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Bayesian Additive Modeling of Maternal Mortality in Ghana

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Abstract

Maternal mortality is a critical measure for quality of health system in any country and hence many countries have made concerted efforts to check its occurrence. Various stakeholders involved in the management of health system in Ghana have been tasked to ensure women do not die whilst giving birth. This study was conducted on a sample of 1,052 women selected from all the ten administrative regions of Ghana in which 188 maternal deaths occurred. Two main analytical tools, namely the Zero-Inflated Negative Binomial Regression and Bayesian Additive Posterior Modeling using *INLA* were used. Age at death, Marital Status, and Place of Death emerged as the most significant determinants of maternal mortality in Ghana. It was realized that high number of maternal deaths were recorded in the least developed regions with Northern Region having the highest number of Maternal Deaths. It is therefore important for stakeholders to devise a road map of getting health workers to accept postings to the rural areas and also provide well resourced health facilities to stem this menace.

Keywords: *Maternal mortality; Zero-Inflated Negative Binomial Regression; INLA; Posterior mean*

1 Introduction

Maternal mortality refers to death of either a pregnant woman or death of a woman within 42 days of delivery, miscarriage, termination or ectopic pregnancy resulting from pregnancy and its related complications and management[1]. It is an important health indicator of any country that stakeholders consider when managing maternal and child outcomes. Insufficient data on mortality has hindered the success in fighting against maternal mortality even in the developed countries[2]. In Africa and most parts of the developing world, major causes of maternal mortality are largely due to socio-economic variables such as poverty, education, inadequate skilled birth attendance, inadequate health facilities among others which limit access to health services. Other causes of maternal mortality can be grouped into direct and indirect causes. The direct causes are Hemorrhaging (uncontrolled bleeding or severely bleeding), sepsis (infection), hypertensive disorders, eclampsia,

prolonged or obstructed labor, and unsafe abortion. The indirect causes are anemia, malaria, hepatitis, heart diseases, and HIV/AIDS[3, 4, 5, 7]. Various African Governments have hugely invested in enhancing maternal outcomes over the years but results are still far from meeting the global target of 70 deaths per 100,000 live births. The recent prevalence of maternal mortality in some African countries are Sudan (295), South Sudan (1,150), Ethiopia (401), Egypt (37), Libya (72), Algeria (112), Mauritania (766), Senegal (315), Nigeria (917), Cote d'Ivoire (617) and Ghana (308). Clearly, these figures are really alarming in most African countries with its attendant consequences[6].

There has been considerable efforts by stakeholders in reducing the prevalence of maternal mortality over the years but the aforementioned factors including the delays in the decision to seek care, in reaching care, and in receiving care still post a major challenge in combating this menace. To stem this problem, the government of Ghana has established Community-Based Health Planning and Services (CHIPS) compounds in most rural and hard-to-reach areas and in peri-urban areas staffed with midwives and other health professionals to promote health education and improve access to skilled delivery services to these under served communities. These efforts notwithstanding has not succeeded in eradicating maternal deaths in the country, not even meeting the MDGs target of 70 deaths per 100,000 population by 2030.

Different methods have been used for the study of maternal mortality in literature such Univariate, bivariate and multivariate statistics [18, 19, 20], Poisson regression [3], stepwise multivariate logistic regression [14, 17], deprivation indices, rate ratios, and log-linear regression [15], and the Three Delay Model [7].

These frequentist approach enumerated above does not account for the dynamics in the data and therefore requires a Bayesian approach to fully account for the dynamics of the data. Also, the data has a lot of zeros and requires application of the models for modeling excess zeros. This study therefore seeks to model factors responsible for the continuous surge in maternal deaths in Ghana and proffer solutions to mitigate same using Bayesian Additive Posterior Modeling and the Zero-Inflated Negative Binomial Regression.

The paper is structured as follows; methodology and data source is presented in Section 2, results and discussion in Section 3, and conclusion in Section 4.

2 Methodology

2.1 Zero-Inflated Negative Binomial Regression

Zero-Inflated Negative Binomial (*ZINB*) regression usually provide good fit for overdispersed data and data that has excess zeros, in which case the data distribution makes use of the negative binomial distribution and the logit distribution. Possible values in this case for the response variable are: 0, 1, 2, 3,

Assuming each observation has two possible cases: suppose if case 1 occurs, the count is zero, whilst the occurrence of case 2, the count (including zeros) are generated according to the negative binomial model. Suppose that case 1 occurs with probability $1 - \pi$. Hence, the probability distribution of the *ZIMB* random variable y_i can be written

$$p_r(y_i = j) = \begin{cases} \pi_i + (1 - \pi_i) g(y_i = 0) & \text{if } j = 0 \\ (1 - \pi_i) g(y_i) & \text{if } j > 0 \end{cases}$$

where π_i is the logistic link function defined below and $g(y_i)$ is the negative binomial distribution given by

$$g(y_i) = p_r(Y = y_i | \mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1}) \Gamma(y_i + 1)} \left(\frac{1}{1 + \alpha \mu_i} \right) \left(\frac{\alpha \mu_i}{1 + \alpha \mu_i} \right)^{y_i} \quad (1)$$

The negative binomial component can include an exposure time, t and a set of k regressor variables (the x 's). The expression relating these quantities is

$$\mu_i = \exp(\ln(t_i) + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki}) \quad (2)$$

often, $x_1 \equiv 1$ in which case β_1 is called the intercept. The regression coefficients $\beta_1, \beta_2, \dots, \beta_k$ are unknown parameters to be estimated from a dataset with estimates $b_1, b_2, \dots, b_k$. The logistic component includes an exposure time t and a set of m regressor variables (the z 's). Note that the z 's and the x 's may or may not include terms in common.

2.2 Bayesian Additive Posterior Modeling

2.2.1 Latent Gaussian Models

Let y_i be an observation or response belonging to the exponential family with mean, μ_i linked to a structured additive predictor η_i by a link function $g(\cdot)$, such that $g(\mu_i) = \eta_i$. The structured additive predictor η_i accounts for effects of various covariates in an additive way as

$$\eta_i = \alpha + \sum_{j=1}^{n_f} f^{(j)}(\mu_{ij}) + \sum_{k=1}^{n_\beta} \beta_k Z_{ki} + \epsilon_i \quad (3)$$

where $\{f^{(j)}(\cdot)\}$ s are known functions of the covariates μ , the $\{\beta_k\}$ s are the linear effect of covariates Z and the ϵ_i s are unstructured terms. This model has varying applications due to the many different forms that the unknown functions $\{f^{(j)}\}$ can assume. Latent Gaussian models are a subset of all Bayesian additive models with a structured additive predictor as in equation (3), namely those which assign a Gaussian prior to α , $\{f^{(j)}(\cdot)\}$, $\{\beta_k\}$, and $\{\epsilon_i\}$. Let $\mathbf{X}$ denote the vector of all the latent Gaussian variables, and θ the vector of hyperparameters, which are not necessarily Gaussian [8].

The Bayesian generalized linear models use the $f(\cdot)$ terms to either relax the linear relationship of the covariates or introduce random effects or both [9]. Random effects makes it possible to account for overdispersion caused by unobserved heterogeneity, or for correlation in longitudinal data and can be introduced by defining $f(\mu_i) = f_i$ and letting $\{f_i\}$ be independent, zero mean, and Gaussian [10].

2.2.2 Latent Gaussian Models: notations and basic properties

Let $\mathbf{X}$ be all the n Gaussian variables $\{\eta_i\}$, α , $\{f^{(j)}\}$ and $\{\beta_k\}$. The density $\pi(X|\theta_1)$ is Gaussian with (assumed) mean zero and precision matrix $\mathbf{Q}(\theta_1)$ with hyperparameters θ . Denote by $N(X, \mu, \Sigma)$, then $N(\mu, \Sigma)$ Gaussian density with mean μ and covariance (inverse precision) Σ at configuration $\mathbf{X}$. Let $\pi(\mathbf{y}|\mathbf{X}, \theta_2)$ denote the distribution for the n_d observational variables $\mathbf{y} = \{y_i : i \in \mathcal{I}\}$ which are assumed conditionally independent given $\mathbf{X}$ and θ_2 . Let $\theta = (\theta_1^T, \theta_2^T)^T$ with $\dim(\theta) = m$. The posterior for a singular $\mathbf{Q}(\theta)$ is

$$\pi(\mathbf{X}, \theta|\mathbf{y}) \propto \pi(\theta) \pi(\mathbf{X}|\theta) \prod_{i \in \mathcal{I}} \pi(y_i|x_i, \theta) \quad (4)$$

$$\propto \pi(\theta) |\mathbf{Q}(\theta)|^{\frac{1}{2}} e^{\left[\frac{1}{2} \mathbf{X}^T \mathbf{Q}(\theta) \mathbf{X} + \sum_{i \in \mathcal{I}} \log\{\pi(y_i|x_i, \theta)\}\right]}. \quad (5)$$

The imposed linear constraints are denoted by $\mathbf{A}\mathbf{X} = \mathbf{e}$ for a $k \times n$ matrix $\mathbf{A}$ of rank k . The main aim is to approximate the posterior marginals $\pi(\mathbf{x}|\mathbf{y})$, $\pi(\theta|\mathbf{y})$ and $\pi(\theta_j|\mathbf{y})$. Most latent Gaussian models satisfy two basic properties properties;

1. the latent field $\mathbf{X}$, which is often of large dimension, $n = 10^2 - 10^5$, admits conditional independence properties. Thus the latent field is a Gaussian Markov Random Field (*GMRF*) with a sparse precision matrix $\mathbf{Q}(\theta)$ [11].
2. the number of hyperparameters, m is small, say $m \leq 6$.

Both properties are usually required to produce fast inference, but exceptions exists [12].

2.2.3 Integrated Nested Laplace Approximation

The posterior marginals can be written as

$$\pi(\mathbf{x}_i|\mathbf{y}) = \int \pi(x_i|\theta, y) \pi(\theta|y) d\theta, \quad (6)$$

$$\pi(\theta_j|\mathbf{y}) = \int \pi(\theta|y) d\theta_{-j}, \quad (7)$$

and these are used to construct nested approximations

$$\tilde{\pi}(\mathbf{x}_i|\mathbf{y}) = \int \tilde{\pi}(x_i|\theta, y) \tilde{\pi}(\theta|y) d\theta, \quad (8)$$

$$\tilde{\pi}(\theta_j|y) = \int \tilde{\pi}(\theta|y) d\theta_{-j}. \quad (9)$$

thus, $\tilde{\pi}(\cdot|\cdot)$ is an approximated (conditional) density of its arguments. Approximations to $\pi(x_i|y)$ are computed by approximating $\pi(\theta|y)$ and $\pi(x_i|\theta, y)$ and using numerical integration (i.e. a finite sum) to integrate out θ . The nested approach makes Laplace approximations very accurate when applied to Latent Gaussian models. The approximation of $\pi(\theta|y)$ is computed by integrating out θ_{-j} from $\tilde{\pi}(\theta|y)$ of the marginal posterior of θ :

$$\tilde{\pi}(\theta|y) \propto \frac{\pi(\mathbf{X}, \theta, \mathbf{y})}{\tilde{\pi}_G(\mathbf{X}|\theta, \mathbf{y})} \Big|_{\mathbf{x}=\mathbf{x}^*(\theta)} \quad (10)$$

where $\tilde{\pi}_G(\mathbf{X}|\theta, \mathbf{y})$ is the Gaussian approximation to the full conditional of $\mathbf{X}$ and $\mathbf{x}^*(\theta)$ is the mode of the full conditional for $\mathbf{X}$, for a given θ . The proportionality sign in equation (10) is due to the fact that the normalizing constant for $\pi(\mathbf{X}, \theta|y)$ is unknown.

A tractable way to improve Gaussian approximation is to compute the Laplace approximation

$$\tilde{\pi}_{LA}(x_i|\theta, \mathbf{y}) \propto \frac{\pi(\mathbf{X}, \theta, \mathbf{y})}{\tilde{\pi}_{GG}(\mathbf{X}_{-i}|x_i|\theta, \mathbf{y})} \Big|_{\mathbf{x}_{-i}=\mathbf{x}_{-i}^*(x_i, \theta)} \quad (11)$$

where $\tilde{\pi}_{GG}$ is the Gaussian approximation to $\mathbf{X}_{-i}|x_i, \theta, \mathbf{y}$ and $\mathbf{x}_{-i}^*(x_i, \theta)$ is the model configuration. To make it computationally efficient, set $\mathbf{x}_{-i}^*(\mathbf{x}_i, \theta) \approx \mathbf{E}_{\tilde{\pi}_G}(\mathbf{X}_{-i}|x_i)$. The right-hand side is evaluated under the conditional density that is derived from the Gaussian approximation $\tilde{\pi}_G(\mathbf{X}|\theta, \mathbf{y})$.

2.3 Source of Data for Analysis

The data used for this study was obtained from the Ghana Statistical Service Demographic and Health survey conducted from March - July, 2020 and covered the whole country[13]. All methods used for the analysis were performed in accordance to the relevant guidelines and regulations of the Service

3 Results

The study used a secondary data from the Ghana Demographic and Health Survey 2020. It consists of 1,052 women selected from the 10 administrative regions of Ghana. A total of 188 maternal deaths were recorded representing (17.87%). The highest number of deaths was recorded in the Northern Region, 31(16.49%) followed by Western Region 24(12.77%). Details of the mortality situation are as contained in the table 1 below. The least number of maternal mortality in the country was recorded in Ashanti and Upper East Regions with 11(5.85%) each.

Table 1: **Regional Mortality Distribution**

Region	Number of Maternal Deaths
Western	24
Central	21
Greater Accra	21
Volta	17
Eastern	19
Ashanti	11
Brong Ahafo	18
Northern	31
Upper East	11
Upper West	15

3.1 Zero-inflated Negative Binomial Regression

Based on the results from the Zero-Inflated Negative Binomial Regression model, Age at Death, Marital Status, Educational Level, and Place of Death are the significant determinants of maternal mortality in the study since their P -values are all less than 0.05. Interestingly, whilst Region was linked to a decrease in maternal mortality with an estimated coefficient of -1.296541, the District rather contributed to increase in maternal mortality with estimated coefficient of 0.015867. However, both variables did not have significant contributions to the maternal mortality situation in this study. Details of the causes of maternal mortality are presented in Table 2 below. $\theta = 5174.1971$ and log-likelihood: -478.9 on 23 Df.

Table 2: **ANOVA based on the Negative Binomial Regression**

Variables	Estimate	Standard Error	Z Value	$P_r(> Z)$
Intercept	-9.864739	2.887612	-3.416	0.000635
Region	-1.296541	NA	NA	NA
District	0.015867	NA	NA	NA
Age at Death	0.244889	0.049346	4.963	6.95e-07
Marital Status	2.208348	0.334051	6.611	3.82e-11
Educational level	-0.436595	0.194265	-2.247	0.024613
Work (last 12 months)	-1.452806	1.035938	-1.402	0.160794
Religion	0.009955	0.061705	0.161	0.871837
Ethnic Group	0.012407	0.027137	0.457	0.647515
Place of Death	-1.169344	0.309039	-3.784	0.000154
Season she Died	-0.469467	0.722684	-0.650	0.515941

3.2 Bayesian Posterior Model Using INLA

The results of the Bayesian posterior model based on the $R - INLA$ package is presented in Table 3 below. There is a strong and negative relationship between Region and Maternal mortality since the posterior mean for Region is -0.033 and lies within the credible interval. There is also a strong negative relationship between Age at Death and Maternal mortality since the posterior mean for District is -0.038 and lies within the credible interval. The relationship between Marital Status and Maternal mortality is strong and negative since its posterior mean of -0.072 lies in the credible interval. Educational Level and Maternal mortality has a strong relation with a posterior mean of 0.035 and contained in the credible interval. Work in last 12 months has a strong and negative relationship with Maternal mortality since it has posterior mean of -0.709 and lies within the credible interval. There is also strong and positive relationship between Religion and Maternal mortality with a posterior mean of 0.005 and lies within the credible interval. Ethnic Group had a strong and positive relationship with a posterior mean of 0.005 and lies within the credible interval. Place of Death and Season where she died both have strong and positive relationship with Maternal mortality with posterior means of 0.255 and 0.200 respectively. The district of residence which was stratified as the random effect had strong positive relationship with Maternal Mortality with a posterior mean of 18851.00 and lies within the credible interval.

Table 3: **Posterior Estimates (Mean, Standard Deviation, and 95% Credible Interval) of the Covariate Coefficient Vector β**

Variables	Mean	Std Error	0.025 quant	0.5 quant	0.975 quant
Intercept	-7.694	0.559	-8.793	-7.694	-6.597
Region	-0.033	0.027	-0.086	-0.033	0.020
District	18851.00	17190.10	574.35	13672.39	64898.73
Age at Death	-0.038	0.009	-0.056	-0.038	-0.020
Marital Status	-0.072	0.070	-0.214	-0.070	0.062
Educational Level	0.035	0.33	0.030	0.035	0.100
Work (last 12 months)	-0.709	0.187	-1.084	-0.706	-0.349
Religion	0.005	0.011	-0.020	0.006	0.024
Ethnic Group	0.005	0.006	-0.009	0.005	0.016
Place of Death	0.255	0.056	0.143	0.255	0.364
Season of Death	0.20	0.149	-0.089	0.201	0.496

4 Discussion

Maternal deaths continue to be on the rise despite efforts of various stakeholders to stem this menace. It is a major indicator of the performance for health systems in any country. Therefore the Government of Ghana, Ministry of Health and the Ghana Health Service in collaboration with relevant stakeholders have been relentless in curbing this menace to improve the quality of life in the country. The high numbers of maternal deaths across the 10 regions is a testament of the worrying status of our health system as a country. Another important revelation in this study is the level of education emerging as a significant variable in determining the outcome of delivery. This is intrinsically linked to the decision making process regarding the occurrence of the three types of delays in seeking healthcare [7]. Thus occurrence of such delays complicates the health conditions of such women and badly influence health outcomes of such expectant mothers. This is particularly common in rural and under served communities especially where both couple are illiterates and are more prone to resort to traditional methods of managing pregnancies and its related complications [7, 3]. The situation in Ghana is more precarious as most critical health staff such as doctors and nurses hardly accept postings to rural and deprive communities. It is important among others to investigate the causes of the high maternal mortality in these under served communities and institute policies and measures to curtail future occurrences [16].

Age at death is also an important risk factor as identified in this study because, apart from the reduction in fitness level and other adverse health conditions associated with age, younger women are less experience in managing pregnancies and related conditions and may also be experiencing their first child birth. This calls for much care from pregnancy to delivery especially those with known unpleasant health conditions [14].

Marital status is another significant determinant of maternal mortality. This maybe due to the fact that married women tend to get improve care and support during pregnancy than the single ones. Also, husbands of these married women may assist in taking vital decisions leading to a reduction in the delays that could lead to complications and its associated risks [15].

Whilst only four variables: Age at Death, Marital Status, Educational Level, and place of Death were significant under the Zero-Inflated Negative Binomial Regression, four more variables emerged significant under the Bayesian Additive Posterior modeling. These are Region, Religion, Ethnic Group and Season of Death. This means the Bayesian posterior modeling with Laplace approximation fits the data well and optimize information gain than the Zero-Inflated Negative Binomial regression.

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