications but also retains the fundamental properties of the baseline distribution. Abdulhameed et al. [51] applied Marshall–Olkin method to develop a novel family of distributions characterized by a diverse range of shapes. Alnoor et al. [52] highlighted that the marshall–Olkin distribution effectively accommodates complex dependence structures and tail behaviors, enhancing its applicability across various fields. Mathew and Chesneau [53] observed that beyond traditional distribution models, the Marshall–Olkin (MO) distribution is particularly valuable when integrated within the location-scale family to address non-normal data patterns. Furthermore, it enhances distributional flexibility while preserving a structure similar to generalized linear models, making it a powerful tool for analyzing real-world data, particularly for modeling slightly asymmetric response variables. In addition, the MarshallOlkin method facilitates the derivation of closed-form expressions for probability density functions, cumulative distribution functions, and quantile functions, thereby enhancing simulation studies and maximum likelihood estimation. Khamis et al. [54] evaluated the performances of Marshall–Olkin distributions in modeling real-world datasets, comparing them to traditional models and emphasizing their practical significance in statistical analysis.

The cumulative density function derived from Marshall–Olkin methodology is given by:

$$G(y;\alpha)=\frac{F_0(y)}{\alpha+(1-\alpha)F_0(y)},\quad y\in\mathbb{R},\quad \alpha\in\mathbb{R}^+ \tag{3}$$

Where F_0 denotes the baseline cumulative distribution function, and α represent the additional parameter introduced. Eq. (3) provides a framework for deriving new parametric distributions. Consequently, the corresponding probability density function can be expressed as:

$$g(y;\alpha)=\frac{\alpha f_0(y)}{\alpha+(1-\alpha)F_0(y)^2},\quad y\in\mathbb{R},\quad \alpha\in\mathbb{R}^+ \tag{4}$$

where f_0 represents the baseline probability density function.

Reparameterized Marshall Olikin family of distribution

Reparameterized Marshall–Olkin Family of distribution enables the joint modeling of quantile, scale, and asymmetry parameters, making it well-suited for analyzing non-homogeneous populations. These models are constructed by integrating Marshall–Olkin methodology within the location-scale family of distribution thereby enhancing data fitting through shape-regulating parameters that capture intricate distributional patterns across different quantiles. Furthermore, the availability of closed-form expressions for the probability density function (PDF), cumulative distribution function (CDF), and quantile function significantly enhances computational efficiency in simulation studies, particularly when employing the inverse transform method.

The probability density function (pdf) of the Reparameterized Marshall–Olkin (RPMO) family of distribution is expressed as:

A random variable Y follows a RPMO distribution if its PDF is expressed as:

$$g(y;\xi_q,\sigma,\alpha)=\frac{\alpha f_0(u_q)}{\sigma[\alpha+(1-\alpha)F_0(u_q)]^2} \tag{5}$$

where

$$u_q=\frac{y-\xi_q}{\sigma}+F_0^{-1}\left(\frac{\alpha q}{1+q\alpha-q}\right)$$

Here, $\xi_q\in\mathbb{R}$, $\sigma\in\mathbb{R}^+$, and $\alpha\in\mathbb{R}^+$ denote the q-quantile, scale, and skewness parameters, respectively. Additionally, f_0 represent the baseline pdf belonging to the location-scale family denoted as $Y\sim\text{RPMO}(\xi_q,\sigma,\alpha,f_0)$.

The cummulative density function (cdf) of the RPMO family of distribution is given by:

Let $Y\sim\text{RPMO}(\xi_q,\sigma,\alpha,f_0)$, then the cdf of Y is expressed as

$$G(y;\xi_q,\sigma,\alpha)=\frac{\alpha F_0(u_q)}{\sigma[\alpha+(1-\alpha)F_0(u_q)]^2} \tag{6}$$

where

$$u_q=\frac{y-\xi_q}{\sigma}+F_0^{-1}\left(\frac{\alpha q}{1+q\alpha-q}\right)$$

Here, $\xi_q\in\mathbb{R}$, $\sigma\in\mathbb{R}^+$, and $\alpha\in\mathbb{R}^+$ remain the q-quantile, scale, and skewness parameters respectively. Additionally, F_0 represents the baseline CDF belonging to the location-scale family which is denoted by $Y\sim\text{RPMO}(\xi_q,\sigma,\alpha,F_0)$.

The quantile function qF of the RPMO family of distribution is given as

Let $Y\sim\text{RPMO}(\xi_q,\sigma,\alpha,F_0)$, the quantile function (qf) is expressed as: $Q(y;\xi_q,\sigma,\alpha)=$

$$\sigma\left[F_0^{-1}\left(\frac{\alpha p}{1+p\alpha-p}\right)-F_{0^{-1}}\left(\frac{\alpha q}{1+q\alpha-q}\right)\right]+\xi_q$$

where $p \in (0,1)$ and $q \in (0,1)$. Note that if $p = q$, then $Q(p; \xi_q, \sigma, \alpha) = \xi_q$.

The BMI data in this study was modeled using the Reparameterized Marshall–Olkin (MO) distribution, which effectively captures complex dependency structures, asymmetry, and tail behavior. The reparameterization process adjusts the distribution parameters to capture significant features such as the location, scale, and skewness of the data, thereby improving the model's fit to the response variable. Within this framework, the parameters are linked to covariates through a quantile regression based approach, where a link function effectively captures the influence of predictors across the distribution. The choice of parameters for reparameterization depends on the study objectives, with certain parameterizations offering greater computational efficiency. Its applicability becomes particularly pronounced when the parameters μ, σ, ν, and τ are orthogonal or nearly orthogonal. Each distribution is defined by four key functions: d, p, q, and r, representing the probability density function (PDF), cumulative distribution function (CDF), quantiles (inverse CDF), and random number generation functions, respectively. This study employs the Normal and Student-t distributions as the baseline distribution due to their fundamental role and adaptability in statistical modeling, particularly within the location-scale family of distributions. This methodology enhances the development of more flexible and robust models by integrating additional parameters that account for asymmetry, making it effective for capturing skewness and kurtosis in datasets.

Model estimation

The statistical model employed in this study is based on the Generalized Additive Linear Models for Location Scale and Shape (GAMLSS), as initially proposed by Rigby and Stasinopoulos [55]. Assuming the response variable Y follows the Reparameterized Marshall–Olkin family of distributions parameterized by location (μ), scale (σ), skewness (ν), and kurtosis (τ) is expressed as:

Let $Y \sim \text{RPMO}(\mu, \sigma, \nu, \tau)$

$\eta_1 = g_1(\mu) = X_1\beta_1 + s_{11}\text{x}_{11} + \cdots + s_1 J_1(\text{x}_1 J_1)$

$\eta_2 = g_2(\sigma) = X_2\beta_2 + s_{21}\text{x}_{21} + \cdots + s_2 J_2(\text{x}_2 J_2)$

$\eta_3 = g_3(\nu) = X_3\beta_3 + s_{31}\text{x}_{31} + \cdots + s_3 J_3(\text{x}_3 J_3)$

$\eta_4 = g_4(\tau) = X_4\beta_4 + s_{41}\text{x}_{41} + \cdots + s_4 J_4(\text{x}_4 J_4)$

Where $Y \overset{\text{ind.}}{\sim} \mathcal{R}PMO(\mu, \sigma, \tau, \nu)$ represents the four parameter distribution of the response variable Y which is typically associated with location (μ), scale (σ), shape(τ and ν) respectively. The design matrices X_k incorporate the linear additive terms in the model, while β_k represents the linear coefficient parameters. Additionally, the smoothing functions $s_{kj}(\text{x}_{kj})$ capture the nonlinear relationship between the explanatory variables x_{kj} where $k = 1,2,3,4$ and $j = 1, \ldots, J_k$. The predictors $\eta_1, \eta_2, \eta_3, \eta_4$ correspond to the parameters μ, σ, ν, and τ respectively.

To implement the GAMLSS framework for statistical modeling, several R packages have been developed and are available through the comprehensive R Archive Network (CRAN) [https: //www.r-project.org/]. This study employs the Maximum Likelihood (ML) approach for parameter estimation which requires solving a system of nonlinear equations derived from the score vector of the log-likelihood function. Due to the unavailability of closed-form solutions for maximum likelihood estimators, numerical optimization techniques will be used to obtain the estimates. The GAMLSS framework in R was utilized to perform the iterative numerical optimization required for maximum likelihood estimation (MLE) facilitating model implementation alongside comprehensive diagnostic analyses. This approach offers necessary flexibility to capture the complex relationships between covariates and distribution parameters within the proposed models. Consequently, GAMLSS serves as a robust and efficient technique for model fitting while ensuring methodological rigor and accuracy.

Data analysis and result

This study employed advanced statistical techniques to estimate the conditional quantile of the response variable, emphasizing the influence of covariates across various quantiles. Furthermore, a spatial component was integrated to account for geographical disparities, enhancing the model's ability to capture spatial heterogeneity.

Table 1 presents a summary statistics of the socioeconomic and demographic factors influencing the prevalence of overweight and obesity. This study analyzed a dataset comprising 15,741 women aged 15 to 49, categorized based on socioeconomic and demographic characteristics. The findings show that approximately 59% of respondents reside in rural areas, highlighting a significant rural population compared to their urban counterparts, which constitute about 41.47%. A considerable proportion of the women (33.12%) have no formal education. Conversely, only 10.66% attained a higher level of education. Access to protected water sources is prevalent, with 71.71% of respondents having access, whereas 28.29% rely on unprotected water sources. The data indicate that 53.90% of the participants have access to improved toilet facilities, while nearly half (46%) rely on non-improved sanitation. More than half (55.67%) of the women have access to electricity in their household. The study further examined media exposure, a crucial factor influencing health awareness. Only 16% of participants reported reading newspapers, while 55% regularly listened to the radio, and 51% watched television. Wealth distribution analysis revealed that 22% of participants belonged to the middle-income and richer wealth index categories, whereas 20% were classified as either the richest or the poorest. Employment status, a key indicator of economic stability, showed that majority of women (65%) are of the working class, while 35% were unemployed.

Tables 2 and 3 present results of the Generalized Additive Model for Location, Scale, and Shape (GAMLSS) analysis, focusing on the Reparameterized MarshallOlkin Normal and Student-t distribution for Overweight at shape parameter tau = 0.75 and Obesity at shape parameter tau = 0.69 respectively. The model considers the response variable as a function of multiple predictors, highlighting distinct relationships between various covariates and Body Mass Index (BMI) among women of childbearing age in Nigeria. These

Table 1
Frequency distribution of variables included in the analysis.

Variable	Frequency	Percentage
Place of Residence		
Rural	21,501	58.53
Urban	15,235	41.47
Educational Attainment		
No Education	14,398	33.12
Primary	5,684	15.47
Secondary	14,969	40.75
Higher	3,917	10.66
Water Source		
Protected	26,342	71.71
Unprotected	10,394	28.29
Toilet Facilities		
Improved	19,799	53.90
Non-Improved	16,937	46.10
Electricity		
Yes	20,452	55.67
No	16,284	44.33
Read Newspaper		
Yes	5,716	15.56
No	31,020	84.44
Listen to Radio		
Yes	20,309	55.28
No	16,427	44.72
Watch Television		
Yes	18,913	51.48
No	17,823	48.52
Household Wealth Index		
Poorest	15,725	17.91
Poorer	7,155	19.48
Middle	7,761	21.13
Richer	7,909	21.53
Richest	7,327	19.95
Employment Status		
Working	23,980	65.28
Not Working	12,756	34.72
Total	**379,662**	**100.00**

relationships are assessed through estimated coefficients, standard errors, t-values, and corresponding p-values for each predictor. The results reveal that urban-dwelling women do not exhibit significantly higher overweight and obesity rates compared to their rural dwelling counterparts, suggesting that residing in urban areas does not uniformly contribute to increased BMI. Educational attainment emerges as a critical factor, with women who have completed primary, secondary, or higher education exhibiting higher BMI levels. Conversely, those without formal education tend to have lower BMI. Access to protected drinking water, improved toilet facilities, and electricity significantly correlate with lower rates of overweight and obesity. Additionally, the analysis reveals a positive association between household wealth index categories and increased BMI, with wealthier women of childbearing age demonstrating a higher prevalence of overweight and obesity. Media exposure particularly television, is identified as a significant predictor of higher BMI levels. In contrast, engagement with newspapers and radio does not exhibit a significant impact on body weight. In terms of demographic factors, age is positively correlated with BMI, revealing that body weight tends to increase with advancing age across the study population.

Table 4 presents a comprehensive summary of quantile residuals derived from the Generalized Additive Model for Location, Scale, and Shape (GAMLSS) highlighting its robustness and efficiency in capturing the distribution of the response variable. The result show that, on average, the observed values deviate minimally from the predicted values across the analyzed quantiles. When the residuals approach 0 across quantiles, it implies that the model accurately captures the central tendency of the data, suggesting a high level of predictive accuracy. The variance measures the spread of the residuals around the mean. A variance close to 1 suggests that the residuals exhibit homoscedasticity, indicating consistent model performance across the observed data range. This further highlights the effectiveness of both the RPMON and RPMOT models in capturing data variability and central tendency. The coefficient of skewness reflects the symmetry of residual distribution, where a value near 0 denotes symmetrically distributed residual pattern. Similarly, the coefficient of kurtosis measures the peakedness and tail behavior of the quantile residual distribution relative to a normal distribution. A kurtosis value exceeding 3 indicates a leptokurtic distribution suggesting heavier tails and a sharper peak relative to a normal distribution. The Filliben correlation coefficient evaluates the strength of the relationship between observed and predicted values across the quantiles. A value approaching 1 signifies a strong linear relationship between empirical and theoretical quantiles, suggesting that the model's assumptions are well satisfied. Despite variations in the tau parameter, the quantile residuals and their distributional properties remain stable. This consistency indicates that the model maintains robust performance and a good fit across different quantile levels resulting consistent residual summaries. The result shows that the model (RPMON and

Table 2
Comparison of normal vs. student-T distributions at $\tau = 0.69$.

Variable	Normal			Student-T		
	Estimate	Std. Error	t value	Estimate	Std. Error	t value
(Intercept)	18.807111	3.297371	5.704	18.298226	7.279892	2.514
Place of Residence						
Urban	−0.046033	0.077340	−0.595	−0.005909	0.081944	−0.072
Educational Attainment						
Primary	0.809473	0.104559	7.742	0.853690	0.110756	7.708
Secondary	0.959073	0.098317	9.755	1.002518	0.103674	9.670
Higher	1.269823	0.150261	8.451	1.376141	0.158810	8.665
Water Source						
Protected	−0.199751	0.081094	−2.463	−0.215731	0.085892	−2.512
Toilet Facility						
Improved	−0.087700	0.077941	−1.125	−0.084458	0.082565	−1.023
Electricity						
Yes	−0.198208	0.089784	−2.208	−0.185528	0.095045	−1.952
Mass media Newspaper						
Yes	0.194294	0.103751	1.873	0.257384	0.109992	2.340
Listening to Radio						
Yes	0.001171	0.074574	0.016	0.016100	0.079079	0.204
Watch Television						
Yes	0.403880	0.088005	4.589	0.430843	0.093217	4.622
Household Wealth Index						
Poorer	0.623082	0.108957	5.719	0.655860	0.115220	5.692
Middle	1.079985	0.127179	8.492	1.150794	0.134456	8.559
Richer	1.762279	0.153930	11.449	1.907057	0.162662	11.724
Richest	2.691278	0.176499	15.248	2.931770	0.186981	15.680
Employment Staus						
Working	0.311159	0.072188	4.310	0.320185	0.076467	4.187
Ps(age)	0.120252	0.003693	32.564	0.134613	0.003912	34.413

Table 3
Comparison of normal vs. student-T distributions at $\tau = 0.75$.

Variable	Normal			Student-T		
	Estimate	Std. Error	t value	Estimate	Std. Error	t value
(Intercept)	19.537372	1.838642	10.626	18.999525	5.581676	3.404
Place of Residence						
Urban	−0.046151	0.077296	−0.597	−0.005912	0.081943	−0.072
Educational Attainment						
primary	0.809341	0.104501	7.745	0.853689	0.110756	7.708
secondary	0.958875	0.098268	9.758	1.002514	0.103673	9.670
higher	1.269365	0.150169	8.453	1.376135	0.158809	8.665
Water Source						
Protected	−0.199615	0.081052	−2.463	−0.215730	0.085891	−2.512
Toilet Facility						
Improved	−0.087495	0.077898	−1.123	−0.084454	0.082564	−1.023
Electricity						
Yes	−0.198488	0.089736	−2.212	−0.185530	0.095045	−1.952
Mass Media Newspaper						
Yes	0.194129	0.103685	1.872	0.257382	0.257382	2.340
Listening to Radio						
Yes	0.001035	0.074533	0.014	0.016098	0.079078	0.204
Watch Television						
Yes	0.403998	0.087956	4.593	0.430847	0.093216	4.622
Household Wealth Index						
Poorer	0.622811	0.108904	5.719	0.655860	0.115219	5.692
Middle	1.079693	0.127116	8.494	1.150792	0.134455	8.559
Richer	1.761759	0.153850	11.451	1.907051	0.162661	11.724
Richest	2.690261	0.176400	15.251	2.931761	0.186980	15.680
Working Status						
working	0.311140	0.072150	4.312	0.320185	0.076467	4.187
Ps(age)	0.120218	0.003691	32.574	0.134953	0.003912	34.500

Table 4
Summary of the quantile residuals.

Statistic	RPMON ($\tau = 0.75$)	RPMON ($\tau = 0.69$)	RPMOT ($\tau = 0.75$)	RPMOT ($\tau = 0.69$)
Mean	0.0332315	0.03314383	0.05409189	0.05409532
Variance	1.026355	1.024794	1.017361	1.017342
Coefficient of Skewness	0.3776951	0.3767324	0.6435656	0.6435497
Coefficient of Kurtosis	3.113945	3.10673	3.549969	3.549871
Filliben Correlation Coefficient	0.9957174	0.9957239	0.9883867	0.988387

RPMOT) effectively captures the central tendency and variability of the data. The strong correlation between observed and predicted values across quantiles underscores the model's reliability and predictive efficiency, making it well-suited for analyzing complex distributional patterns.

The residual plots for both the Reparameterization Marshall–Olkin Normal (RPMON) and Student-T (RPMOT) distributions show the model performances and goodness-of-fit across different quantile levels. In Fig. 1, the residuals are randomly scattered around zero indicating symmetrically random distribution without any identifiable patterns. This suggests that the model effectively captures both the central tendency and variability within the data. The randomness further confirms the absence of heteroscedasticity or systematic bias, affirming that the model assumptions hold. Fig. 2 presents the residual plot for the RPMOT distribution at $\tau = 0.75$. The residuals plots display a random scatter around zero, demonstrating significantly improved distributional behavior compared to RPMON. However, slight evidence of heavier tails suggests that the RPMOT distribution can effectively account for extreme values or outliers. These attributes enhance the model's ability to effectively capture variability in datasets with heavy-tailed distributions while maintaining predictive accuracy. Fig. 3 exhibits a behavior similar to that of Fig. 1 where the residuals are evenly distributed around the zero line, reflecting homoscedasticity. This uniform spread indicates that the model is robust at this quantile levels, showing consistent predictions without any systematic deviations. For the RPMOT distribution at $\tau = 0.69$ as depicted in Fig. 4, the residuals continue to show a random scatter around the zero line. This reinforces the model's robustness in capturing data characteristics across quantiles. The minimal clustering or deviations further validate the reliability of the RPMOT distribution at these quantile level. Overall, the plots indicate that the residuals behave well. In all figures, the top two plots (residuals against fitted values of μ and residuals against the index) display a random scatter around the horizontal zero line. Additionally, the kernel density estimate of the residuals approximates a normal distribution, while the normal Q-Q plot is nearly linear with an intercept of 0 and a gradient of 1. These findings highlight the effectiveness of both the RPMON and RPMOT distributions in capturing the underlying data structure across the examined quantiles. While RPMON yields a slightly more symmetric residual distribution, RPMOT offers greater flexibility in handling datasets with potential outliers. This makes both models reliable, depending on the specific characteristics of the dataset.

The worm plots, illustrated in Figs. 5 through 8, provide a comprehensive visual assessment of the residuals from the RPMON and RPMOT models based on their corresponding quantiles. These plots are pivotal in evaluating how well each distribution fits the underlying data structure. The worm plot for RPMON at $\tau = 0.75$ (Fig. 5) reveals that the residuals closely cluster around the horizontal zero line, with minimal deviations observed. This suggests a strong adherence to the normality assumptions inherent in the model, indicating robust predictive capabilities at this quantile. Similarly, the plot for RPMON at $\tau = 0.69$ (Fig. 6) illustrates comparable behavior, further reinforcing the model's effectiveness. The absence of considerable curvature or systematic patterns in the residuals ensures that the model adequately captures the central tendency and variability of the data, thereby validating its robustness across different quantile levels. In contrast, the worm plot for RPMOT at $\tau = 0.75$ (Fig. 7) exhibits a pattern analogous to that of RPMON but with slightly greater residual deviations from the zero line. This observation aligns with the intrinsic characteristics of the Student-T distribution, which accommodates heavier tails and is thereby capable of incorporating outliers within the dataset. Despite these fluctuations, the minor deviations do not substantially detract from the model's overall fit, confirming its flexibility and suitability for data exhibiting greater variability. At $\tau = 0.69$ (Fig. 8), the RPMOT worm plot continues to demonstrate robust behavior, with residuals maintaining proximity to the zero line and lacking pronounced curvature or clustering. This outcome suggests the model's capability in accurately reflecting the underlying distribution of the data at this quantile, thus supporting a high level of predictive accuracy. In all worm plots, the residual points remain closely aligned with the horizontal zero line, showing no significant systematic bias or curvature. This suggests that both the RPMON and RPMOT models correspond well with the theoretical quantiles. Notably, RPMON exhibits slightly tighter alignment with the zero line compared to RPMOT, indicating better adherence to normality assumptions. However, RPMOT's greater flexibility makes it more suitable for datasets with heavier tails or extreme observations. Across different quantile levels, the worm plot demonstrates consistent behavior, reinforcing the models robustness. Across all worm plots, both RPMON and RPMOT models exhibit minimal systematic bias and maintain a near-linear relationship with the theoretical quantiles. The consistent proximity of residual points to the horizontal zero line implies that both distributions effectively capture the data characteristics without significant deviations. While RPMON demonstrates tighter adherence to normality, RPMOT's flexibility makes it particularly advantageous for datasets featuring heavier tails or outliers.

The spatial effect maps in Figs. 9–12 provide a comprehensive visualization of geographical variability in the location parameter μ as modeled by the RPMON and RPMOT distributions. These maps offer valuable insights into regional disparities in weight related metrics, particularly obesity prevalence across Nigeria, highlighting critical areas that require targeted public health interventions. The RPMON maps illustrate regions with relatively uniform and lower obesity prevalence, suggesting areas that may be less exposed

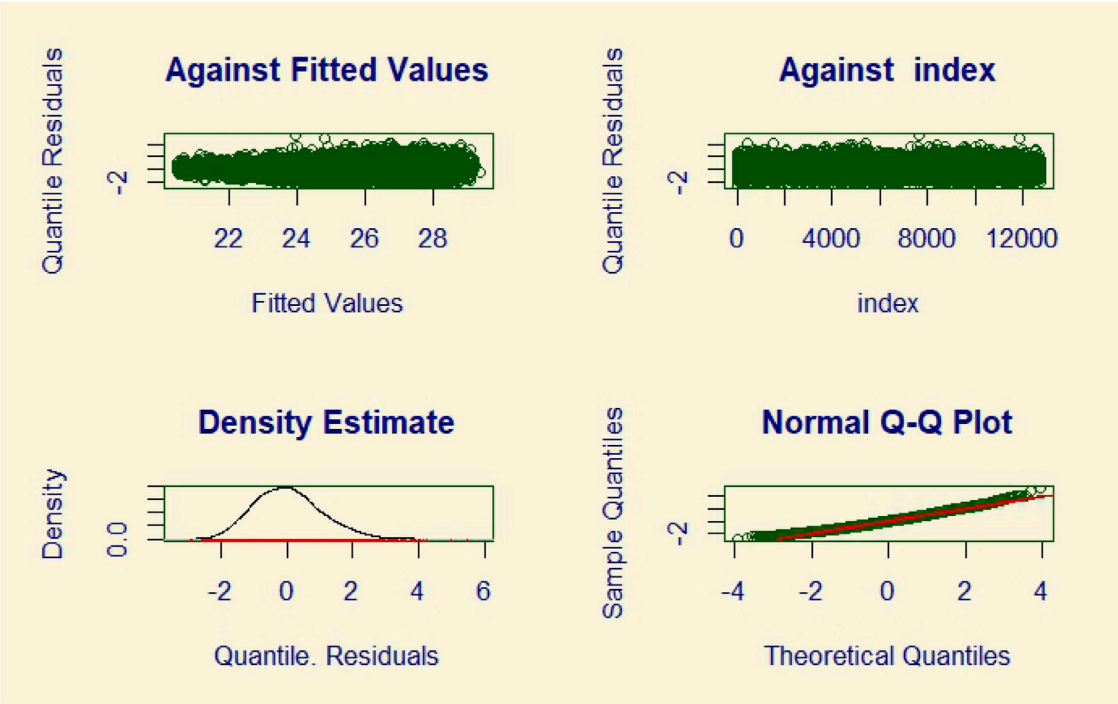

Fig. 1. Residual plot of Reparameterization MarshallOlkin normal distribution at shape parameter tau = 0.75.

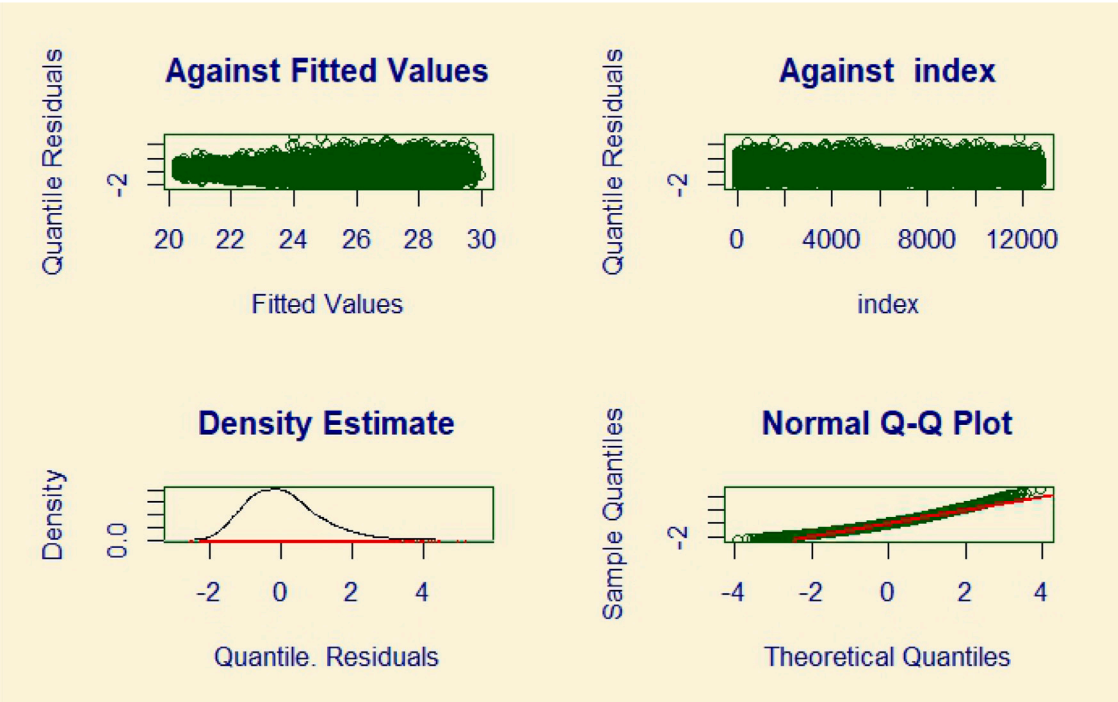

Fig. 2. Residual plot of Reparameterization MarshallOlkin Student-T Distribution at tau = 0.75.

to obesity risk factors. In contrast, regions marked by warmer shades (red, orange, and yellow) indicate a heightened prevalence and pinpointing specific locales that may necessitate immediate intervention. The flexibility of the RPMOT distribution further enables the identification of regions with greater variability in obesity rates, particularly those exhibiting extreme values or outliers.

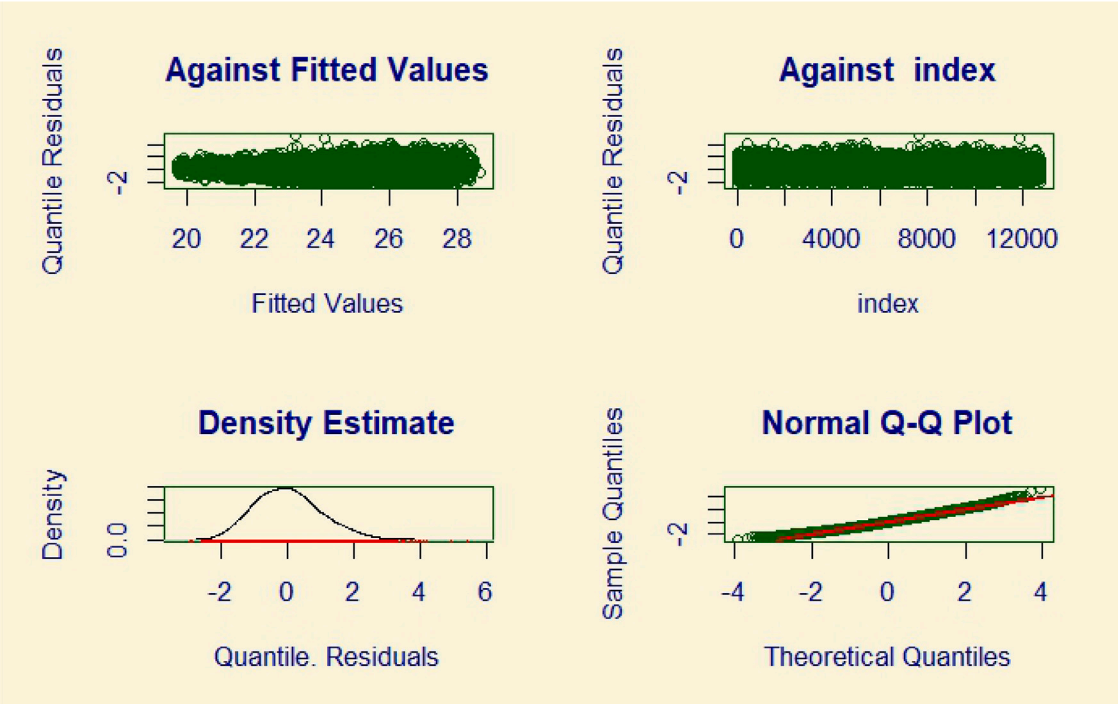

Fig. 3. Reparameterization MarshallOlkin Normal Distribution at shape parameter tau = 0.69.

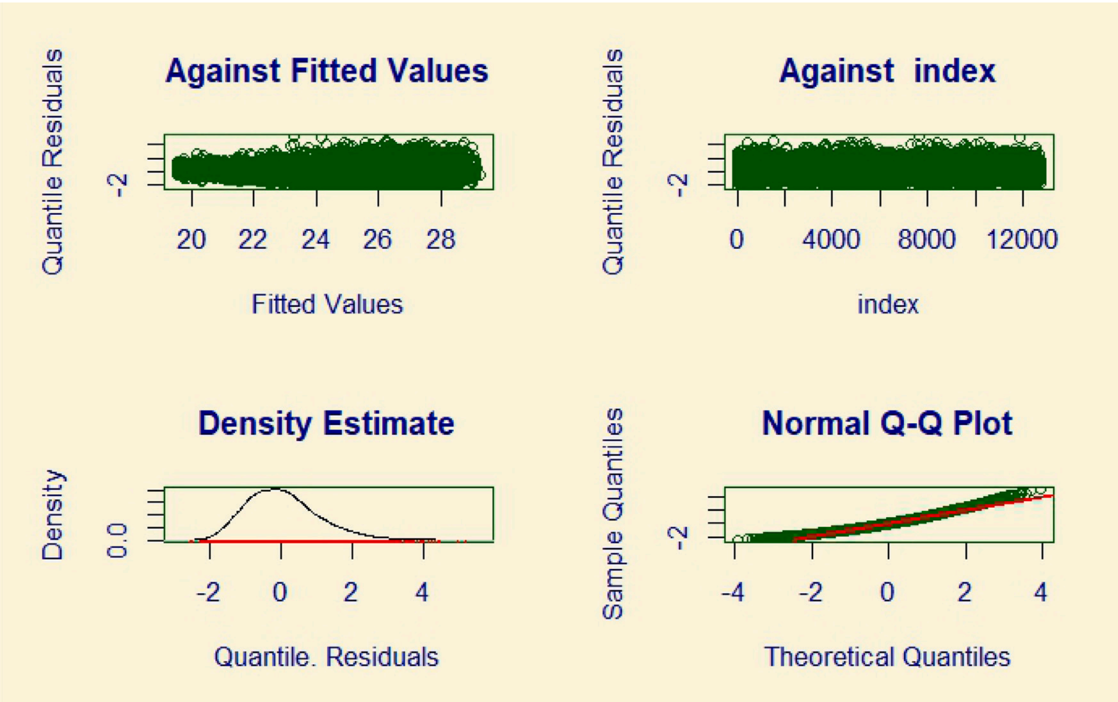

Fig. 4. Residual plot of RPMOT distribution at tau = 0.69.

These findings are essential for understanding the social and economic determinants influencing obesity prevalence across diverse geographical contexts. Furthermore, the results emphasize the role of geographical dimensions in health analytics. Traditional models often overlook spatial disparities, which may lead to suboptimal interventions that fail to account for region-specific determinants

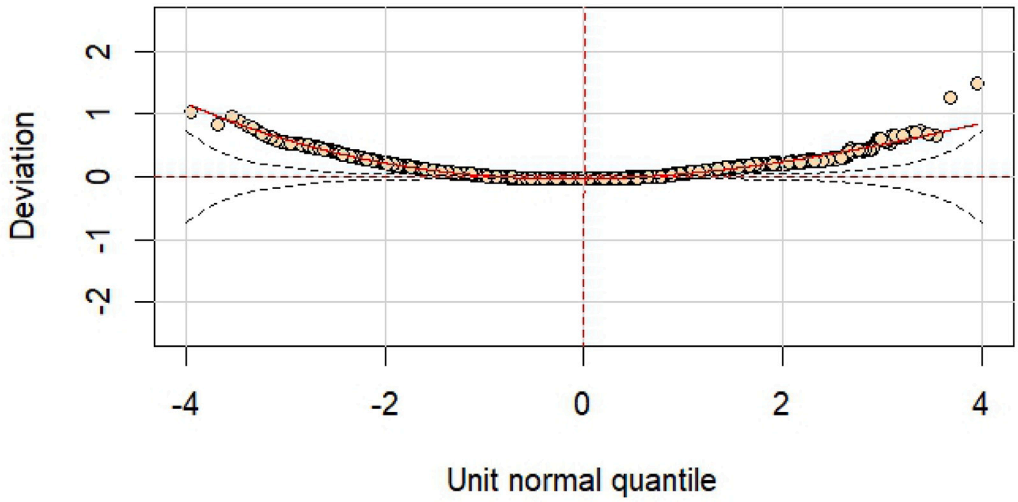

Fig. 5. Worm plot RPMON at tau = 0.75.

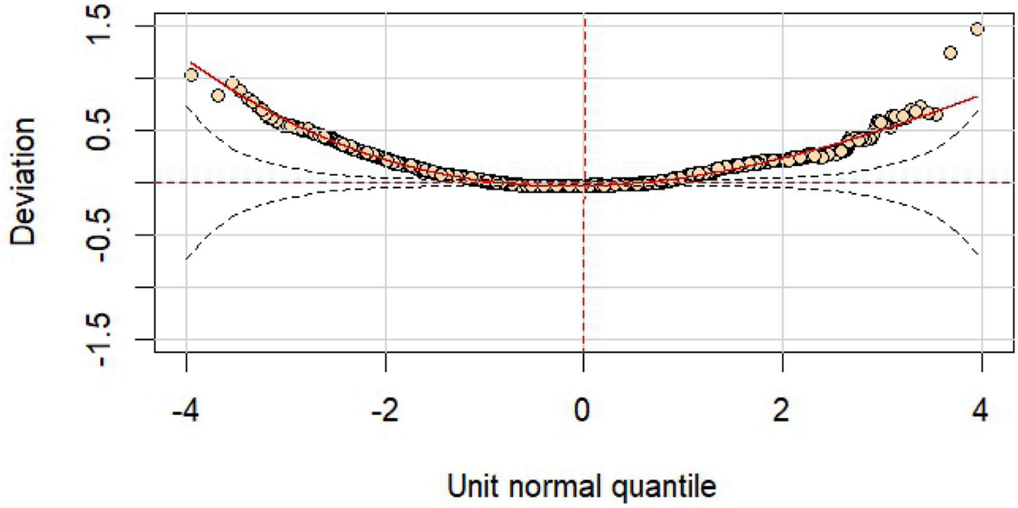

Fig. 6. Worm plot RPMON at tau = 0.69.

of obesity. Integrating spatial analysis aids policymakers and public health practitioners to develop more targeted context specific strategies to mitigate obesity and its associated health risks.

Table 5 presents a comparison of different GAMLSS (Generalized Additive Models for Location, Scale, and Shape) models fitted using the Reparameterized Marshall-Olkin Normal (RPMON) and Reparameterized Marshall-Olkin Student-t (RPMOT) distributions at shape parameter $\tau = 0.69$ and $\tau = 0.75$ respectively. The models are evaluated based on the following criteria Global Deviance (GD), Akaike Information Criterion (AIC), and Schwarz Bayesian Criterion (SBC). For both values of $\tau = 0.69$ and $\tau = 0.75$, the RPMON models have lower GD, AIC, and SBC values compared to their respective RPMOT counterparts. Additionally, the effect of tau on model fit within the same distribution was investigated. For the RPMON distribution, the model with $\tau = 0.69$ has slightly lower GD, AIC, and SBC values compared to the model with $\tau = 0.75$, suggesting a slightly better fit with $\tau = 0.69$. For the RPMOT distribution, the differences in GD, AIC, and SBC values between $\tau = 0.69$ and $\tau = 0.75$ are negligible, suggesting that the choice of tau value does not significantly impact the model fit. Therefore the RPMON model with $\tau = 0.69$ appears to be the best-fitting model based on its lower GD, AIC, and SBC values compared to the other model considered.

Conclusion

Understanding the global prevalence of overweight and obesity among women of childbearing age, particularly in Nigeria, is essential for formulating effective interventions and policies to address the public health challenge. This underscores the importance

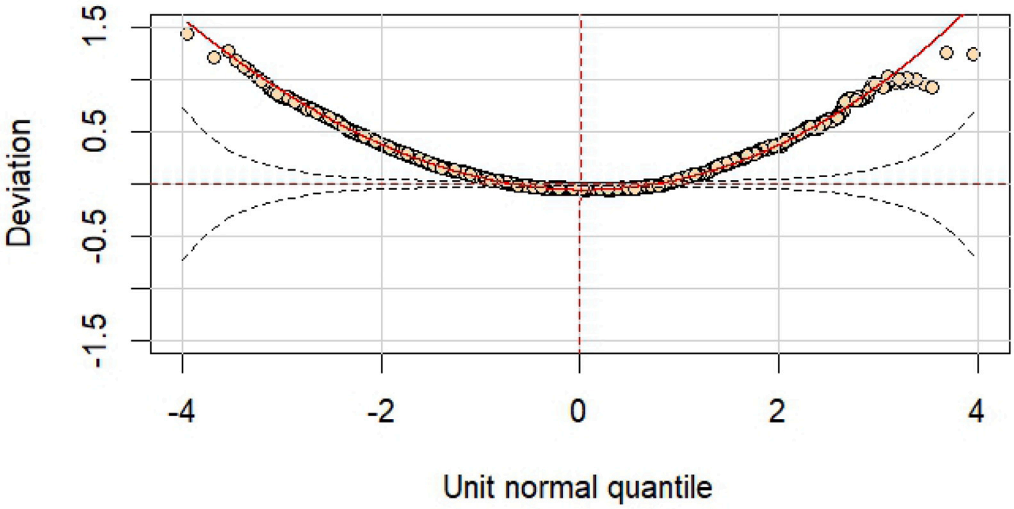

Fig. 7. Worm plot RPMOT at tau = 0.75.

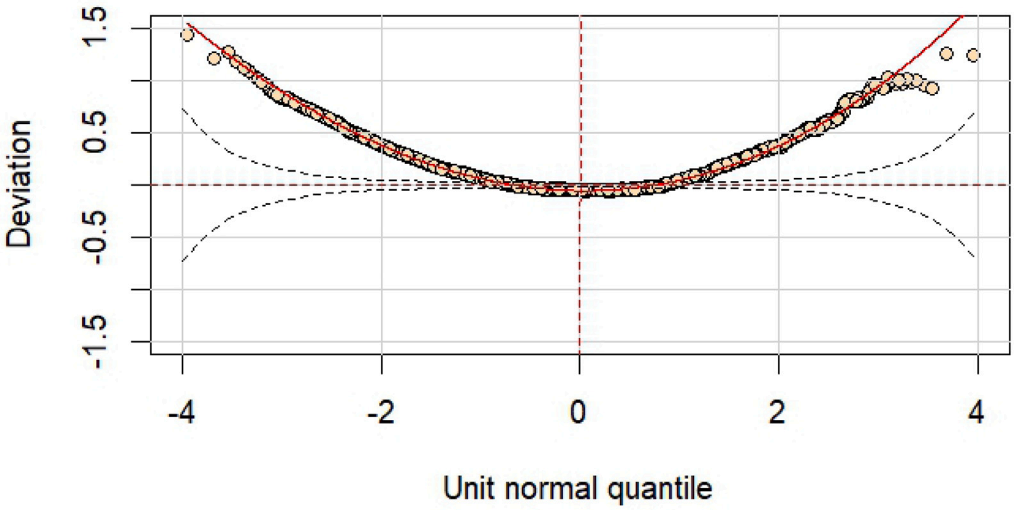

Fig. 8. Worm plot RPMOT at tau = 0.69.

Table 5
Estimate for Model Selection criteria for the two distributions at tau = 0.75 and 0.69.

Family	GD	AIC	SBS
RPMON tau = 0.75	71 393.14	71 433.14	71 582.19
RPMON tau = 0.69	71 392.92	71 432.92	71 581.97
RPMOT tau = 0.75	72 102.69	72 142.69	72 291.68
RPMOT tau = 0.69	72 102.68	72 142.68	72 291.73

of comprehensive strategies that integrate social and economic factors to promote healthier lifestyles and mitigate obesity. This study identifies key determinants influencing overweight and obesity among women of childbearing age in Nigeria. Additionally, it explores the applicability of the Reparameterized Marshall–Olkin family of distributions as an appropriate methodology for modeling response variables with slight asymmetry on the real number line within the Generalized Additive Model for Location, Scale, and Shape (GAMLSS) framework in R. The best-fitting model was selected based on GD, AIC, and BIC. The limitation of this study is its incapacity to include additional factors that could potentially influence overweight and obesity. These factors encompass dietary information, information on physical activities, and individual biomarkers and genetic information. The unavailability of relevant

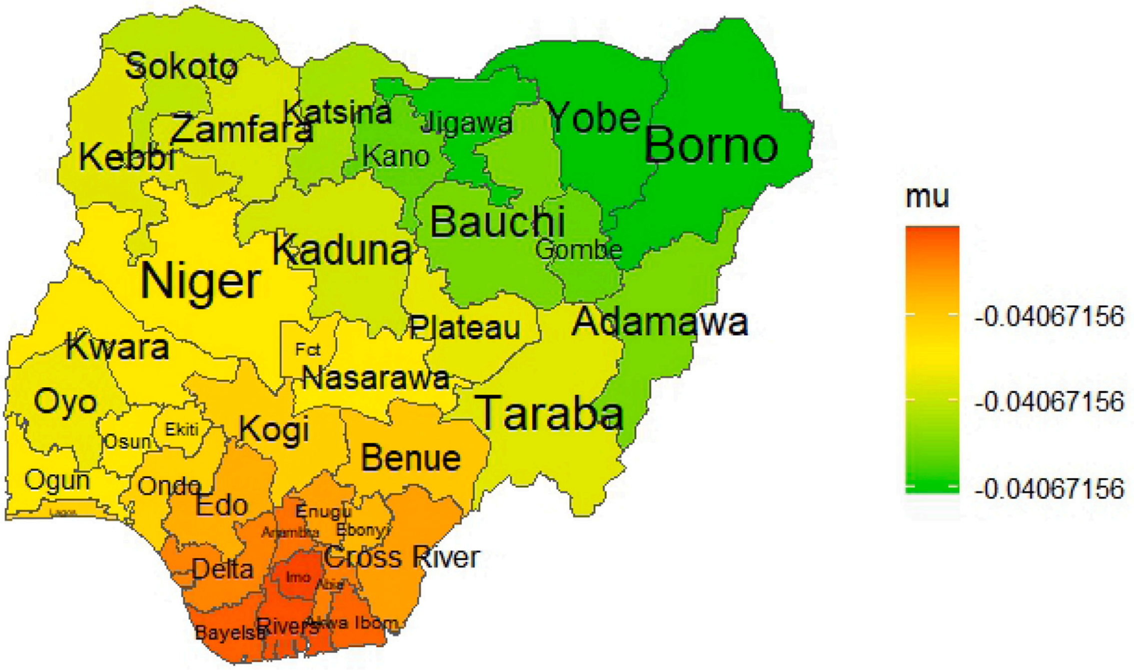

Fig. 9. Map of Nigeria Showing the spatial effect RPMON for μ parameter at tau = 0.75.

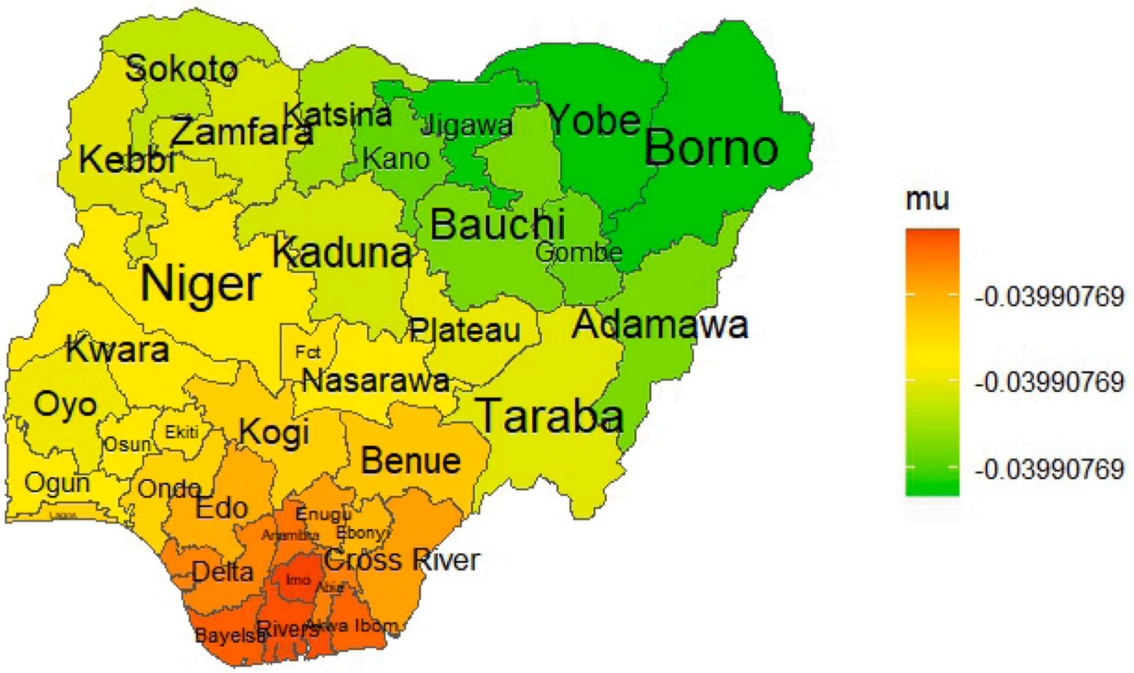

Fig. 10. Map of Nigeria Showing the spatial effect RPMON for μ parameter at tau = 0.69.

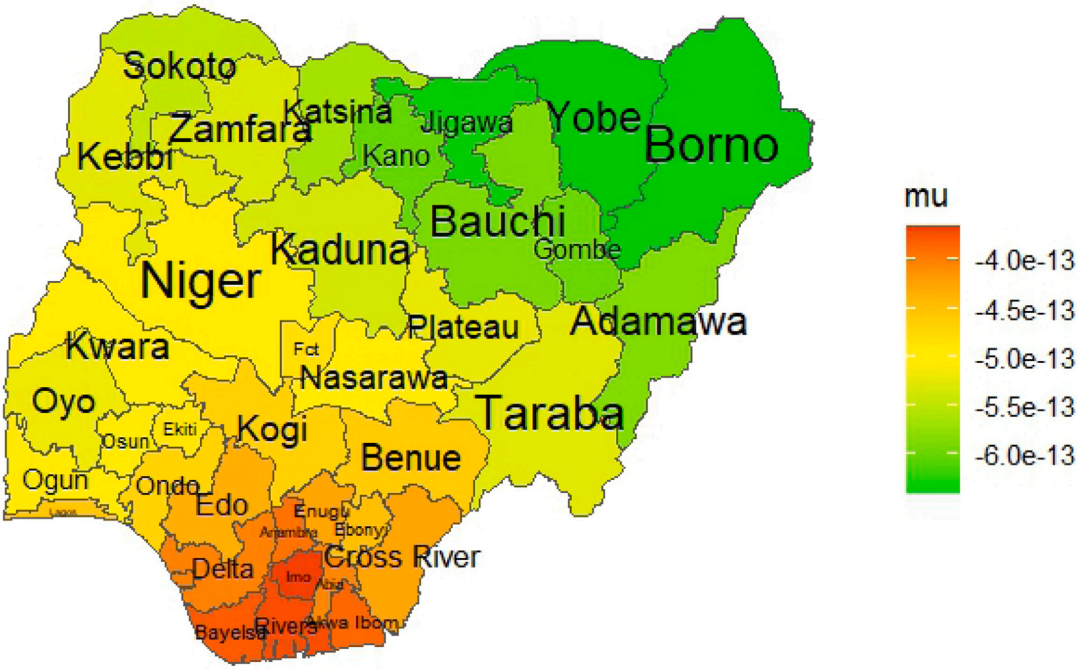

Fig. 11. Map of Nigeria Showing the spatial effect RPMOT for μ parameter at tau = 0.75.

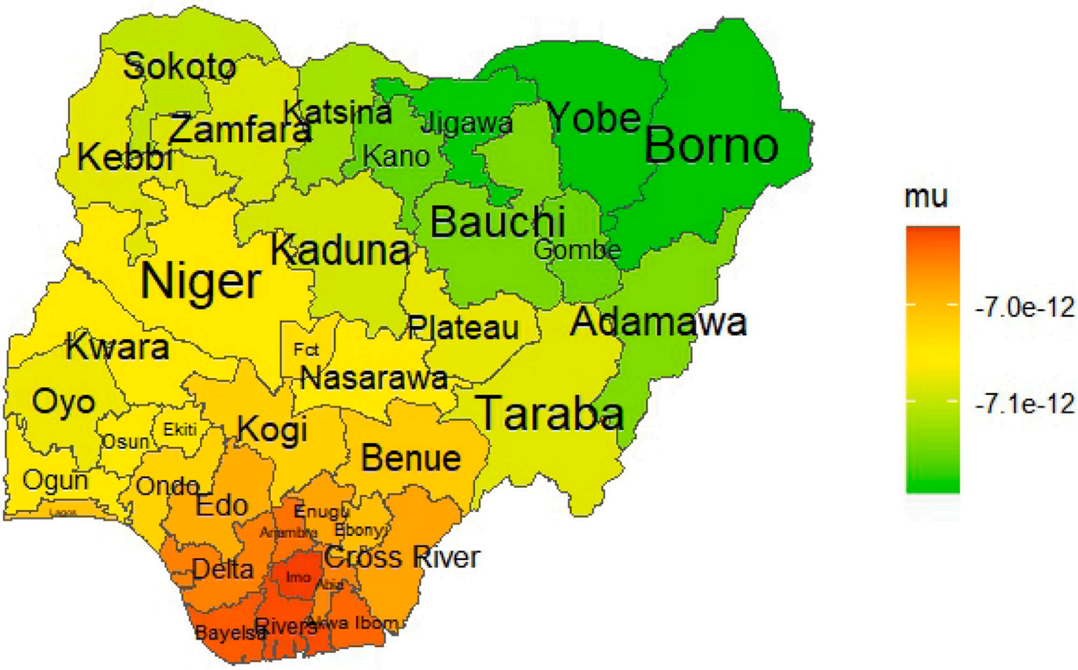

Fig. 12. Map of Nigeria Showing the spatial effect RPMON for μ parameter at tau = 0.69.

data prevented their integration into the study. Therefore, future investigations should take into account these factors to gain a more comprehensive understanding of the phenomenon.

CRediT authorship contribution statement

Omolola Olubukola Fadugba: Conceptualization, Study design, Investigation, Data curation, Methodology, Writing – review & editing. **Ezra Gayawan:** Project supervision, Resources. **Osafu Augustine Egbon:** Conceptualization, Formal analysis, Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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