Spatial Patterns Of Childhood Mortality And Morbidity In Sub-Saharan Africa: A Bayesian Geo-Additive Multinomial Models Approach

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- Introduction,Motivation and Objective

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- Model Specifications

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- Data Application& Results

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Introduction

- Most countries in sub-Saharan Africa had missed the target in achieving the Millennium Development Goals (MDGs) for maternal and child health by 2015.
- Diarrhoea, cough and fever are the leading causes of childhood morbidity and mortality in sub-Saharan Africa (SSA)
- An estimated 3.5 million deaths each year are due to diarrhoea worldwide, 80% of which occur in under-5 children [4].
- WHO estimates that the global burden of disease due to environmental factors is 24%, and these factors are responsible for 23% of all deaths each year.

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- In Nigeria, the upward trend of childhood mortality are mainly due to parasitic and infectious diseases such as diarrhea, malaria, acute respiratory and measles contributes a leading cause of child deaths Adetunji (1991); Grais et al.(2007).
- Despite a global decline in under-five mortality rates (U5MR) in recent decades, the situation still remains persistently high in Sub-Saharan African (SSA) countries with higher at 86 deaths per 1000 live births [3].
- Neonatal deaths accounts for one-third of under-five deaths in SSA . In Nigeria, the under-five mortality estimates have declined tremendously from 193 to 128 per 1000 live births in 1990 to 2013, but infant mortality had not varied substantially, IMR 75 to 69 per 1000 live births in 1990 to 2013 [7].

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Geographical Maps and Spatial Data Point Patterns

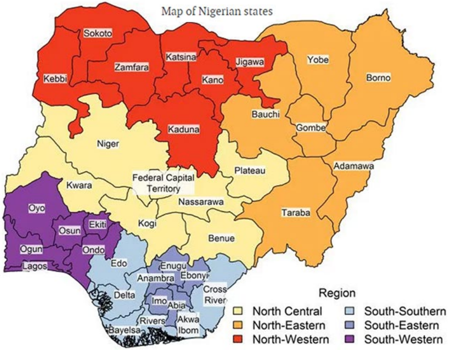

Figure: Geographical Map of Nigeria showing 36 states and Federal Capital Territory , Abuja)

- Nigeria : Most populous in Sub- Saharan Africa and 7^{th} the largest in the world with about 180 million
- Land mass 975,225 sq. km
- Administratively, made up 36 states and FCT, Abuja (2nd level) and 774 local govt. areas(3rd level)

Discretization and Data Collection designs

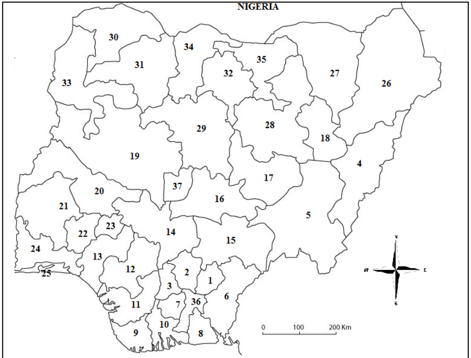

Figure: Discretization of the administrative(State) boundaries of Nigeria

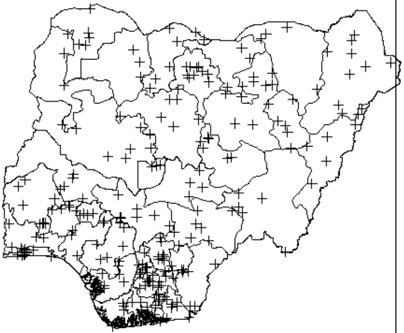

Figure: Pattern Point Plots Showing Data collection in 2013 Nigeria DHS

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Survey Design

Table: Variable name, variable types, and response categories covariates used in the analyses

Covariate name	Covariate type	Response categories/range	co
Response outcomes	Binary	death/alive, disease/no disease	
Child's sex	binary	Female (-1) , male (1)	
Residence	binary	rural(-1), urban (1)	
Antenatal	binary	no attendance(-1), attendance (1)	
medu	Categorical	no prim, prim, sec, high	
wealth index	Categorical	poorest, poor, middle, rich, richest	
Mother's age	Categorical	$< 20, 21 - 29, 30 - 39, 40 - 59$(ref.)	
Child's age	continuous	0-59 months	
Mother's bmi	continuous	mbmi$=wt(kg)/h^2(m^2)$	
Geographical information	location Coordinates (longitude, latitude)	region index $s = 1, \ldots, 37$	

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Study designs 2013 Nigeria DHS

- A representative sample selected from 38,948 women aged between 15 and 49 years from 38,522 households.
- A two-stage stratified sampling design was implemented to collect the data. The
- Using a structured questionnaire, data was collected on reproductive health and birth histories, demographic and their children nutritional status, among other
- GPS receivers were also used to locate the coordinates of the sample households.
- Let $j = 1, ..., N_i$ denote individuals child within groups $i = 1, ..., I$, where i may index, for example, time units, geographical (spatial) units, socioeconomic groups, etc.
- $(y_i, w_i, x_i, s_i), i = 1, \ldots, n$, where y_i represent individual child i dichotomous health outcome, w_i are measurable categorical covariates, x_i presents metrical variable (e.g. child's age in months, mother body mass index), s_i denote the location index , $i = 1, 2, \ldots, 37$.

The Statistical Models

- let a be binary outcome of a child dying between age 0- 11 month classified as infant mortality

$$y_{ij1} = \begin{cases} 1 & \text{if the child dies between 0-11 months} \\ 0 & \text{otherwise} \end{cases}$$

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- a child has pneumonia(Acute respiratory infection, ARI) in the last 2 weeks prior to the survey

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$$y_{ij3} = \begin{cases} 1 & \text{if the child has disease} \\ 0 & \text{otherwise} \end{cases}$$

- a child's z-score (height-for-age) is classified as acutely stunting

$$y_{ij4} = \begin{cases} 1 & \text{if the child (height-for-age) is } < -2.00 \\ 0 & \text{otherwise} \end{cases}$$

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Multinomial Model

- Let Y_{ijk} and $\pi_i jk$ be the child health status and probability of the child heath outcome respectively, Y_{ijk} then follows a Multinomial distribution, and written as $Y_{ijk} \sim MN(1, \pi_{ijk})$ where $\boldsymbol{\pi_{ijk}} = (\pi_{ij1}, \pi_{ij2}, \pi_{ij3}, \pi_{ij4})\prime$.

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- The probability of the child health defects can be defined thus:

$$\pi_{ijk} = \frac{\exp(\eta_{ijk})}{1 + \sum_{k=1}^{k} \exp(\eta_{ijk})}, k = 1, 2, 3, 4 \tag{2}$$

Let the relation $Y \rightarrow X$ be given as, $Y = X\beta + \varepsilon$, by taking $\varepsilon \sim N(0, \tau^2)$ as error or residual term

Model Specifications

We proposed the following predictors

M1 : $\eta_i = w'\beta + x_i\prime\gamma$

The model performance is assessed using

- Deviance information criteria (DIC) proposed by Spiegelhalter et al.[8], defined as $DIC = D(\bar{\theta}) + pD$

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$$\begin{aligned}
\text{M1} &: \eta_i = w'\beta + x_i\prime\gamma \\
\text{M2} &: \eta_i = w_i'\beta + \underbrace{f(x_1) + \ldots f(x_p)} \\
\text{M3} &: \eta_i = w_i'\beta + f_j(x) + \theta_{random}(s_i)
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\text{M5} \quad &: \eta_i = w_i'\beta + f_j(x) + \phi_{district} + \theta_{random}
\end{aligned}
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Prior Distributions of Spatial effects

In spatial statistics, we adopt as proposed Besag et.al [5]

- Unstructured Hetereogeneity(uncorrected) effect is modelled by i.i.d Gaussian Random prior

$$\theta_{unstr} \sim N(0, \sigma^2_{unstr}) \tag{3}$$

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- Structured (correlated) Spatial effect is modeled by Gaussian intrinsic Conditional auto-regressive (CAR) error defined as

$$\phi(s)|\phi(t), t \neq s, \tau^2 \sim N\left(\sum_{t \in \delta_s} \frac{\phi(t)}{N_s}, \frac{\tau^2}{N_s}\right) \tag{4}$$

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- where N_s is the number of adjacent regions and $t \in \delta_s$ denotes that the region t is a neighbor of region s. Thus, the conditional mean of $f_{str}(s)$ is an un-weighted average of function evaluations of neighboring regions t.

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Prior Distributions fixed and Non-linear effects

- Fixed effects prior,
  an independent diffuse prior, i.e. $p(\beta) \propto const.$.
- Non-linear effects of Continuous covariates
- We adopt by Bayesian P$-$ splines prior as suggested in the work Fahrmeir and Lang,[10] , which permits $f(x)$ to be written as a linear combination of $\mathbf{B}-$spline):

$$f(x) = \sum_{j=1}^{d} \beta_{kj} \mathbf{B}_j(x)$$

  where $\boldsymbol{\beta} = (\beta_1, \ldots .\beta_p)\prime$ corresponding vector of the unknown regression coefficients.
- the smoothing spline can be modified by a flexible first or second Gaussian order random walk defined by

$$\beta_j = \beta_{j-1} + u_j; \qquad \beta_j = 2\beta_{j-1} - \beta_{j-2} + u_j \tag{5}$$

- with Gaussian errors $u_j \sim N(0; \tau^2)$ and indep. diffuse priors, $\beta_1, \beta_2, \ldots \propto const.$ where variance assume ,$\tau^2 \sim IG(a, b)$), with hyper-parameters a and b, which is used to controls the smoothness

Data Applications and Implementations

Bayesian inference was performed using Markov chain Monte Carlo (MCMC) simulation technique.
Data cleaning and re-coding was done in R environment and *R-INLA* package used to implement the model in this work.

NIGERIA 2013 DHS

Spatial Mapping of infant mortality and Diseases Morbidity

Tanzania 2010 DHS

Bayesian Joint Spatial Modelling of Anemia and Acute Malnutrition among under-five children

Model Performance Using DIC

Table: Frequency distribution of infant mortality & morbidity in 2013 NDHS

Defects	No	Yes	%
Mortality	28566	2886	9.2%
Diarrhea	28491	2968	9.4%
Fever	28430	3691	11.7%
Pneumonia	28694	1155	3.7%
Cough	28380	2812	8.9%

Table: Deviance Information Criteria (DIC)values for Model selection

Model	Mortality	Diarrhea	Fever	Pneumonia	Stunting	Remark
M_1	3123.67	18479.2.	21716.6	28021.3	2752.0	least
M_2	3301.29	17993.3	21384.4	26956.4	2601.2	Poor
M_3	3109.26	17251.0	20265.9	24125.6	2534.3	Moderate
M_4	3058.94	17649.4	18823.3	24042.2	2104.4	Moderate
M_5	2921.94	15079.1	17230.3	17492.2	2046.1	Best model

Posterior estimates of Categorical Covariates

TABLE OF POSTERIOR ODDS

Posterior Odd ratios of risk factors of infant Mortality and Diarrhea for Model 3

		Infant mortality			Childhood Diarrhea		
Var.	par	mean	0.025quant	0.975quant	mean	0.025quant	0.975quant
Const.	β_0	1.705	1.541	1.886	0.215	0.199	0.233
Male	β_1	0.973	0.914	1.035	1.001	0.968	1.036
Multiple(twin)	β_2	0.962	0.878	1.053	1.525	1.418	1.640
Birth weight							
Very cbw	β_3	0.974	0.818	1.160	1.512	1.359	1.681
Low cbw	β_4	1.014	0.917	1.120	0.747	0.703	0.793
high cbw	β_5	0.979	0.886	1.083	0.878	0.828	0.931
Urban	β_6	1.010	0.939	1.087	1.045	1.001	1.091
Breastfed	β_7	0.391	0.338	0.451	0.910	0.828	1.001
Space (≥ 2)	β_8	1.122	1.044	1.207	0.961	0.916	1.007
Mother's edu.							
Prim	β_9	1.030	0.929	1.142	1.074	1.006	1.146
Sec.	β_{10}	1.089	0.982	1.208	0.972	0.911	1.038
High	β_{11}	0.933	0.806	1.080	1.016	0.920	1.122
Mother's age							
$<$ 20 yrs	β_{12}	0.924	0.806	1.059	1.248	1.138	1.369
30-39 yrs	β_{13}	1.032	0.944	1.128	0.902	0.852	0.955
$\geq$ 40yrs	β_{14}	0.983	0.875	1.105	0.979	0.904	1.061
Vit. A	β_{15}	0.841	0.760	0.929	1.029	0.980	1.080
Antenatal	β_{16}	0.992	0.877	1.122	0.933	0.880	0.990
DPT1	β_{17}	0.995	0.887	1.117	0.924	0.878	0.973
Vaccine	β_{18}	0.949	0.837	1.077	1.031	0.983	1.082

Posterior Odd ratios of risk factors of Childhood fever and Acute Respiratory infection (ARI)

		Fever			Pneumonia		
var.	par.	mean	0.025quant	0.975quant	mean	0.025quant	0.975quant
(Intercept)	β_0	0.268	0.248	0.290	0.853	0.764	0.952
breast1	β_1	0.906	0.827	0.992	0.973	0.843	1.124
Male	β_2	0.981	0.950	1.013	0.996	0.937	1.060
Twin	β_3	1.428	1.332	1.532	1.120	1.007	1.245
vlbw	β_4	1.487	1.339	1.648	1.142	0.948	1.377
lowbw	β_5	0.787	0.743	0.833	0.894	0.806	0.992
hhcbw	β_6	0.910	0.861	0.963	1.005	0.909	1.110
urban	β_7	1.002	0.962	1.044	0.896	0.834	0.963
space	β_8	0.993	0.950	1.038	1.035	0.959	1.117
prim	β_9	1.040	0.978	1.105	1.037	0.938	1.147
sec	β_{10}	0.970	0.913	1.030	0.894	0.810	0.985
high	β_{11}	1.104	1.008	1.209	0.926	0.808	1.061
mage20	β_{12}	1.125	1.025	1.233	1.042	0.908	1.195
mage30	β_{13}	0.892	0.845	0.942	0.911	0.833	0.997
mage40	β_{14}	1.079	1.001	1.163	1.088	0.962	1.231
Vit. A	β_{15}	0.993	0.949	1.040	0.951	0.876	1.033
Antenatal	β_{16}	0.925	0.876	0.977	0.991	0.899	1.092
DPT1	β_{17}	0.995	0.947	1.045	0.997	0.918	1.082
vaccine	β_{18}	0.976	0.932	1.022	0.928	0.852	1.011

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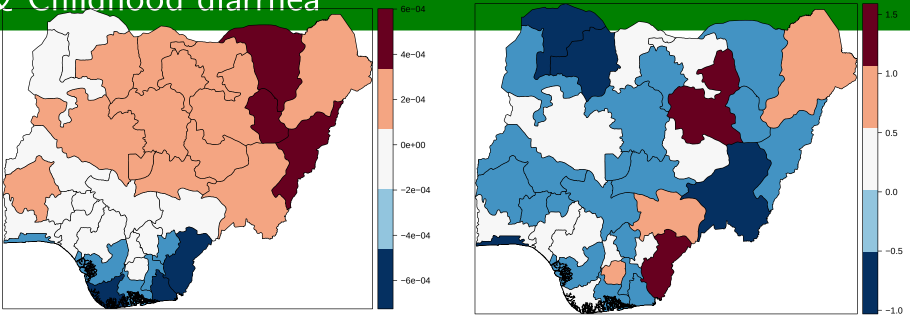
PREDICTIVE MAPS

Predictive Mapping of Posterior Mean of Infant mortality & Childhood diarrhea



- The dark blue region represents low prevalence(strictly negative) and white colour region (null)indicates insignificant

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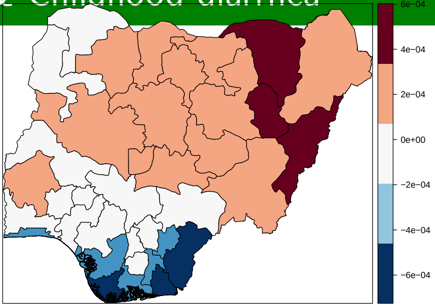

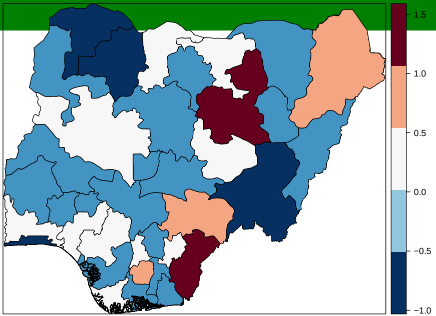

- The dark blue region represents low prevalence(strictly negative) and white colour region (null)indicates insignificant
- The dark red and brown regions are high prevalence (strictly positive)

  Left : High infant mortality prevalence are observed in many states in the North of Nigeria, and Oyo state (S-W), may be due to high poverty rate and low maternal education .

  Right :: High prevalence Diarrhea detected in states of Borno, Bauchi(N-E), Benue, Abia(S-E), Cross-rivers(S-S)

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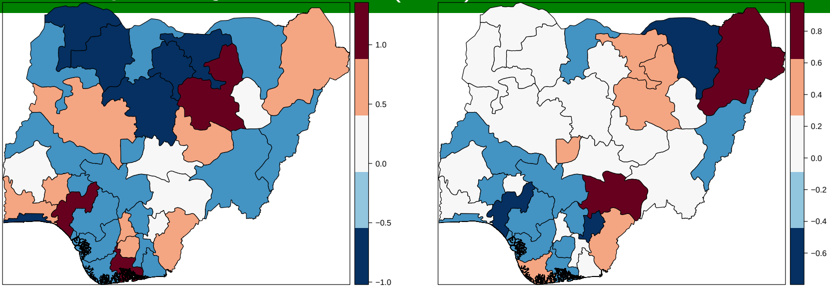
Predictive Mapping of Posterior Mean of childhood fever & Acute Respiratory Infection (ARI)



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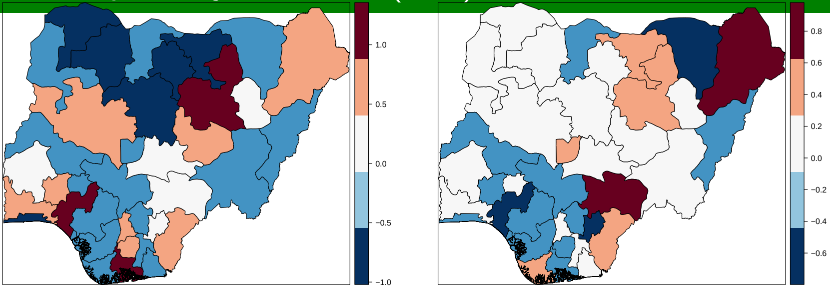
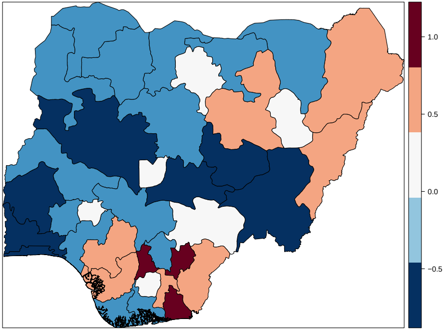


- The dark blue region is low prevalence(strictly negative) and the white region is a null region indicating insignificant
- The dark red and brown regions are high prevalence (strictly positive)
  Left: High risk of fever detected in some states: Borno, Bauchi, Niger, Benue (north-east), Ogun,Osun, Ondo(S-W),& Rivers, Imo, Abia & Cross-rivers
  Right: High prevalence ARI observed in (N-E)Borno, Bauchi, Jigawa, FCT, Abuja, Benue, and (S-S zone) Bayelsa, Cross-rivers states

Spatial Residual plot of Posterior mean of acute malnutrition (stunting)

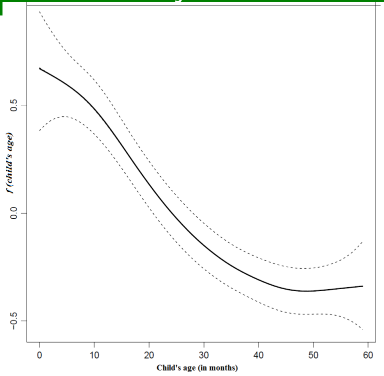


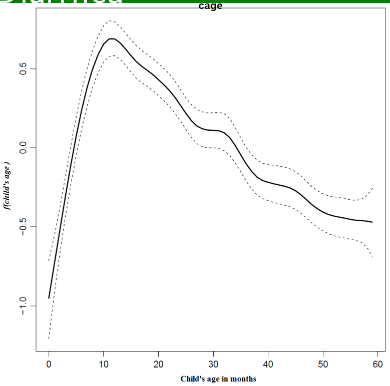
- The dark blue region is low prevalence of acute stunting.
- The dark red and brown region is high(positive)prevalence of acute stunting, strictly positive. High incidence are detected in Akwa, Anambra, Abia, Cross-rivers, Ebonyi states ; Delta and Edo; & Adamawa, Borno and Bauchi States (North- East region).
- The white region is a null region indicating insignificant

Non-linear smooth plots of continuous covariate effect of child age (months)

Plots of Smooth function estimates of Continuous covariate

Non-linear Plots of effects of child's age (months) on infant mortality & Childhood Diarrhea





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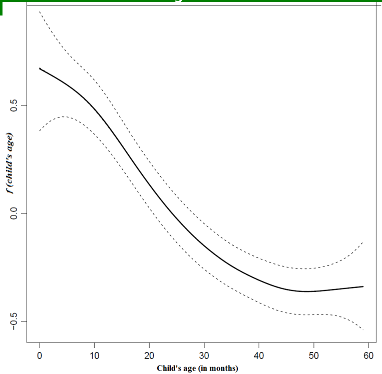
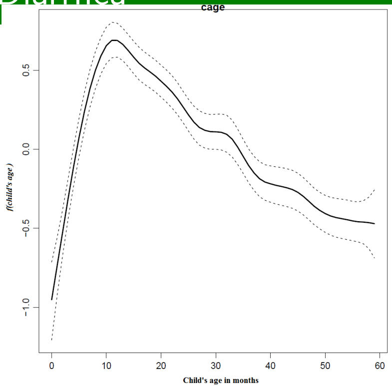
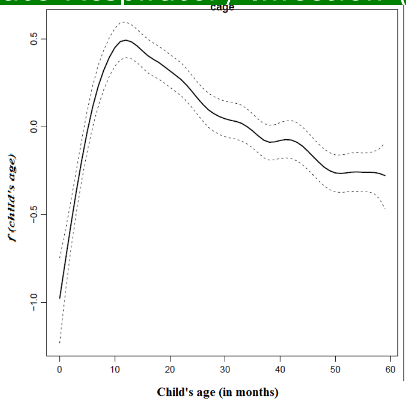
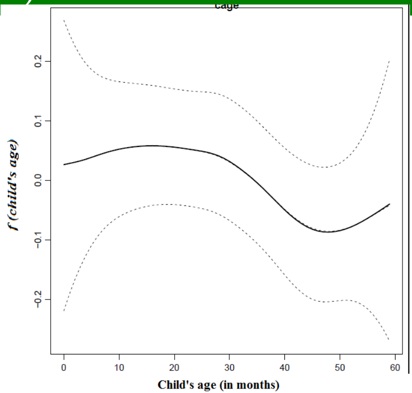




- **Left : infant mortality** it resembles a flipped J-shape, the chance of child survival improves steadily as the child grows older i.e. risk of the child dying at infancy decreases steeply as he grows older.
- **Right : Diarrhea**represents an inverted-U shape, the fever risk attained highest at age 8 months at infancy, and the risk deceases steadily soon after as the child grows older

Non-linear Plots of effects of Child age on the risk fever & Acute Respiratory Infection (ARI)





- **Left:** Figure represents an inverted-U shape, the fever risk attained highest at age 10 months at infancy, and the risk deceases steadily soon after as the child grows older

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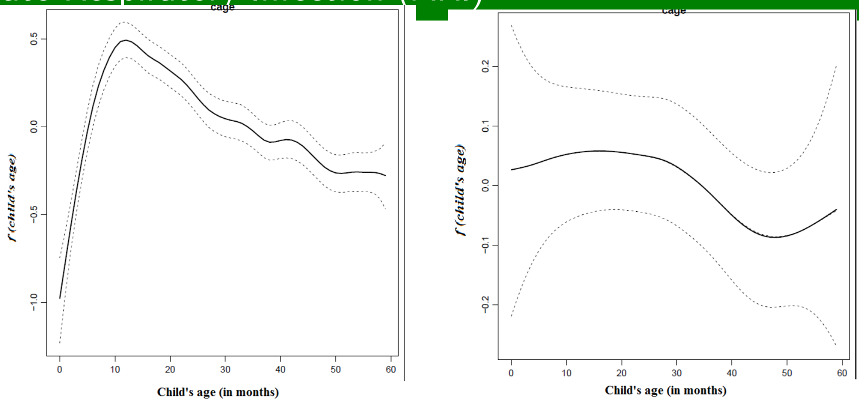
Non-linear Plots of effects of Child age on the risk fever & Acute Respiratory Infection (ARI)



- **Left:** Figure represents an inverted-U shape, the fever risk attained highest at age 10 months at infancy, and the risk deceases steadily soon after as the child grows older
- **Right :** Respiratory Infection resembles a flipped S-shape, the it attains lowest predicted risk at child age 4.25 years(50 months) old

- In the present study, the maps showed the estimated smooth geographical variation of specific-district(state) effects, after controlling for other covariates.
- These maps represent other risk factors not directly observed, but had an impact on the risk of infant mortality risk and childhood disease morbidity.
- These residual spatial plots might probably be related to ecological factors, such as varying deprivation inequalities including severity and depth of poverty
- Childhood infectious diseases including malaria, HIV/ AIDs, pneumonia, diarrhoea and malnutrition are directly contributed to the risk of child mortality [1].
- Unobserved contextual and Environmental factors often contributed to geographic inequality in the mortality and morbidity prevalence depicting spatial dependence.

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SUMMARY POINTS

LESSONS LEARNED

In the present study;

- The risk factors presented in the Tables posterior odd ratios can be used to formulate policy intervention for specific- individual needs, household or community.
- The smooth curves of the risk provide tools for epidemiologists and health practitioners to monitor critical point in the life of the child
- The predictive of maps of "hot spot " regions, which can assist government and developing partners to channel scarce health resource in an effective manner.

Concluding Remarks

- In this work, we have explored a flexible and robust approach to investigate the influence of different kinds of covariates on the child's health status in Nigeria.
- Our method tackles small area estimation of specific district(state) effects, which would have been ignored in classical regression regression due to the spatial correlation in the regions.
- The findings can guide in evidence-based allocation of scarce health resources in the sub-region with the aim of improving the chance of child survival.
- Multivariate analysis revealed the risk factors such like non-antenatal attendance, multiple birth, short birth intervals, low maternal education, and poor sanitation were associated with infant mortality and childhood morbidity.

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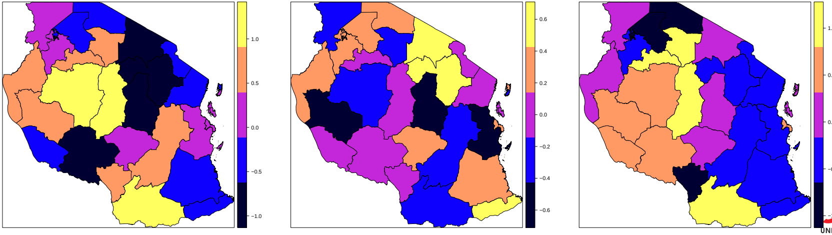
Tanzania 2010 DHS

Spatial Modeling of anemia , Stunting and Wasting

Using the propose approach, we performed spatial mapping the prevalence of acute malnutrition among under-children in Tanzania.
We estimated the risk of the Anemia, stunting and wasting jointly from 2010 Tanzania DHS data.



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Research work in progress

Project Topic: Spatial Analysis of poverty, malnutrition and mortality among under-five children in Sub-Saharan Africa

- Semi-parametric Multinomial ordinal model to analyze spatial patterns of child birth weight in Nigeria; **Published** : *Inter. Journal of Environmental Res. and Public Heath.2016*
- Bayesian Spatial Modeling of risk of childhood anemia in Tanzania; **Published** : *Proceeding of 58th Annual Conference of South African Statistical Association SASA2016 : Held at University of Cape Town, South Africa: ISBN 978-1-86822-682-5*
- Multivariate Joint Spatial Modeling of childhood anemia and Acute Malnutrition in Sub-Saharan Africa: A cross sectional survey of geographic inequalities of Ghana, Burkina Faso, Mozambique and Tanzania **Under-review**: *PLOS ONE*
- Spatial Modeling of Birthweight and Bio-Social determinants of Childhood Mortality in Nigeria: **Under-review**: *Jour. of Economics & Behavioural Studies*
- Bayesian Joint modeling of Disease Co-morbidity among under five children in Nigeria and Tanzania; *UKZN College Research Day: Postgraduate Presentation 2016.*
- Does a geographical contextual factor determine regional variations in child underweight in Sub-Saharan Africa?: Case study of DHS data from Nigeria, Ghana, Ethiopia, Tanzania, Mozambique *Work in progress*

Shell Petroleum Oil pipelines in the Niger Delta Regions of Nigeria

- (a) Shell Petroleum pipelines transverse through a village in the Niger Delta region of Nigeria
- (b) A staff of Shell Cooperation at work to identify a fault of oil spillage

Rural Village Settlement in Northern Regions of Nigeria

- (a) Farm settlement in Northern Regions of Nigeria
- (b) Youngsters playing Snooker at a village square in Northern Nigeria
- This is an indicative of connectedness that inter-plays between Poverty, Ecology, Public Health and insecurity in the region

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Thank you.