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Weighted Bayesian Fractional Regression Model for Estimating Community Deaths in Africa

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Abstract:

Death registration systems in Africa often don't capture all the events, especially those deaths that occur in the community. Knowing accurately how many people die in a community is extremely important. It helps understand why people are dying and how to improve the official records. In this study, we use the available national data to estimate the deaths that take place outside the health facilities, that is the community deaths. Weighted Bayesian fractional regression model is used to study different factors that explain community death rates in Africa. These factors include the quality of the health system, the economic conditions people live in, characteristics of the geography, and other external influences. We used a variety of existing information sources to gather and assess data to meet our research objectives. To make sure our findings were strong, we checked them using different methods. We then checked how good our model was using the Deviance Information Criterion, comparing it against the unweighted Bayesian fractional regression model. We then prioritised each factor based on how big an effect it has on community deaths in Africa using dominance analysis. Our study emphasises the need of assessing and improving current public awareness programmes and policy initiatives that target community mortality in Africa. Additional research is required to enhance our comprehension of community mortality, considering the many factors our study has uncovered. Therefore, we suggest conducting comprehensive investigations that specifically examine the variables that contribute to community fatalities. This would greatly enhance the existing body of research on how to address and reduce community mortality in Africa.

Keywords- Community Deaths, Weighted Bayesian Fractional Regression, Deviance Information Criterion, Dominance Analysis.

I. Introduction

Throughout recent years, there has been an increasing scholarly focus on the precise estimation of mortality rates inside residential settings throughout the African continent. Home fatalities, often referred to as community deaths, are instances of mortality that transpire outside the confines of healthcare establishments, typically transpiring inside the individual's own residence. Accurate estimation of the prevalence of fatalities occurring inside residential settings is of paramount importance in comprehending the comprehensive mortality impact within a certain populace and in providing valuable insights for public health actions. The precise assessment of mortality rates occurring within households in Africa has significant importance for several reasons. To begin with, fatalities occurring inside residential settings serve as a significant metric for assessing the overall health condition of a certain community. Limited access to healthcare and diagnostic capabilities, as well as stringent testing, and practices, implies that reported cases and fatalities are anticipated to represent a fraction of the genuine numbers [1]. Due to a lack of reliable data, low-income and middle-income nations (also known as LMICs) have a difficult time pinpointing the factors that lead to mortality in their populations. This is often due to deaths occurring outside of formal medical settings and minimal contact with healthcare services, resulting in a lack of proper documentation and registration [2].

Estimating the number of fatalities that occur in African communities with sufficient precision is essential in the realm of public health for the purposes of comprehending the extent of the disease burden and creating effective treatments. This issue presents a particularly difficult challenge in Africa for a number of reasons, including a lack of resources and an insufficient infrastructure for healthcare, as well as cultural practises that might have an effect on the reporting and documenting of fatalities. The absence of trustworthy data is a significant obstacle when attempting to estimate the number of fatalities that occur within African communities. Because there is a paucity of data that can be relied upon, it is impossible to acquire an accurate picture of the exact number of fatalities that are happening in communities. In addition, the procedure that is used to gather data in Africa is rife with uncertainty and inaccuracy, which frequently leads to a reduction in the accuracy of the reported cases and fatalities in Africa. According to [3], in many African nations, for instance, sick children often do not have access to official healthcare, and the majority of fatalities take place inside family homes.

The primary objective of this study is to use a weighted Bayesian fractional regression model to gain insights into the many elements, including health systems, socio-economic conditions, geographical factors, and external influences, that contribute to community mortality rates in Africa. Additionally, the aim is to ascertain the extent to which the explanatory factors contribute to the explanation of community fatalities, hence establishing their dominance.

A systematic literature review conducted by [4] studied home-death obstacles and facilitators. The 2006–2016 research examined PubMed, EMBASE, Ovid, CINAHL, and PsycINFO. They identified seven main barriers to home deaths: a lack of knowledge, skills, and support among healthcare professionals and informal carers, the burden on informal carers and families, difficulty recognising death, inadequate processes like advance care planning and discharge, and patient-specific challenges due to their condition or social circumstances. The research found four main facilitators of home deaths: patient and healthcare professional support, competent personnel, coordination, and communication. [5] estimated national and sub-national death registration completeness. They employed random-effects models to estimate the logit of death registration completeness based on registered crude death rate, under-five mortality rate, population age structure, and under-five death registration completeness. [6] studied age-specific mortality. Death registration accuracy was assessed using empirical completeness. The traditional and similar dying methods were used using a model life table. Also, [7] examined short-term mobility before death in Burkina Faso and Senegal adults. Age and nativity were major drivers of migration before death in specific locations, and a fraction of fatalities occurred outside the HDSS site. [8] studied non-traumatic adult fatalities in Botswana and variables that affect where individuals die, such as age, gender, occupation, district of residence, and cause of death. Home fatalities accounted for 36% of all deaths, with unexplained causes being the most common. HIV/AIDS, cardiovascular disease, and cancer dominated hospital fatalities. Females, those over 80, and those in cities or rural areas were more likely to die at home.

According to the research presented in [9], a sizeable portion of the deaths that take place in low- and middle-income countries (LMICs) take place inside the confines of the home. According to the results of the study, the domestic death rate of low- and middle-income countries is around 60% higher than the domestic mortality rate of high-income countries, which is 27%. This would imply that a larger number of deaths in low- and middle-income countries take place outside of established healthcare institutions such as hospitals and clinics. This suggests that a sizable number of fatalities escape detection by traditional monitoring techniques, which results in an underestimate of the true burden of disease. Estimating the number of fatalities that occurred inside African communities using a fractional regression model is one possible solution to this issue. This research used widely available national and sub-national data to estimate the predicted number and percentage of home deaths in a population to cover the essential information vacuum. African countries may improve their civil registration systems and learn where deaths occur.

The subsequent sections of the research are structured as follows: In the second part, we provide the weighted Bayesian fractional regression models as a method for doing data analysis. Section 3 of the paper elucidates the utilisation of the weighted Bayesian fractional regression model in the context of community death data pertaining to 47 African nations as designated by the World Health Organisation (WHO). Section 4 provides a conclusion and recommendations.

II. Materials and Methods

A. Data Description

This research primarily examines the fraction of fatalities that occur outside of health facilities. To establish our model framework, we collected data from several sources, including the World Health Organisation (WHO), World Bank, among others. The model structure is shown in Figure 1. The approach we propose builds upon the work of [9] as an expansion. The variables included in the models encompass the health system, socio-economic, geographic features, and other external factors.

a. Health System Covariates

1. The logarithm of health expenditure per capita is obtained from the World Health Organisation Global Health Expenditure Database.

2. The Global Burden of Disease Study's Universal Health Care (UHC) effective coverage indicator. The UHC index has 23 indicators that include many healthcare categories, including promotion, prevention, treatment, rehabilitation, and palliation. These indicators are applicable to five distinct age groups within the population. The indicators include both objective measurements of the extent to which health system interventions are implemented, as well as assessments of the resulting outcomes. The index used a weighting system to assign value to the variables, taking into consideration their potential impact on health outcomes as measured by disability-adjusted life-years.

3. The present study examines the stated rates of home births as documented by reputable sources such as UNICEF, Multiple Indicator Cluster Survey, and Demographic and Health Survey data.

4. The proportion of available medical professionals in each country.

b. Socio-economic Covariates

1. The Socio-Demographic Index (SDI) used by the Global Burden of Disease (GBD) is calculated as the geometric mean of three key indicators: the fertility rate among individuals below the age of 25, the average level of education for those aged 15 and above, and the lag distributed income per capita.

2. The education index of the Human Development Index (HDI) by the United Nations (UN) is used as a metric to gauge the average number of years spent in schooling. Additionally, the income index is included, together with the education index, to calculate the geometric mean of these two indexes.

3. Income level of each country by classification as determined by the World Bank.

c. Geographic Covariate

1. The proportion of individuals residing in urban regions, as determined by the United Nations Population Division.

d. External Factors Covariates

1. Natural Disaster Index, the primary component of the World Risk Report (WRR) is the WorldRiskIndex (WRI), which has been developed by the Institute for Environment and Human Security (EHS) at the United Nations University (UNU) in collaboration with Bündnis Entwicklung hilft (BEH).

2. WHO-determined health seeking behaviour that attempts to help countries better comprehend where their populations seek care in order to govern their health systems.

3. Health inequality from the WHO global health observatory.

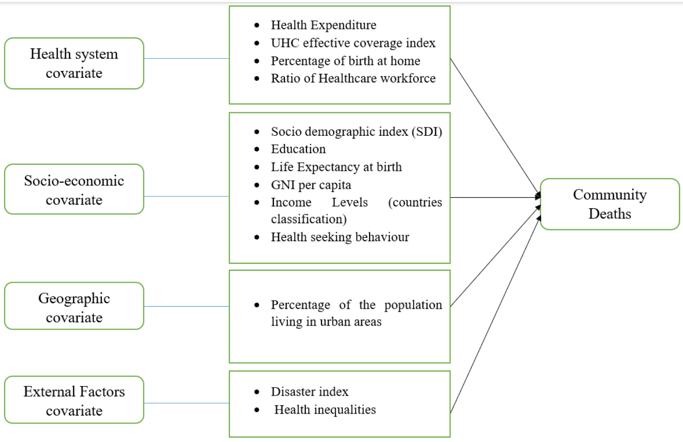

Figure 1: Conceptual Framework

B. Fractional Response Model and the Likelihood Function

The Fractional Regression model (FRM) was proposed by [10] as a solution to the limitations faced by linear and nonlinear econometric models when dealing with bounded dependent variables.
Let Y_i be the fraction of deaths that occur outside the health facility. In a fractional regression model, the response variable is a fractional outcomes bounded between 0 and 1. It is common to assume that the response variable follows a beta distribution, which is suitable for modeling continuous outcomes constrained within a specific range with the probability density function of the beta distribution is given by:

$$f(y;\alpha,\beta) = \frac{1}{B(\alpha,\beta)}\left[y^{\alpha-1}(1-y)^{\beta-1}\right]$$

where y is the random variable, α and β are the shape parameters, and $B(\alpha,\beta)$ is the beta function. The beta function is defined as:

$$B(\alpha,\beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1}dt$$

The mean and variance of the beta distribution are given by:

1. $\mu = \frac{\alpha}{\alpha+\beta}$

2. $\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$

To establish a connection between the linear predictor and the mean function in a fractional regression model, we often use the logit-link function [11]. The logit-link function transforms the expected value of the response variable (which lies between 0 and 1) onto the entire real line. The logit transformation is defined as the natural logarithm of the ratio of the expected value to its complement:

$$\text{logit}(E(Y \mid \mathbf{x}; \beta)) = \mathbf{x}^T \beta$$

where $\beta = (\beta_0, \beta_1, \beta_2, \cdots, \beta_p)$ and $\mathbf{x} = (1, x_1, x_2, \cdots, x_p)$ are $(p+1)$ column vectors which refers to the regression coefficients and predictor variables, respectively.
Assuming that the observed response of the i^{th} fraction of community death is y_i and the explanatory variable values are represented by the vector $\mathbf{x}_i$, we define w_i as the corresponding weight. We adopt the approach presented in [12] and [13] to establish the weighted likelihood function, which is given by

$$L(\beta) = \prod_{i=1}^{n} P(Y_i = y_i \mid \mathbf{x}; \beta)^{w_i} \tag{II..1}$$

Here, $P(Y_i = y_i \mid \mathbf{x}; \beta)$ represents the probability density function of the beta distribution, which depends on the expected value of the response variable given the predictor variables and the regression coefficients.

C. Estimation of Parameters

a. Prior Distribution

In Bayesian analysis, the prior distribution, $\pi(\beta)$, represents our initial belief about the parameter β. A wide range of prior distributions can be found in the Bayesian literature [14]. The term "non-informative prior," also known as a "vague, flat, or diffuse prior," in Bayesian analysis is often used to denote the absence of any previous information about the parameter of interest. Jeffrey's prior [15] is another sort of non-informative prior that is often used with a single parameter. The Fisher information matrix $I(\beta)$ and $\pi(\beta) \propto \sqrt{|I(\beta)|}$ are used to calculate Jeffrey's prior, which is scale-invariant. A weakly informative prior known as the unit information prior incorporates information from a single data point [16]. The spike-and-slab prior [17] is helpful for variable selection, especially in situations in which the number of explanatory variables is higher than the number of data points. On the other hand, an informative prior is utilised to combine both the information that we already know and the uncertainty that we have on the parameter of interest [18]. In this study, we used three instructive priors that have been meticulously created, justified, and presented.
Assuming that each of the regression coefficients is independent of the others $\beta_j (j = 0, 1, \cdots, p)$ [19], the joint prior distribution for β can be formulated as follows:

$$\pi(\beta) = \prod_{j=0}^{p} \pi(\beta_j|\lambda_j, \sigma_j) \tag{II..2}$$

Here, $\pi(\beta_j|\lambda_j, \sigma_j)$ represents the marginal prior for the j^{th} coefficient. Including this marginal prior into the joint prior distribution for β will create the joint prior distribution, and three different types of priors are considered for $\pi(\beta_j|\lambda_j, \sigma_j)$.

The first prior considered is a Normal prior [20], which is described by the following density function:

$$\pi(\beta_j|\lambda_j, \sigma_j) = \frac{1}{\sigma_j\sqrt{2\pi}} exp\left\{-\left(\frac{\beta_j - \lambda_j}{\sqrt{2}\sigma_j}\right)^2\right\}$$

The Normal prior is characterized by location and scale parameters λ_j and σ_j, respectively, which determine the shape of the distribution. In order to impose a constraint similar to $L2$ norm that performs regularization akin to Ridge regression [21], all λ_j's are set to 0.

A Laplace prior [22] is the second prior distribution that we utilized, and its density is given by:

$$\pi(\beta_j|\lambda_j, \sigma_j) = \frac{1}{2\sigma_j} exp\left\{-\frac{|\beta_j - \lambda_j|}{\sigma_j}\right\}$$

The prior distribution with location and scale parameters λ_j and σ_j, respectively, is commonly referred to as the double exponential prior. When $\lambda_j = 0$, this prior acts as an $L1$ norm constraint, while also performing regularization similar to the LASSO [23].

We considered a third prior, which is a Cauchy distribution [24] characterized by its density function.

$$\pi(\beta_j|\lambda_j, \sigma_j) = \left[\pi\sigma_j\left(1 + \left(\frac{\beta_j - \lambda_j}{\sigma_j}\right)^2\right)\right]^{-1}$$

The location and scale parameters of the Cauchy prior are denoted by λ_j and σ_j, respectively. Notably, when $\lambda_j = 0$, this prior is known to induce more substantial shrinkage than the Normal and Laplace priors [25].

b. Posterior Means

The focus of the Bayesian regression model is on the posterior distribution $\pi(\beta|\mathbf{y}, \mathbf{x})$, which is obtained by multiplying the likelihood function $f(y|\beta)|f(y)$ and the prior distribution $\pi(\beta)$.

$$\pi(\beta|y) = \frac{f(y|\beta)\,\pi(\beta)}{f(y)}$$

Where

$$f(y) = \int_{\beta} f(y|\beta)\, g(\beta)\, d\beta$$

The normalizing constant of integration, also known as the marginal likelihood, is independent of β. It can be difficult to compute, and as a result, the evaluation of the posterior distribution is also challenging. To simplify this, the common practice is to exclude the normalizing constant and express it as:

$$\pi(\beta|y) \propto f(y|\beta)\,\pi(\beta)$$

Now by combining the likelihood function (Eq. II..1) with the prior distribution (Eq. II..2), we obtain the joint posterior distribution of β.

$$\pi(\beta|\mathbf{y},\mathbf{x}) \propto L(\beta) \times \pi(\beta) = \prod_{i=1}^{n} P(Y_i = y_i \mid \mathbf{x};\beta)^{w_i} \times \prod_{j=0}^{p} \pi(\beta_j|\lambda_j,\sigma_j) \quad \text{(II..3)}$$

The symbols $L(\cdot)$ and $\pi(\cdot)$ represent the likelihood function and the prior distribution, respectively. The generation of posterior samples using Monte Carlo techniques [26] or a Gibbs sampler [27] is not viable due to the absence of a closed-form representation of a conventional statistical distribution for the joint posterior distribution of β. The Metropolis algorithm proposed by [28] is recommended for addressing this issue.

c. The Metropolis Algorithm

We made use of the Metropolis method to roughly estimate the posterior means of β. starting with a certain parameter vector state, $\beta^{(s)}$, we generated a new state using the following procedure:

1. Sample a proposal state β^*

   $$\beta^* \sim P^*\left(\beta|\beta^{(s)}\right)$$

   where $P^*(\cdot)$ is the proposal distribution to be explained later.

2. Calculate the acceptance ratio r

   $$r = \frac{\pi(\beta^*|\mathbf{y},\mathbf{x})}{\pi\left(\beta^{(s)}|\mathbf{y},\mathbf{x}\right)}$$

   where $\pi(\cdot|\mathbf{y},\mathbf{x})$ is the posterior distribution of β

3. Accept or reject the proposal with

   $$\beta^{(s+1)} = \begin{cases} \beta^*, \text{with probability min(r,1)} \\ \beta^{(s)}, \text{with probability 1-min(r,1)} \end{cases}$$

The proposal distribution $P^*(\cdot)$ for β is considered as multivariate-normal (MVN):

$$\beta|\beta^{(s)} \sim \text{MVN}\left(\beta^{(s)}, \Sigma^p\right)$$

The proposal variance-covariance matrix Σ^p is similar to the variance-covariance matrix of the ordinary least squared method.

$$\Sigma^p = \left[\hat{\sigma}^2\left(\mathbf{x}^T\mathbf{x}\right)^{-1}\right]k$$

with $\hat{\sigma}^2$ being the sample variance of $\{log(y_1+0.5), log(y_2+0.5), \cdots, log(y_n+0.5)\}$. We advise starting with $k=1$ in order to establish a suitable Σ^p. If this decision results in an extremely low or high acceptance rate, we advise adjusting Σ^p using different values of $k>0$ until a realistic acceptance rate is reached.

d. Model Selection

[29] was the first to propose the Deviance Information Criterion (DIC). It is a generalisation of the Akaike Information Criterion (AIC) for hierarchical modelling. DIC is especially helpful in Bayesian model selection problems where the posterior distributions of the models have been derived through Markov chain Monte Carlo (MCMC) simulation. The most applicable model was chosen using the Deviance Information Criterion (DIC), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) values. [30] introduced the Bayesian information criterion as an alternative to the [31] information criterion. Schwarz derived BIC as an approximation to an asymptotic transformation of the Bayesian posterior probability of a candidate model. In contexts with a large sample size, the fitted model favoured by BIC should correspond to the candidate model that is a posteriori most probable; that is, the model that is rendered most plausible by the available data. Priors are not required for the computation of BIC, which is based on the empirical log-likelihood. Assuming that two candidate models are considered equally probable a priori, the Bayes factor is the ratio of the models' posterior probabilities. The model with the highest posterior probability is determined by whether or not the Bayes factor is less than one. The definitions of AIC, BIC, and DIC are given as:

$$AIC = -2\ln(L) + 2k \quad \text{(II..4)}$$

Where:

L is the likelihood of the model.

k is the number of model parameters.

$$BIC = -2\ln(L) + k\ln(n) \quad \text{(II..5)}$$

Where:

L is the likelihood of the model.

k is the number of model parameters.

n is the sample size.

$$DIC = D(\bar{\theta}) + p_D \quad \text{(II..6)}$$

Where:

$D(\bar{\theta})$ is the posterior mean of the deviance.
p_D is a penalty term for model complexity.

The penalty term p_D is often computed as:

$$p_D = \bar{D} - D(\bar{\theta})$$

Where:

$\bar{D}$ is the average deviance over the posterior samples.

e. Bayesian R-squared:

An important consideration in a regression model is to determine the percentage of variability in the response variable that is explained by the independent variable(s). The Bayesian R^2 proposed by [32] uses the variance of the predicted values divided by the variance of predicted values plus the expected variance of the errors. i.e,

$$R^2 = \frac{\sigma_{fit}}{\sigma_{fit} + \sigma_{res}} \tag{II..7}$$

where,

1. σ_{fit} is the variance of the modeled predictive means
2. σ_{res} is the modeled residual variance

f. Predictor Relative Importance

The phrase "relative importance analysis", encompasses many techniques used to identify the contributions of linked variables inside a regression model and to estimate their significance. There are several relative importance analysis techniques applied by researchers some are Dominance Analysis by [33] and Relative weight anlysis by [34]. These two approaches are the most popular ones, and they are also the ones that are often cited as the preferred processes for determining the relative significance of predictor variables [35]. Following the idea by [36] we used the dominance analysis to compute the relative importance of the independent variables.

D. Software

The Bayesian analysis was conducted using a R package developed by [37]. The brms package offers a software interface for the purpose of fitting Bayesian generalised (non-)linear multivariate multilevel models by using the Stan programming language. The statistical software stata version 17 and excel were used to produce frequency distributions, graphical representations, and cross-tabulations.

III. Results and Discussion

We used the suggested technique in this section to analyse data from the 47 WHO African nations that were covered in the prior section. We investigated the weighted Bayesian fractional regression model for model fitting. The Bayesian R-square goodness-of-fit were used to determine how well these models matched the actual data. The best model for the data was then chosen using Deviance Information Criterion (DIC). The implications of community deaths in Africa were then estimated and discussed using the appropriate model.

Table 1: Description of Variables

	Variable	Description
1	y (dependent variable)	fraction of community deaths
2	x_1	log(Health Expenditure)
3	x_2	Universal Health Coverage
4	x_3	Percentage of Birth at Home
5	x_4	Health Inequality
6	x_5	Social Demographic Index
7	x_6	Health Seeking Behavior
8	x_7	Percentage of Pop. In the Urban Areas
9	x_8	Life Expectancy at Birth
10	x_9	Mean Educational Years
11	x_{10}	Gross National Income
12	x_{11}	Disaster Index
13	x_{12}	Ratio of Healthcare Workforce
14	x_{13}	Income Level Classification

A. Descriptive Statistics

Table 2: Descriptive Statistics Table

Variable	Categories/Type	Mean	Std. dev.	Min	Max
y	Quantitative	0.6500136	0.2278802	0.04	0.998
x_1	Quantitative	5.130365	0.9531708	3.621	7.476
x_2	Quantitative	46.15532	9.777032	22.3	64.9
x_3	Quantitative	11.1	16.62187	1	88.5
x_4	Quantitative	37.28298	21.98528	0.5	90.1
x_5	Quantitative	0.4400213	0.1394749	0.162	0.724
x_6	Quantitative	0.5265575	0.1477599	0.2815632	0.8395367
x_7	Quantitative	43.59591	19.43731	12.5	89.8027
x_8	Quantitative	62.07711	5.138073	52.5254	76.3767
x_9	Quantitative	10.87322	2.079068	5.54251	15.17353
x_{10}	Quantitative	4979.467	5441.278	731.7867	25830.62
x_{11}	Quantitative	5.870851	6.164477	0.48	34.37
x_{12}	Quantitative	0.3429681	0.4913541	0.0162	2.4717

Table 2 provides an overview of the analytic sample, displaying the descriptive statistics for the variables utilised in this research. In summation, it can be observed that a significant proportion, approximately 65%, of mortalities in Africa transpire beyond the confines of healthcare facilities. The mean health expenditure per capita in Africa is \$164, with a minimum value of \$37.34 and a maximum value of \$1,765.17. The mean universal health coverage in Africa is 46.16. The mean proportion of home births is 11.1%. Additionally, it is worth noting that the proportion of individuals residing in urban regions stands at 43.60%. The mean life expectancy at birth is 62 years, whereas the mean number of years of schooling is 10.87 years. The mean value of the gross national income is \$4,979.47. According to the natural disaster index, the 47 African countries under the jurisdiction of the World Health Organisation (WHO) have an average probability of 5.87% for experiencing a natural disaster. This indicates that Africa possesses a moderate level of susceptibility to such events, with the lowest recorded probability being 0.48% and the highest reaching 34.37%. The mean value of the healthcare workforce ratio is 0.34.

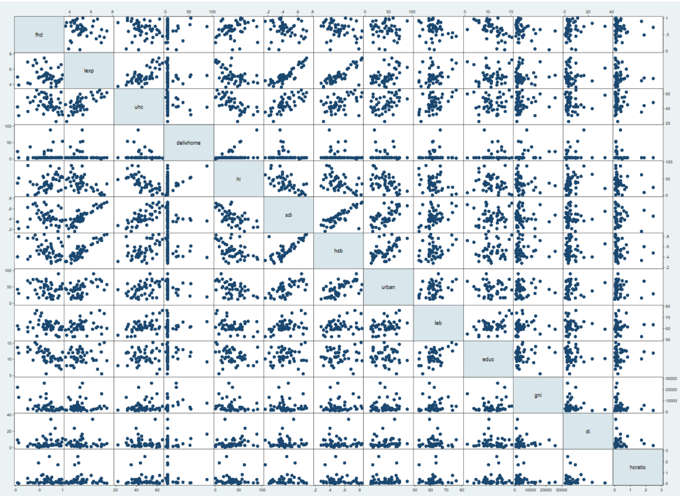

Figure 2: Scatter plot Matrix of the variables

The scatter plot matrix reveals several noteworthy correlations. Firstly, there is a negative correlation between fractional home deaths and health expenditure. Additionally, a negative correlation is observed between fractional home deaths and universal health coverage. Conversely, a positive correlation is evident between fractional home deaths and the percentage of home delivery. Furthermore, a positive correlation is observed between fractional home deaths and health inequality. Furthermore, it was noted that there exists an inverse correlation between fractional home deaths and the social demographic index. Additionally, a negative association was found between fractional home deaths and health-seeking behaviour, as well as the percentage of individuals residing in urban areas. Moreover, fractional home deaths displayed a negative relationship with life expectancy at birth, average educational years, the ratio of healthcare workforce, and gross national income. There exists a positive correlation between fractional home deaths and the disaster index.

Table 3: Normality test Results

	Test type	Test Statistic	P-value
1	Pearson test	65.64	2.64e-08
2	Shapiro test	0.95	1.59e-07
3	Anderson Darling test	2.73	6.70e-07
4	Lilliefors test	0.11	9.98e-07

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results of the normality test are shown in Table 3. Various types of tests indicate that the distribution of responses is not normal. Given the variability in community mortality rates falling within the range of 0 to 1 and the departure from normal distribution, it is advisable to use an alternative approach. Hence, a fractional regression model was used in consideration of the inherent characteristics of the proportion of community deaths.

B. Estimation of Community Deaths

Table 4: Posterior estimates with 95% credible intervals (CI) of the estimated coefficients for WBFR

Variable	Categories/Type	Estimate	Est. Error	Q2.5	Q97.5
Intercept		1.341142	0.4147571	0.5282331	2.154051
x_1	Quantitative	-0.9744168	0.1169453	-1.203625	-0.7452083
x_2	Quantitative	-0.0127012	0.0055768	-0.0236315	-0.0017708
x_3	Quantitative	0.0090048	0.0023809	0.0043383	0.0136713
x_4	Quantitative	0.1732216	0.0636578	0.0484547	0.2979886
x_5	Quantitative	-0.6276504	0.475733	-1.56007	0.304769
x_6	Quantitative	-0.9831012	0.3312814	-1.632401	-0.3338015
x_7	Quantitative	0.0027189	0.0021391	-0.0014736	0.0069114
x_8	Quantitative	-0.0042092	0.0021917	-0.0085048	0.0000865
x_9	Quantitative	-0.1176975	0.019363	-0.1556482	-0.0797467
x_{10}	Quantitative	-0.0000314	8.55E-06	-0.0000481	-0.0000146
x_{11}	Quantitative	0.0015803	0.0027188	-0.0037484	0.006909
x_{12}	Quantitative	-0.2137235	0.0994344	-0.4086114	-0.0188356
x_{13}	High-income (ref)				
	Upper-middle-income	0.0174515	0.008015	0.0017423	0.0331606
	Lower-middle-income	0.071471	0.027699	0.0171803	0.125761
	Low-income	0.1159666	0.001896	0.1122497	0.119683

$AIC = 577.58,\ BIC = 730.5425,\ DIC = 67.462,\ \text{Bayes}R^2 = 0.4589$

Table 5: Posterior estimates with 95% credible intervals (CI) of the estimated coefficients for BFR

Variable	Categories/Type	Estimate	Est. Error	Q2.5	Q97.5
Intercept		2.3417	2.2076	-1.9851	6.6684
x_1	Quantitative	0.4489	0.2704	-0.0812	0.9789
x_2	Quantitative	-0.0230	0.0233	-0.0686	0.0227
x_3	Quantitative	0.0271	0.0100	0.0075	0.0467
x_4	Quantitative	-0.0053	0.0083	-0.0216	0.0109
x_5	Quantitative	-2.1577	1.8943	-5.8705	1.5551
x_6	Quantitative	-1.7422	1.3943	-4.4751	0.9906
x_7	Quantitative	0.0094	0.0084	-0.0071	0.0259
x_8	Quantitative	0.0276	0.0344	-0.0398	0.0951
x_9	Quantitative	-0.2246	0.0805	-0.3824	-0.0669
x_{10}	Quantitative	-0.0001	0.0000	-0.0001	-0.0000
x_{11}	Quantitative	0.0034	0.0183	-0.0324	0.0393
x_{12}	Quantitative	0.1202	0.2214	-0.3138	0.5541
x_{13}	High-income (ref)				
	Upper-middle-income	-1.8406	0.7226	-3.2569	-0.4244
	Lower-middle-income	-0.5007	0.7159	-1.9038	0.9025
	Low-income	-0.1313	0.7776	-1.6554	1.3927

$AIC = 832.054,\ BIC = 856.106,\ DIC = 108.453,\ \text{Bayes}R^2 = 0.1320$

Tables 4 and 5 provide the findings of the models in both their weighted and unweighted forms, respectively. The log health expenditure, universal health coverage, percentage of births that take place at home, health inequality, health-seeking behaviour, mean educational years, gross national income, ratio of health workforce, and income level classification are all factors that, according to the weighted model, have a significant impact on community deaths. When we look at the model without weights, we can see that the proportion of births that occur at home, the mean number of years spent in school, and the gross national income all have a considerable impact on community deaths. When everything is said and done, the weighted fractional model identifies nine primary important drivers of community deaths, while the unweighted model identifies just three major determinants of deaths in a community.

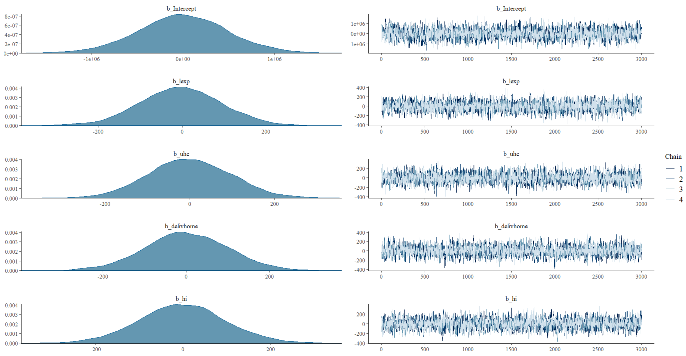

Figure 3: Trace plot of variables

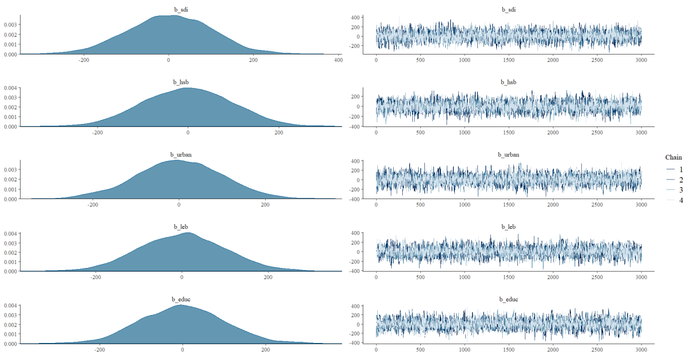

Figure 4: Trace plot of variables

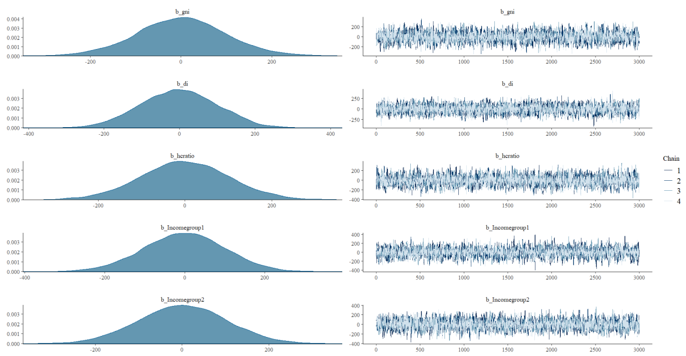

Figure 5: Trace plot of variables

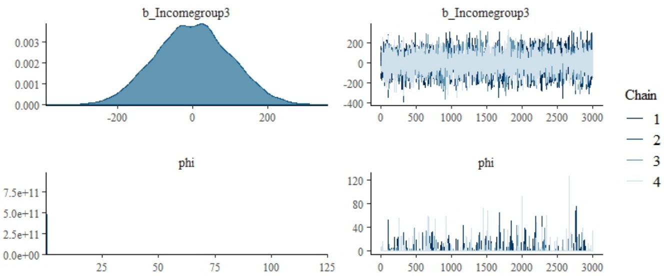

Figure 6: Trace plot of variables

The intermingling of the chains is evident. The data exhibits a significant amount of variability, as shown by the fluctuation of values, resulting in the exploration of the whole distribution. Thus far, the observed chain exhibits satisfactory behaviour and seems to converge towards the stationary distribution.

Table 6: Dominance Statistics

Variable	Dominance Stat.	Stand. Domin. Stat.	Ranking
x_1	0.065136842	0.141941255	3
x_2	0.015052632	0.032801551	5
x_3	0.013136842	0.028626808	6
x_4	0.008210526	0.017891755	7
x_5	0.004789474	0.010436857	10
x_6	0.030036842	0.065454003	4
x_7	0.003489474	0.007603996	13
x_8	0.004515789	0.009840465	12
x_9	0.126989474	0.276725809	2
x_{10}	0.007184211	0.015655286	8
x_{11}	0.004652632	0.010138661	11
x_{12}	0.005405263	0.011778739	9
x_{13}	0.1703	0.371104816	1

Based on the findings presented in Table 6, it is evident that the healthcare system covariates contribute to 21.51% of the explained variability. Additionally, the socio-economic covariates account for a substantial portion of the explained variability, specifically 74.92%. Furthermore, the geographic covariate is responsible for a minimal 0.76% of the explained variability, while the external factors covariates contribute to 2.81% of the explained variability. This suggests that the socio-economic covariate is a significant factor in predicting the occurrence of community deaths.

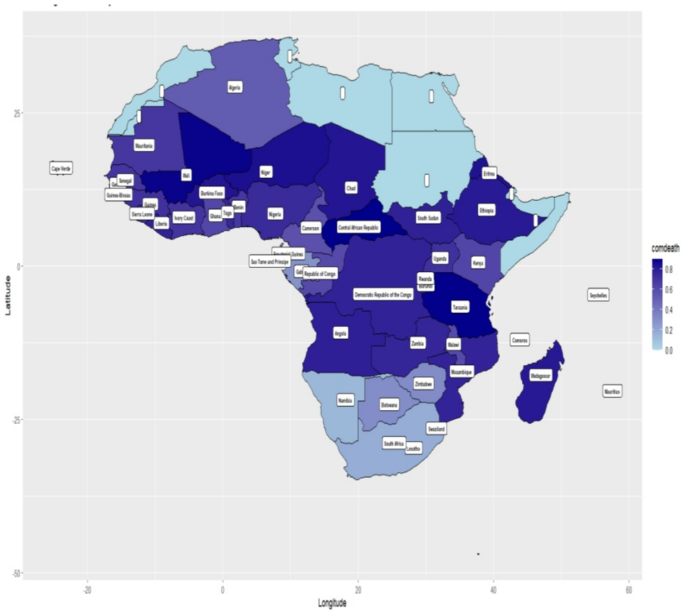

Figure 7: Percentage of Community Deaths in Africa

On the basis of the model that we developed, Figure 8 presents a projection of the proportion of community deaths across 47 nations in Africa. It is plain to observe that a larger proportion of fatalities in the community corresponds to a darker shade of blue.

IV. Conclusion

Upon conducting a thorough analysis employing the weighted Bayesian fractional regression model, a multitude of factors, each with a significant impact, were pinpointed as pivotal determinants of mortality rates within communities. These encompass factors such as the logarithm of health expenditure, the degree of universal health coverage, the proportion of births occurring domestically, the level of health inequality within the community, the propensity for health-seeking behaviour, the mean duration of education, the gross national income, the relative ratio of health workforce, and the classification of income level.
In stark contrast, a similar analysis devoid of the incorporation of the weights from the model, delineated that mortality rates in communities primarily hinge on three crucial factors: the fraction of births transpiring at home, the mean duration of educational pursuits, and the gross national income of the respective communities.
In essence, the weighted fractional model offers a comprehensive understanding by identifying nine primary catalysts of community mortality rates. Conversely, the unweighted model provides a more narrowed perspective by recognising only three as the major determinants of community deaths.
Our research underscores the necessity of evaluating and ameliorating existing public-awareness campaigns and policy initiatives tailored towards community deaths across the African continent. Given the varying determinants our study identified, more research is needed to increase the understanding of community mortality. Hence, we propose the execution of in-depth studies focusing on the factors contributing to community deaths, which would significantly augment the extant literature on addressing and mitigating community mortality in Africa.

Author contribution

Conceptualization: Issah Matinu Abdul
Analysis: Issah Matinu Abdul
Methodology: Issah Matinu Abdul
Visualization & Software: Issah Matinu Abdul
Writing-Review & Editing: Issah Matinu Abdul, Joseph K. Mung'atu, & Kipruto Hillary

Conflicts of Interest

All authors have read and agreed to the published version of the manuscript.

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RESEARCH ARTICLE OPEN ACCESS

Weighted Bayesian Fractional Regression Model for Estimating Community Deaths in Africa

SUPPLEMENTARY MATERIAL

S1- Estimates of Percentage of Community Deaths with 95% Credible Interval
S2- Estimates of Total Community Deaths with 95% Credible Interval
S3- Estimates of Total Deaths by Age Groups

Table S1 Estimates of Percentage of Community Deaths with 95% Credible Interval

sn.	Country	Est. Comm. deaths	Std. Error	95% CI	
				Lower Limit	Upper Limit
1	Algeria	0.519422	0.127236	0.270039	0.768804
2	Angola	0.791124	0.046279	0.700417	0.881831
3	Benin	0.686291	0.104668	0.481141	0.891441
4	Botswana	0.309403	0.102368	0.108762	0.510043
5	Burkina Faso	0.8272	0.087007	0.656666	0.997733
6	Burundi	0.770211	0.105278	0.563866	0.976556
7	Cabo Verde	0.645855	0.162195	0.327953	0.963758
8	Cameroon	0.57129	0.157959	0.261691	0.88089
9	Central African Republic	0.896892	0.042082	0.814411	0.979373
10	Chad	0.827296	0.072006	0.686164	0.968429
11	Comoros	0.675825	0.108932	0.462318	0.889332
12	Congo	0.606405	0.1094	0.391981	0.820829
13	Cote d'Ivoire	0.700945	0.120298	0.465161	0.936728
14	Democratic Republic of the Congo	0.779842	0.100343	0.583171	0.976514
15	Equatorial Guinea	0.350093	0.13638	0.082788	0.617398
16	Eritrea	0.836987	0.071559	0.696731	0.977243
17	Eswatini	0.467574	0.118944	0.234443	0.700704
18	Ethiopia	0.812838	0.072762	0.670224	0.955451
19	Gabon	0.286968	0.087879	0.114726	0.45921
20	Gambia, The	0.785604	0.103431	0.582879	0.988329
21	Ghana	0.620924	0.148642	0.329586	0.912262
22	Guinea	0.715892	0.119351	0.481964	0.94982
23	Guinea-Bissau	0.76059	0.114417	0.536333	0.984846
24	Kenya	0.624844	0.105408	0.418244	0.831444
25	Lesotho	0.607828	0.119454	0.373698	0.841958
26	Liberia	0.783232	0.0985	0.590172	0.976292
27	Madagascar	0.817126	0.051415	0.716352	0.917899

28	Malawi	0.597529	0.116413	0.36936	0.825698
29	Mali	0.885345	0.022082	0.842065	0.928625
30	Mauritania	0.691419	0.132507	0.431705	0.951133
31	Mauritius	0.19781	0.049293	0.101197	0.294424
32	Mozambique	0.776554	0.101472	0.57767	0.975439
33	Namibia	0.13203	0.042509	0.048711	0.215348
34	Niger	0.850073	0.068065	0.716666	0.983479
35	Nigeria	0.741453	0.101994	0.541545	0.94136
36	Rwanda	0.759401	0.105635	0.552356	0.966445
37	Sao Tome and Principe	0.519053	0.146139	0.232621	0.805485
38	Senegal	0.692828	0.109473	0.478262	0.907395
39	Seychelles	0.317409	1.44E-02	0.289185	0.345633
40	Sierra Leone	0.71827	0.109733	0.503194	0.933346
41	South Africa	0.173013	0.057102	0.061093	0.284932
42	South Sudan	0.783245	0.083076	0.620416	0.946073
43	Tanzania	0.89241	0.01269	0.867536	0.917283
44	Togo	0.750308	0.067629	0.617756	0.882861
45	Uganda	0.712196	0.089698	0.536389	0.888003
46	Zambia	0.767764	0.032551	0.703963	0.831564
47	Zimbabwe	0.315863	0.049476	0.21889	0.412836

Table S2 Estimates of Total Deaths with 95% Credible Interval

sn.	Country	Number of Comm. Deaths (a)	95% CI		Number of Facility Deaths (b)	Total Deaths (a+b)	95% CI		Population 2022
			Lower Limit	Upper Limit			Lower Limit	Upper Limit	
1	Algeria	104,317	54,233	154,401	110,715	215,032	164,948	265,117	44,903,225
2	Angola	218,620	193,554	243,686	553	219,172	194,106	244,238	35,588,987
3	Benin	84,148	58,994	109,302	48,152	132,300	107,146	157,454	13,352,864
4	Botswana	7,577	2,663	12,490	18,244	25,821	20,908	30,735	2,630,296
5	Burkina Faso	163,767	130,005	197,529	68,149	231,916	198,154	265,678	22,673,762
6	Burundi	72,252	52,895	91,609	22,869	95,120	75,764	114,477	12,889,576
7	Cabo Verde	2,289	1,162	3,416	1,589	3,878	2,751	5,005	593,149
8	Cameroon	133,350	61,084	205,616	86,420	219,769	147,503	292,036	27,914,536
9	Central African Republic	55,763	50,635	60,891	8,634	64,397	59,269	69,525	5,579,144
10	Chad	177,716	147,399	208,033	16,513	194,230	163,912	224,547	17,723,315
11	Comoros	4,841	3,312	6,370	2,024	6,865	5,335	8,394	836,774
12	Congo	24,995	16,157	33,833	21,127	46,122	37,283	54,960	5,970,424
13	Cote d'Ivoire	173,366	115,049	231,682	95,451	268,817	210,500	327,133	28,160,542
14	Democratic Republic of the Congo	725,388	542,450	908,327	228,595	953,983	771,044	1,136,922	99,010,212
15	Equatorial Guinea	5,174	1,224	9,124	9,294	14,468	10,517	18,418	1,674,908
16	Eritrea	20,390	16,973	23,807	3,253	23,642	20,226	27,059	3,684,032
17	Eswatini	6,331	3,174	9,487	10,019	16,350	13,193	19,506	1,201,670
18	Ethiopia	662,494	546,258	778,729	72,124	734,618	618,382	850,853	123,379,924
19	Gabon	4,876	1,949	7,803	11,730	16,606	13,680	19,533	2,388,992
20	Gambia, The	15,644	11,607	19,680	4,601	20,245	16,208	24,281	2,705,992
21	Ghana	155,490	82,534	228,446	101,412	256,903	183,947	329,859	33,475,870
22	Guinea	96,777	65,154	128,400	2,704	99,481	67,857	131,104	13,859,341

23	Guinea-Bissau	13,661	9,633	17,689	3,714	17,375	13,348	21,403	2,105,566
24	Kenya	266,817	178,596	355,038	178,919	445,735	357,514	533,956	54,027,487
25	Lesotho	19,672	12,095	27,250	17,736	37,408	29,830	44,986	2,305,825
26	Liberia	35,950	27,089	44,811	2,295	38,245	29,384	47,106	5,302,681
27	Madagascar	167,851	147,151	188,552	32,701	200,552	179,852	221,253	29,611,714
28	Malawi	82,991	51,300	114,681	46,107	129,098	97,408	160,789	20,405,317
29	Mali	179,855	171,063	188,647	14,606	194,461	185,669	203,253	22,593,590
30	Mauritania	23,740	14,823	32,658	11,641	35,382	26,464	44,299	4,736,139
31	Mauritius	2,630	1,346	3,915	7,779	10,409	9,124	11,694	1,262,523
32	Mozambique	219,030	162,934	275,126	70,513	289,543	233,447	345,640	32,969,518
33	Namibia	3,577	1,320	5,835	25,334	28,912	26,654	31,169	2,567,012
34	Niger	174,760	147,334	202,186	6,661	181,421	153,995	208,847	26,207,977
35	Nigeria	2,070,083	1,511,954	2,628,212	279,193	2,349,276	1,791,147	2,907,405	218,541,212
36	Rwanda	64,200	46,697	81,704	26,546	90,746	73,242	108,250	13,776,698
37	Sao Tome and Principe	740	331	1,148	718	1,457	1,049	1,866	227,380
38	Senegal	69,244	47,799	90,689	35,137	104,381	82,936	125,825	17,316,449
39	Seychelles	293	267	319	630	923	897	949	100,060
40	Sierra Leone	55,118	38,614	71,622	30,039	85,157	68,653	101,661	8,605,718
41	South Africa	117,471	41,480	193,461	651,813	769,284	693,294	845,275	59,893,885
42	South Sudan	93,025	73,686	112,364	41,569	134,594	115,255	153,933	10,913,164
43	Tanzania	353,079	343,238	362,920	102,868	455,947	446,106	465,788	65,497,748
44	Togo	52,980	43,620	62,340	21,816	74,796	65,436	84,155	8,848,699
45	Uganda	191,925	144,548	239,302	65,215	257,139	209,762	304,516	47,249,585
46	Zambia	104,252	95,588	112,915	27,157	131,409	122,746	140,072	20,017,675
47	Zimbabwe	45,754	31,707	59,801	56,582	102,336	88,289	116,382	16,320,537

Table S3: Estimate of Total Deaths by Age

sn	country	0	1-4	5-14	15-24	25-34	35-54	55-74	75+	Total
1	Algeria	19,136	3,139	3,023	3,041	4,415	25,428	70,998	85,852	**215,032**
2	Angola	51,466	18,597	10,790	11,073	13,294	34,713	51,040	28,199	**219,172**
3	Benin	28,692	11,657	10,764	8,875	8,828	17,921	27,099	18,465	**132,300**
4	Botswana	2,157	635	501	1,021	1,857	6,661	8,457	4,531	**25,821**
5	Burkina Faso	46,260	25,927	16,193	16,268	15,498	31,857	50,154	29,759	**231,916**
6	Burundi	16,919	4,866	11,316	7,697	7,866	15,336	19,678	11,442	**95,120**
7	Cabo Verde	126	20	33	57	131	567	1,065	1,880	**3,878**
8	Cameroon	43,748	16,374	9,876	12,120	15,677	39,417	50,383	32,176	**219,769**
9	Central African Republic	17,268	6,000	3,653	4,789	4,808	9,602	13,961	4,315	**64,397**
10	Chad	47,010	19,339	26,219	16,660	14,877	26,988	29,471	13,665	**194,230**
11	Comoros	1,063	251	210	287	298	957	2,165	1,632	**6,865**
12	Congo	6,380	1,984	1,526	2,128	2,983	10,484	13,753	6,883	**46,122**
13	Côte d'Ivoire	58,013	16,092	11,110	16,270	20,478	57,860	59,382	29,612	**268,817**
14	Democratic Republic of the Congo	219,479	83,461	84,027	64,951	61,750	119,903	195,942	124,470	**953,983**
15	Equatorial Guinea	2,799	800	533	558	963	2,739	3,836	2,240	**14,468**
16	Eritrea	2,919	669	1,444	1,716	1,410	3,262	6,695	5,528	**23,642**
17	Eswatini	1,316	396	340	790	1,655	4,415	5,196	2,243	**16,350**
18	Ethiopia	122,067	33,949	47,975	56,664	56,085	107,875	182,828	127,174	**734,618**
19	Gabon	1,824	551	416	598	953	3,259	5,183	3,823	**16,606**
20	Gambia	2,767	1,173	1,953	1,682	1,580	3,428	4,452	3,209	**20,245**
21	Ghana	30,110	7,450	19,782	18,850	20,340	45,584	69,726	45,059	**256,903**
22	Guinea	22,418	7,907	7,806	6,804	6,741	11,842	20,451	15,511	**99,481**
23	Guinea-Bissau	3,193	1,246	817	991	1,239	3,322	4,338	2,230	**17,375**

24	Kenya	45,832	14,754	12,487	25,524	44,022	123,008	114,810	65,299	**445,735**
25	Lesotho	4,677	1,170	914	1,836	3,641	9,243	10,850	5,076	**37,408**
26	Liberia	7,906	2,037	1,495	1,865	2,021	6,526	9,999	6,396	**38,245**
27	Madagascar	31,267	8,853	13,514	14,326	14,223	31,835	53,831	32,702	**200,552**
28	Malawi	16,806	5,444	4,214	7,340	10,535	28,605	29,547	26,606	**129,098**
29	Mali	49,090	23,673	13,505	12,780	11,421	23,657	36,997	23,340	**194,461**
30	Mauritania	7,189	2,066	1,288	1,504	1,357	4,305	9,974	7,698	**35,382**
31	Mauritius	160	25	22	122	222	1,381	4,353	4,122	**10,409**
32	Mozambique	63,002	16,554	11,145	15,718	19,454	53,272	74,033	36,366	**289,543**
33	Namibia	2,057	699	536	1,272	2,483	7,389	9,297	5,178	**28,912**
34	Niger	43,124	28,163	10,399	10,102	8,860	20,505	38,795	21,473	**181,421**
35	Nigeria	496,505	193,411	279,197	188,241	174,530	340,859	440,567	235,968	**2,349,276**
36	Rwanda	12,609	3,555	2,666	4,061	5,509	15,944	28,152	18,249	**90,746**
37	Sao Tome and Principe	78	12	33	76	74	283	484	419	**1,457**
38	Senegal	14,100	5,860	4,563	5,128	5,490	14,928	29,753	24,559	**104,381**
39	Seychelles	18	3	4	16	34	147	347	355	**923**
40	Sierra Leone	21,359	6,955	3,956	4,324	3,926	11,026	21,126	12,484	**85,157**
41	South Africa	35,731	10,193	7,562	22,711	60,390	173,965	278,268	180,465	**769,284**
42	South Sudan	23,168	10,099	17,990	11,733	7,913	22,852	27,894	12,944	**134,594**
43	Tanzania	91,617	25,687	16,833	20,636	22,274	71,781	126,251	80,868	**455,947**
44	Togo	13,071	4,093	5,684	5,750	5,675	11,903	18,729	9,891	**74,796**
45	Uganda	49,230	15,049	10,695	17,676	22,831	51,230	63,861	26,567	**257,139**
46	Zambia	26,527	9,211	6,108	8,162	10,577	28,523	28,541	13,760	**131,409**
47	Zimbabwe	12,764	4,585	3,419	5,983	8,573	24,629	27,308	15,074	**102,336**
	Total	**1,815,016**	**654,635**	**698,534**	**640,779**	**709,764**	**1,661,216**	**2,380,022**	**1,465,756**	**10,025,721**

