International Journal of Statistical Distributions and Applications
2024; 10(1): 10-15
http://www.sciencepublishinggroup.com/j/ijsda
doi: 10.11648/ijsd.20241001.12
ISSN: 2472-3487 (Print); ISSN: 2472-3509 (Online)

Count Models of Mortality for Children Under Five Years in Kenya

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To cite this article:

Esther Mwau, Samuel Mwalili, Thomas Mageto. (2024). Count Models of Mortality for Children Under Five Years in Kenya. *International Journal of Statistical Distributions and Applications*, *10*(1), 10-15. https://doi.org/10.11648/ijsd.20241001.12

Received: October 16, 2023; **Accepted**: November 6, 2023; **Published**: February 5, 2024

Abstract: Child mortality under the age of five (U5M) is a critical public health concern influenced by several factors. Child mortality rate can be used to gauge a country's health status and progress towards achieving sustainable development goals. These Goals, were established in 2015 by the United Nations General Assembly, to be accomplished by 2030. The SDG Goal 3 target 2 Strives to achieve a substantial reduction in under-5 mortality rates, with the ambitious goal of lowering them to 25 or fewer deaths per 1,000 live births by the year 2030. Reducing the deaths of toddlers aged five and below is a crucial objective for developing countries, particularly in regions of the continent of Africa that lie south of the Sahara This study delves into the distribution and determinants of U5M in Kenya, employing count models to scrutinize the spatial dynamic distribution and socio-economic variables utilizing information obtained from the 2014 Kenya Demographic Health Survey (KDHS). By uncovering geographical variations in U5M rates, this research aims to inform the design of integrated interventions, thereby reducing the financial burden associated with these interventions and averting redundant resource allocation. The study revealed that region, mothers' level of education, and socioeconomic factors were significant risk factors associated with under-five mortality. The findings of this study contribute to a more targeted and efficient approach to addressing child mortality, ultimately improving the well-being of Kenya's youngest population.

Keywords: Under-Five Mortality, Poisson, Negative Binomial

1. Introduction

Child mortality is still a pressing issue in the world. This rate can be used to gauge a country's health status and progress towards achieving sustainable development goals. These Goals were established in 2015 by the United Nations General Assembly, to be accomplished by 2030. The SDG Goal 3 target 2 Strives to achieve a substantial reduction in under-5 mortality rates, with the ambitious goal of lowering them to 25 or fewer deaths per 1,000 live births by the year 2030 [1]. Children under five years worldwide continue to die primarily from malnutrition, pneumonia, diarrhea, malaria, and measles. From 1990 onwards, there has been significant global progress in decreasing childhood mortality. In 1990, the number of under-5 deaths stood at a staggering 12.6 million, a figure that has substantially decreased to 5 million by the year 2020. This represents a substantial 60% reduction in under-5 mortality, translating to a decline from 93 deaths per 1,000 live births in 1990 to 37 in 2020. To put this into perspective, in 1990, tragically, 1 in 11 children didn't reach their fifth birthday, while by 2020, this figure had significantly improved, with only 1 in 27 children facing such a fate [2]. However, SSA continues to have the highest rates of childhood mortality in the world at 74% deaths per live births. The rates for child mortality in the sub-Saharan region in comparison to those in Europe and North America are significantly higher, with a staggering 1 in 27 children born in 2020 not living to see their fifth birthday, according to [3]. Which is a high number of preventable deaths. Researchers have discovered Childhood mortality in Kenya and Sub-Saharan Africa is an existential threat with a range of causes that impact different countries, these causes include, demographics, socioeconomics, and access to resources [4]. The severity of the threat varies depending on these factors, and it is important to understand them to effectively address the issue by utilizing a multi-level modeling method to highlight notable variations between Africa and Asia, with Asia having an advantage [5]. These variations were adjusted at the cluster level to consider child mortality. Another research by [6] demonstrated that under-5 mortality levels are influenced by the socioeconomic and demographic circumstances of households and communities. These studies have called for further research on childhood mortality due to the differing socioeconomic statuses in various regions.

This study employs count models to analyze the spatial distribution and indicators of childhood mortality among under-five children in Kenya. Public health authorities may use this study to effectively allocate resources and implement control measures. Additionally, emphasizing spatial interventions can yield substantial benefits in terms of control measures' effectiveness [7]. Therefore, identifying geographical patterns in U5M indicators will be of great help in the planning of integrated interventions can lead to cost reduction in the delivery of interventions, and prevent duplication of resource delivery systems.

2. Literature Review

Several studies have highlighted the persistently high under-five mortality rates in Non-Mediterranean Africa. The region's health systems face challenges in delivering quality healthcare, resulting in increased childhood mortality [8]. Despite global progress in reducing under-5 mortality, sub-Saharan Africa continues to lag, necessitating a focus on tailored interventions to address this pressing issue [3].

W. H. Mosley et al. [9] developed an analytical framework for the study of determinants of child survival in developing countries. One of the earlier studies showed that a decrease in child mortality rates among the offspring of mothers without formal education could be attributed to the decrease in obstacles to healthcare access for kids less than five years old in various nations. This encompasses the reduction of topographical and financial obstacles to healthcare services, resulting in enhanced accessibility to health services [10]. The analyses also indicated that mothers' educational attainment plays a significant role in determining child mortality in various countries, alongside the household's socioeconomic status. A different recent study in India [11] unveiled that child mortality rates were influenced by a range of factors, including place of residence, child's gender, household wealth, maternal education, and birth order. Additionally, they highlighted the significant impact of rural-urban disparities on these mortality rates. This finding highlights the need for further attention to be paid to the specific needs and challenges faced by children living in rural areas to reduce mortality rates among countries experiencing high childhood mortality.

When analyzing count data with low mean values and skewed distributions, it is often recommended to utilize count models like Poisson and negative binomial regression [12]. These models have gained popularity over time in analyzing under-5 mortality data. Traditional regression models may not account for the discrete nature and right-skewed distribution of mortality rates. Studies have shown that count models provide a better fit and more accurate results when analyzing count data, like under-5 mortality rates [13].

The high U5M rates in sub-Saharan 10 Africa, including Kenya, underscore the need for tailored interventions to address the region's unique challenges. The count models mentioned earlier are valuable tools in the identification of significant risk factors and inform the design of targeted interventions [14]. These models will help a country like Kenya to study and understand the risk factors that contribute to under-5 childhood mortality (U5M) in order to achieve Sustainable Development Goal 3.2, which seeks to reduce U5M rates. Count models, including Poisson regression and negative binomial regression, take into account the discrete and right-skewed nature of the outcome variable [13]. This review highlights the persistent challenges of under-5 mortality, with Kenya being one of the countries experiencing the challenges which include: Maternal health, education level, region of residence, and socioeconomic status have been identified as critical risk factors influencing childhood mortality. The application of the above-count models is essential for accurately analyzing under-5 mortality data. To attain SDGs 3.2 which aims to decrease the under-five child mortality rate in Kenya, evidence-based interventions tailored to the specific risk factors and geographic patterns are crucial.

3. Methodology

A Generalized Linear Model (GLM) expands the scope of linear models by incorporating a link function to relate them to the response variable. Additionally, it enables the variance of each measurement to be dependent on its predicted value, thereby enhancing its predictive power. Generalized linear models were formulated by [15].

A GLM is defined as

$$E(Y|X) = \mu = x\beta \tag{1}$$

In modeling count variables the most used distribution is the Poisson distribution. The Poisson distribution tells us how likely it is to observe a certain number of occurrences within a given period. Such observation is given by

$$\Pr(Y_i = y_i) = \frac{e^{-\lambda}\lambda^{y_i}}{y_i!} \tag{2}$$

A key property in Poisson distribution is that;

$$E(Y_i) = Var(Y_i) = \lambda \tag{3}$$

From the above equation, we can obtain a Poisson regression model by allowing λ to depend on covariates through a link function

$$Log\ (\lambda) = x_i\beta \tag{4}$$

We can therefore estimate λ through the maximum likelihood method where we find the set of parameters that makes the probability as large as possible.

$$L(\lambda|x_1 \dots x_n) = \prod \frac{e^{-\lambda}\lambda^{y_i}}{y_i!} \quad (5)$$

Obtaining the log-likelihood of the above equation, we therefore

$$l(\lambda;\ x_1 \dots x_n) = -n\lambda + \ln(\lambda)\sum_{j=1}^{n} x_j - \sum_{j=1}^{n} \ln(x_j!) \quad (6)$$

Calculating the derivative of the natural log-likelihood function with respect. to λ we thus obtain;

$$\frac{d}{d\lambda}(\lambda; x_i \dots x_n) = \frac{d}{dy}(-n\lambda) + \ln(\lambda \sum_{j=1}^{n} x_j - \sum_{j=1}^{n} x_j\,!)) \quad (7)$$

Taking the previous equation's derivative, and equating it to zero, and then solving for the value of λ, we obtain the MLE as given below

$$\lambda = \frac{1}{n}\sum_{j=1} xj \quad (8)$$

Thus, the MLE of λ is the average of the observed data points $x_1, x_2, \dots, x_n$..

In real-life situations, the mean may be greater than the variance thus we are faced with a problem of over-dispersion thus we use a negative binomial. To account for the over-dispersion, an additional parameter(s) r and θ will need to be estimated which account for the over-dispersion.

A negative binomial is defined as

$$P(Y_i = k) = (\Gamma(r+k)/(\Gamma(k+1)*\Gamma(r)))*((\theta^r*\lambda^k)/((\theta+\lambda)^{(r+k)})) \quad (9)$$

Where Y_i is the random variable representing the number of successes until r failures occur. k is the number of successes (non-negative integer) we want to find the probability for. Γ is the gamma function. θ is the probability of success in each Bernoulli trial. r is the number of failures needed to stop the process (also called the shape parameter or the dispersion parameter). The gamma function is a mathematical expression that extends the concept of factorials to complex numbers.

It is particularly useful for non-negative integer values, Γ (n)=(n1)!.

$$\mu = E(Y_i) = r * (1 - \theta)/\theta \quad (10)$$

$$Var(y_i) = r * (1 - \theta)/\theta^2 \quad (11)$$

The likelihood of the negative binomial is therefore given as

$$L(\lambda,\theta;y_1,y_2,\dots,y_n) = [(\Gamma(r) * \theta^r)((\theta + \lambda)^r)]^n * [\lambda^{P}(x_i)]^n * \Pi\ [(\Gamma(r + x_i)/(x_i + 1) * \Gamma(r)))/((\theta + \lambda)^{(r+xi)})] \quad (12)$$

Since it is easier to work with the log-likelihood we therefore obtain the log-likelihood for the above equation which is given as;

$$lnL(\lambda,\theta;y_1,\dots,y_n) = n * ln(\Gamma(r) * \theta_r)n * ln((\theta+)_r + n * ln(\lambda\Sigma(x_i)) + (\Gamma(r + x_i)) - \Sigma ln((x_i + 1) * \Gamma(r)) - \Sigma ln((\theta + \lambda) * (r + x_i) \quad (13)$$

We therefore obtain the derivative of the above equation with respect to r

$$lnL(\lambda,\theta;y_1,\dots,y_n) = n * ln(\Gamma(r) * \theta_r)n * ln((\theta+)_r + n * ln(\lambda\Sigma(x_i)) + (\Gamma(r + x_i)) - \Sigma ln((x_i + 1) * \Gamma(r)) - \Sigma ln((\theta + \lambda) * (r + x_i) \quad (14)$$

While with respect to θ we have

$$\frac{dnL}{d\theta} = n * \left(\frac{d}{dx}(\ln(\ \Gamma(r) * \theta^r))\right) + (\frac{d}{dx}(\ln((\theta + 1)^r)) - \sum(\frac{d}{dx}(\ln((\theta + \lambda) * (r + x_i)))) \quad (15)$$

We then set the derivatives of λ and θ to 0 to find the maximum likelihood estimates.

4. Data Analysis and Results

4.1. Introduction

The overarching goal of this research is to uncover both the geographic patterns and the determinants that contribute to children's loss of lives among those under the age of five in Kenya. Our analysis therefore employed Poisson and negative binomial regression models to examine the data, ultimately assessing the efficacy of each model.

The data set employed for this study was obtained from the comprehensive and extensive [16], which employed samples derived from the population and housing census estimates in the nation. Eligible respondents for this study included all women aged 15 to 49 years old, and information regarding children born within the five years leading up to the survey.

The dependent variable, the outcome variable was the total number of under-5 deaths in the household.

4.1.1. Data Description

1. The educational attainment of the mother is what is referred to as the mother's level of education. Which is grouped into four categories as follows no formal education, primary education, secondary education, and higher education levels. This factor is important in various studies and research since the level of education the mother has attained can have a significant impact on the development and well-being of the child.
2. The wealth index serves as an indicator of a family's socioeconomic status, with classifications ranging from the poorest to the richest. These classifications include the poorest, poorer, middle, richer, and richest categories, which provide insights into a family's financial resources and overall economic well-being.
3. The type of residence pertains to the specific location where an individual dwells, which can either be classified as urban or rural depending on the environment and surroundings.
4. Region- This refers to the specific region in Kenya a mother comes from.

Bar graph showing the distribution of mortality in Kenyan counties.

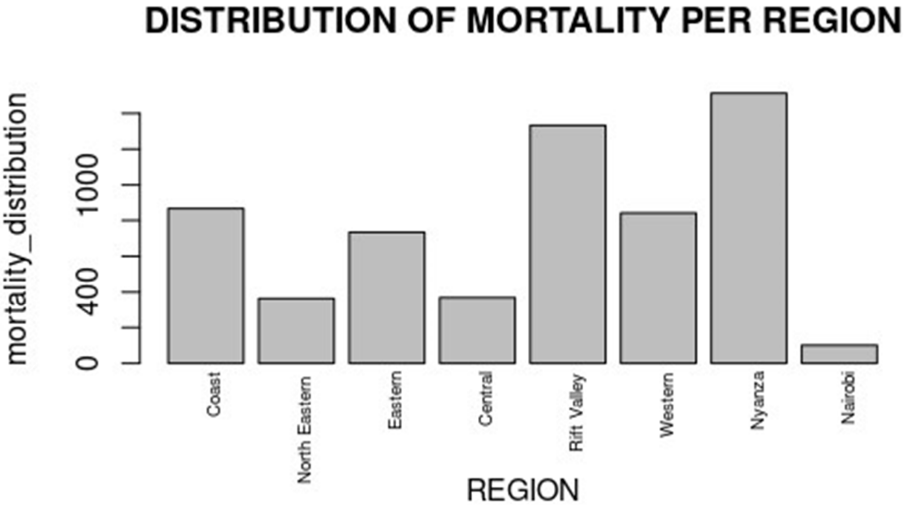

Figure 1. *Mortality Distribution in the 8 regions.*

4.2. Data Analysis and Results

The analysis of the influence of each predictor variable on the outcome variable was evaluated using R software Version 4.3.1.

4.2.1. Model Fitting and Estimation

From the above-mentioned models, the following results.

4.2.2. Poisson Regression Model Results

Table 1. *Poison regression results.*

Predictors	IRR	CI	P-value
Intercept	0.44	0.40-0.49	<0.01
North eastern	0.64	0.56-0.72	<0.01
Eastern	0.66	0.60-0.73	<0.01
Central	0.81	0.71-0.92	<0.01
Rift valley	0.70	0.64-0.76	<0.01
Western	1.58	1.43-1.75	<0.01
Nyanza	1.95	1.79-2.13	<0.01
Nairobi	0.94	0.76-1.16	0.569
Poorer	0.99	0.92-1.07	0.810
Middle	0.87	0.80-0.94	0.001
Richer	0.77	0.71-0.85	<0.01
Richest	0.58	0.52-0.65	<0.01
Primary	0.61	0.56-0.66	<0.01
Secondary	0.25	0.23-0.28	<0.01
Higher	0.19	0.16-0.23	<0.01
Rural	0.98	0.92-1.04	0.533
R^2 Nagelkerke	0.645		
AIC	32261.76		

The Incidence Rate Ratio (IRR) quantifies the impact of a unit change in the variable on the rate of occurrence of an event or outcome. An IRR less than 1 indicates a decrease in the incidence rate, while an IRR greater than 1 denotes an increase.

When it comes to region variables, an IRR below 1 (such as North Eastern's incidence ratio of 0.64) indicates that being in that region is linked to a lower incidence rate compared to the reference category, which isn't displayed in the table.

When looking at wealth index variables, an incidence rate ratio (IRR) below 1 (such as the category of "richer" with an IRR of 0.77) suggests that as the wealth index goes up, the incidence rate of under-five child mortality goes down. Therefore, individuals in higher wealth categories are less likely to experience this type of mortality. When it comes to wealth index variables, an incidence ratio of less than 1 (such as for the richer category with a ratio of 0.77) means that as the wealth index goes up, the incidence rate of under-five child mortality goes down. This suggests that individuals in higher wealth categories are less prone to experiencing such mortality.

In the education variable, an IRR (Incidence Rate Ratio) of less than 1 signifies a decrease in incidence ratio values. This decrease indicates that as the level of education increases, the incidence rate also decreases. We can therefore say, that children born to female parents with higher levels of education face a reduced risk of experiencing premature mortality before reaching the age of 5.

Confidence intervals (CIs) offer a range of values that encompass the probable true IRR with a specific level of confidence (usually 95 percent).

4.2.3. Negative Binomial Regression Results

Table 2. *Negative binomial.*

Predictors	IRR CI P-value
Intercept	0.43 0.38-0.49 <0.001
North eastern	0.65 0.55-0.76 <0.001
Eastern	0.67 0.60-0.76 <0.001
Central	0.80 0.69-0.93 0.004
Rift valley	0.72 0.65-0.80 <0.001
Western	1.56 1.37-1.77 <0.001
Nyanza	1.91 1.70-2.15 <0.001
Nairobi	0.95 0.71-0.97 0.663
Poorer	1.00 0.91-1.10 0.952
Middle	0.88 0.79-0.97 0.014
Richer	0.78 0.70-0.87 <0.001
Richest	0.59 0.52-0.68 <0.001
Primary	0.62 0.56-0.69 <0.001
Secondary	0.26 0.23-0.30 <0.001
Higher	0.20 0.16-0.24 <0.001
Rural	0.98 0.91-1.06 0.666
R^2 Nagelkerke	0.725
AIC	300528.27

The p-values are used to determine the statistical significance of each predictor variable. In conventional practice, a predictor is deemed statistically significant when the p-value falls below 0.05, indicating a confidence level of 95%.

From the negative binomial results, the incidence rate ratios (IRRs) of the regions which are the first seven variables are compared to the intercept. For instance, the IRR for North Eastern is 0.65, meaning that its incidence rate 0.65 times that of the baseline group.

There are different socio-economic levels, represented by poorer, middle, richer, and richest. The IRRs show how the incidence rate changes depending on socioeconomic status. Specifically, the richest group has an IRR of 0.59, indicating a lower incidence rate compared to the baseline group.

The occurrence of a particular phenomenon, in the context of education, tends to differ based on the level of education attained by an individual. This variability can be observed through the Incidence Rate Ratios (IRRs) that are reported.

The predictor "Rural" distinguishes between rural and urban areas. An IRR of 0.98 indicates a slightly lower incidence rate in rural regions when compared to urban areas. Nevertheless, a p-value of 0.666 suggests that there is no statistically significant difference.

The R2 Nagelkerke metric is utilized to assess the logistic regression model's fitness to the given data. A score of 0.725 implies that the model can effectively explain a significant portion of the variance observed in the outcome variable. Moreover, the AIC value for this particular situation is 30528.27.

4.2.4. Model Comparison

AIC (Akaike Information Criterion) measures model fit while penalizing for parameter count. Lower AIC values imply a better fit.

Two models, the negative binomial and the Poisson models, were applied to the data and compared using the Akaike Information Criterion, a common tool for assessing statistical models. The Poisson model resulted in an AIC of 32261.76, while the negative binomial model resulted in an AIC of 30528.27. Therefore, the negative binomial model was deemed a more suitable fit for the data. The spatial patterns distribution of under-5 mortality in Kenya.

4.3. Discussion

This study aimed to examine the geographical distribution and determinants associated with the loss of lives of children under five in Kenya. To achieve this objective, we employed both the Poisson count model and the negative binomial count model to examine the factors linked to the risk of under-five mortality in Kenya. After comparing the AIC of both models, upon investigation, it was found that the negative binomial model provided a more suitable fit. Indicating better predictive ability than the Poisson model.

In agreement with the results of [7], Children of mothers who have attained a secondary education exhibit an increased probability of survival in contrast to those whose mothers have not acquired any formal education or have only completed elementary education. Additionally, it was discovered that region and socioeconomic status are significant predictors of child mortality. It was also noted that certain regions have higher child mortality rates, while the wealthiest socioeconomic group and individuals with higher education levels experienced lower child mortality.

To reduce under-five mortality, efforts should be made to enhance maternal education levels as educational programs and initiatives that focus on maternal health, child nutrition, and disease prevention should be implemented and made accessible to all mothers, regardless of their socioeconomic status or geographic location, hence a positive effect on the survival of children will be significant.

5. Conclusion

The research aimed to conduct a comprehensive analysis of the child mortality rate among children aged under five years across the entire nation. To achieve this, we utilized the KDHS data from 2014, which was selected due to its vast sample size and detailed information on children born in the country within five years preceding the survey. The selected factors were the region where a child lives, the mother's education level, wealth index, and type of residence. The negative binomial model revealed that region, mothers' level of education, and socioeconomic factors were significant risk factors associated with under-five mortality. The research has generated substantial insights into the incidence of child mortality and the associated risk factors within the context of Kenya. This can guide policymakers and stakeholders in collaborating to lower under-five mortality rates, enhance child health outcomes, and secure a brighter future for the nation's children by implementing interventions in areas with higher child mortality rates and among individuals with lower socioeconomic status. Further research should investigate eligible women's understanding of factors contributing to child mortality.

Acknowledgments

I'm grateful to God for guiding me through this experience. I also extend my sincerest thanks to my supervisors, Professor Samuel Mwalili and Dr. Thomas Mageto, for their support and expertise throughout the work. The valuable input and helpful suggestions they provided have been instrumental in influencing the course of my research. I sincerely thank the esteemed faculty and staff at the Department of Statistics and Actuarial Sciences for fostering an exceptional academic environment and providing invaluable resources that facilitated my studies. I am profoundly grateful to my esteemed classmates, for their unwavering encouragement and exemplary expertise. Furthermore, I deeply appreciate the individuals and organizations who graciously provided their data and assistance in publishing this work. Finally, I would like to convey my sincere gratitude to my family and James for praying and encouraging me throughout my academic journey.

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Conflicts of Interest

The authors declare no conflicts of interest.

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