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A spatial survival model for risk factors of under-five mortality in Kenya

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Submitted to the School of Mathematics in partial fulfilment for a degree in Master of Science in Biometry

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Master Thesis

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Abstract

Background
Child mortality refers to death of a child between 0 and five years old. Kenya like many Sub-Saharan countries faces a burden of child mortality, and has made efforts towards reducing the same. The main The main objective of the study is to evaluate the spatial variation in under-five mortality in Kenya using spatial survival methods.

Methods
Data on child mortality was collected through the Demographic Health Survey 2014. The survey collected information on children, demographic indicators related to the mother and child, and various social and economic attributes. Intrinsic Conditional Autoregressive Models were fitted to account for spatial dependence and clustering to estimate the hazard at county level, together with a cox-proportional hazard model to estimate the risk factors associated with child mortality.

Results
The spatial cox proportional hazard model was identified as the best fit based of the Deviance Information Criterion (DIC). There exists a spatial structure on the hazard of death in the Kenyan counties. Counties with the highest hazard of death include counties around central Kenya (Laikipia, Nyandarua, Nyeri, Kiambu, Machakos and Makueni), although most counties have similar hazards. The lowest hazard is found in Western Kenya counties and Nyanza. Sex of the child, sex of household head, age of respondent at first birth, level of education, and whether a child is in a multiple birth are significant risk factors of child mortality.

Conclusion
This study brings out the spatial disparities that exist in the country on child mortality in Kenya. The specific counties have mortality rates that are county-specific, with neighbouring counties having similar hazards for death of a child. is important therefore for interventions to take into consideration the effect of where a child is born(county) to reduce mortality.

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Declaration and Approval

I the undersigned declare that this dissertation is my original work and to the best of my knowledge, it has not been submitted in support of an award of a degree in any other university or institution of learning.

Signature Date

KILEMI DANIEL
Reg No. I56/24858/2020

In my capacity as a supervisor of the candidate's dissertation, I certify that this dissertation has my approval for submission.

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Dedication

This research project is dedicated to God, my parents, family and friends, Deltas SSACAB and the supervisory team for their support and contribution towards its completion.

Contents

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Kilemi Daniel

Nairobi, 2020.

1 INTRODUCTION

1.1 Background Information

Child mortality rate also known as under-five mortality rate refers to the probability of dying between birth and exactly five years of age of both male and female children expressed as deaths of children per 1000 live births. This includes the death of infants; children up to one year old, and the death of children from one year to five years. The world health organization listed infant mortality as taking a big chunk (75 percent of all under five deaths) listing 4.1 million deaths for infants. The year 2018 recorded approximately 5.3 million children and infant deaths. The risk of a child dying before they are five years of age in the WHO Africa region was 76 per 1000 live births which was 8 times higher than the WHO European region [Organization, 2018].

A closer look at the differences in this decline in urban and rural areas [Kimani-Murage et al., 2014] showed that the gap has narrowed from 1993 to 2008. The decline was shown as more rapid and significant in rural areas, although the drag in urban areas mortality decline was attributed to the high risk of mortality in slum areas on the Nairobi, Kisumu and Mombasa metropolitan areas, also serving as the major cities in Kenya. A flagging of the slum effect on child mortality was therefore key as a policy in helping maintain a low level of mortality in the urban regions.

There exists various causes of the existential threat of child mortality in Kenya and Sub-Saharan Africa. Literature exists; capturing these effects from The Demographic Health Surveys (DHS). Although their significance varies in magnitude from country to country, demographic, socio-economic and availability of amenities such as drinking water are among the key factors shown to influence the existing patterns in child mortality [Ezra et al., 2016].

Having established the decrease in trend over the past three decades; an attempt to explain the causes of the decline was found to have been the political changes in the country starting from 2003, external aid etc. The overall effect of these otherwise indirect causes of childhood mortality had a significant effect on direct causes such as maternal literacy, household wealth, sexual and reproductive health and maternal and infant nutrition [Keats et al., 2015].

The country again trailed its East African counterparts in the decline of under-five mortality. Adequate use of antenatal care services reduced the risk of under-five mortality by

4.2 percent, while use of skilled service delivery care services reduced the risk of mortality by 1.8 percent. A decrease in coverage of these services therefore had adverse effects on mortality of children in Kenya.[Machio, 2017]

Accessing health services was classified as critical mortality, while the individual characteristics such as wealth index, level of education and nutrition also played a role in the mortality of under-five children. A multi-level modeling approach revealed significant differences between Africa and Asia, in favor of the Asians; and maintained a presence of significant determinants at cluster level for child mortality. [Misselhorn and Harttgen, 2006]

The Child mortality rate in Ethiopia had a similar declining trend, with the decline attributed to duration of breastfeeding. Higher birth intervals were shown to also cause a decline in mortality compared to infants born less than two years of the preceding child. Wide spacing of births allowed more time for taking care of the child and ensured that there were maternal nutrients to take care of the second child [Susuman, 2012].

The other key source of variation in child mortality was captured in [Adetunji, 1995] as age of the mother at birth and breastfeeding duration. Secondary school mothers faced harsh economic conditions in Nigeria, dedicating most of their time into surviving the conditions as opposed to spending time breastfeeding their children. Dividing the time between taking care of a child and surviving the hard economic conditions in Sub-Saharan African countries has therefore been shown to affect child mortality.

Maternal education level appeared to be a singleton determinant of the level of child mortality in Nigeria, albeit in a similar socio-economic environment, argued by most policy makers as the major issues responsible for any significant change in mortality. [Caldwell, 1979] Education has also been known to affect utilization of health services by mothers [Babalola and Fatusi, 2009], advanced by [Machio, 2017] as one of the determinants that reduce the risk of mortality.

In addition, factors such as the environment and lifestyle of communities in third-world countries have also been shown to have a direct impact on the health of such communities. [P et al., 2001] found a significant association between the mortality of a child and risk factors such as geographic mobility, the age of weaning and religious beliefs. This has shed some light for an investigation of other factors affecting child mortality other than the health and education of a mother, or utilization of antenatal care.

The credit given to improvement of health services as a sole contributor to the lowering of child mortality even in the third world countries has been overrated. Agricultural nations, covering most of the countries in Africa and South Asia, show a significant effect of the place of residence and ethnicity- encompassing the cultural practices of a particular community [Suwal, 2001].

The importance of the improvement in health services cannot however be excluded on a journey to understand the predictors of mortality; there is a high infant mortality for children born outside a health facility [Kaguthi et al., 2018] in Siaya County Kenya. The distance to such a facility also had a major impact for children in rural Ethiopia [Okwaraji et al., 2012].

There are also factors individual to a child that significantly affect their survival. The birth order, the interval between each child and whether a child is a twin are important factors in determining mortality. [Cunningham, 2003]

[Mosley and Chen, 2003] outline a framework for the study of mortality in third world countries. The surface level causes of death, say a disease, is caused by other background socioeconomic factors. They group proximate determinants causes of death into five broad categories:

- Maternal factors: age of the mother, gender, first birth.
- Environmental contamination: water, air, food, soil, inanimate objects.
- Nutrient deficiency in a child or mother: calories, vital minerals.
- Injury: accidents and intentional injuries.
- Personal illnesses: preventive measures, treatment and taking deliberate health measures.

The first four categories of determinants serve as the prelude to the onset of a disease or a causal effect to a biological problem, after which the fifth category takes over to eventually cause mortality.

Various studies have been done to investigate the specific significant factors both individual and socio-economic which affect the probability of survival of under-five children [Ezra et al., 2016]. [Ayele et al., 2017] found out in a study of mortality in under five children in Ethiopia that the chances of death for a child before age five reduce if the mother does not give birth again until the child is of age, therefore birth interval plays a significant role. Short birth intervals, teenage pregnancies and pregnancies of over 35 year old mothers had an increased risk of death [AJ and SL, 1995]. Hazard of death increased with increasing age of the mother.

Adequate use of maternal health care services [Gayawan, 2014], have been known to increase the survival probability of children. Use of skilled delivery care services and antenatal care is also associated with reduced risk of death for under-five children [Machio, 2017].

A household's environmental and social-economic characteristics also have a statistical impact on mortality [Mutunga, 2007]. Wealthier families have a lower hazard of death, households having electricity also have higher chances of survival, while household size is negatively related to mortality, smaller households have higher hazards of death. Environmental factors such as access to safe drinking water, sanitation facilities and households using low polluting fuels have higher chances of survival.

The effect of cultural practices cannot be overlooked. Inappropriate neonatal care, late initiation of breastfeeding, stopping breastfeeding early, discarding colostrum and not practicing exclusive breastfeeding were related to cultural practices were found to have a significant effect on under-five mortality.

1.2 Statement of the problem

Child mortality has always been an area of interest in demography. The World Health Organisation, the Ministry of Health in Kenya and such planning agencies have maintained policies that ensure monitoring and reduction of child mortality rates to zero. Many studies have focused on the national level determinants of mortality.

Due to the introduction of counties in 2010, when the new constitution was promulgated, interest has therefore been to know the sub-national causes or disparities in the burden of child mortality. This study incorporates mapping of county frailties to investigate the distribution of disparities existing on the counties. This provides an opportunity to study the area specific distribution of child mortality burden to inform policy implementation towards an area specific interventions.

1.3 Objectives

The main objective of this study is to evaluate the spatial variation in under-five mortality in Kenya using a Spatial Cox Proportional Hazards model. Specific objectives include;

- Compare the performance of a spatial frailties cox proportional hazard model with a non-frailty Cox model.
- Determine the influence of demographic factors and socio-economic on under-five mortality.
- Map out spatial differences on child mortality in Kenyan counties.

1.4 Justification of the study

The interest in child mortality has remained key in interventions aimed in reducing the death of under-five mortality and the Agenda Four initiative. Although national level estimates have guided said intervention, the application of intervention equally to all areas in the country leave parts with high mortality rates under served.

A sound approach would therefore be an approach with area specific intervention; the approach to said areas informed by studies that bring out the differences in child mortality accross space. Studies have also been done and used classic regression models, and might not effectively capture regional differences if they exist, a spatial approach is therefore necessary to bring out these differences to ensure interventions are guided by empirical data.

2 LITERATURE REVIEW

2.1 Introduction

This chapter provides a review on survival analysis, and specifically the inclusion of spatial models to analyze survival data.

2.2 Survival Analysis

Survival analysis: which describes the time until an occurrence of an event of interest, has become a critical tool in analyzing child mortality. Survival models focus on how many will survive, say children after a certain period of time and the rate of failure, as well as ascertain the underlying factors that generate shortened or prolonged survival [Banarjee, 2016]. The interest in this case therefore is the risk factors associated with time to death of a child or an infant and the relationship between the time T to death with a set of predictors. The preference of survival analysis over classical regression techniques previously used is the ability to capture the effect of the proximate determinants through time.Cox models have therefore been successfully applied in the modeling of child survival data. The Cox model usually depends on a baseline hazard of death of a child and the set of covariates known to affect the probability of survival [Prentice, 1992].

Cox models assume that the survival of an individual is dependent on a baseline survival and a set of risk factors, say sex of a child. But in reality this is not true since survival data are dependent especially when a sample of individuals is grouped into clusters such as clinical centers, geographical locations or the normal cluster sampling procedures. This dependency, if ignored, it might bias any results needed for a modelling such risk factors. This has therefore necessitated the introduction of frailties, unmeasured or unobserved random effects present either at cluster level or a geographical location. These effects enable capturing the heterogeneity present among individuals in a study.

Such random effects can be the cause of regional disparities evidenced in literature, suggesting a presence of community level characteristics that influence health outcomes [Core, 2015]. These community level variables include region, place of residence, the infrastructure in the community, community hospital delivery and community poverty levels. Mothers who reside in communities with high proportions of hospital delivery have a lower risk of death in infancy. Community level characteristics are more significant when explaining regional variations in child mortality, consistent with [Khan and Awan, 2017].

Urban areas have also been shown to have a lower risk of death at infancy and childhood, [Ayele et al., 2017] compared to other regions in Ethiopia.

2.3 Spatial Survival Analysis

Spatial analysis deals with modeling problems geographically, usually under the assumption that there is a geographic effect on the overall effects one wants to model. At the end of the analysis, the results are then interpreted after factoring in a geographic effect. It should be noted that these geographic effects can also be estimated, and their significant contribution to the problem being modelled interpreted.

Geo-statistical methods, applying probabilistic methods to geographically related phenomena, are used to model out the spatial correlation within a data layer. This is on the assumption that points located closed to one another should be close in their values of the random variable assumed to be spatially correlated.

In spatial survival analysis; the concept of time to an occurrence of an event, which describes the failure mechanism of an event of interest say death of a child; the failure mechanism is assumed to be correlated on areas or points (representing locations) that are close together.

Spatial survival methods are an improvement to the already existing models from cox models to frailty models. This enables capturing of spatial random effects as well as cluster specific random effects, clearly put by [Mani et al., 2019] as family effects. This section therefore deals with introduction of a spatial frailty term. Spatial survival analysis refers to the modelling and analysis of geographically referenced time to event data. Spatial survival analysis is used to analyze clustered survival data when the clustering arises from geographical regions or strata [Banarjee, 2016]. Spatial models used for georeferenced individuals introduce spatial frailties. The underlying understanding is that the expected hazard rates will be more similar in neighbouring regions, owing to underlying factors such as access to health care services that vary spatially.

The spatial random effects (frailties) are unobserved heterogeneity apart from the determinants or main effects. Controlling for these unobserved differences mostly at either region level or location level captures effectively the effects of covariates such as maternal education.

The question on considering spatial random effects is in part based on getting the region in which a child was born or lived as a significant determinant on mortality for time to death of infants and children [Hesam et al., 2018]. An event of interest (death) may therefore have happened due to the influence of the location where the event occurred. These location factors are known as spatial factors [Proceedings, 2017].

From the foregoing, these regional disparities that exist accross nations and regions, [Ezra et al., 2016] and [Kazembe et al., 2007] raise an important question on the nature of frailties. To capture the effect of regions, apart from the frailty term existing among clusters, a spatial frailty effect is therefore important.

The introduction of spatial models to model time to death is therefore important, as the characteristics of determinants of mortality vary spatially, and a group of individuals is likely to experience the same cultural influence in a certain area and its neighboring regions. Regions and their adjacent areas therefore experience similar spatial correlations [Li et al., 2014]as opposed to proximate areas. Advances in technology have produced data sets on proximate determinants and also captured various GPS coordinates specific to individuals or groups.

High risk areas of mortality in Uganda included the south west and the north west according to [Kazembe et al., 2012]. These variations exist apart from the factors considered as covariates in the model. These further support the existence of these unobserved variations existing among regions, and necessitates a spatial approach.

Using a spatial Cox regression model to analyze child survival and assess influence of individual specific factors, the effect of malaria prevalence and group-specific factors approximated by geographical location of under-five children in Malawi, [Kazembe et al., 2007] found a significant presence of spatial variation with an increased hazard of death on lake-shore regions and southern Malawi. Among these spatial variations, bio-demographic and socio-economic variables such as maternal age on child mortality.

Data from 10 West African countries by [Ezra et al., 2016] showed significant spatial inequalities. A full geo-additive discrete time survival model with spatial frailties fared better at the presence of other proximate determinants, showing clear differences in geographical patters for infant and child mortality. These subtle region-specific differences were able to be uniquely discerned by use of a geo-additive survival model.

An analysis by [Hesam et al., 2018] of data on gastrointestinal cancer patients in Iran's two provinces, comparing a no-frailty cause specific hazard survival model, a frailty model and a spatial frailty model. Spatial frailty models performed better than a non-spatial frailty model. A persistent spatial pattern showed a presence of missing, unknown and unobserved , spatially varying covariates relevant for time until death for gastrointestinal cancer patients. A multivariate conditional auto-regression distribution brought out an additional spatial story to the data other than the effect of prognostic factors for time to death from cancer thus showing a need for a model factoring in spatial effects.

Substantive district level spatial variations existed for childhood mortality in Rwanda. These district specific spatial variations found out by [Niragire et al., 2017] by fitting a full

Bayesian geo-additive continuous time hazard model were associated with higher hazard of death in two of Rwanda's districts. Any determined intervention would therefore need to focus on these region specific disparities for effectiveness.

2.3.1 Bayesian Methods in Spatial Survival Analysis

Survival methods; modelling time to event data, have evolved from Cox models [Prentice, 1992], to frailties which extend the Cox models to allow modelling of heterogeneity between clusters and modelling multivariate data, [Ibrahim et al., 2011] and spatial models that utilize the geo-statistical models coupled with standard survival models to make inference on geo-referenced data.

One key aspect of survival analysis is the non-parametric and semi-parametric nature of the hazard function; deviating from the usual parametric assumptions. This introduces a Bayesian aspect that allows inference on the posterior distribution of the model estimates and parameters. Bayesian survival models deal with summarizing a parameter by an entire distribution of values instead of one fixed value as used in classical analysis. A posterior distribution comprises a prior distribution about a parameter, a likelihood model on the observed values. Depending on the assumed prior distribution and likelihood, the posterior distribution is either available analytically or approximated, for example by using Markov Chain Monte Carlo (MCMC) methods [Stata, 2018]

Bayesian approaches have been implemented in survival analysis with frailties and spatial frailties, these methods exist in literature. Spatial survival models allow for spatial autocorrelation at neighbouring regions. [Darmofal, 2008] uses a Bayesian approach to model to time the announcement of House Members and considers a Conditional Autoregressive (CAR) prior for the spatial frailty term. The spatial shared frailty models outperform standard non-frailty models and also non-spatial frailty models. The capturing of spatial dependence produces important changes in the effect of covariates in the analysis.

[Ezra et al., 2016] made inference on their study on Geographical variations in infant and child mortality using a Bayesian setup on the posterior distribution of the parameters. Significant geographical variations for mortality existed across the West African countries.

Multivariate Conditional Auteregressive priors were used by [Hesam et al., 2018] in modelling gastrointestinal cancer survival data, with a presence of spatially correlated covariates.

This study reports the spatial analysis of under-five mortality in Kenya to address the spatial disparities using spatial survival methods and using the KDHS in 2014. The KDHS survey 2014 introduced counties previously absent in the other surveys. Information provided included the geographical locations and geo-references of the counties. The focus is the significant regional variations present in the country. We use Cox regression methods for time to death of under five-children, compare spatial and non-spatial frailties in a Bayesian setting. Covariates included in the model are pre-selected according to existing literature. This study adopts three categories; demographic and biological factors inherent to the mother and the child, and socio-economic factors, and most certainly the geographical variations are captured in the model.

3 METHODOLOGY

3.1 Data

The data used in this study is sourced from the Kenya Demographic and Health Survey 2014. This is an initiative sponsored by the United States Agency for International Development (USAID) with partnership with other Kenyan research agencies. The data collected provides information to help monitor the population and health status in Kenya. The DHS programme has been run in many nations to provide periodic updates, outlooks and estimates of various indicators such as maternal and child health and individual level information pertaining to the health of such individuals in a specific country. The 2014 KDHS survey was the first of its kind to provide county level estimates since the promulgation of the New Constitution 2010. Authorisation to use this data set was obtained under request from to the DHS online authorization under the project Spatial Survival Analysis of Under-five mortality in Kenya.

The Kenyan agencies provide the personnel to conduct the survey. The survey uses samples from the country's population and housing census estimates. Using a two stage sampling frame, Enumeration Areas (EAs) in the census serve as the primary sampling unit. Clusters are selected in the first stage from the Enumeration Areas, while households are selected in the second stage. All mothers aged 15-49 years old are eligible respondents and information about children born 5 years prior to the survey is obtained.

3.1.1 Study Variables

The variables used in the study are pre-selected based on existing literature on significant determinants of child mortality. The focus of this study is the existence of spatial variations and differences in child mortality across regions. The demographic and socioeconomic variables include sex of the child, maternal age at birth, age of respondent at first birth, sex of household head, Wealth Index, Highest Education level and the type of place of residence. The geo-referenced regions were the counties and coordinates (displaced) provided.

The primary outcome is the mortality of a child, defined as the time to death of a baby born before his or her fifth birthday. The variables are shown in Table 1;

Table 1. Key Variables Description

Determinants	**Definition**
Outcome Variable	
Death of a child	A child dying between age zero and 5 years old
Demographic Risk Factors	
Sex of the child	Child is male or female
Sex of household head	Household head is male or female
Age of respondent at first birth	Continous for age of respondent in years
Maternal age at birth	Age of the mother at the time of birth
Child is twin	Whether a child is born in a set of twins and above
Socio-economic risk factors	
Type of place of residence	Residence, rural or urban
Highest Level of Education	Education qualification attained, none, primary, secondary or tertiary
Wealth Index	Grouping by earnings, and other considerations for an index

3.1.2 Data Structure

The KDHS data, 2014, has the child's age at death, and the number of months the child lived before dying, a range of discrete values from 0-60 months. The data structure is as shown below; $(t_{ij}, x_{ij}, s_i) : i = 1, \cdots, m; j = 1, \cdots, n_i$, where

- t_{ij} is a random survival time for child j within region/location s_i,
- x_{ij} is a related p-vector of covariates, and
- ${s_i}_{i=1}^{m}$

The KDHS data is georeferenced where $s_i \in \mathbb{R}^{\not\models}$ is recorded as latitude and longitude for the observations, usually displaced by 2km in urban areas and 10km in rural areas to protect identity of respondents. The assumption of correlation proposed by [Li et al., 2014] grants credibility to the displacement such that areas around the specific location will have almost similar amenities, religion, ethnic background, roads, access to health facilities and other socio-economic determinants. A data set containing the Kenyan counties information is also provided and is merged with the KDHS data set to enable estimation of the regional (areal) differences.

3.2 Survival Methods

Two models are compared in this study, the first model with no frailty assumption on the cluster levels, the second model will include spatial frailties on the survival of under-five children. The event of interest is modelling survival times, the time taken until an event of death has occurred for an individual child. Survival information on each child is recorded by $(t_i, \delta_i), i \in 1, \cdots, N$ where $t_i \in 1, \cdots, 60$ is the child's observed survival time in months and δ_i is the survival indicator where $\delta_i = 1$ if the child is dead and $\delta_i = 0$ if the child is still alive [Ezra et al., 2016]. Further suppose that the child is a part of a sample from N counties, the number of children in each county is n_i where $i = 1, \cdots, N$ and $\sum_{i=1}^{N} = n$.

3.2.1 Cox Proportional Hazard Models

The proportional hazards models stem from [Prentice, 1992] as a key assumption that the hazard ratio of an individual is constant over time, the hazard for an individual is proportional to the hazard for any other individual. The hazard model dependent on the baseline hazard and a set of covariates is shown as;

$$h(t_{ij;x_{ij}}) = h_0(t_i j) e^{\sum_{i=1}^{n_i} \beta_i X_{ij}} \tag{1}$$

where t is the survival time, $h(t)$ is the hazard function, $b_1, b_2 \cdots b_p$ is the impact of the covariates $X_1, X_2 \cdots X_p$, h_0 is the baseline hazard function, the survival when there are no risk factors associated with death while e^{b_i} denotes the hazard ratios $(H.R)$.

3.2.2 Spatial Frailty Models

Let t_{ij} be the time to death or censoring for subject j in stratum (hospital, region) i, $j = 1, \cdots, n_i$ and $i = 1, \cdots, n$, while x_{ij} denotes the individual specific covariates such as age, sex, education and others. Introducing a frailty term extends the model to [Banarjee et al., 2003];

$$h(t_{ij;x_{ij}}) = h_0(t_i j) w_i e^{\sum_{i=1}^{n} \beta_i X_{ij}} \tag{2}$$

where w_i denotes the random effect which is a random variable also introduced multiplicatively to the baseline hazard. Let $W_i = logw_i$, then the frailty term is captured effectively in the exponent term as shown below;

$$h(t_{ij};x_{ij}) = h_0(t_{ij})e^{\sum_{i=1}^{n} \beta_i X_{ij} + W_i} \tag{3}$$

W_i captures the differences between the stratum (clusters) that are not captured by the main effect. An example of W_i (non-spatial) are normal random variables with mean 0 and a variance σ^2, [Banarjee et al., 2003]

$$W_i \sim^{iid} N(0, \sigma^2) \tag{4}$$

when $\sigma^2 = 0$ the model reduces to the proportional hazard model.

Conditional Autoregressive Models

The spatial frailty term is assumed to have an Intrinsic Conditional Autoregressive Model: the model pools information from neighbouring regions to make inference about a certain parameter estimate. Let $a_{ij} = 1$ if areas $N_i and N_j$ share a non-trivial border and $a_{ii} = 0$ otherwise, this spatial interaction is modelled conditionally as a normal random variable ϕ which is a N-length vector [Morris et al., 2018];

$$\phi = (\phi_1, \cdots, \phi_n)^T \tag{5}$$

The conditional distribution of each ϕ_i is conditional on the sum of the weighted values of its neighbours $(w_{ij}\phi_j)$ and has unknown variance [Morris et al., 2018];

$$\phi_i | \phi_j, j \neq i \sim N(\sum_{j=1}^{n} w_{ij}\phi_j, \sigma^2) \tag{6}$$

The joint distribution of $\phi = (\phi_1, \cdots, \phi_n)^T$ is a multivariate normal variable centered at 0 [Morris et al., 2018]. The variance of ϕ is given as a precision matrix Q and is the inverse of the covariance matrix σ thus we have $\Sigma = Q^{-1}$, and

$$\phi \sim N(0, Q^{-1}) \tag{7}$$

The precision matrix Q is constructed from the adjacency matrix and the diagonal matrix. The adjacency and diagonal matrix describe the neighbourhood structure of the region N. The adjacency matrix is an NXN matrix where every entry $n_{ij} = 1$ if regions n_i and n_j are neighbours and 0 otherwise. The diagonal matrix is an NXN matrix where each diagonal element n_{ii} contains the number of neighbours of region n_i and all the off-diagonal entries are 0.

Consider a map of four regions as shown below

n1	n2	n3	n4
1	2	3	4

where the relation of 1 2 mean 1 is neighbouring 2 and only 2, and so on. The adjacency matrix for the four regions is therefore;

$$\begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

and the diagonal matrix is;

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

From the adjacency matrix, the precision matrix Q is symmetric and positive definite, and is defined as;

$$Q = D(I - \alpha A) \tag{8}$$

where D and A is the diagonal and adjacency matrices respectively. $\alpha, for 0 < \alpha < 1$ controls for spatial dependence, and is a scale to make Q positive definite.

Intrinsic Conditional Autoregressive Models

In the ICAR model, each ϕ_i is conditional on the average of its neighbours, with mean equal to the average of its neighbours. The variance decreases as the number of neighbours increases, assuming a strong correlation around many neighbours. The distribution of each phi_i is given as;

$$\phi_i|\phi_{i\ j} \sim n(\frac{\sum_{i\ j}\phi_i}{d_i}, \frac{\sigma_i^2}{d_i}) \tag{9}$$

where σ_i^2 is unknown spatial variance. As the specification above for the CAR model, the joint probability density for ϕ is centered at 0 and has precision matrix Q. Assuming a variance $\sigma^2 = 1$, the joint specification results into;

$$p(\phi) = exp(\frac{-1}{2}\sum_{i\ j}(\phi_i - \phi_j)^2) \tag{10}$$

which is a $pairwisedifference$ formulation, each $(\phi_i - \phi_j)$ is only dependent on the distance between the values of the neighbouring regions. Adding $\sum_N \phi_i = 0$ centers this model, and the log probability of this model is constrained to be between 0 and 1.

To calculate the precision matrix, we proceed as above, but the α controlling for spatial dependence is removed, and therefore we have;

$$Q = D(I - A) \tag{11}$$

The determinant of this matrix is 0, but with some data it is positive definite. The advantage of the ICAR over the CAR model is the reduction of computation time, and capturing the spatial dependence mainly by the distance between the values of the neighbouring regions.

3.2.3 Bayesian approach

For an estimation of the model parameters, a Bayesian approach is used and assigned priors for the model parameters, and the distribution of the baseline survival function.

An intrinsic conditional auto-regressive (ICAR) prior was assumed to model the spatial structure [Ezra et al., 2016]. The prior models the mean for each area ϕ_i, which is conditional on areas neighbouring it is normally distributed with mean equal to the average of the neighbouring areas ϕ_l and variance is inversely proportional to the number of neighbours m_i as above.

For the semi-parametric survival function, the baseline survival function is modeled using a Transformed Bernstein Polynomial (TBP) prior, usually centered around a given parametric family and selects only smooth densities [Zhou et al., 2017]. The prior $TBP_L(\alpha, S_\theta(\cdot))$ is defined as

$$S_0(t) = \sum_{j=1}^{L} w_j I(S_\theta(t)|j, L-j+1), \tag{12}$$

where $W_L \sim Dirichlet(\alpha, \cdots, \alpha)$, and $W_L = (w_1 . \cdots, w_L)^T$ is a vector of positive weights, $I(\cdot|a,b)$ denotes a beta cumulative distribution function with (a,b) as parameters and $S_theta(\cdot) : \theta \in \Omega$ is a parametric family of survival functions. The log-logistic

$$S_0(t) = (1 + (e^{\theta_1} t)^{exp(\theta_2)})^{-1} \tag{13}$$

is considered for this study as the prior specification for the baseline survival function.

Vague normal priors are chosen for the regression coefficients as well. Posterior inference on the parameters were computed using Markov Chain Monte Carlo iterations carried out through a Bayes approach [Zhou et al., 2017]. The likelihood function based on on $(w_L, \theta, \beta, \phi)$ is given by;

$$L(w_L, \theta, \beta, \phi) = \prod_{i=1}^{k} \prod_{j=1}^{n_i} [Sx_{ij}(a_{ij}) - Sx_{ij}(b_{ij})]^{I(a_{ij}<b_{ij})} f x_{ij}(a_{ij})^{I(a_{ij}=b_{ij})} \tag{14}$$

and the posterior distribution given as;

$$p(w_L, \theta, \beta, \phi) = p(\theta, \beta, \phi) L(w_L, \theta, \beta, \phi) \tag{15}$$

where $p(\theta, \beta, \phi)$ is the prior distribution of the parameters and $L(w_L, \theta, \beta, \phi)$ is the likelihood function obtained from the observed values.

Model comparison is done using the Deviance Information Criterion (DIC).

Analysis was carried out in the R-software for statistics with the spBayesSurv package. A burn-in period of 5,000 iterations was considered, and displayed after every 1,000 saved iterates and run for 615 seconds on an HP Intel Core i3 Laptop computer. Small values of DIC indicated better performing models.

4 RESULTS

4.1 Introduction

Chapter four gives the results of the model comparison of the models fitted, spatial disparities in the risk of child mortality, and the results of the mortality determinants considered.

4.2 Model Comparison

The Deviance Information Criterion is used to compare the global performance of the two models. A small value of DIC indicates a better model fit. The first model was fitted using the Proportional Hazards assumption on the child mortality data, where the response was the hazard of death dependent only on the baseline hazard and a set of covariates. The DIC value for this model (3384.992) is larger compared to the spatial model as shown in table 2.

The second model is fitted with the spatial frailty term, and has the lowest value of the Deviance Information Criterion (3344.661) and therefore the better fit. This model assumed unobserved variation (heterogeneity) at the geographical regions, specifically various counties in Kenya. The model improves significantly when a spatial frailty term is introduced, to account for randomness apart from the independent explanatory variables. Adjusting for the spatial variation lends more credence to the interpretation of the factors influencing child mortality in Kenya.

The Watanabe Akaike Information Criterion deals with the predictive power of a model. Lower values indicate a model with a high predictive power. The Spatial Proportional Hazards model has the lowest WAIC, and as a result has more predictive power. The next section deals with the diagnostics of the model and also presents the results of the regression coefficients.

Table 2. Model Comparison Results

Model	**Deviance Information Criterion (DIC)**	**Log Pseudo Marginal Likelihood(LPML)**	**Watanabe-Akaike Information Criterion(WAIC)**
Cox Proportional Hazards (No Frailty)	3384.992	-1694.956	3389.639
Proportional Hazard Spatial Frailty Model	3344.661	-1682.77	3362.434

4.3 Goodness of Fit tests

The Markov Chain Monte Carlo estimation involves estimating model parameters in a Bayesian set-up. The MCMC sampler explores the parameter space of a certain parameter, resulting from prior knowledge about the parameter and the likelihood of the observed values. The number of iterations set by the user requires the sampler to sample from the sample space. To ensure mixing, the resulting chain selection of parameters should result in a stationary distribution of the parameters, such that the sampler picks values of a parameter in the parameter space and such that the values are around the expected value of the distribution.

Trace plots are therefore a time series plots of the Markov Chain, and to ensure convergence, should be stationary. Figure 2 and Figure 3 show trace plots of the coefficients $\beta_1, \cdots, \beta_14$ and for the mixing of τ (the variance of the spatial frailty term). The mixing is stationary, and therefore a good model performance.

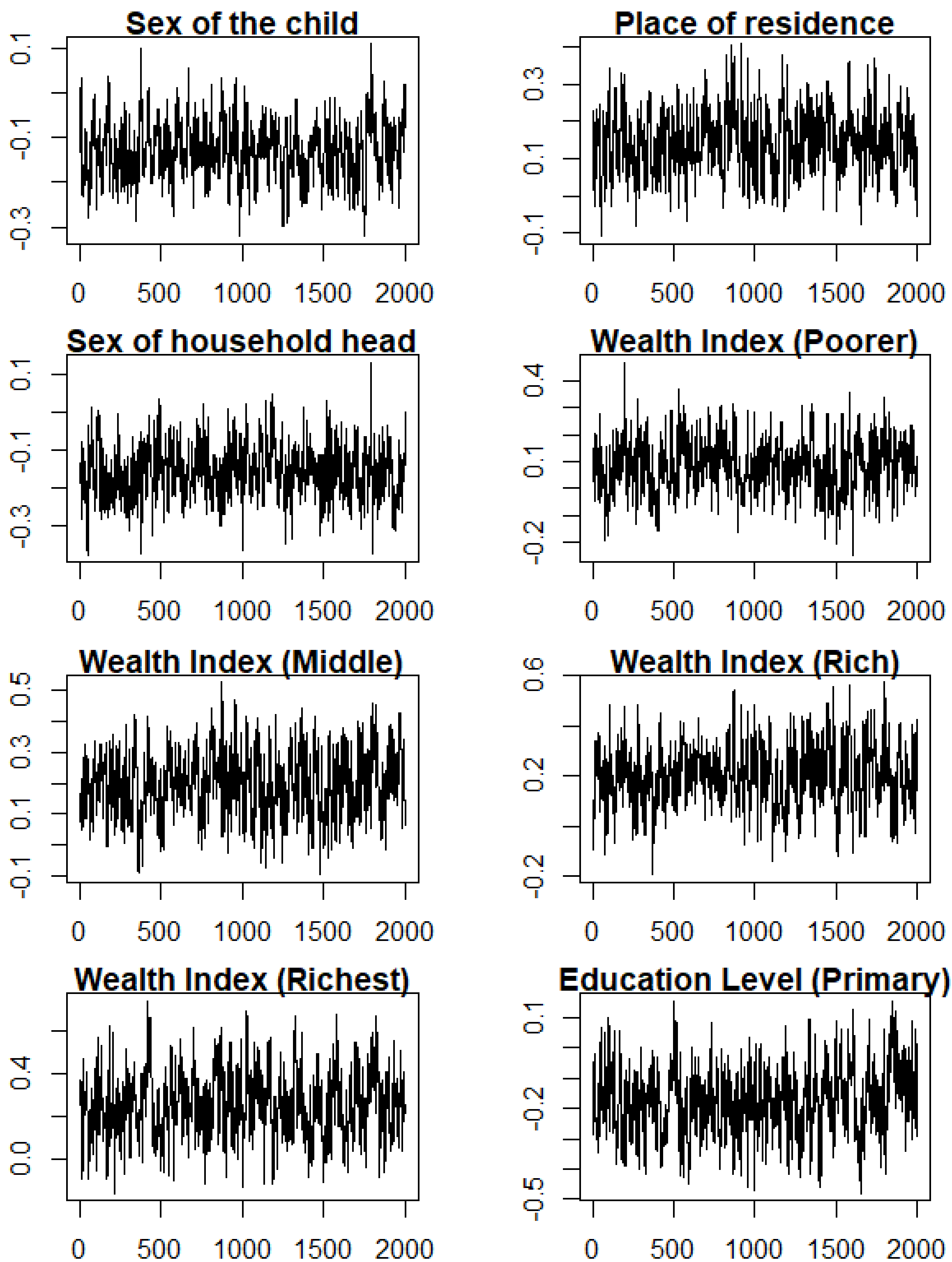

Figure 1. MCMC Mixing of Regression Coefficients

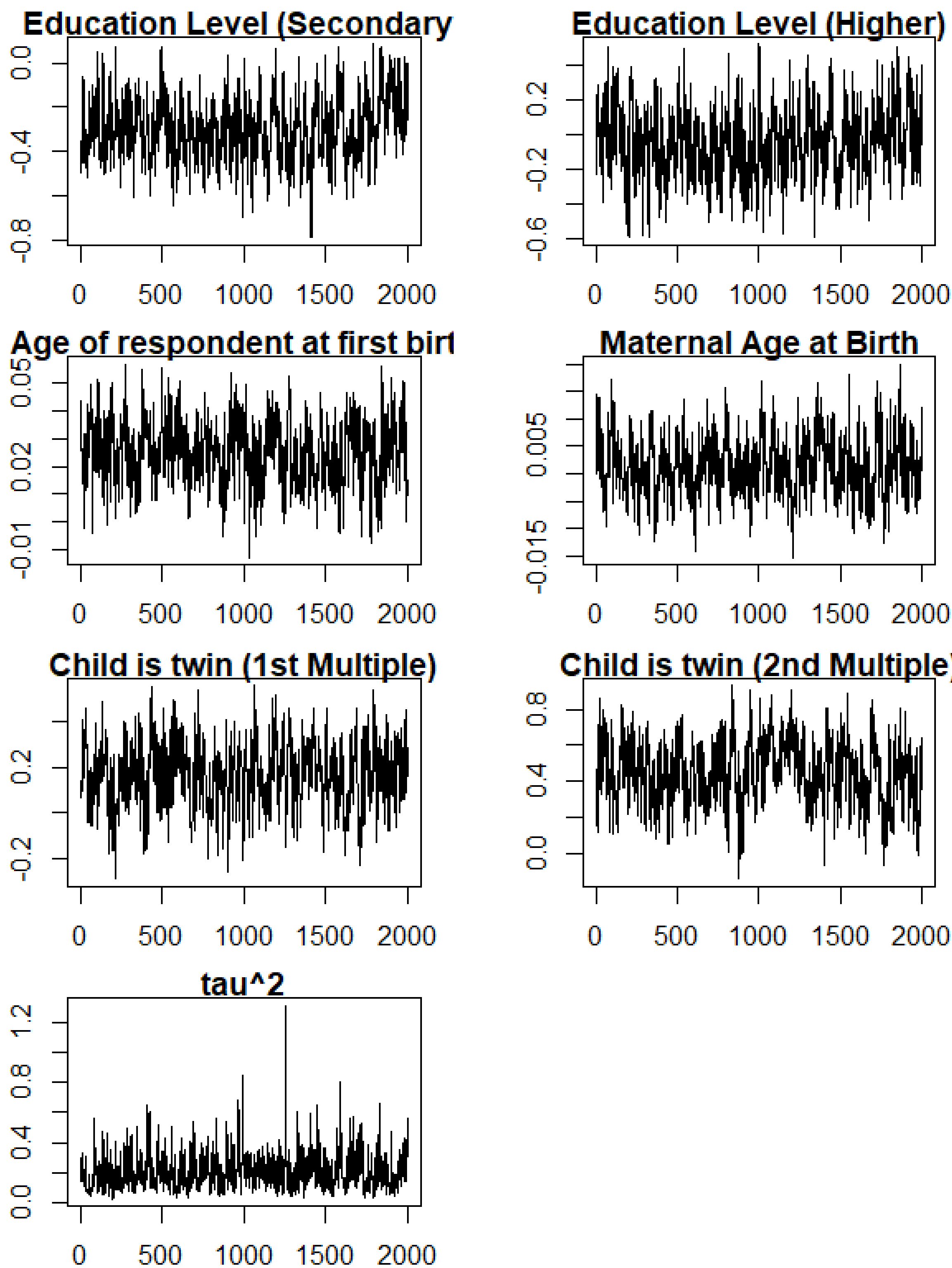

Figure 2. MCMC Mixing of Regression Coefficients (cont)

Cox-Snell residuals (the residuals of observed data points and a predicted value) are a type of standardized residuals used in reliability of the fitted model. The Cox-Snell residue assesses the goodness of fit of the model is assumed to be appropriate if the hazard plots are approximately straight with slope one. The Cox-Snell plot in figure 3 shows that the model is a good fit.

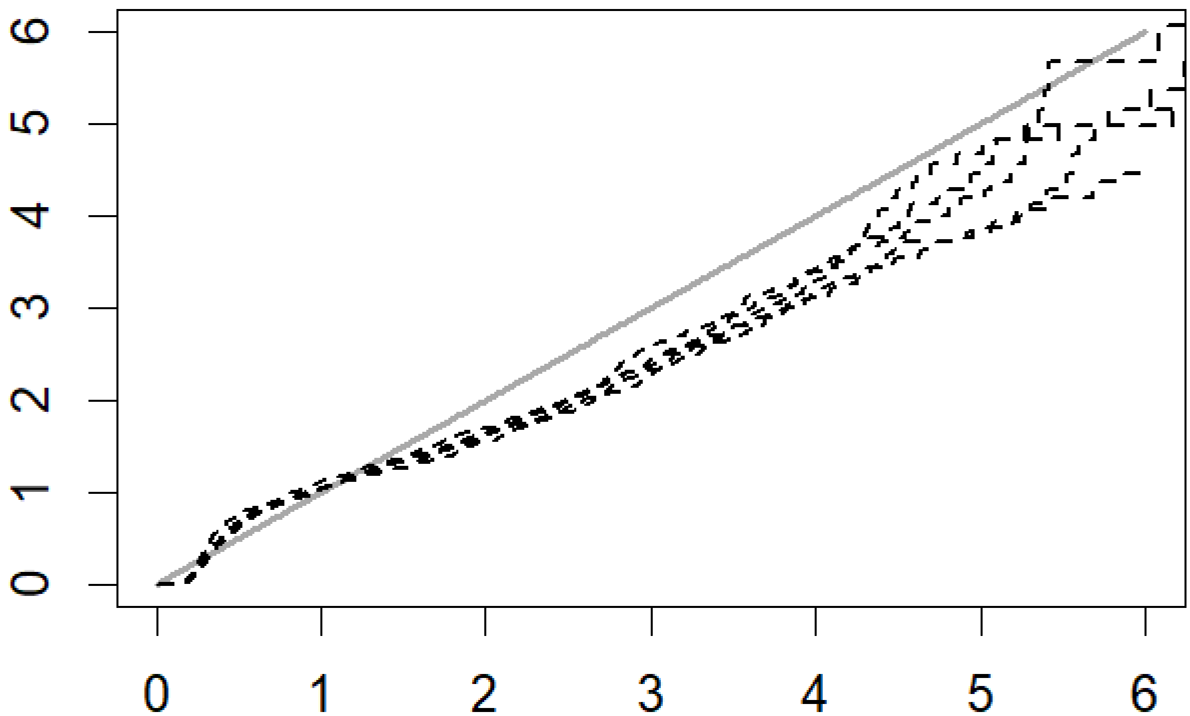

Figure 3. Cox Snell Plot

The spatial frailty model fitted has a Deviance Information Criterion (DIC) of 3344.661, WAIC of 3362.44, compared to the other model fitted; it has the best fit on the data. The posterior variance of the Conditional Autoregressive frailty is shown in table 3. The mean of the posterior variance is 0.2001, and significant with a 95 per cent confidence interval of (0.0578,0.4649). The presence of unexplained variation save for the variation of the main effects is statistically important, and improves the model.

Table 3. ICAR Frailty Variance

ICAR Frailty	Mean	Median	Std Deviation	95% Lower CI	95% Upper CI
Variance	0.2001	0.1776	0.1117	0.0578	0.4649

4.4 Regression Coefficients

The results of the regression coefficients are presented in table 4. Sex of the child, age of respondent at first birth, sex of the household head and whether a the family has a multiple set of twins are significant demographic risk factors associated with child survival. Significant socio-economic risk factors associated with child survival include highest level of education (secondary).

The posterior mean for the sex of the child is -0.1304 and the median is -0.1315. The hazard ratio is $exp(-0.1304) = 0.877$, the probability of survival is therefore higher in female children by 12.23 percent compared to male children, holding all other predictors constant. Male children have therefore a high risk of death. The 95 percent confidence interval of the hazard ratio is (0.7761,0.9921).

The mean for the sex of the household head is -0.1550 and the median is -0.1579. Adjusting for sex of the child, level of education, age of respondent at first birth; for a child born in female headed households, the computed hazard is 0.8564, and therefore the probability of survival increases by 14.36 percent compared to male headed households.

Age of respondent at first birth has a mean and median of 0.025. There is a positive association i.e. an increased risk of death for children for an increase in age at first birth. There is an increase of risk of death by 2.5 percent for a unit increase in age of a respondent at first birth. The probability of survival of a child decreases with an increase in age at first birth.

Families with multiple set of twins have a high risk of child mortality. The mean is 0.4438, with an hazard ratio of 1.5586, children born as a second set of twins have a high risk of death by 55.86 percent compared to children born in single births. A child born in a 2nd set of twins has a low survival probability.

The respondent's level of education is significant at secondary level. Respondents who have attained a secondary level of education in Kenya have a mean of -0.2982 and a hazard ratio 0.7422, therefore the risk of child mortality in respondents who have attained secondary education decreases by 25 percent compared to respondents who have not had any education at all. There is therefore an increased survival probability for children born at families whose respondents have attained secondary level education. Primary level of education as well as higher education level (beyond secondary) are not significant risk factors associated with child mortality.

Table 4. Determinants of Mortality

Variable	**Mean**	**Median**	**Std Dev**	**95% CI-Low**	**95% CI-Upper**
Sex of the child (Female)	-0.1304	-0.1315	0.0636	-0.2535	-0.0079
Type of place of residence (Rural)	0.1424	0.1374	0.083	-0.02	0.3102
Sex of household head (Female)	-0.155	-0.1579	0.0693	-0.2813	-0.0159
Wealth Index (Poorer)	0.0851	0.0856	0.0952	-0.0979	0.2751
Wealth Index (Middle)	0.1952	0.1959	0.102	-0.0038	0.3824
Wealth Index (Richer)	0.2017	0.202	0.1188	-0.0291	0.4229
Wealth Index (Richest)	0.2512	0.2451	0.1533	-0.0292	0.5688
Highest Level of Education (Primary)	-0.1756	-0.1719	0.1095	-0.3869	0.0499
Highest Level of Education (Secondary)	-0.2982	-0.297	0.1385	-0.5533	-0.0128
Highest Level of Education (Higher)	-0.046	-0.0461	0.2001	-0.4231	0.3574
Age of respondent at first birth	0.0251	0.0254	0.0112	0.0041	0.0463
Maternal age at birth	0.0013	0.001	0.0056	-0.0089	0.0126
Child is twin (1st Multiple)	0.1642	0.1754	0.1421	-0.1285	0.4325
Child is twin (2nd Multiple)	0.4438	0.4416	0.1749	0.0951	0.7585

4.5 Frailties map

Figure 4 shows the posterior frailties on the variance of the spatial term v_i added to the cox proportional hazards model to form a spatial frailties model. The variance is 0.2001. and is significant at 0.05, the confidence interval is $(0.05776.0.4649)$. There is therefore an influence of the random effects, meaning that the risk of under five mortality is not homogeneous across space.

Adjusting for the effect of the covariates such as the sex of the child, level of education, maternal age, and sex of household head, the are other unobserved spatially varying covariates relevant for child survival in Kenya. These unknown or unobserved variables are accounted for in this study by considering spatial correlation between random effects during regions.

In figure 4 we can identify a cluster of counties with higher median frailties or a higher hazard (counties with yellow colors) located centrally in the country. Children from these counties (Makueni, Machakos, Kiambu, Nyandarua, Nyeri and Laikipia) were shown to have the highest risk of mortality adjusted for effects of covariates.

Medium level frailties were identified clustered around counties (Garissa, Tana River, Kilifi and Lamu), Meru and Tharaka-Nithi counties, counties in Rift Valley (Nandi, Uasin Gishu and Elgeyo Marakwet), and Narok and Kisii counties.

Counties in Western Kenya and Nyanza also have low frailties, bringing out the spatial correlation (counties with purple color) related to death from other causes apart from the main effects of the independent variables.

The highest number of counties however, (counties with green color) have the same frailties, similar hazard. These are counties in Northern Kenya, South Rift, and counties bordering Tanzania on the South West. The others are Mount Kenya region counties (Kirinyaga, Embu and Murang'a) showing an homogeneous risk of death of a child.

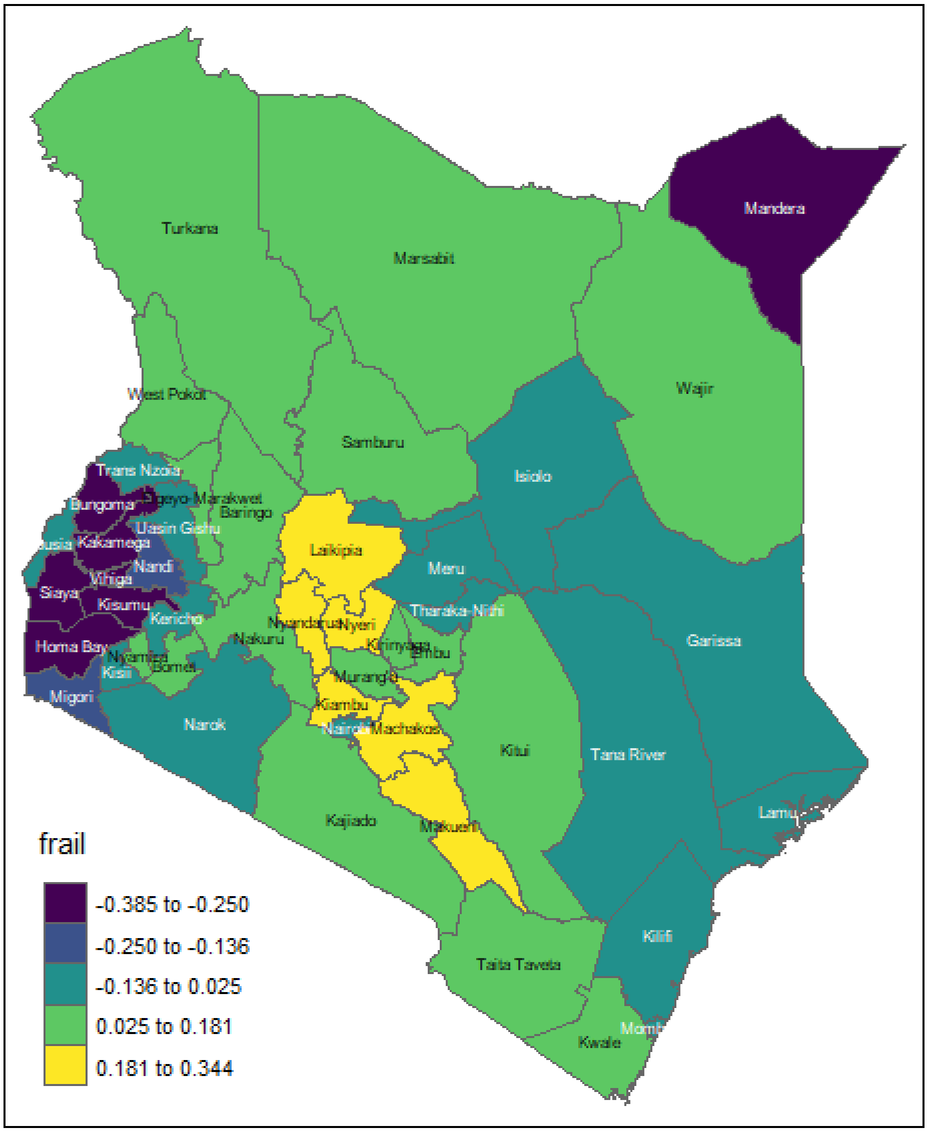

Figure 4. Frailties accross the country

5 DISCUSSION AND CONCLUSION

5.1 Discussion

The aim of the study was to bring out the spatial disparities on child mortality existing in the counties in Kenya. The spatial frailty proportional hazards model was used to determine the risk factors associated with under-five mortality in the country. Two models, the proportional hazard model without any frailty assumption and a frailty model assuming variations accross space were compared.

In addition to the risk factors explaining the main effect, there exists unobserved spatially varying covariates relevant for risk factors of child mortality. The ICAR spatial survival model was used to model these unobserved effects to model the correlation and or clustering between these regions. This study therefore analyzes time to death of a child using spatial survival models. The spatial model performed better compared to the non-spatial model, similar to [Hesam et al., 2018].

The results show that patterns of child mortality in Kenya have a spatial structure, which is similar for neighbouring counties around Centra Kenya, although majority of the counties appear to have similar (frailties), similar spatial distribution. This may be explained by similarities in access to healthcare and other amenities, and the variance in space, similar to [Ezra et al., 2016].

After adjusting for the spatial structure, sex of the child, respondent's age at birth, multiple births were found to be significant risk factors associated with child mortality. Sex of the child and whether a child is in a multiple birth (twins), also found by [Ezra et al., 2016] were important risk factors associated with child mortality. The sex of the house-hold head was also found significant. The level of education, also found out by [Gayawan, 2014], was an important risk factor for child mortality. Children from mothers who have attained secondary education have higher chances of survival compared to children from mothers who have no education or primary education. It is important therefore for most mothers to attain secondary education level in the country for a reduction in the risk of child mortality.

5.2 Conclusion

This study brings out the spatial disparities that exist in the country on child mortality in Kenya. The specific counties have mortality rates that are county-specific, although neighbouring counties have similar hazards of death of a child. It is important therefore to consider interventions that take into consideration the effect of where a child is born from (county) when providing intervention to reduce the risk of mortality.

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