Spatio-temporal analysis of sub-national under-five mortality rates in a developing country context

Rasheed A. Adeyemi

UNIVERSITY OF KWAZULU-NATAL

Supervisors : Zewotir. T

Ramroop. S

Presented at College of Agriculture, Engineering & Science, School of Mathematics,Statistics & Computer Science

October,25 2018

Outline

Outline

Outline

Outline

Outline

Outline

Objective

The analysis of geographical variation in mortality rates or disease incidence has many uses

- Area and time-specific mortality rates or disease incidence are of great interest for health care and policy purposes.
- Facilitate effective allocation of resources and targeted interventions
- Sample size often too small at granular space-time scale for reliable estimates
- Bayesian approach to 'borrow strength' over space and time to improve reliability of the model estimate
- identify areas of unusually high risk so that action may be taken;

Background and MDG

- Improving the child's health is one of the eight Millennium Development Goals(MDGs) that were adopted by governments at the United Nations Millennium Submit in 2000, with the fourth Goal committed to reducing child mortality by two-third between 1990 and 2015.
- At the end MDG era, the pace of progress toward these goals substantially varied at the national level, demonstrating an essential need for tracking even more local trends in child mortality.
- With the adoption of the Sustainable Development Goals (SDGs) in 2015, regional government(s) should possess adequate information to track the progress being made

Crude Mortality rate

Consider a country of 6 political regions with the death rates or disease incidence

Region	Observed (O_i)	Pop (N_i)
NE	400	10000
NC	400	1000
NW	400	4000
SE	400	6000
SS	400	1800
SW	400	2200
Total	2400	25000

$$\hat{\theta} = \frac{\sum_i^6 O_i}{\sum_i^6 Pop_i} = \frac{2400}{25000} = 0.096$$

96 deaths per 1,000 live births

Standardized Mortality Ratio (SMR)

Refer to 6 political regions with the following death cases

Region	Obs. (O_i)	Pop. (N_i)	Exp. (E_i)	SMR
NE	400	10000	960	0.417
NC	400	1000	96	4.167
NW	400	4000	384	1.041
SE	400	6000	576	0.694
SS	400	1800	173	2.312
SW	400	2200	211	1.900
Total	2400	25000		

$$E_i = r_i N_i$$

$$SMR_i = \frac{O_i}{E_i}$$

Pooled Data from Nigeria DHS 2008 & and 2013

- A multi-stage, cluster sampling method was used to gather information from interviewees (respondents). The data for the study were from 2008 and 2013 NDHS.
- In the pooled dataset, information was obtained from 72,333 married women aged 15-49 years old, consisting of 33385 women from the 2008 survey, and 38,948 women from the 2013 survey.
- The spatial - temporal analysis used information from 60,129 live born infants of the recent birth of a mother within five years prior to the mother's interview.
- Out of which, 6057 deaths were recorded from 17, 389 couples, consisting of 8731 couples from 2008 and 8658 couples from 2013 NDHS.

Motivation

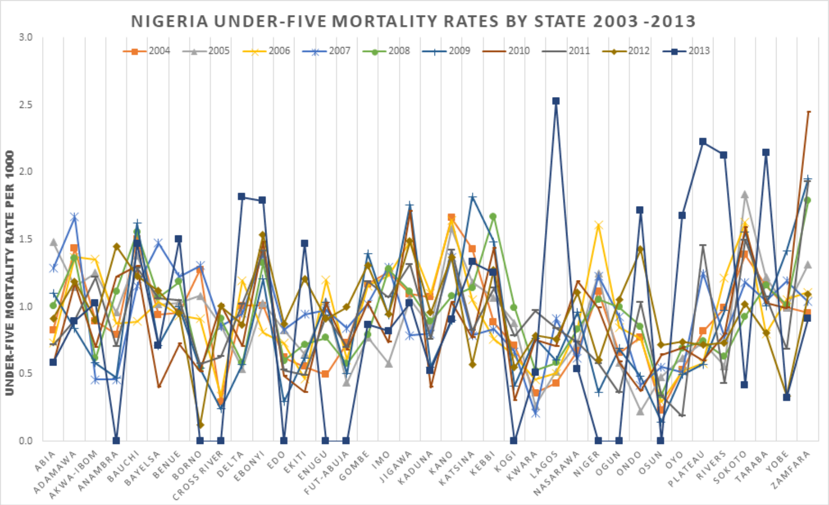

Figure 1: Trend Plot SMR Mortality Rates Nigeria 2003-2013

Mapping standardized mortality Rates 2006 in Nigeria

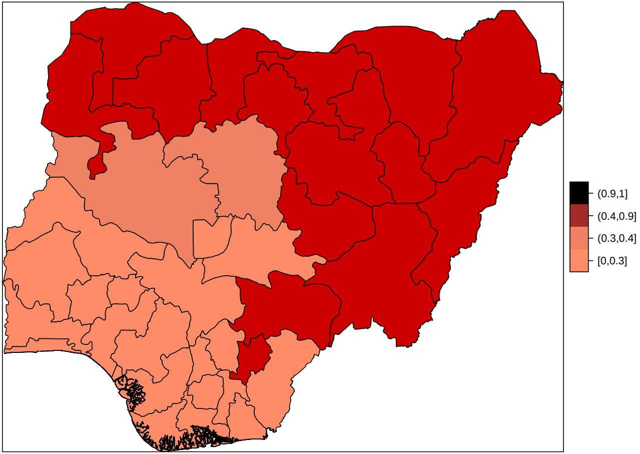

Figure 2: Spatial Plot of under- five Mortality Rates Nigeria

The Model formulation

- Counts of observed cases of under-five mortality, $\mathbf{Y}_{it}$, in each of state, $i = 1, \ldots 37$, 37 states (districts), t in time period in year
- : apportion the variability in the data to fixed effect covariates, space, time, and space-time interaction .

$$\eta_{it} = intercepts + \underbrace{C_k + S_i + T_t}_{\text{Main effects}} + \underbrace{CS_{it} + CT_{it} + ST_{it} + CST_{it}}_{\text{interraction effects}} \tag{1}$$

- intercepts- overall area specific intercept
- $\mathbf{C_{it}}$ i.e. represents covariates (mother's educational level, mothers' age at first birth, LBW, poverty status,etc
- S- space, T-Time,

The Model

- Consider disease incidence or mortality rates O_{it} (in areas i and time periods t) and corresponding expected numbers of cases e_{it} , then , the observed count is assumed Poisson distribution and model is:

$$
\begin{aligned}
O_{it} &\sim \text{Poisson}(\mu_{it}) = \text{Poisson}(e_{it}\theta_{it}) \\
\log \mu_{it} &= log(e_{it}) + \log \theta_{it} \\
&= \log(e_{it}) + \alpha + \phi_i + \psi_i + \delta_t
\end{aligned}
$$

- the log relative risks

$$\theta_{it} = \alpha + \phi_i + \psi_i + \delta_t \text{ with } \theta_{i1} = \exp(\alpha + \phi_i + \psi_i) \qquad (2)$$

- Their diffuse hyperprior are specified by the precision, $\tau_\phi = 1/\sigma^2_\phi, \tau_\psi = 1/\sigma^2_\psi$and$\tau_\delta = 1/\sigma^2_\delta$

Spatio-Temporal Models

From Equation (**??**) is modeled as

- Taking logarithm of the relative risk, RR

$$\log(\theta_{it}) = \beta + \underbrace{\alpha_t + \gamma_t}_{Time} + \underbrace{\phi_i + \psi_i}_{space} + \underbrace{\delta_{it}}_{space \times time} \tag{3}$$

- $\beta-$ overall risk level
- α_t- temporally structured effect of time, t in years
- γ_t- independent effect of time, t in years
- ϕ_i- spatially structured effect of district (state) i
- ψ_i- independent effect of district i, i.e. $\psi_i|\sigma^2 \sim \mathrm{N}(0,\ \sigma_u^2)$
- interaction models for δ_{it}

Prior Distributions for model parameters

From Equation (**??**) is modeled as

- Taking logarithm of the relative risk, RR, written as a Poisson Log linear model

$$\log(\theta_{it}) = \beta + \alpha_t + \gamma_t + \phi_i + \psi_i + \delta_{it} \tag{4}$$

$$(\phi_i|\phi_{-i}, \sigma^2_\phi, W) \sim N\left(\frac{\sum_{j=1}^{N} w_{ij}\phi_i}{\sum_{j=1} w_{ij}}, \frac{\sigma^2_\phi}{\sum_{j=1} w_{ij}}\right)$$

$$\psi_i|\sigma^2_\psi \sim N\left(0, \sigma^2_\psi\right)$$

$$\alpha_t|\alpha_{t-1}, \sigma^2_\alpha \sim N\left(\alpha_{t-1}, \sigma^2_\alpha\right)$$

$$\gamma_t|\sigma^2_\gamma \sim N\left(0, \sigma^2_\gamma\right)$$

$$\delta_{it}|\delta_{-it}, \sigma^2_\delta \sim N\left(m_{it}, \sigma^2_\gamma v_{it}\right)$$

Type I interaction

Model I: Independent interaction effect is modeled by combining two indept. and identical Gaussian distr. space and time, iid prior for δ_{it}

$$\delta_{it}|\delta_{-it}, \sigma_\delta^2 \sim N\left(0, \sigma_\delta^2\right)$$

The joint distribution is expressed

$$p(\delta|\sigma_\delta^2) \propto \exp\left(-\frac{1}{2\sigma_\delta^2}\delta^T K_\delta \delta\right)$$

where $K_\delta = K_\phi \bigotimes K_\gamma \left(\text{rank } \mathbf{1}_{(kT \times kT)}\right)$

Type II interaction

Model II: A temporally structured effect of time, α_t assumed a random walk and iid for space (state)

- First order Random Walk $RW1$

$$\alpha_t|\alpha_{-t}, \sigma^2_\alpha \sim N\left(\frac{1}{2}(\alpha_{t-1} + \alpha_{t+1}), \sigma^2_\alpha)\right)$$

  and the joint distribution expressed as,

$$p(\alpha|\sigma^2_\alpha) \propto \exp(-\frac{1}{2\sigma^2_\alpha}\alpha^T K_\alpha \alpha)$$

  where $K_\delta = K_\gamma \bigotimes K_\phi$ (rank$K \times (T-1)$)

- the second-order random walk $(RW2)$ model for regular locations has the density

$$p(\delta_{it}|\delta_{-it}, \sigma^2_\delta) \propto \exp\left(\frac{1}{2\sigma^2_\delta}\sum_{t=3}^{T}\sum_{i=1}^{I}(\delta_{it} - 2\delta_{i,t-1} + \delta_{i,t-2})^2\right)$$

Type III Spatio-temporal interaction

Model III: Spatial trends differ over time - Intrinsic autoregression prior

$$\delta_{it}|\delta_{-it}, \sigma_\delta^2 \sim N\left(\frac{1}{m_i}\sum_{j\ j\sim i}\delta_{it}, \frac{\sigma_\delta^2}{m_i}\right)$$

The improper joint distribution can be expressed as

$$p(\delta|\delta_{-it}, \sigma_\delta^2) \propto \exp\left(-\frac{\sigma_\delta^2}{2}\delta^T K_\delta \delta\right)$$

where $K_\delta = K_\phi \bigotimes K_\gamma$ (rank$(K-1)T)$)

Type IV Spatio-temporal interaction

Model IV: The interaction -conditional depends on neighbors regions and second order random random for Time (year)
$p(\delta_{it}|\delta_{-it}, \sigma^2_\delta) \propto$

$$\exp\left(\frac{1}{2\sigma^2_\delta}\sum_{t=3}^{T}\sum_{i\neq j}\left((\delta_{it} - 2\delta_{i,t-1} + \delta_{i,t-2}) - (\delta_{j,t-2} - 2\delta_{j,t-1} + \delta_{j,t})\right)^2\right)$$

The improper joint distribution can be expressed as

$$p(\delta|\delta_{-it}, \sigma^2_\delta) \propto \exp\left(-\frac{1}{2\sigma^2_\delta}\delta^T K_\delta \delta\right)$$

where $K_\delta = K_\gamma \bigotimes K_\phi$ (rank$(K-1)(T-1)$)

Model Summary

Table 1: *Model formulation for under five mortality NHS2008 and 2013, with Model Ma $\alpha_t \sim rw1(\sigma^2_\delta)$ and Mb $\alpha_t \sim rw2(\sigma^2_\delta)$*

Models	Code	Linear Predictor	δ_{it}
Main effect	Ma	$\mu + \gamma_t + \alpha_t + \phi_i + \psi_i$	$--$
Main effect	Mb	$\mu + \gamma_t + \alpha_t + \phi_i + \psi_i$	$--$
Type I	M1	$\mu + \gamma_t + \alpha_t + \phi_i + \psi_i + \delta_{it}$	$\gamma_t \sim iid$, $\psi_i \sim iid$
Type II	M2	$\mu + \gamma_t + \alpha_t + \phi_i + \psi_i + \delta_{it}$	$\alpha_t \sim rw2$, $\psi_i \sim iid$
Type III	M3	$\mu + \gamma_t + \alpha_t + \phi_i + \psi_i + \delta_{it}$	$\alpha_t \sim iid$, $\phi_i \sim ICAR$
Type IV	M4	$\mu + \gamma_t + \alpha_t + \phi_i + \psi_i + \delta_{it}$	$\alpha_t \sim rw2$, $\phi_i \sim ICAR$

Model implementation

- The hierarchical Bayesian space–time models were fitted using the Integrated Nested Laplace Approximation (INLA) [Rue, Martino and Chopin (2009)] as implemented in the INLA package.
- INLA provides a fast alternative to MCMC for approximating the marginal posterior distributions of Markov random field (MRF) models.

Model comparison

Table 2: *Model comparison: pD is the effective degrees of freedom, as defined for the calculation of the deviance information criteria (DIC), which also uses the deviance evaluated at the posterior mean, $D(\hat{\theta})$; LCPO is defined as Pits $\log(CPO_{it})$ and Watanabe-Akaike information criterion (WAIC) for under five mortality from NDHS 2008 & 2013.*

Models	pD	$D(\hat{\theta})$	DIC	WAIC	CPO	logScore
Ma	30.35	610.77	2284.68	2300.02	36.326	2.827
Mb	30.81	611.17	2285.08	2301.10	36.326	2.828
I	121.27	552.64	2226.91	2226.46	34.889	2.778
II	74.84	557.69	2231.13	2245.85	36.480	2.770
III	109.43	565.01	2239.44	2253.59	34.350	2.808
IV	99.86	530.14	2204.00	2210.00	36.325	2.734

Results & Discussion

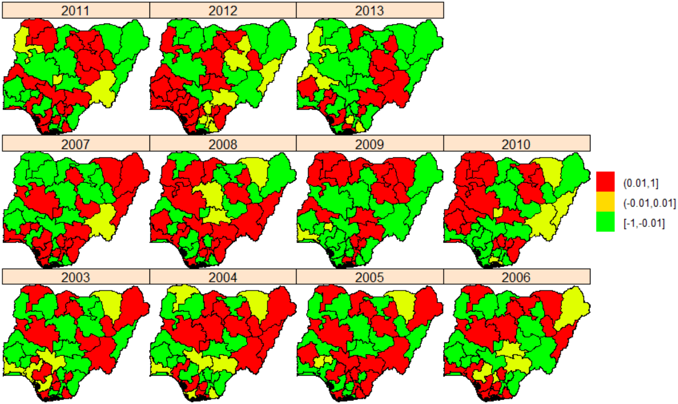

Figure 3: Posterior mean of the spatio-temporal interaction δ_{it} for under-five mortality under M1 (nonspatially or temporally structured interaction).

Spatio-temporal interaction effects Model II

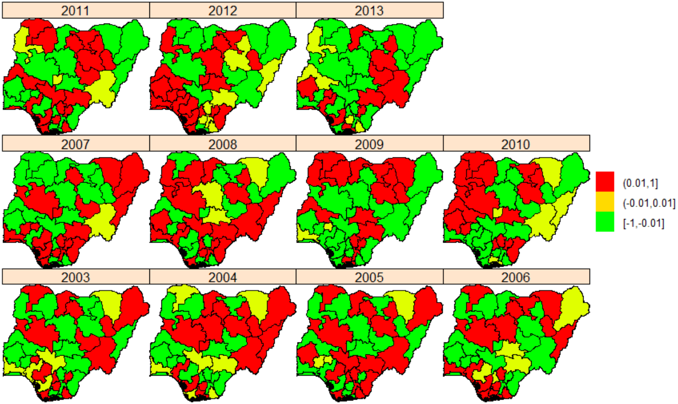

Figure 4: Posterior mean of the spatio-temporal interaction δ_{it} for under-five mortality in Nigeria under M2 (temporally structured interaction).

Spatio-temporal interaction effects Model III

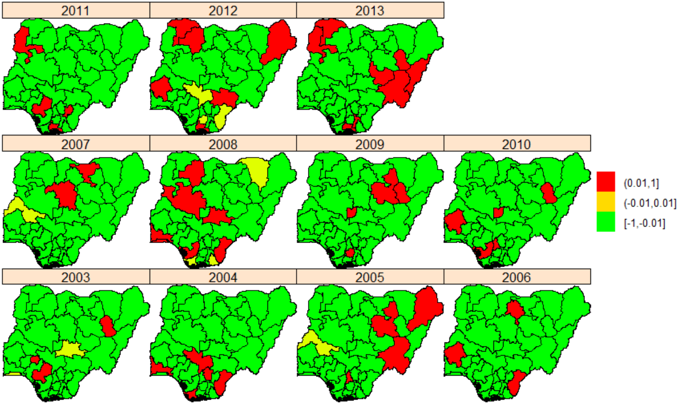

Figure 5: Posterior mean of the spatio-temporal interaction δ_{it} for under-five mortality in Nigeria under Model M3 (spatially structured interaction).

Spatio-temporal interaction effects Model IV

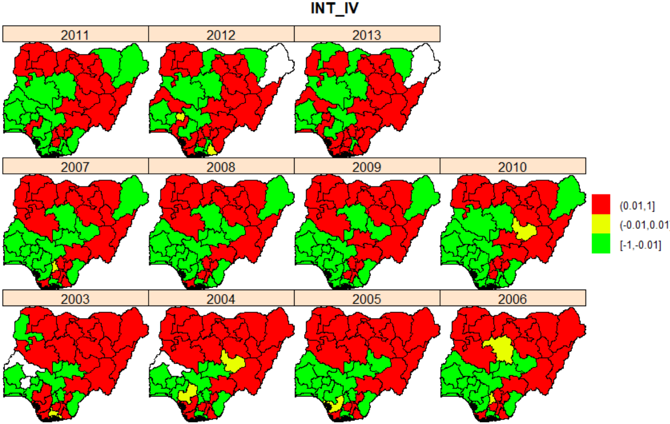

Figure 6: Posterior mean of the spatio-temporal interaction δ_{it} for under-five mortality in Nigeria under Model M4 (spatially and temporally structured interaction)

Check for spatial autocorrelation in the residuals

Examination of auto-correlation of lag 1

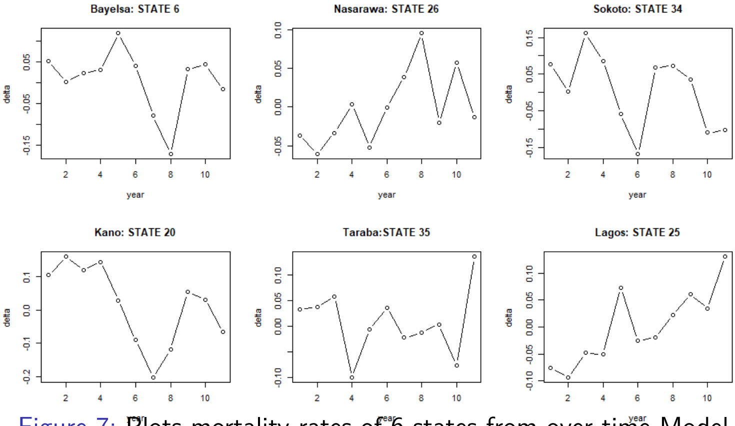

Figure 7: Plots mortality rates of 6 states from over time Model I

Temporal auto-correlation function (ACF) effects Model I

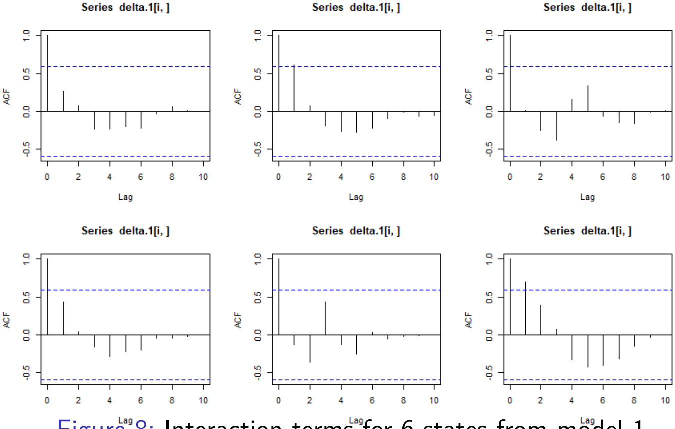

Figure 8: Interaction terms for 6 states from model 1

Examination of Space-Time interaction

- To see if a more complex interaction model is warranted we evaluate the autocorrelation function for the δ_{it} , with one each i (i.e. each area).
- Map the auocorrelations at lag 1.
- The rationale for this is that:
  - We would expect to see positive correlations if there is temporal structure in the residuals (Type II interaction).
  - If there were no evidence of temporal structure but a spatial pattern in the autocorrelations then we would see clustering in the map (Type III interaction).
  - If there were positive correlations and spatial clustering then Type IV is appropriate.

Model Diagnostic cont. . . . & Discussion

- With Model M3, Figure **??** showed spatially auto-correlation, but temporally hetereogeinty in child mortality rates was also found across the whole Nigeria.
- Refer to Model M4, Figure **??** significant clusters of high childhood mortality were detected in the Northern regions of Nigeria, which exhibited both spatially and temporally dependency .
- Clusters of the child mortality are exhibited in Model IV
- Spatial heterogeneity exhibited in Models I & Model II

Concluding Remarks

- we discuss a spatio-temporal Bayesian hierarchical model to estimate small-area U5M at sub-national level.
- provincial sub-populations in Nigeria can widely vary, direct estimates of mortality rates can show evident uncertainty when considering small-area inequality across provinces (states)
- we proposed a model where district-level U5M rates estimates can borrow strength from each other in order to reduce uncertainty related to the estimates
- preliminary results show geographical inequalities in the prevailing U5M mortality at the sub-national level, but declining temporal trend at slow rate since 2000

Recommendation

To attain SDG 2025 and prevent needless loss of under-five child, the Recommendations:

- **Improving primary health centers(PHC)** -government should embark on enduring process by improving the quality services and number of skilled health attendance/workers at PHC
- **Provision of sanitation and hygienic toilet facilities at public centres:** motor parks (or taxi rank), rail station, market place and schools
- **Increase immunization coverage and national treatment of vaccine for prevention of disease (VPD)**- vaccination against disease infection and ;
- **Strengthening women empowerment programme** -such as increased education of women, comprehensive family planning services and child spacing

Research Output & Future Direction

- Adeyemi et al(2016) Semi-parametric Mutinomial Ordinal Models to analyze the spatial patterns of child birthweight in Nigeria **published** *Int. J. Environ. Res. Public Health* **2016**, *13, 1145;* doi:10.3390/ijerph13111145
- Bayesian Mutinomial Ordinal Models to analyze the risk factors and spatial patterns of childhood anemia in Tanzania **published** Proceeding of 58^{th} Annual Conference of South African Statistical Association
- Bayesian Mutinomial Ordinal Model to analyze the spatial patterns of childhood anemia in sub-Saharan Africa *Paper Presented at 58^{th} Annual Conference of SASA, Held at University of Capetown 28 Nov.–2 Dec.2016*
- Multivariate Spatial Joint Mapping of the risk of Childhood Anemia and Malnutrition in sub-Saharan Africa: A cross-sectional study of small-scale geographical disparities **Revision Stage** PLOS ONE Journal

Research Output & cont......

- Investigating Geographical patterns and environment risk factors for under-five mortality in Nigeria: A Bayesian Hierarchical model approach **submission Stage**
- Spatial Patterns Of Childhood Mortality And Morbidity In Sub-Saharan Africa: A Bayesian Geo-Additive Multinomial Models Approach *Paper Presented at UKZN College Research Day Oct. 2017.*
- Bayesian Joint modeling of Disease Co-morbidity among under five children in Nigeria and Tanzania; *Accepted for Presentation 2016.*: *UKZN College Research Day: Postgraduate*
- Spatial and Spatio-Temporal modeling of regional variations in Malnutrition and Disease morbidity in Sub-Saharan Africa?: A Case study of DHS data from Nigeria, Burkina faso, Ghana, & Mozambique *Future research work*

Acknowledgements

- We acknowledge the permission granted to us by MEASURE DATA, Demographic and health Survey, ICF Macro, Calverton, USA to use the data under **Project Topic:** Spatial Analysis of poverty, malnutrition and mortality among under-five children in Sub-Saharan Africa.
- The first author also appreciate the study fellowship/support received from the Federal University of Technology , Minna-NIGERIA for undergoing his postgraduate study in South Africa.

References I

- Besag, J., York, J., & Molli, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the institute of statistical mathematics*, 43(1), 1-20.

- Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Van Der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 64(4), 583-639.

- UNICEF. World Bank; United Nations (2015). Levels & trends in child mortality report 2014: estimates developed by the UN Inter-Agency Group for Child Mortality Estimation.[cited 2015 Feb 17].

- Fahrmeir, L., & Lang, S. (2001). Bayesian inference for generalized additive mixed models based on Markov random field priors. Applied statistics, 201-220.

References II

Banerjee, S., Carlin, B. P., and Gelfand, A. E. (2014).
Hierarchical modeling and analysis for spatial data.
Crc Press.

Besag, J., York, J., and Mollié, A. (1991).
Bayesian image restoration, with two applications in spatial statistics.
Annals of the institute of statistical mathematics, 43(1):1–20.

Best, N. and Hansell, A. L. (2009).
Geographic variations in risk: adjusting for unmeasured confounders through joint modeling of multiple diseases.
Epidemiology (Cambridge, Mass.), 20(3):400.

Congdon, P. (2017).
Representing spatial dependence and spatial discontinuity in ecological epidemiology: a scale mixture approach.
Stochastic Environmental Research and Risk Assessment, 31(2):291–304.

References III

Dobra, A., Lenkoski, A., and Rodriguez, A. (2011).
Bayesian inference for general gaussian graphical models with application to multivariate lattice data.
Journal of the American Statistical Association, 106(496):1418–1433.

Downing, A., Forman, D., Gilthorpe, M. S., Edwards, K. L., and Manda, S. O. (2008).
Joint disease mapping using six cancers in the yorkshire region of england.
International Journal of Health Geographics, 7(1):41.
BMC medical research methodology, 11(1):172.

MacNab, Y. C. (2011).
On gaussian markov random fields and bayesian disease mapping.
Statistical Methods in Medical Research, 20(1):49–68.

References IV

Waldhoer, T., Wald, M., and Heinzl, H. (2008).
Analysis of the spatial distribution of infant mortality by cause of death in Austria in 1984 to 2006.

Kinyoki DK, Manda SO, Moloney GM, Odundo EO, Berkley JA, Noor AM, et al.
Modelling the Ecological Comorbidity of Acute Respiratory Infection, Diarrhoea and Stunting among Children Under the Age of 5 Years in Somalia.
International Statistical Review. 2017;85(1):164–176.

Kaombe, T. M., & Namangale, J. J. (2012). Modelling Distribution of Under-Five Child Diarrhoea across Malawi. In Association (SAMSA) Conference (Vol. 26, p. 67).

Rue, H., & Held, L. (2005). Gaussian Markov random fields: theory and applications. CRC press.

References V

Danzhen You, Phillip Bastian, Jingxian Wu, and Tessa Wardlaw.
Levels and trends in child mortality. report 2013. estimates developed by the un inter-agency group for child mortality estimation.
2013.

Jean-Christophe Fotso.
Child health inequities in developing countries: differences across urban and rural areas.
International journal for equity in health, 5(1):9, 2006.

National Population Commission (NPC).
National Population Commission and Nigeria demographic and health survey 2008 icf macro.
Calverton Maryland: ICF Macro, 2009.

References VI

National Population Commission, Abuja and Macro, ICF Macron Calverton Maryland, USA.
Nigeria Demographic and health survey 2013.
2014.

Elizabeth Omoladun Oloruntoba, Taiwo Bukola Folarin, and Adejumoke Idowu Ayede.
Hygiene and sanitation risk factors of diarrhoeal disease among under-five children in ibadan, nigeria.
African health sciences, 14(4):1001–1011, 2014.


Thank you