IOSR Journal Of Humanities And Social Science (IOSR-JHSS)
Volume 21, Issue 3, Ver. II (Mar. 2016) PP 84-91
e-ISSN: 2279-0837, p-ISSN: 2279-0845.
www.iosrjournals.or

Spatial Modelling and Mapping of Socio-Demographic Determinants of Infant Mortality in Kenya

Dr Robert Mathenge Mutwiri (Ph.D.)
Department of Pure and Physical sciences, Kenya Methodist University, Kenya,
School of pure and applied sciences, Kiriinyaga university college, Kenya.
P.O Box 143 – 10300
Kerugoya, Kenya.
Mutwiri@outlook.com

***Abstract**: This paper addresses the problem of monitoring the infant and child mortality from point referenced data. Indicators of the determinants of child survival based on Mosley and Chen framework are derived and used to model the spatial distribution of infant mortality. Spatial generalised linear model which assumes a Bernoulli distribution to model the indicator determinants of child survival. A smooth map of the predicted values at both sampled and the un sampled is produced. We find evidence of spatial autocorrelation in the data and the smooth map indicates the hot spot of infant mortality where more resources are needed to attain the millennium development goal four.*

***Key words**: Infant mortality; Indicators; Geostatistics; Spatial Generalized Linear models; Bayesian Spatial Modelling; Mapping.*

I. Introduction

More than 10; 000 new-born babies die each day from health problems that can either be prevented or treated. Infant mortality, the probability of dying between birth and exactly one year of age is considered a standard indicator of societal well being throughout the world. The rates of infant mortality can reflect levels of social and economic development, levels of care and the effectiveness of preventive programs as well as post birth services to both mothers and their children (Fukuda et al., 2004). In Kenya, approximately eight out of every 100 children born die before their fifth birthday, representing a huge wastage of potential manpower. From figures of 119 death per 1; 000 live births in 1969 to 88 per 1; 000 in 1979; declining further to 66 per 1; 000 in 1989; the national infant mortality rate has not shown any evidence of improvement CBS et al. (2010).

Studies on infant and child health have generally followed the Mosley and Chen conceptual framework (Mosley and Chen, 1984), classifying risk factors into four pri-mary categories: socio-economic; demographic; biological; and environmental factors (Mustafa and Odimegwu, 2007; Omariba et al., 2007; Ikamari, 2000; Hobcraft, 1993; Mutunga, 2007). Some of the key socio-economic and demographic determinants of in-fant death identified often in the literature are mother's religion, education, occupation and socio-economic status (Balk et al., 2004; Gemperli and Vounatsou, 2003; Gemperli et al., 2004; Dansu and Asiribo, 2007; Hill et al., 2001; Mustafa and Odimegwu, 2007; Hobcraft, 1993; Kaduuli, 1988, 2007; Kalipeni, 1993; Ngianga-Bakwin Kandala; Chen Ji and Cappuccio, 2007; Kazembe et al., 2007; Govindasamy and Ramesh, 1997). Proxi-mate/biological determinants of infant mortality have included the place of delivery, mode of delivery, gestational age, weight of child at birth, vaccination, and birth spacing. Of these proximate determinants, breast feeding has consistently been described as a key pre-dictor of infant survival (Butz and Habicth, 1982; Mustafa and Odimegwu, 2007; Omariba et al., 2007; Hafsa et al., 2009). Studies in Kenya and other regions in Sub-Saharan have also attributed the increase in infant and child mortality to increase in HIV prevalence over the last two decades (McElroy et al., 2001; CBS et al., 2010).

The need to account for spatial dependency and heterogeneity when analysing data has been mentioned extensively in the literature (Kalipeni, 1993; Gemperli and Vounatsou, 2003; Balk et al., 2004; Gemperli et al., 2004; Dansu and Asiribo, 2007). Accounting for spatial autocorrelation when analysing spatially aggregated data has been seen to improve both parameter estimation and prediction. Spatial prediction has largely been based on the assumption that points that are closer are more correlated than points far apart Tobler (1979) first law of Geography.

This study utilizes a Bayesian spatial logistic regression approach to demonstrate how the geospatial models proposed by (Diggle et al., 1998) can be adopted to model point referenced infant survival data. Despite being computationally intensive and faced with challenges in achieving convergence in certain instances, Bayesian MCMC approaches are currently, the most practical to spatial prediction, the primary goal in geospatial models (Diggle et al., 1998). In addition, adjusting for the socio-economic, demographic, biological and environmental indicators, this paper also develops a risk map of infant death in Kenya.

This paper is divided into five sections. The first is a description of the status of infant mortality in Kenya and an explanation of the place of geospatial models in statistical literature. The second section gives a brief description of Spatial generalized linear Models (SGLMs) and the use of Bayesian modelling approaches. The data and the model formulated are described in Section 3.2, followed by a presentation of the results and findings of the study in Section 4. The final section of this paper discusses the findings of this paper in relation to others in the literature.

II. Bayesian Geostatistical Modeling

In Demographic and Health surveys, data is available at sampling sites x_i, i = 1,…,n; where the response variable Y_i (in this case infants deaths) is observed. At each location x_i, the response variable Y_i is associated with a covariates vector $Z = (z_{i1}; z_{i2,}…,z_{ik})$; where k is the number of covariates. Geospatial models approaches mainly account for spatial dependence in the response or covariates to predict risk of infant death at the un-sampled areas.

2.1 Model Description

Generalized Linear Models (GLMs), developed by Nelder and Wedderburn in 1972; allow for regressions when responses are distributed as one of the members of the exponential family (Nelder and Wedderburn, 1972). In GLMs, the response variables $Y_{1,}…,Y_n$ are assumed to be mutually independent with expectations μ_i, i = 1,….,n, related to a linear predictor by the equation

$$g(\mu_i) = \beta_0 + \sum_{j=1}^{k} \beta_j Z_{ij}$$

where g is a known function called the link function and $_j$ are the regression coefficients. An important extension of GLMs is the Generalized Linear Mixed Model (GLMM) Breslow and Clayton (1993); Lee and Nelder (1996) in which the response variables $Y_1,….,Y_n$ are assumed to be mutually independent conditionally on the realized values of a set of latent variables $U_1,….,U_q$. In GLMMs, the conditional expectations

$$\mu i = E(Y_{ij}|U_1 = u_1,….,U_q = u_q)$$

are related to the linear predictors by $g(\mu_i) = \beta_0 + \sum_{j=1}^{k} \beta_j Z_{ij}$, where *g(.)* is the link function as in GLMs. Spatial generalized linear mixed models (SGLMs) are GLMMs in which the latent variables $U_1…,U_q$ are derived from a stationary spatial Gaussian stochastic process, S; with mean 0; variance ^{2} and correlation function $\rho(x,; x^{'}) = corr(S(x_i), S(x^{'}_i))$ (Diggle et al., 2002; Ben-Ahmed et al., 2010). In the GLSM, the response variables $Y_1…,Y_n$ are assumed to be mutually independent conditionally on S (Diggle et al., 2002). Such a process is said to be isotropic if the covariance and correlation functions are dependent on the Euclidean distance, h =||x-x'||, between locations x and x' and not direction. The conditional expectations $\mu_i = E(Y_i|S(x_i))$ are given by $g(\mu_i) = \beta_0 + \sum_{j=1}^{k} \beta_j Z_{ij} + S(x_i)$ where g(.) is the link function as in GLMs. A general issue in such models concerns the choice of the parametric family of $\rho(h)$ with a good fit to the data (see Banerjee et al., 2003; Chiles and Delfiner, 1999). In most applications (h) is assumed monotone non-increasing in h; with a scale parameter ϕ.

2.2 Inference and Prediction

The likelihood functions for GLSM are generally not expressible in closed form but only as integrals of high dimension. Standard methods of approximating such integrals are of unknown accuracy in geostatistical setting and so Markov Chain Monte Carlo (MCMC) algorithms have been suggested for the computation of GLSM parameters and prediction (Diggle et al., 2002).

Letting θ denote the set of parameters that define the covariance structure of our GLSM model, the MCMC algorithms we use proceeds as follows: we first sample from the conditional distribution of given the process S(.). We then sample from the conditional distribution of S(.) given Y, θ and β); where Y = $(Y_1,…,Y_n)$', and finally, from the distribution of β given the process Y and S(.). We then use the Langevin-Hastings algorithm, known to yields more efficient results than the random walk Metropolis algorithm Christensen and Waagepetersen. (2002), to simulate from the posterior distribution of S(.) given Y. When follows a uniform prior and δ^2 a scaled inverse- χ^2 prior distribution, the joint posterior distribution is given as

$$f(\beta, S, \delta^2, \phi|Y) \alpha f(\beta, S; Y) f(S|\delta^2,\phi) f(\delta^2) f(\phi),$$

where $f(S|\delta^2,\phi)$is the distribution of the spatial random effects, and $f(\beta, S, \delta^2, \phi|Y)$ is the posterior distribution of the parameters obtained by the Langevins algorithms.

For prediction, if Y_0 is a vector of the responses at new, unobserved, site $x_{0i,}$ i =1,….,$n_{0,}$ the Bayesian predictive distribution of Y_0 given $\hat{\beta}, \hat{S}, \hat{\delta}^2, \hat{\phi}$ is given by

$$f(Y \mid \hat{\beta}, \hat{S}, \hat{\delta}^2, \hat{\phi}) = \int f(Y_0 \mid \hat{\beta}, S_0) f(S_0 \mid \hat{S}, \hat{\delta}^2, \hat{\phi}) dS_0,$$

where $\hat{\beta}$, $\hat{\delta}^2$ and $\hat{\phi}$ are the maximum likelihood estimates of the corresponding parameter and S_0 denotes the signal at the new sites.

Simulation-based Bayesian spatial prediction is performed by consecutive drawing samples from the posterior distribution, the distribution of the spatial random effects at new locations and the Bernoulli-distributed predicted outcome. MCMC algorithms used in this work are provided within the packages ***geoR*** and **geoRglm**, (Christensen and Ribeiro Jr, 2002), freely available within the open-source R statistical software (www.cran.r-project.org)

III. Data Description And Model Formulation

3.1 The Data Description

The data used in this study was the 2003 Kenya Demographic and Health Survey (KDHS). The sample was selected using a two-stage stratified random sampling design that relied on a sampling frame maintained by the CBS. Fieldwork conducted between April and September 2003 and achieved an overall response rate of 97% of households and 96% of women aged 15-49 who were eligible for an individual interview. The interview included a retrospective maternity history that collects data on date of birth, survival status, and age at death for all children each woman has given birth to.

The 2003 DHS covered 8,195 women aged 15-49 and 3578 men aged 15-54 from 400 Enumeration Areas (EAs) throughout Kenya. The survey collected detailed information relating to demographic, child health care and GIS coordinates for EA's in both urban and rural areas. We aggregated the data into proportions of infant deaths and covariates at enumeration area (EA) level and subsequently used them to predict IMR at unsampled locations. Aggregation of point referenced data into census tracts or regions are reflective of data collection and/or modelling rather than administrative units are modifiable and contain artefacts related to degree of spatial aggregation or replacement of boundaries. Based on the Mosley and Chen analytical framework Mosley and Chen (1984), existing literature and constrained by variables measured in the KDHS, the variables used in this study are presented in Table 1.

For spatial modelling, the data were aggregated for each of the 400 sampled EA's and the outcome variable, proportion of infant deaths, along with other aggregated EA level predictors calculated. The map surface of Kenya was divided into 10,000 pixels of approximately 25 km 25 km, for which model predictions of infant mortality rates were made, excluding areas for which no census data apply, such as nature reserves and game parks. Socio-economic and demographic data were extracted from 2003 KDHS data for each of the sampled EA's and for each of the pixels. The value for each pixel was calculated by summing the variable according to there respective category values over the EA in proportion to the number of births observed in the EA. The aggregated EA level variables considered were: the Proportion mothers aged less than 19 years at first birth; the Proportion infants never breast feed, the Proportion births interval less than 2 years; the Proportion of births of order one; the Average Wealth index and the Proportion mothers with no formal education.

Table 1: Individual level determinants of infant survival

Socio-demographic	**Socio-economic**	**Environmental**	**Proximate**
Mother's migration status	Mother's education	Source of water	Place of delivery
Sex of household head	Mother's occupation	Toilet facility	Sex of child
Mother's age at first birth	Socio-economic status	Cooking fuel	Mother's age at birth
Religion	Partner's education	Mother smokes	Birth order
Region			Birth size
			Birth interval

3.2 Model Formulation

The observations of the response variable Y_i; i = 1,….,400, represent the number of observed cases in each of the 400 clusters sampled. All possible covariates were first tested in a non-spatial univariate logistic regression models to determine their potential associated with infant survival. Variables that were not associated with infant survival in the non-spatial models were not explored further. Only those variables found to be significant were incorporated in the prediction model.

To account for the unexplained spatial variation of infant mortality, we postulate a stationary Gaussian process S with mean 0; variance ^{2} and an isotropic correlation function . Conditional on $S(x_i)$; the number, y_i; of infant deaths out of n_i live births from the i^{th} EA were assumed to be a realization of independent Binomial random variable with probability of infant death p_i: The Bayesian geostatistical linear model implemented was of the form $y_i \sim bin(n_i, p_i)$; with

$$\log it(p_i) = \beta_0 + Z_i'\beta + S(x_i) \quad 3.1$$

where $\beta = (\beta_1, \ldots, \beta_n)'$, is a vector of fixed parameters, Z_i' a vector of predictor values and $S = \{S(x_1),\ldots,S(x_n)\}$ is a stationary Gausssian process with mean function $\mu(x) = E[S(x)]$; covariance function $\gamma(h) = Cov\{S(x), S(x + h)\}$ and exponential correlation function $\rho(\theta) = \delta^2 \exp(d_{ij}/\phi)$; is the parameter that measures the rate of correlation decay, and d_{ij} the distance between the locations i and j:

The parameters in the above model were estimated using the Bayesian methodology described by Diggle et al. (1998). Independent vague uniform priors were chosen for the parameters β; δ^2 and ϕ and, following suggestions by Ribeiro Jr et al. (2003), values of were selected from a discrete set of values to cover the different degrees of mean square differentiability for the process S: Five fixed values {0.1; 0.2; 0.3; 0.4; 0.5} were tried for δ . For each one of the fixed values, the Markov chain was run for 5,000 iterations to get a sample of 500 values from the posterior distributions for β, δ^2 and ϕ. Each sample taken every 10-th iteration after the time at which we judged that the chain has converged. Convergence occurred generally after about 10,000 samples, on the basis of inspection of sample traces.

IV. Results

4.1 Logistics Regression Analysis for Aggregated Data

Table 2 presents the results of a non-spatial logistic regression analysis for aggregated EA level covariates. The results indicate that the proportion of infants never breastfed, the proportion of births of interval less than 2 years, the average wealth index, the province of residence and the dominant ethnic community in cluster are key factors associated with infant death. All these predictors, except the Province of residence, were include in the subsequent analysis.

Table 2: Infant mortality by selected (aggregated) variables

Model term	**AIC**	**Deviance**	**df**	**p-value**
Null	1209	317.64	379	
Proportion of mothers < 19 years at first birth	1210	0.7	1	0.4033
Proportion of infants never breast feed	276.8	40.84	1	< 0:001
Proportion of births interval less than 2 years	1193	17.73	1	< 0:001
Proportion of births order one	1209	1.12	1	0.2892
Average Wealth index	1172	38.44	1	< 0:001
Proportion of mothers with No formal education	1210	0.52	1	0.4728
Province of residence	1197	25.283	7	< 0:001
Dominant ethnic community in cluster	1192	44.958	14	< 0:001

4.2 Spatial Logistics Regression Analysis For Aggregated Data

Table 3 presents results of the best fitting models identified for both the non-spatial (frequentist) logistic regression and the corresponding (Bayesian) generalized linear spatial model. The fixed effects parameters for both models showed well known patterns linking infant mortality to the covariates selected. Five variables which were significantly correlated with infant mortality in the univariate, non-spatial, logistic regression did not retain their statistical significance and were dropped in the final model. The four covariates that retained their significance in the spatial logistic regression analysis were Breast feeding, Births interval, Wealth index and Ethnicity. Adjusting for the effect of the other covariates, the risk of infant death increased significantly with both the proportion of infant never breastfed (AOR= 7.45, 95% CI=3.90-14.01) and the proportion of births within intervals of less than 2 years (AOR=1.20, 95% CI = 1.09-1.34). Areas with higher aver-age Wealth index had significantly lower rates of infants mortality (AOR=0.76, 95% CI =0.71-0.90). Risk of infant death was significantly lower for Kikuyu (AOR= 0.61, 95% CI=0.50-0.73), Kamba (AOR= 0.63, 95% CI=0.47-0.84) and Kalenjin (AOR= 0.70, 95% CI=0.50-0.99) communities compared to the Luo community. In general, confidence intervals were considerably narrower in the case of the spatial model as compared with the non-spatial. The adjusted relative risk associated with each of the continuous covariates

(breast feeding, birth interval and wealth index) were also smaller for the spatial model. With regard to Bayesian inference, an inspection of the sample traces plots for $\theta = (\delta^2, \phi)$ and $\beta = (\beta_0, \beta_1, \beta_2, \ldots..,\beta_{17})$ obtained by fitting of the (SGLM) model, shows a reasonable degree of convergence to a stationary distribution (see Figure 2). Each trace consists of 500 values sampled from the posterior distributions of θ and β. The histograms of the empirical posterior distributions of the parameters $\beta 1 \leq j \leq 17$ show that these posterior distributions are approximately Gaussian (see Figure 1). The parameters δ^2 and ϕ in Table 3 measure the variance of the spatial process and the rate of correlation decay (smoothing parameter), respectively. The results indicates a small value of with posterior median of 0:3 (95% CI : 0:28; 0:32) suggesting a strong spatial correlation because this parameter measures the range of the geographical dependency, which is defined as the minimum distance at

which spatial correlation between locations is below 5 percent. In our exponential setting it can be calculated as $3/\phi = 10$ (10 km; 95% CI: 9:38 10:71 km). This implies a non-vanishing correlation between all sampled points and results in very smooth maps for the predicted random effects.

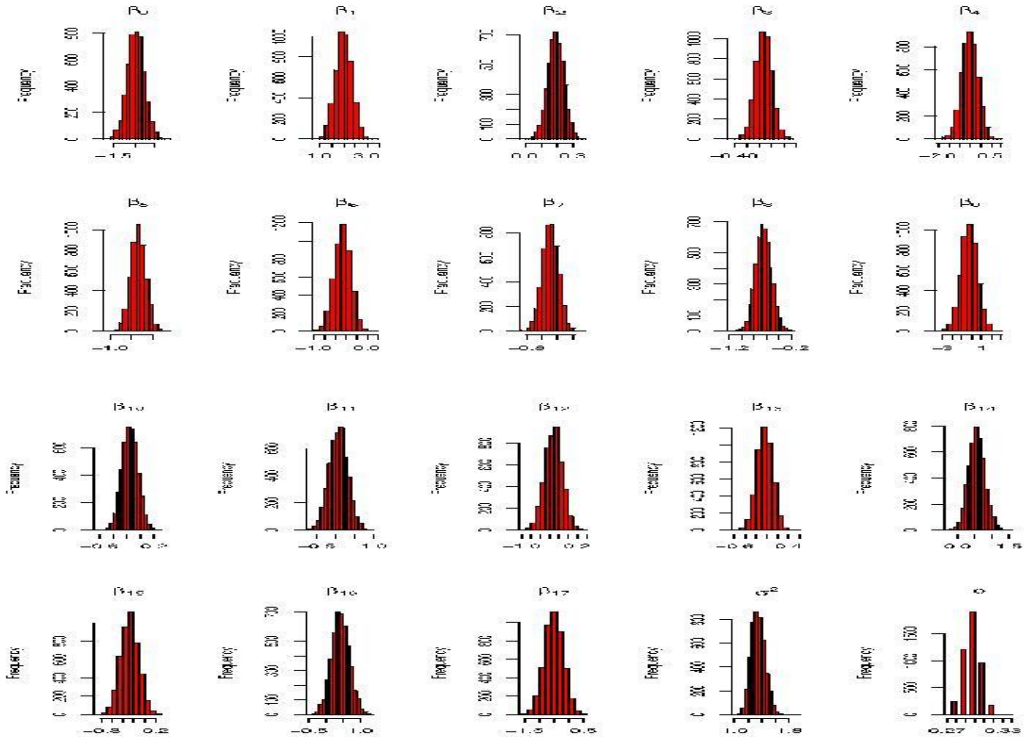

Figure 1: Histogram showing the MCMC output every 100-th iteration.

Table 3: Parameter estimates, relative risk and 95% confidence/credible intervals from non-spatial and spatial logistic regression models of probability of infant deaths

	Non-spatial Model		Spatial Model	
	(95% Confidence Interval)	exp( )	(95% Credible Interval)	exp( )
Intercept	-0.92(-1.27,-0.57)	0.4	-0.96(-1.37, -0.55)	0.38
Breast feeding	2.61(1.73,3.49)	13.6	2.01(1.36, 2.64)	7.46
Births interval	0.2(0.02,0.38)	1.22	0.19(0.09, 0.29)	1.21
Wealth index	-0.18(-0.26,-0.10)	0.84	-0.28(-0.34, -0.22)	0.76
Ethnicity				
Luo (Ref)	1			
Embu	-0.7(-1.80,0.40)	0.5	-0.5(-1.25, 0.22)	0.61
Kalenjin	-0.49(-0.84,-0.14)	0.61	-0.35(-0.69, -0.01)	0.7
Kamba	-0.55(-0.90,-0.20)	0.58	-0.47(-0.76, -0.18)	0.63
Kikuyu	-0.69(-0.96,-0.42)	0.5	-0.5(-0.7, -0.31)	0.61
Kisii	-0.61(-1.00,-0.22)	0.54	-0.65(-0.89, -0.38)	0.52
Kuria	-0.74(-1.96,0.48)	0.48	-0.3(-1.94, 1.35)	0.74
Luhya	-0.41(-0.68,-0.14)	0.66	-0.15(-0.38, 0.07)	0.86
Masai	-0.55(-1.08,-0.02)	0.58	0.07(-0.39, 0.53)	1.07
Meru	-0.7(-1.19,-0.21)	0.5	-0.31(-0.68, 0.05)	0.73
Mjikenda	-0.65(-1.02,-0.28)	0.52	-0.04(-0.32, 0.24)	0.96
Somali	-0.56(-0.89,-0.23)	0.57	-0.28(-0.59, 0.04)	0.76
Taita/Taveta	-0.3(-1.10,0.50)	0.74	0.43(-0.08, 0.94)	1.54

Turkana	-0.87(-1.63,-0.11)	0.42	-0.51(-1.12, 0.08)	0.6
Others	0.11(-0.69,0.91)	1.12	0.56(0.12, 1.02)	1.75
δ^2			1.34(1.17,1.55)	
ϕ			0.30(0.28,0.32)	

Figure 3 presents the smoothed risk map of infant mortality in Kenya adjusting for socio-demographic indicators. Then map shows some considerable variation in the predicted values with high mortality rates clustering in Nyanza region and low values in central Kenya, part of Rift valley and Eastern provinces. The figure also presents the mean estimates of the residual smooth spatial effects and the corresponding predicted variances of the probability of infant death map.

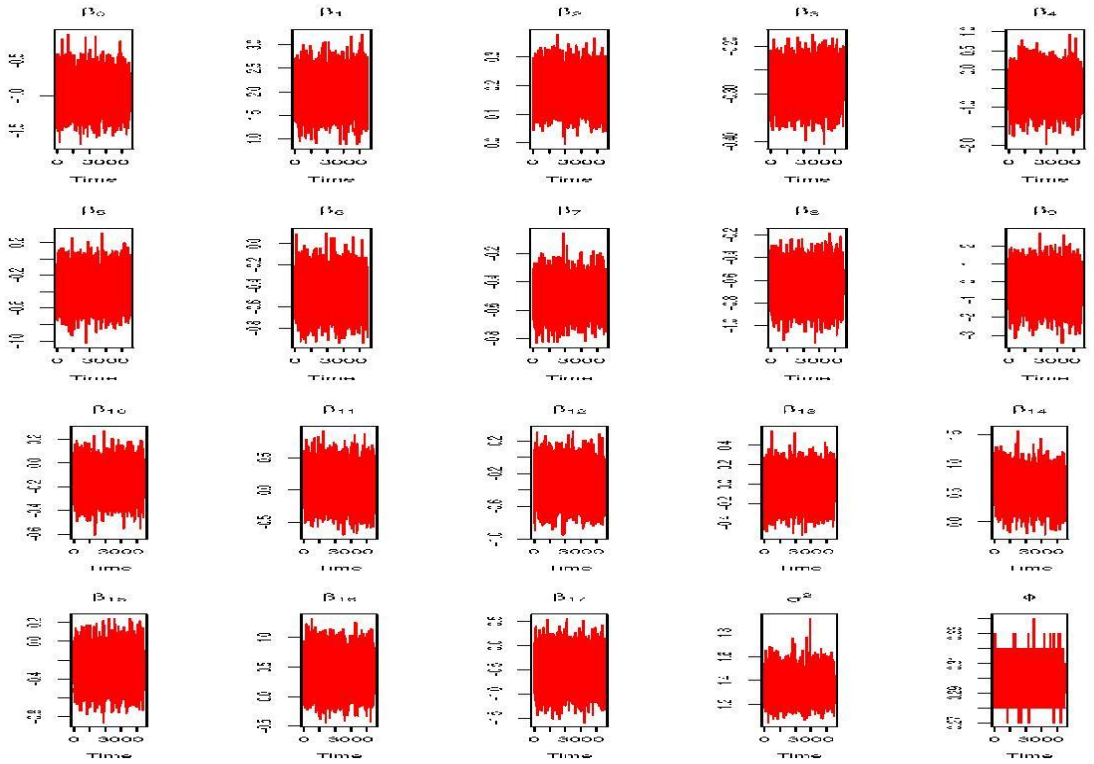

Figure 2: Time series plots showing the MCMC output every 100-th iteration

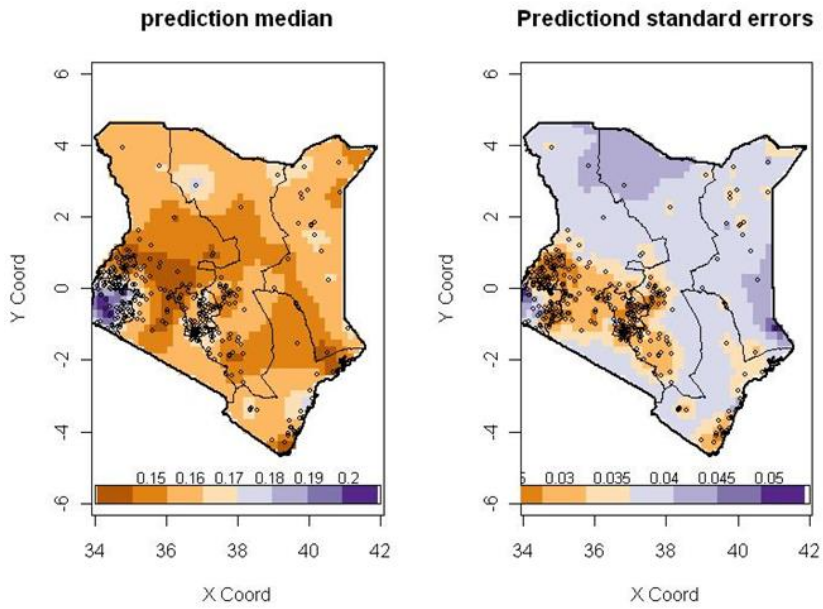

Figure 3: Spatial prediction of distribution of Infant Mortality Rate in Kenya: (left) Risk of infant death with Brown indicating high risk and Purple indicating low risk; (right) the predicted variance of probability of infant

death.

V. Discussion

In this study Bayesian spatial models were fitted to assess the geographical patterns and determinants of infant mortality in Kenya. Results confirmed strong geographical dif-ferences in mortality risk and the importance of a number of risk factors such as breast feeding, birth interval, average wealth index and community in which a child is born. The relationships highlighted above have some very important policy implications at the re-gional and community levels. Consistent with other studies, breast feeding, birth interval, socioeconomic status and the community in which a child is born are the most important determinant of infant mortality which is consistent with the literature (Mustafa and Odimegwu, 2007; Omariba et al., 2007; Ikamari, 2000).

The last two decades have significant growth in the development and application of spatial statistics in epidemiological and public health. These developments have included: the description and estimation of spatial patterns; the modelling of data in the presence of spatial correlation; and spatial prediction at unobserved locations. For Gaussian data, the generalized least squares (GLS), maximum likelihood and restricted maximum likelihood approaches have been employed extensively giving reliable estimates of the regression coefficients conditional on the covariance parameters. For non-Gaussian data, on the other hand, statistical estimation has relied primarily on the theory of generalized lin-ear mixed models (GLMM). For large point-referenced spatial data, GLMMs are highly parameterized and estimation is generally hampered by computational problems. Un-der the frequentist paradigm, therefore, Penalized Quasi-Likelihood methods have been employed extensively as they are pervasive in standard statistical software package. Estimates, especially those for the covariance parameters, are however biased. Bayesian MCMC methods on the other hand have given unbiased estimates of the parameters and the associated standard error. Bayesian methods have also been cited as having computational advantages for problems larger than the ones the maximum likelihood methods can handle.

Since our results depend on areas sampled, the limitations of this study hinges primarily on the sampled areas. Only a few areas were sampled in North eastern and upper Eastern regions due to large traveling distance and low population density in these areas. This may lead to a bias with regard to prediction at un-sampled locations. Other limitation include the lack of population density data and infant level HIV prevalence data at sampled areas which may significantly confound the predicted results. Despite the limitations discussed above, we feel that this study fills a gap in knowledge of geographical variations of infant mortality in Kenya. The maps identify areas of increased risk and patterns which have important implications for health policy aimed at reducing all cause infant mortality by two thirds by 2015.

Acknowledgment

The author would like to thank the editors and reviewers for the comments that have greatly improved my write-up.

References

[1]. Balk, D., Pullum, T., Storeygard, A., and Neuman, M. (2004). A spatial analysis of childhood mortality in west africa. Pop Space Place, 10:175–216.
[2]. Banerjee, S., Wall, M., and Carlin, B. (2003). Frailty modeling for spatially correlated survival data, with application to infant mortality in minnesota. Biostatistics, 4:123142.
[3]. Ben-Ahmed, K., Bouratbine, A., and El-Aroui, M.-A. (2010). Generalized linear spatial models in epidemiology: A case study of zoonotic cutaneous leishmaniasis in tunisia.
[4]. Journal of Applied Statistics, 37(1):159170.
[5]. Breslow, N. and Clayton, D. (1993). Approximate inference in generalized linear mixed models. Journal of the American Statistical Association, pages 9–25.
[6]. Butz, W. and Habicth, J. (1982). Biological and behavioural influences on the mortality of malaysian infants,.
[7]. CBS, MOH, and Macro, O. (2010). Kenya demographic and health survey 2003. Techni-cal report, Central Bureau of Statistics (CBS) [Kenya], Ministry of Health (MOH), and ORC Macro. (2004).
[8]. Chiles, J. and Delfiner, P. (1999). Geostatistics: modeling spatial uncertainty, volume 344. Wiley-Interscience.
[9]. Christensen, O. and Ribeiro Jr, P. (2002). georglm: A package for generalised linear spatial models. R News, 2(2):26–28.
[10]. Christensen, O. and R.P.Waagepetersen. (2002). Bayesian prediction of spatial count data using generalized linear mixed models. Biometrics,, 58:280–286.
[11]. Dansu, B. and Asiribo, O. (2007). Spatial association between malaria pandemic and mortality. Data Science Journal, 6:145–153.
[12]. Diggle, P., Moyeed, R., Rowlingson, B., and Thomson, M. (2002). Childhood malaria in the gambia: a case-study in model-based geostatistics. Journal of the Royal Statistical Society: Series C (Applied Statistics), 51(4):493–506.
[13]. Diggle, P., Moyeed, R. A., and Tawn, J. A. (1998). Model-based geostatistics. Applied Statistics, 47:299–350.
[14]. Fukuda, Y., Nakamura, K., and Takehito, T. (2004). Wide range of socioeconomic factors associated with mortality among cities in japan. Health Promotion Intinternational, 19(2):177–87.
[15]. Gemperli, A. and Vounatsou, P. (2003). Fitting generalized linear mixed models for point-referenced spatial data. Journal of Modern Applied Statistical Methods, 2:481–495.
[16]. Gemperli, A., Vounatsou, P., Kleinschmidt, I., Bagayoko, M., Lengeler, C., and Smith, T. (2004). Spatial patterns of infant

mortality in mali: The effect of malaria endemicity.
[17]. American Journal of Epidemiology, 159:64–72.
[18]. Govindasamy, P. and Ramesh, B. (1997). Maternal education and the utilization of mater-nal and child health services in india. Technical report, International Institute for Pop-ulation Sciences Mumbai, India Macro International Inc. Calverton, Maryland, U.S.A.
[19]. Hafsa, H., Maheen, L., Habibullah, K., and Muhammad, H. K. (2009). Infant morbidity leading to infant mortality. Gomal Journal of Medical Sciences, 7(2):121–123.
[20]. Hill, K., Bicego, G., and Mahy, M. (2001). Childhood mortality in kenya: An examination of trends and determinants in the late 1980s to mid 1990s. Johns Hopkins Population Center Working Paper.
[21]. Hobcraft, J. (1993). Women's education, child welfare and child survival: a review of the evidence. Health Transition Review, 3(2):159–173.
[22]. Ikamari, L. (2000). Sibling mortality correlation in kenya. Journal of biosocial Scence, (32):265–278.
[23]. Kaduuli, S. (1988). Infant and child mortality in eastern africa: Causes and differentials. Accessed on September 26, 2011.
[24]. Kaduuli, S. (2007). Infant mortality in lesotho: Parental education and demographic factors. SSRN.
[25]. Kalipeni, E. (1993). Determinants of infant mortality in malawi: A spatial perspective. Social science Medical, 37(2):183–193.
[26]. Kazembe, L. N., Christopher, C. A., and Kleinschmidt., I. (2007). Spatial analysis of the relationship between early childhood mortality and malaria endemicity in malawi. Geospatial Health, 2(1):41–50.
[27]. Lee, Y. and Nelder, J. (1996). Hierarchical generalized linear models. Journal of the Royal Statistical Society. Series B (Methodological), pages 619–678.
[28]. McElroy, P. D., Ter Kuile, F. O., Hightower, A. W., Hawley, W. A., Phillips-Howard, P. A., Oloo, A. J., Lal, A. A., and Nahlen, B. L. (2001). All-cause mortality among young children in western kenya. vi: the asembo bay cohort project. The American journal of tropical medicine and hygiene, 64(1 suppl):18.
[29]. Mosley, W. H. and Chen, L. C. (1984). An analytical framework for the study of child survival in developing countries. Population and Development Review, 10:25–45.
[30]. Mustafa, H. E. and Odimegwu, C. (2007). Socioeconomic determinants of infant mortal-ity in kenya: Analysis of kenya dhs 2003. Journal of Humanities and Social Sciences, 2(2):1–16.
[31]. Mutunga, C. (2007). Environmental determinants of child mortality in kenya. Unknown Journal, (2007/83).
[32]. Nelder, J. and Wedderburn, R. (1972). Generalized linear models. Journal of the Royal Statistical Society. Series A (General), pages 370–384.
[33]. Ngianga-Bakwin Kandala; Chen Ji, N. S. S. S. and Cappuccio, F. P. (2007). Spatial analysis of risk factors for childhood morbidity in nigeria. American. Journal. Tropical. Medicine. Hygiene., 77(4):770–778.
[34]. Omariba, D. R., Beaujot, R., and Rajulton, F. (2007). Determinants of infant and child mortality in kenya: an analysis controlling for frailty effects. Springer Sci-ence+Business Media B.V., 26:266–321.
[35]. Ribeiro Jr, P., Christensen, O., and Diggle, P. (2003). geor and georglm: Software for model-based geostatistics. In Proceedings of DSC, page 2. Citeseer.
[36]. Tobler, W. R. (1979). Smooth pycnophylactic interpolation for geographical regions. Journal of the American Statistical Association, 74(367):519–530.