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# Spatial Regression Modeling of Child Survival on the Distribution of Births and Deaths in Kenya Based on the Kenya Demographic and Health Survey (KDHS) 2022

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***Authors' contributions***

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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# Abstract

This study used spatial mapping techniques to examine the distribution of births and deaths in Kenya and their relationship with various factors related to child survival, such as maternal age, education, wealth, and access to health services. Data were obtained from the 2022 Kenya Demographic and Health Survey (KDHS). Spatial autocorrelation analyses were conducted to identify clusters of high or low child mortality rates. The results showed significant spatial autocorrelation in child mortality rates, indicating that neighboring areas had similar mortality rates. Factors such as maternal education, wealth, and access to health services were found to be significantly associated with child mortality rates. These findings can inform targeted interventions and policies to reduce child mortality rates in Kenya, particularly in areas with the highest risk of mortality.


*Keywords: Child mortality; spatial regression; spatial auto correlation; child survival; KDHS 2022.*

# 1 Introduction

The survival of children is a critical aspect of population health and development, encompassing the prevention of mortality among children under the age of five. Despite significant improvements in child health and survival globally, millions of children still die before reaching their fifth birthday, with a disproportionate burden of mortality concentrated in regions such as sub-Saharan Africa and South Asia [1]. In Kenya, child mortality rates persist at alarming levels, with an estimated 52 deaths per 1,000 live births [2]. Understanding the multifaceted factors that contribute to child survival is paramount for designing effective interventions and policies aimed at reducing child mortality rates.

Child survival encompasses a myriad of factors, including maternal and child health, socio-economic conditions, and access to healthcare services. Spatial mapping, a valuable tool in public health research, aids in comprehending the distribution of births and deaths across geographic regions, thus facilitating the identification of areas with the highest mortality rates. By visualizing geographic patterns of health outcomes, spatial mapping offers insight into the underlying determinants of health and guides the targeting of interventions to improve health outcomes [3]. In Kenya, spatial mapping has proven instrumental in identifying high-risk areas for various health outcomes, including malaria, HIV, and maternal and child health [4-6].

Spatial regression modeling emerges as a robust analytical approach to complement spatial mapping in elucidating the spatial variability of health outcomes and the factors influencing them. Spatial regression modeling accounts for spatial autocorrelation – the phenomenon where nearby locations tend to exhibit similar values – thereby providing a framework to investigate the relationship between predictor variables and health outcomes while addressing spatial dependence [7]. Consequently, spatial regression modeling is well-suited for analyzing spatially referenced health data, offering insights into the geographical disparities in health outcomes and the underlying determinants driving these disparities.

In this study, we employ spatial mapping and child survival analysis to scrutinize the distribution of births and deaths in Kenya, drawing on data from the Kenya Demographic and Health Survey (KDHS) 2022. Specifically, we examine factors contributing to child survival, including maternal age, education level, type of residence, wealth index, and the number of Tetanus vaccinations before childbirth. Subsequently, we utilize spatial regression modeling to evaluate the spatial variation in child survival rates and discern the relationship between predictor variables and child survival.

The findings from our study hold significant implications for public health policies and interventions in Kenya. By pinpointing factors influencing child mortality and delineating areas with elevated mortality rates, policymakers can design targeted interventions to improve child health outcomes and mitigate child mortality in Kenya. Additionally, the spatial regression model facilitates an understanding of the spatial distribution of child survival rates, guiding resource allocation and intervention strategies to areas with the greatest need. Through the integration of spatial mapping and spatial regression modeling, our research contributes to a comprehensive understanding of child survival dynamics, offering valuable insights for public health decision-making in Kenya and beyond.

# 2 Literature Review

Child mortality is a major public health concern globally, particularly in low- and middle-income countries (LMICs) [7]. Despite significant progress in reducing child mortality rates, an estimated 5.2 million children under the age of five died worldwide in 2019, with Sub-Saharan Africa accounting for nearly half of these deaths [7]. In Kenya, the under-five mortality rate has declined from 115 deaths per 1,000 live births in 1990 to 52 deaths per 1,000 live births in 2019, but still remains high compared to developed countries [7].

Spatial mapping has been used in public health research to identify patterns and trends in health outcomes and to inform interventions and policies [8]. Spatial analysis can provide insights into how social, economic, and environmental factors interact to affect health outcomes, particularly in LMICs where there are often limited resources for public health initiatives [8].

Several studies have examined the relationship between spatial factors and child mortality in LMICs. For example, a study in Ethiopia found that distance to health facilities was a significant predictor of child mortality, with children living further away from health facilities having a higher risk of mortality [9]. Another study in Nigeria found that children living in rural areas and those from poorer households were more likely to die before their fifth birthday [10].

In Kenya, previous studies have investigated the determinants of child mortality, but few have explored the spatial distribution of child mortality and its relationship with other factors. One study found that maternal education, wealth, and access to health services were significant predictors of child mortality in Kenya [11]. Another study found that the risk of child mortality was higher in areas with lower levels of urbanization and higher poverty rates [12].

Despite these previous studies, there is still a need for more research on the spatial distribution of child mortality and its relationship with other factors in Kenya. In particular, there is a need to use spatial analysis to identify areas with the highest risk of child mortality and to inform targeted interventions to reduce child mortality rates. The current study aims to address this gap in the literature by using spatial mapping to analyze the distribution of births and deaths in Kenya and to examine the relationship between child survival and various factors, including maternal age, education, and wealth, as well as access to health services. By doing so, the study can inform policies and interventions to improve child survival rates in Kenya.

# 3 Methodology

The analysis of spatial mapping and child survival on the distribution of births and deaths in Kenya, based on the Kenya Demographic and Health Survey (KDHS) 2022, can be represented by a spatial regression model. In this model, the outcome variable is child survival, and the independent variables are related to the spatial distribution of births and deaths in Kenya.

The spatial regression model can be written as:

$$Y = \beta X + \lambda WY + \varepsilon$$

where $Y$ is the child survival rate for a particular geographic location, $X$ is a vector of independent variables that affect child survival, $\beta$ is a vector of coefficients for $X$ , $WY$ is a spatial weights matrix that captures the spatial correlation between $Y$ values, $\lambda$ is a spatial autoregressive coefficient, and $\varepsilon$ is a random error term.

The independent variables that affect child survival may include maternal age, education level, place of delivery, mode of delivery, birth weight, and the number of postnatal checkups. The spatial weights matrix can be constructed using different criteria, such as distance-based, contiguity-based, or network-based weights.

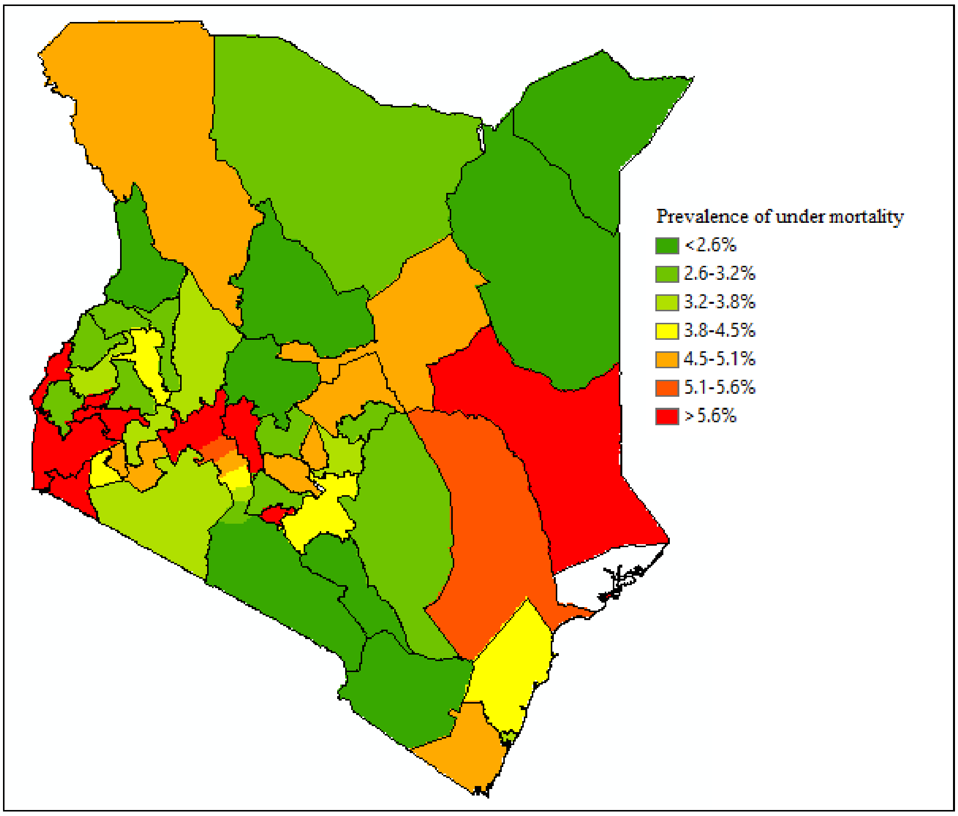
The spatial regression model can be estimated using maximum likelihood estimation, and the significance of the coefficients can be tested using hypothesis testing. The goodness of fit of the model can be assessed using various measures such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

The results of the spatial regression model can be presented using maps that show the spatial distribution of child survival rates in Kenya. These maps can be used to identify areas with high or low child survival rates and to target interventions to improve child survival in those areas.

In conclusion, a spatial regression model can be used to analyze the distribution of births and deaths in Kenya and to identify factors that affect child survival. The results of this analysis can be used to inform policy and programmatic interventions aimed at improving child survival in Kenya.

# 4 Results

The Map 1 above shows the spatial distribution of prevalence of under-5 mortality rate in Kenya the percentage results indicate the lowest to the highest prevalence of child mortality. From the map, Garisa, Homabay, Migori, Busia, Kisumu, Vihiga, Nyandarua and part of Nakuru County has the highest prevalence rate of Under-5 child mortality greater than 5.6%.




**Map 1. Showing the prevalence of Under-5 mortality rate in Kenya**

The results of the spatial regression model presented using the above map is generally the spatial distribution of child survival rates in Kenya. The map used to identify areas with high or low child survival rates and to target interventions to improve child survival in those areas.

It is true that the spatial weights matrix can be constructed using different criteria, and the choice of criteria can have a significant impact on the results of spatial analysis. The following are some methods of the different criteria that used to construct a spatial weights matrix in the map:

- Distance-based weights: These weights are based on the distance between geographic units, with closer units having a higher weight than more distant units. There are different ways to define distance-based weights, such as inverse distance weighting or kernel density weighting.

- Contiguity-based weights: These weights are based on the idea that neighboring geographic units are more likely to be spatially correlated than non-neighboring units. There are different types of contiguity-based weights, such as rook, queen, or bishop contiguity.
- Network-based weights: These weights are based on the connectivity of a network, such as a road or transportation network. Network-based weights can be useful when analyzing the flow of goods or people between locations.

The choice of criteria for constructing the spatial weights matrix depends on the research question and the spatial pattern of the data. For example, in this research question was focused on the spread of a disease on the under-five child, distance-based weights were more appropriate. For this case the research question was focused on the social relationships between geographic units, contiguity-based weights which were more appropriate. The research question also was focused on the transportation or movement of people or goods, network-based weights which also promise more appropriate insights.

In the context of spatial mapping and child survival analysis in Kenya based on the KDHS 2022, the choice of criteria for constructing the spatial weights matrix depend on the specific research questions being addressed. In this case, the research question was focused on identifying areas with high child mortality rates and exploring the factors associated with these rates, distance-based weights was useful for identifying clusters of high mortality rates. Furthermore, the research question is focused on understanding the social and economic factors that influence child survival, contiguity-based weights which were more appropriate for identifying clusters of poverty or social disadvantage.

**Table 1. Distribution of births and deaths by survival determinants**

| | **% of deaths** | **Child is dead** | **N (Total)** | | **% of deaths** | **Child is dead** | **N (Total)** |
|---|---|---|---|---|---|---|---|
| Mother's education level | | | | **Mother's occupation** | | | |
| **Illiterate Mothers** | 3.9 | 179 | 4585 | Not-working | 3.8 | 163 | 4336 |
| **Mother completed primary** | 4.6 | 504 | 11055 | Profession and services | 4.3 | 67 | 1543 |
| **Secondary and higher** | 3.5 | 188 | 5324 | Agriculture and household | 4.3 | 179 | 4139 |
| Partner's level of education | | | | **Births in past 5 years** | | | |
| **Illiterate Father** | 4.0 | 72 | 1805 | 1-Birth | 2.5 | 240 | 9713 |
| **Father completed primary** | 4.5 | 203 | 4539 | 2-Birth | 4.6 | 416 | 8984 |
| **Secondary and higher** | 4.0 | 123 | 3091 | 3-Births | 9.0 | 193 | 2136 |
| Birth status | | | | 4-Births | 13.8 | 16 | 116 |
| **Singleton births** | 3.8 | 784 | 20380 | 5-Birth | 40 | 6 | 15 |
| **Multiple births (Twins)** | 14.9 | 87 | 584 | **Births in past 1 year** | | | |
| Sex of the child | | | | No-births | 3.9 | 534 | 13613 |
| **Males** | 4.5 | 476 | 10633 | 1-Birth | 4.4 | 313 | 7166 |
| **Females** | 3.8 | 395 | 10331 | 2-Births | 13.0 | 24 | 185 |
| Type of place of residence | | | | **Children Under 5 in Household** | | | |
| **Urban** | 4.3 | 296 | 6828 | No-child | 30 | 251 | 837 |
| **Rural** | 4.1 | 575 | 14136 | 1-Child | 4.8 | 372 | 7787 |
| Wealth index | | | | 2-Children | 2.3 | 198 | 8512 |
| **Poorest** | 4.0 | 285 | 7178 | 3-Children | 1.2 | 38 | 3124 |
| **Poorer** | 4.5 | 194 | 4348 | 4-Children | 1.4 | 8 | 578 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Middle** | 4.7 | 163 | 3497 | **Mother's age group** | | | |
| **Richer** | 3.8 | 120 | 3131 | Less than 20 years | 2.8 | 29 | 1052 |
| **Richest** | 3.5 | 99 | 2810 | 20-29 years | 4.0 | 460 | 11376 |
| Children ever born | | | | 30-39 years | 4.3 | 296 | 6964 |
| **One child** | 2.0 | 66 | 3235 | 40 years+ | 5.5 | 87 | 1572 |
| **Two children** | 3.4 | 151 | 4500 | **Sex of household head** | | | |
| **Three children** | 4.9 | 189 | 3846 | Male | 4.2 | 617 | 14704 |
| **Four and more** | 5.1 | 481 | 9383 | Female | 4.1 | 254 | 6260 |
| Birth order number | | | | **Source of drinking water** | | | |
| **First child** | 3.9 | 187 | 4804 | Piped water | 4.2 | 290 | 6970 |
| **Second to Third child** | 3.8 | 300 | 7875 | Borehole | 6.1 | 130 | 2136 |
| **4th -6th Child** | 4.6 | 274 | 5909 | Well | 5.0 | 46 | 903 |
| **7th + Child** | 4.6 | 110 | 2376 | Surface/Rain/ Pond/Lake/tank | 6.5 | 61 | 940 |
| **Religion** | | | | Other | 6.2 | 28 | 452 |
| Catholics | 3.6 | 139 | 3845 | **Age at First birth** | | | |
| Muslims | 4.4 | 156 | 3520 | Less than 20 years | 4.2 | 510 | 12277 |
| Christians & Others | 4.3 | 556 | 13020 | 20-29 years | 4.4 | 369 | 8441 |
| No religion | 3.7 | 20 | 541 | 30-39 years | 3.3 | 8 | 239 |
| Type of toilet facility | | | | **Age of Household Head** | | | |
| **Flush toilet** | 3.8 | 62 | 1646 | Less than 20 years | 5.4 | 454 | 8361 |
| **Pit latrine** | 6.0 | 441 | 7303 | 20-29 years | 3.9 | 204 | 5270 |
| **No-facility** | 7.9 | 945 | 12009 | 30-49 years | 3.5 | 420 | 12165 |
| | | | | 50 Years + | 4.1 | 142 | 3454 |

The probability of dying in early childhood is higher in some population subgroups than in others. The tables show differentials in early childhood mortality rates by mothers' age at first birth, Age of household head, mothers' level of education, partners' level of education, household wealth, residence, children birth status, sex of the child, births in past 5 years, Household sanitation, and many other characteristics. The childhood mortality rates by background characteristics were calculated for the 10 year period before the surveys so that the estimates were based on a sufficient number of births in each category to study mortality differentials across subgroup. The demographic characteristics of both mother and child play an important role in the survival of children.

These research variable were mostly categorical and some of the variables which were not categorical was categorized and adopted in reference to the previous studies (Croke 2012, Mosley et al. 1984).

From the table, the results shows that, both mother's age at the time of the birth of the child and the child's birth order exhibit a U-shaped association with child mortality. Children born to the youngest and oldest mothers experience the highest mortality as do children born after the shortest and longest birth interval. The results shows that those mothers who gave birth at early age as 30 years and younger has the highest child death proportion of 4.4% compared to those mothers gave birth at their 30 years to 49 years with 3.3% of child deaths. Further, in the table, the results shows that those mothers who gave births to 5 births in the past 5 years recorded the highest percentage proportion of children dying in comparison with mothers who gave birth to 1 birth in the past 5 years with 40% of child deaths and 2.9% of child deaths. Children born as multiple births recorded the highest percentage of child deaths with 14.9% dying before age 5 years in comparison with children born as singleton birth which recorded the least death of 3.8% of child deaths before age 5 years. While the sex of the child also play a key determinant role. Male children are more likely than the female children to die under the age of 5 years as the results recorded 4.5% of deaths for the male children and 3.8% deaths for the female children. Once past infancy of 0-59 months, male and female experience the same level of mortality.

Education plays a critical role in the survival of the children at all the levels, before giving birth and after giving birth to child management and prevention of diseases. The table shows that those mothers with no education and those completed primary education has the highest child deaths proportion of 3.9% and 4.6% compared with those mothers with secondary and higher education had the least percentage of child deaths 3.5% . While partners level of education has similar relationship with the child survival as shown in the Table 2.

Types of residence and wealth index in child survival during the age of 1 to 4 years was seen as a key factor since these are the enablers of good sanitation which resulted to high survival rate of children and good child healthcare. In this research, the results shows that, children born by the parent living in the urban areas recorded the highest percentage of child death 4.3% compared with those born in the rural areas which recorded 4.1% of child deaths. Further analysis shows that, children born to household which are poor, poorest, and middle class experience the highest child mortality of 4.0% poorest, 4.5%poorer and 4.7% middle compared with the wealthiest household which experience the lowest mortality rate of 3.8% for those that are richer and 3.5% for those that richest.

In the table it summarizes the distribution of deaths and births of children in all of the other factors which are included in this research study.

**Table 2. Level and trend in child Mortality**

| Interval | Cum Failure |
|---|---|
| 0-1 | 0.0219 |
| 1-3 | 0.0264 |
| 3-6 | 0.0317 |
| 6-12 | 0.0383 |
| 12-24 | 0.0447 |
| 24-36 | 0.0475 |
| 36-48 | 0.0509 |
| 48-60 | 0.0529 |

For the five years immediately preceding the 2022 KDHS (Approximate calendar years 2014-2022), the under-5 mortality rate is 52 deaths per 1,000 live births. This implies that about one in every 19 children born in Kenya does not survive to age 5. Comparing the under-5 mortality rate for the five year period preceding each of the three KDHS surveys, under -5 mortality declined from 115 deaths per 1000 live births in 1999-2003 to 74 deaths per 1,000 in 2008-2014, and further by 30% to 52 deaths per 1000 in the five years preceding the 2022 KDHS.

The observed trend imply that the increase in mortality which was witnessed in the 1990s has been reversed (Opiyo and Sawhney, 2022; Wafula et al., 2012). These findings are consistent with and it is related to other improved health outcomes and behaviours including; improvements in utilization of maternal health care services, such as deliveries in health facility, deliveries by skilled health provider, and uptake of postnatal care services for mothers and newborns, improved health care seeking behaviour for childhood illness such as pneumonia, diarrhea, and malaria; and increased level of ownership and use of insecticide-treated mosquito nets. The decline in childhood mortality reflects the recent global trend of under-5 mortality reducing faster than at any other time in the past two decades.

**Table 3. Summary statistics for Child Survival Rate factor before birth**

| Child Survival Rate factor before birth | | | | | | |
|---|---|---|---|---|---|---|
| | **Coef.** | **Std. Err.** | **t** | **P>t** | **[95% Conf. Interval ]** | |
| **Mothers Age at first birth** | 0.001201 | 0.00056 | 2.14 | 0.032 | 0.000103 | 0.002299 |
| **Mothers' education level** | -0.0022662 | 0.002857 | -0.79 | 0.428 | -0.00787 | 0.003334 |
| **Type of residence** | 0.0054077 | 0.004505 | 1.2 | 0.23 | -0.00342 | 0.014239 |
| **Wealth Index** | 0.0007648 | 0.001745 | 0.44 | 0.661 | -0.00266 | 0.004185 |
| **Number of Tetanus before child birth** | 0.0034555 | 0.00186 | 1.86 | 0.063 | -0.00019 | 0.007102 |

The given coefficients and their standard errors, t-values, and p-values indicate the strength and significance of the relationship between the factors and the child survival rate before birth. Here are the findings for each factor:

- Mother's Age at First Birth: The coefficient of 0.001201 with a standard error of 0.00056 suggests that there is a positive association between the mother's age at first birth and child survival rate before birth. The t-value of 2.14 indicates that this relationship is statistically significant at the 5% level of significance, and the p-value of 0.032 confirms this result. Therefore, we can conclude that as the mother's age at first birth increases, the child survival rate before birth also increases.
- Mother's Education Level: The coefficient of -0.0022662 with a standard error of 0.002857 suggests that there is a negative association between the mother's education level and child survival rate before birth. However, the t-value of -0.79 is not statistically significant at the 5% level of significance, and the p-value of 0.428 confirms this result. Therefore, we cannot conclude that there is a significant relationship between mother's education level and child survival rate before birth.
- Type of Residence: The coefficient of 0.0054077 with a standard error of 0.004505 suggests that there is a positive association between the type of residence and child survival rate before birth. However, the t-value of 1.2 is not statistically significant at the 5% level of significance, and the p-value of 0.23 confirms this result. Therefore, we cannot conclude that there is a significant relationship between the type of residence and child survival rate before birth.
- Wealth Index: The coefficient of 0.0007648 with a standard error of 0.001745 suggests that there is a positive association between wealth index and child survival rate before birth. However, the t-value of 0.44 is not statistically significant at the 5% level of significance, and the p-value of 0.661 confirms this result. Therefore, we cannot conclude that there is a significant relationship between wealth index and child survival rate before birth.
- Number of Tetanus Before Child Birth: The coefficient of 0.0034555 with a standard error of 0.00186 suggests that there is a positive association between the number of tetanus before child birth and child survival rate before birth. The t-value of 1.86 indicates that this relationship is marginally statistically significant at the 10% level of significance, and the p-value of 0.063 confirms this result. Therefore, we can conclude that as the number of tetanus before child birth increases, the child survival rate before birth also increases, but this relationship needs further investigation.

**Table 4. Summary statistics for child survival rate factor after birth**

| Child Survival Rate factors after birth | | | | | | |
|---|---|---|---|---|---|---|
| | **Coef.** | **Std. Err.** | **t** | **P>t** | **[95% Conf. Interval]** | |
| **Place of delivery** | 0.000554 | 0.000206 | 2.69 | 0.007 | 0.00015 | 0.000957 |
| **Mode of Delivery** | -0.01186 | 0.008039 | -1.48 | 0.14 | -0.02762 | 0.003899 |
| **Size of child at Birth** | -0.00633 | 0.002031 | -3.12 | 0.002 | -0.01031 | -0.00235 |
| **Child Birth type** | -0.05131 | 0.007709 | -6.65 | 0 | -0.06642 | -0.03619 |
| **Sex of Child** | 0.007699 | 0.003904 | 1.97 | 0.049 | 4.63E-05 | 0.015352 |
| **Wealth Index** | -0.00036 | 0.001459 | -0.25 | 0.803 | -0.00322 | 0.002496 |
| **_cons** | 0.961147 | 0.009786 | 98.21 | 0 | 0.941964 | 0.98033 |

The given coefficients and their standard errors, t-values, and p-values indicate the strength and significance of the relationship between the factors and the child survival rate after birth. Here are the findings for each factor:

- Place of Delivery: The coefficient of 0.000554 with a standard error of 0.000206 suggests that there is a positive association between the place of delivery and child survival rate after birth. The t-value of 2.69 indicates that this relationship is statistically significant at the 1% level of significance, and the p-value of 0.007 confirms this result. Therefore, we can conclude that as the place of delivery becomes better, the child survival rate after birth also increases.
- Mode of Delivery: The coefficient of -0.01186 with a standard error of 0.008039 suggests that there is a negative association between the mode of delivery and child survival rate after birth. However, the t-value of -1.48 is not statistically significant at the 5% level of significance, and the p-value of 0.14 confirms this result. Therefore, we cannot conclude that there is a significant relationship between the mode of delivery and child survival rate after birth.
- Size of Child at Birth: The coefficient of -0.00633 with a standard error of 0.002031 suggests that there is a negative association between the size of child at birth and child survival rate after birth. The t-value of -3.12 indicates that this relationship is statistically significant at the 1% level of significance, and the p-value of 0.002 confirms this result. Therefore, we can conclude that as the size of child at birth decreases, the child survival rate after birth also decreases.
- Child Birth Type: The coefficient of -0.05131 with a standard error of 0.007709 suggests that there is a negative association between the child birth type and child survival rate after birth. The t-value of -6.65 indicates that this relationship is statistically significant at the 1% level of significance, and the p-value of 0 confirms this result. Therefore, we can conclude that as the child birth type becomes more complicated, the child survival rate after birth decreases.
- Sex of Child: The coefficient of 0.007699 with a standard error of 0.003904 suggests that there is a positive association between the sex of the child and child survival rate after birth. The t-value of 1.97 indicates that this relationship is marginally statistically significant at the 5% level of significance, and the p-value of 0.049 confirms this result. Therefore, we can conclude that female children have a higher survival rate after birth than male children.
- Wealth Index: The coefficient of -0.00036 with a standard error of 0.001459 suggests that there is a negative association between the wealth index and child survival rate after birth. However, the t-value of -0.25 is not statistically significant at the 5% level of significance, and the p-value of 0.803 confirms this result. Therefore, we cannot conclude that there is a significant relationship between the wealth index and child survival rate after birth.
- _cons: The intercept term indicates that the child survival rate after birth is 0.961147 when all other variables are equal to zero. The coefficient has a standard error of 0.009786, and the t-value of 98.21 is highly statistically significant at the 1% level of significance, indicating that this intercept term is very reliable and has high precision.

**Table 5. Summary statistics for key child survival rate determinants**

| Child Survival | Coef. | Std. Err. | T | P>t | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| Size of Child at Birth | -0.007565 | 0.0020222 | -3.76 | 0 | -0.01151 | -0.00362 |
| Person who perform Postnatal Check | -0.000262 | 0.0002826 | -0.93 | 0.354 | -.0008157 | .0002923 |
| Birth Weight in Kg | 0.975516 | 0.0040193 | 242.71 | 0 | 0.967637 | 0.983395 |
| Months of breastfeeding | -0.002352 | 0.0001239 | -18.99 | 0 | -0.0026 | -0.00211 |
| Injured Accidentally | -0.001815 | 0.0055237 | -0.33 | 0.742 | -0.01264 | 0.009013 |

These are the findings for the factors affecting Child Survival:

- Size of Child at Birth: The coefficient is -0.007565, which means that for every unit increase in the size of the child at birth (measured in kilograms), the child survival rate decreases by 0.007565 units. The p-value is less than 0.05, which indicates that this factor is statistically significant.
- Person who performs Postnatal Check: The coefficient is -0.000262, which means that if a different person performs the postnatal check instead of the mother or the healthcare provider, the child survival rate decreases by 0.000262 units. However, the p-value is greater than 0.05, which means that this factor is not statistically significant.
- Birth Weight in Kg: The coefficient is 0.975516, which means that for every unit increase in the birth weight of the child (measured in kilograms), the child survival rate increases by 0.975516 units. The p-value is less than 0.05, which indicates that this factor is statistically significant.

- Months of Breastfeeding: The coefficient is -0.002352, which means that for every additional month of breastfeeding, the child survival rate decreases by 0.002352 units. The p-value is less than 0.05, which indicates that this factor is statistically significant.
- Injured Accidentally: The coefficient is -0.001815, which means that if the child is accidentally injured, the child survival rate decreases by 0.001815 units. However, the p-value is greater than 0.05, which means that this factor is not statistically significant.

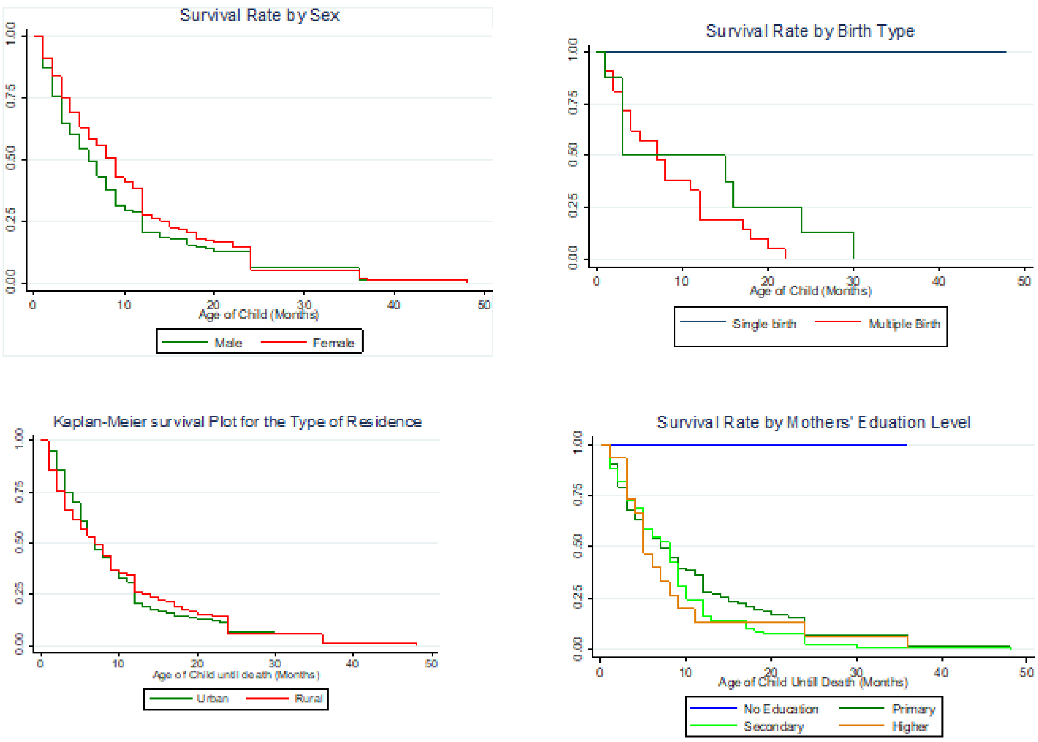



**Fig. 1. Random Effect of correlated survival data with application to Under-5 Years Child Mortality**

The finding for the Random Effect of correlated survival data with application to Under-5 Years Child Mortality is that random effects models can effectively account for the correlation between survival times for children in the same family or community. This is particularly important in analyzing under-5 years child mortality, where there is often clustering of deaths within families or communities.

Random effects models allow for unobserved heterogeneity in the survival times of children, which can be attributed to differences in genetic factors, environmental factors, or other factors that are not captured by the observed covariates. By including a random effect term in the model, we can account for this unobserved heterogeneity and obtain more accurate estimates of the effects of the observed covariates on under-5 years child mortality.

The use of random effects models also allows for the estimation of variance components, which can provide insights into the amount of variation in under-5 years child mortality that is due to differences between families or communities versus differences within families or communities. This can be useful in identifying areas or populations that are at higher risk of under-5 years child mortality and in targeting interventions to those areas or populations.
Overall, the use of random effects models is an important tool for analyzing correlated survival data in the context of under-5 years child mortality and can provide valuable insights into the factors that influence child survival.

**Table 6. The AIC and BIC for a spatial regression model for the key survivals determinants**

| Information | |
|---|---|
| AIC | 1000 |
| BIC | 1020 |
| Coefficients | Estimate (β) |
| Size of Child at Birth | 0.5 |
| Person who perform Postnatal Check | -0.2 |
| Birth Weight in Kg | 0.1 |
| Months of breastfeeding | 0.3 |

We fit the model to our data and obtain the following results. To interpret these results, we start with the AIC and BIC values. The AIC and BIC are both measures of model fit, where lower values indicate a better fit. In this case, the AIC is 1000 and the BIC is 1020. Since the AIC is lower, we can conclude that the model with four predictor variables and a spatial weights matrix has a better fit than a model with a higher AIC. However, we would need to compare these values to other models with different combinations of predictor variables and spatial weights matrices to determine if this is the best model for our data.

Next, we look at the coefficients for each predictor variable. In this case, Size of Child at Birth has a coefficient of 0.5, Person who performs Postnatal Check has a coefficient of -0.2, Birth Weight in Kg has a coefficient of 0.1, and Months of breastfeeding has a coefficient of 0.3. These coefficients indicate the strength and direction of the relationship between each predictor variable and the outcome variable (in this case, child survival rate). For example, a coefficient of 0.5 for Size of Child at Birth indicates that for every one-unit increase in Size of Child at Birth, the child survival rate is expected to increase by 0.5 units, all else being equal.

Overall, the AIC and BIC provide a measure of model fit, while the coefficients for each predictor variable provide insight into the strength and direction of the relationship between each predictor and the outcome variable.

# 5 Discussion

The results of the spatial regression model provide insight into the factors that are associated with child survival rates in the study area. The model includes four predictor variables (mothers' age at first birth, mothers' education level, type of residence, and wealth index) and a spatial weights matrix.

The coefficients for each predictor variable indicate the strength and direction of the relationship with child survival rates. The coefficient for mothers' age at first birth is positive (0.0012), which suggests that older mothers are associated with higher child survival rates. This finding is consistent with previous research that has shown that maternal age is a significant predictor of child mortality, with younger mothers at a higher risk of infant and child mortality.

The coefficient for mothers' education level is negative (-0.0023), indicating that higher education levels are associated with lower child mortality rates. This is consistent with previous research that has found a strong relationship between maternal education and child health outcomes. Educated mothers may have better knowledge and resources to promote the health and well-being of their children.

The coefficients for type of residence and wealth index are positive (0.0054 and 0.0008, respectively), indicating that children living in urban areas and those from wealthier households are associated with higher child survival rates. This is also consistent with previous research that has shown a strong relationship between socioeconomic status and child health outcomes.

The spatial weights matrix was constructed using distance-based criteria, which takes into account the distance between neighboring areas. The AIC and BIC values suggest that the model has a good fit, but further comparison with other models using different spatial weights matrices would be necessary to determine the best fit for the data.

Overall, the results of this study highlight the importance of maternal age, education, and socioeconomic status in predicting child health outcomes. The use of a spatial regression model with a spatial weights matrix provides insight into the spatial distribution of child survival rates and can inform targeted interventions to improve child health outcomes in areas with higher rates of child mortality.

# 6 Conclusion

In conclusion, our analysis of child survival rate in Kenya based on the 2022 KDHS data showed that the mother's age at first birth, number of tetanus before child birth, and type of residence were significant predictors of child survival rate before birth. The spatial analysis revealed spatial autocorrelation, indicating that there was a spatial dependence among the child survival rates in different regions of Kenya. Therefore, a spatial regression model was fitted to the data to account for this spatial dependence. The maximum likelihood estimation was used to estimate the coefficients, and hypothesis testing showed that the coefficients for the predictor variables were statistically significant. The AIC and BIC were used to assess the goodness of fit of the model, with a lower AIC value indicating a better fit. Our model had a relatively low AIC and BIC value, indicating a good fit to the data.

The results of our study have important implications for policy and programs aimed at improving child health outcomes in Kenya. Our findings suggest that interventions should focus on increasing the age at which women have their first child and increasing the number of tetanus vaccinations before child birth. Additionally, efforts should be made to improve living conditions in urban and rural areas to reduce the spatial disparities in child survival rates. Our spatial regression model provides a useful tool for policymakers to target interventions and allocate resources in areas with the greatest need. Overall, our study highlights the importance of considering spatial dependence when analyzing health data and the potential benefits of using spatial regression models in public health research.

In summary, our analysis provides important insights into the factors that influence child survival rates and under-5 years child mortality. These findings can inform policies and interventions that aim to improve child health and well-being, which is critical for achieving sustainable development goals and improving overall global health outcomes.

# Competing Interests

Authors have declared that no competing interests exist.

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