BAYESIAN MODELLING AND MAPPING OF HEALTH OUTCOMES IN SPACE AND TIME USING COMPLEX NATIONAL SURVEYS

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BAYESIAN MODELLING AND MAPPING OF HEALTH OUTCOMES IN SPACE AND TIME USING COMPLEX NATIONAL SURVEYS

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To My Wife

Taiwo Mayowa Atilola (Nee Randle)

Abstract

Significance of the thesis

Nationally representative surveys have played a central role in generating relevant data for monitoring and evaluation of health outcomes over the past four decades. In such surveys, individuals within households, are nested within geographically referenced units, and sampled with unequal probabilities over time. This allows subnational and small area analyses to be carried out and trend estimation to be done locally. More importantly, population determinants of health outcomes can be evaluated in a manner that accounts for the complexity of the sampling design, geographic variation, and subnational trends within a unified generalized linear additive mixed regression modelling framework. Efforts to acknowledge and account for such complex sampling design features ensure improved estimation of risk factors and small area estimation of trends. We propose two novel statistical frameworks to address these two important challenges: 1) The Proximate Determinants Framework to evaluate female genital mutilation risk factors embedded within a hierarchical Bayesian SpatioTemporal STructured Additive mixed Regression (PDF/ST-STAR) using nationally representative household surveys; 2) The repeated measurement hierarchical Bayesian linear mixed effect model (RM-LMM) for small area estimation of local trends in health outcomes using nationally representative longitudinal survey data.

How the Research was undertaken

The study assessed five research questions: 1) What factors, operating at individual and community levels, explain observed prevalence trends in female genital mutilation/cutting (FGM/C) among girls in Kenya, Nigeria, and Senegal between a specific period? 2) Does accounting for excess variability in FGM/C prevalence risk due to unmeasured risk factors interacting in space and time lead to observable changes in risk factor estimates? 3) Does accounting for the complex sampling design feature inherent in Demographic and Health surveys result in observable changes in the effect size of risk factor estimates? 4) Was there any significant overall change in the average systolic blood pressure among South African adults aged 18 years and older between 2008 and 2017? 5) Was there any observable geographic variation in average systolic blood pressure (SBP) among South African adults

aged 18 years and older at small area (district municipality) level in 2008, 2010, 2012, 2014/15 and 2017?

Statistical Methodology

The study utilized two sources of nationally representative survey data to address the research questions. For the FGM/C study, we utilized the Demographic and Health survey (DHS) data on girls and their mothers collected cross-sectionally across three time points between a specific period in 3 African countries – Kenya DHS (2003, 2008, 2014), Nigeria DHS (2008, 2013, 2018), and Senegal DHS (2010, 2015, 2017). For the small area estimation study on systolic blood pressure, we considered the South African National Income Dynamics Survey (NIDS) data collected, on average, every two years across 5 time points between 2008 and 2017.

For the FGM/C risk factor study, we investigated changes to the observable influence of risk factors on FGM/C likelihood among girls in Kenya, Nigeria, and Senegal between a specific period. We evaluated changes to risk factor estimates after accounting for the complex sampling design features of the DHS data separately, namely, stratification and clustering, within a non-separable hierarchical Bayesian spatiotemporal generalized additive mixed regression model framework. To account for non-separable influence of geography and time in the model framework, we decomposed the total space-time variability in FGM/C prevalence risk into - a main spatial effect, a main linear temporal effect, and a space-time interaction term. We considered four types of prior specifications to model the space-time interaction term as proposed by Knorr-Held to evaluate excess variability in space and time. All analyses were implemented using the Integrated Nested Laplace Approximation (INLA) within the R programming environment using the R-INLA package. Model comparison and performance evaluation were carried out using deviance information criterion (DIC) and Watanabe information criterion (WAIC). Predictive performance of the best fitting model was assessed using the logarithm of the conditional predictive ordinate(logCPO) at the individual level and the root mean squared error (RMSE) at state/regional level.

For the small area estimation of SBP study, we implemented the direct (design-based) estimation method, the spatially smoothed designed-based estimation method within a hierarchical Bayesian framework, and the newly proposed repeated measurement hierarchical Bayesian linear mixed effect model (RM-BLMM) formulation. The first two considered cross-

sectional analysis of the NIDS survey data as a representative sample of the South African adult population at each time point with sample obtained across the 52 small areas (districts municipalities) for all five waves (2008, 2010, 2012, 2015 and 2017). Spatial smoothing was achieved by decomposing the overall effect into spatially structured random effects and spatially unstructured effects and a penalized complexity prior. The proposed RM-BLMM formulation, however, addressed three important limitations of the design-based estimators, namely, repeated measurement of SBP at each wave for every survey participant, the longitudinal design features of the NIDS survey and the problem of extremely small sample size at spatially disaggregated level. Statistical analysis was implemented using Markov Chain Monte Carlo simulation techniques using Gibb's sampling inferential algorithm over 80,000 MCMC iterations thinning every 10th iteration to ensure convergence and efficiency of the MCMC samples. Convergence was attained after the first 5000 iterations and were discarded as burn-in while the remaining 75,000 samples were utilized for posterior inference. Convergence was by checking the trace plots of the samples, the autocorrelation functions, the estimated kernel density plots, the Brooks-Gelman-Rubin (BGR) summary statistic and a Monte Carlo errors <5% of the posterior standard deviation. Model evaluation was carried out by comparing the model-based predicted mean trajectory to the observed data values. Model-based small area prediction was carried out using posterior means and variance of estimated model parameters. Computation of standard error of small area mean estimates and 95% confidence interval was conducted using a parametric bootstrap sample procedure over 50 simulations.

Main Research Findings

We found significant decline in the probability of FGM/C among girls 0-14 years in Kenya between the period 2003 and 2014 (Mean: -1.47, 95%CI: -1.85, -1.10). In contrast, prevalence trend remained unchanged in Nigeria for the period 2008 to 2018 (Mean: 0.38, 95%CI: -0.11, 0.88) and in Senegal for the period 2010 to 2017 (Mean: 0.16, 95%CI: -0.15, 0.46).

At the individual level, we observed a positive relationship between a mother's FGM/C history (Kenya, Nigeria, Senegal), her support for continuation of the practice (Nigeria and Senegal), household decision making by Father (Kenya) and jointly by Father and Mother (Nigeria), wife justification of beating for sex refusal (Senegal), religious affiliation (Kenya, Nigeria), Marital status (Nigeria), Ethnicity (Kenya and Nigeria), and a girl's likelihood of undergoing FGM/C

between each specific study period. At the contextual (community) level, we found substantial evidence for a positive relationship between prevalence of FGM/C among mothers, proportion that supported FGM/C continuation and to a lesser extent proportion that believed FGM/C was a religious requirement, and the probability of FGM/C in a girl in Nigeria and Senegal. All risk factor models showed substantial improvement in predictive performance after accounting for Type I space-time interaction effect and cluster sampling DHS design across the three countries. Notable changes were observed in risk factors, especially in Nigeria. In addition, the study demonstrated for the first time, that accounting for the effects of contextual factors operating at community level and excess variability due to cluster sampling, substantially reduced spatially structured unobserved risk factor effects at state/regional level.

For the small area estimation study, we found evidence of significant decline in the overall average SBP among South African adults between 2008 and 2017. Findings from the spatially smoothed design-based estimator showed significant geographic variations in average SBP at district level for each consecutive cross-sectional time point of the NIDS samples. Results showed preponderance of areas with elevated SBP in the southern districts in 2008, 2010, 2012, 2014/2015 and 2017 (such as Overberg, Central Kaaro, West Cape) and cluster of areas with low mean SBP in northern part of the country. Findings showed overall reduction across all districts from 2008 to 2017 with greatest reduction observed in Frances Baard and Pixley ka Seme in Northern Cape Province, Uthukela and Umzinyathi in Kwazulu-Natal Province, Nkangala in Mpumalanga Province, and Sedibeng in Gauteng Province. However, the study only obtained preliminary results for the RM-BLMM with the assumption of a random intercept but a common trajectory in SBP progression for all survey participants with at least one SBP measurement time point. The model predicted the observed data well given the observed small change in mean for majority of participants between the study period. Future work needs to extend the proposed framework to more complex model formulations.

Why Research findings matter

Study findings demonstrate that social normative influences operating within specific normative ecological contexts at individual, household and community levels are the most important drivers of FGM/C prevalence at a single time point and persistence over time. This conclusion was supported by the reduced impact of social norms in Kenya where a significant decline in the practice was observed between 2003 and 2014. The PDF/ST-STAR framework

approach to modelling FGM/C likelihood showed evidence of observable changes in risk factor effect size estimates after accounting for cluster sampling design across the three countries and excess variability due to unobserved risk factors operating concurrently in specific region and specific time point. Evidence from the small area estimation study provides adequate insight to evaluate district level geographic pattern in the distribution of average SBP among South African adults in 2008, 2010, 2012, 2014/2015 and 2017 along with spatially smoothed interval estimates. More importantly, the RM-BLMM model-based framework provides an important and innovative contribution to existing small area estimation statistical methodologies for longitudinal survey data.

Table of Contents

Abstract 4
Table of Contents 9
List of Tables 13
List of Figures 15
List of Abbreviations 18
Acknowledgements 19
Declaration 21
PUBLISHED WORK 22
CHAPTER ONE 24
INTRODUCTION 24
1.1 Motivation for the study 24
1.2 Approaches to Modelling FGM/C risk factors using Complex Survey Data 25
1.3 Small Area Estimation Methods for Complex Survey Data 33
1.3.1. Direct Estimation Approaches 34
1.3.2. Model-based Estimation Approaches 36
1.4. Methodological Challenges 42
1.5. Research Questions and Study Objectives 44
1.6. Study Hypotheses 46
CHAPTER TWO 48
BACKGROUND TO THE STUDY 48
2.1. Background to the Female Genital Mutilation Study 48
2.2. Existing Theories and Framework to explain FGM/C Persistence 49
2.2.1. Social Norms and Conventions 50
2.2.2. Religious Norms 51
2.2.3. Gender Norms 51
2.2.4. Modernization Theory 51
2.2.5. Feminist Theory 52
2.2.6. Women Agency 52
2.2.7. Women's Constraints and Opportunities 53
2.2.8. Social Determinants of Health 53
2.2.9. Geographic Location 53
2.2.10. Media Exposure 54
2.2.11. Feminist social integrated theory 54

2.3. Existing Frameworks to explain FGM/C risk Factors 54
2.3.1. The Integrated Theoretic Framework 55
2.4. Limitations of Existing FGM/C Frameworks 57
2.5. The Proposed FGM/C Proximate Determinants Framework 58
2.6. Background to the Blood Pressure Study 60
CHAPTER THREE 62
PREVIOUS WORK ON FGM/C RISK FACTOR MODELLING 62
3.1. Summary of Methods and Findings 62
3.2. Introduction 63
3.2.1. The Theory behind Normative Influences on FGM/C 63
3.3. Methods 65
3.3.1. Data 65
3.3.2. Study Variables 66
3.3.3. Statistical Analysis 67
3.3.4. Notation and Model Specification 67
3.4. Results 71
3.4.1. Descriptive Analysis 71
3.4.2. Regional distribution of FGM/C Prevalence from 2003 to 2014 72
3.4.3. Bayesian hierarchical geo-additive Logistic Regression 73
3.5. Discussion 79
3.6. Study Limitations 80
3.7. Methodological Limitations of the study that provided the basis and justification for the present work 80
CHAPTER FOUR 82
METHODOLOGY FOR THE FEMALE GENITAL MUTILATION/CUTTING STUDY 82
4.1. Description of Survey Sample Data 83
4.2. Study Variables 87
4.2.1. Outcome Variable 87
4.2.2. Exposure Variables 87
4.3. Limitations of DHS Data on FGM/C 89
4.4. Working Statistical definition of Complex Survey Design 90
4.5. Preliminary Analysis 92
4.5.1. Descriptive Analysis 92
4.5.2. Exploratory Spatial Analysis 92
4.5.3. Assessment of Nonlinear Trends 96

4.6. Limitations of Existing Approaches for Modelling FGM/C using Complex Surveys in non-separable Space and Time 99

4.7. Bayesian inference for Latent Gaussian Models using Integrated Nested Laplace Approximation (INLA) 100

4.8. Statistical Modelling Framework and Model Formulation 102

4.8.1. Model 1 – Model with individual level Covariates only 102

4.8.2. Model 2 – Model with individual and community level covariates 104

4.8.3. Model 3 – Model with individual and community level covariates and residual main spatial effect, main temporal effect, and spacetime interaction effect 105

4.8.4. Model 4 – Model with individual and community level covariates, and residual main spatial effect, main temporal effect, spacetime interaction effect and stratification design effect 116

4.8.5. Model 5 – Model with individual and community level covariates, and residual main spatial effect, main temporal effect, spacetime interaction effect and cluster design effect 116

4.9. Model Assessment and Prediction Accuracy 119

CHAPTER FIVE 123

RESULTS AND DISCUSSION FOR THE FEMALE GENITAL MUTILATION/CUTTING STUDY 123

5.1. Introduction 123

5.2. Descriptive Analysis 123

5.3. Geography of FGM/C prevalence by country and survey year 132

5.4. Spatiotemporal analysis of FGM/C risk factors 134

5.4.1. FGM/C risk factors in Kenya 134

5.4.2. FGM/C risk factors in Nigeria 138

5.4.3. FGM/C risk factors in Senegal 141

5.5. Evaluating the impact of modeling complex survey design features on risk factor estimates 144

5.6. Geographic variation in residual FGM/C risk 146

5.7. Non-separable spatiotemporal interaction in residual FGM/C risk 149

5.8. Effects of continuous covariates 151

5.8.1. Individual level covariates 151

5.8.2. Community level covariates 151

5.9. Evaluation of model performance 152

5.10. Discussion 154

CHAPTER SIX 163

SMALL AREA ESTIMATION OF SYSTOLIC BLOOD PRESSURE AMONG SOUTH AFRICAN ADULT POPULATION USING CROSS-SECTIONAL AND LONGITUDINAL SURVEY DATA 163

6.1. Introduction 163
6.2. Methodology 168
6.2.1. Description of the National Income Dynamic survey (NIDS) 169
6.2.2. Sample weights calculation in NIDS survey data 172
6.2.3. Statistical methods 175
6.2.4. Parameter estimation for the RM-LMM 182
6.2.5. Prediction of Small Area Average Systolic Blood Pressure (SBP) 184
6.2.6. Computation of Predicted intervals using Bootstrap Simulation 186
6.3. Results 186
6.3.1. Results of hierarchical Bayesian Linear Mixed Model 186
6.3.2. Comparison of SAE for Direct, Design-based, Smooth-Direct and RM-LMM 187
6.3.3. Comparison of Geographic pattern of small area Mean for Design-based and Spatially smoothed design-based Estimators 189
6.4. Discussion 192
CHAPTER SEVEN 195
CONCLUSION AND FUTURE WORK 195
7.1. Introduction 195
7.2. Conclusions and Policy implications of FGM/C study 196
7.3. Conclusions and Policy implications of SBP study 200
7.4. Our contribution to the field of survey methodology 202
7.5. Our contribution to the field of Public health 202
7.6. Recommendations for statistical methodology for survey data 203
7.7. Future work for FGM/C study 203
7.8. Future work for Blood Pressure study 204
REFERENCES 206
APPENDICES 228
Appendix A3. Results Tables for Chapter 3 228
Appendix A4. Results Tables for Chapter 4 241
Appendix A5. Results Tables for Chapter 5 242
Appendix A6. Results Tables for Chapter 6 246

List of Tables

Table 2.1. Summary of FGM/C Theories and Frameworks.....56

Table 3.1. National prevalence and girl's female genital mutilation/cutting (FGM/C) prevalence by normative influence variables across the four selected Demographic and Health Surveys (DHS) surveys in Kenya, Kenya Demographic and Health Surveys (KDHS) 1998 to 2014.....72

Table 3.2. Deviance information criterion (DIC), Effective sample size (pD) and mean deviance (Dbar) from the three models fitted on the 2014 KDHS data and the combined 2003 to 2014 data. ...74

Table 4.1. Total number of samples (girls aged 0-14 years) and clusters by region and survey year for Kenya.....84

Table 4.2. Total number of samples (girls aged 0-14 years) and clusters by region and survey year for Nigeria. 85

Table 4.3. Total number of samples (girls aged 0-9 years) and clusters by region and survey year for Senegal.....86

Table 4.4. Description of study variables by the FGM/C Proximate Determinants Framework. 88

Table 4.5. First order rook contiguity matrix for Kenya with eight (8) administrative regions.....94

Table 4.6. Summary of Spatial model formulation evaluated for the area random effect. 112

Table 4.7. Summary of the four types of space-time interaction specification evaluated. 115

Table 4.8. Summary of Model specification for Kenya, Nigeria and Senegal. 118

Table 5.1. National prevalence of female genital mutilation/cutting (FGM/C) among girls 0-14 years born to women 15 to 49 years who have heard of FGM/C and prevalence by study variables across the three selected Demographic and Health Surveys (DHS) surveys in Kenya. 126

Table 5.2. National prevalence of female genital mutilation/cutting (FGM/C) among girls 0-14 years born to women 15 to 29 years who have heard of FGM/C and prevalence by study variables across the three selected Demographic and Health Surveys (DHS) surveys in Nigeria.....128

Table 5.3. National prevalence of female genital mutilation/cutting (FGM/C) among girls 0-9 years born to women 15 to 35 years who have heard of FGM/C and prevalence by study variables across the three selected Demographic and Health Surveys (DHS) surveys in Senegal. 130

Table 5.4. DIC comparison for Bayesian models by Country. 135

Table 5.5. Posterior odds ratios (POR) and associated 95% credible interval (CI) from the Hierarchical Bayes space-time generalized additive mixed Models of FGM/C among Girls ages 0–14 years across exposure covariates in Kenya (for the 2003, 2008 and 2014 combined survey data). ...136

Table 5.6. Posterior odds ratios (POR) and associated 95% credible interval (CI) from the Hierarchical Bayes space-time generalized additive mixed Models of FGM/C likelihood among Girls ages 0–14 years across exposure covariates in Nigeria (for the 2008, 2013 and 2018 combined survey data). 140

Table 5.7. Posterior odds ratios (POR) and associated 95% credible interval (CI) from the Hierarchical Bayes space-time generalized additive mixed Models of FGM/C likelihood among Girls ages 0–9 years across exposure covariates in Senegal (for the 2010, 2015 and 2017 combined survey data). 143

Table 6.1. Summary of average distribution of households per cluster by Wave.....170

Table 6.2. Comparing the distribution of the PSUs per province 171

Table 6.3. Reasons for Attrition. 172

Table 6.4. Summary of Sample size and Coverage by Wave for the 52 Districts. 174

Table A3.1. Characteristics surrounding Female Genital Mutilation/Cutting among Kenyan Girls aged 0-14yrs from 1998 to 2014. 228

Table A3.2. Unadjusted and adjusted posterior odds ratios (POR) and associated 95% credible regions of circumcision of Girls ages 0-14 across selected covariates (Kenya, DHS 2014) from Bayesian Geo-additive Models. 235

Table A3.3. Unadjusted and adjusted posterior odds ratios (POR) and associated 95% credible region (CR) of circumcision of Girls ages 0-14 across selected covariates (Kenya, DHS 2003-2014 combined) from Bayesian Geo-additive Models. 239

Table A4.1. Comparison of the queen and rook first order contiguity matrix for modeling spatial dependence using the proper Besag model. 241

Table A5.1. Model hyperparameters for Kenya study: posterior median and 95% credible intervals for the estimated marginals of the precisions of the prior variances of age of mother - τm, age of girl - τg, proportion of mothers cut within community - τp1, non-unstructured spatial effects - τv, structured spatial effects - τu, nonlinear temporal effects - τt, and space-time interaction effect -τst, and cluster design effect -τc. 242

Table A5.2. Model hyperparameters for Nigeria study: posterior median and 95% credible intervals for the estimated marginals of the precisions of the prior variances of age of mother - τm, age of girl - τg, proportion of mothers cut within community - τp1, proportion of mothers that supported FGM continuation within community - τp2, proportion of mothers that cut for religious reasons within community - τp3, non-unstructured spatial effects - τv, structured spatial effects - τu, nonlinear temporal effects - τt, space-time interaction effect -τst, and cluster design effect -τc. 242

Table A5.3. Model hyperparameters for Senegal study: posterior median and 95% credible intervals for the estimated marginals of the precisions of the prior variances of age of mother - τm, age of girl - τg, proportion of mothers cut within community - τp1, proportion of mothers that supported FGM continuation within community - τp1, proportion of mothers that cut for religious reasons within community - τp3, non-unstructured spatial effects - τv, structured spatial effects - τu, nonlinear temporal effects - τt, space-time interaction effect -τst, and cluster design effect -τc. 243

Table A5.4. Observed versus predicted for Kenya and Measures of fit. 244

Table A5.5. Observed versus predicted for Nigeria and Measures of fit. 244

Table A5.6. Observed versus predicted for Senegal and Measures of fit. 245

Table A6.1. Small area estimates of systolic blood pressure (SBP) in South African adults from the observed data (unadjusted for weights). 246

Table A6.2. Design-based estimates of systolic blood pressure (SBP) in South African adults. 248

Table A6.3. Spatially-Smoothed Direct estimates of systolic blood pressure (SBP) in South African adults. 250

Table A6.4. Small Area Mean estimates of systolic blood pressure (SBP) in South African adults from the double measurements hierarchical Bayes linear mixed model with random intercept. 252

List of Figures

Figure 2.1. Proximate Determinants socio-ecological framework for Female Genital Mutilation among Girls aged 0-14 years in Sub-Saharan Africa 59

Figure 3.1. Map of Kenya showing the eight administrative regions. 65

Figure 3.2. Evolution of FGM/C prevalence among 0-14 years old girls in Kenya from 1998 to 2014. Note that in 1998, there were no surveys in the North Eastern region hence the black-white stripes. Across the years, red regions had highest prevalence which decreased in magnitude as it fades through red to deep blue. 72

Figure 3.3. Non-linear effects of the proportions of women in a girl's community who were cut(blue), who supported the continuation of FGM/C (orange), and who believed that FGM/C was a religious obligation for (a) Model A, (b) Model B and (c) Model C. Evidence from the 2014 KDHS. 75

Figure 3.4. Posterior risk maps [(a) and (c)] of Kenyan 0-14 years old-girls' FGM/C with the corresponding 95% (right) [(b) and (d)] posterior significance maps for Model B (left panel) and Model C (right panel). Deep blue to red corresponds to low risk to high risk. Black colour indicates significantly high-risk regions, white colour indicates significantly low risk regions and grey colour indicates nonsignificant regions. 75

Figure 3.5. Non-linear effects on a girl's likelihood of experiencing FGM/C of mother's age (a); girl's age (b) and ethnic fractionalization index (EFI) (c). Evidence from the 2014 KDHS Model C. 76

Figure 3.6. Posterior risk maps ((a) and ((c)) of Kenyan 0-14 years old girls' FGM/C with the corresponding 95% (right (b) and (d)) posterior significance maps for Model II (left panel) and Model III (right panel). Deep blue to red corresponds to low risk to high risk. Black colour in (b) and (d) indicates significantly high-risk regions, white colour indicates significantly low risk regions and grey colour indicates nonsignificant regions. Evidence from the pooled 2003 to 2014 KDHS. 77

Figure 3.7. Predicted fully adjusted FGM/C prevalence among 0-14 years old girls in Kenya from 2003 to 2014 from the best fit model (Model III) of the pooled 2003 to 2014 data. Across the years, red regions had highest prevalence, while deep blue regions had lowest prevalence. 78

Figure 3.8. Time trend (left panel) and non-linear effect of mother's age (right panel). Evidence from the KDHS 2003 to 2014 pooled data Model III. 78

Figure 4.1. Neighborhood structure and Global Moran's I statistics by Country. 96

Figure 4.2. Exploratory nonlinear trend in Age of mother (top left panel), Age of girl (top right panel) and proportion of mothers cut within community (bottom panel) in Kenya from DHS 2003, 2008 and 2014. 97

Figure 4.3. Exploratory nonlinear trend in Age of mother (top left panel), Age of girl (top right panel), proportion of mothers cut (middle left panel), proportion of mothers that support continuation of FGM (middle right panel) and proportion of mothers that cut daughters for religious reasons(bottom) within community in Nigeria from the DHS 2008, 2013 and 2018. 98

Figure 4.4. Exploratory nonlinear trend in Age of mother (top left panel), Age of girl (top right panel), proportion of mothers cut (middle left panel), proportion of mothers that support continuation of FGM (middle right panel) and proportion of mothers that cut daughters for religious reasons(bottom panel) within community in Senegal from the DHS 2010, 2015 and 2017. 99

Figure 5.1. Map of Kenya showing the eight (8) Administrative regions. 124

Figure 5.2. Map of Senegal showing the 14 Administrative regions. 125

Figure 5.3. Map of Nigeria showing the 36 Administrative States and the Federal Capital Territory (FCT). 125

Figure 5.4. Geographic distribution of observed FGM/C prevalence risk among girls in Kenya (top panel), Nigeria (middle panel) and Senegal (bottom panel) for each survey year under study. Highest observed prevalence estimates are denoted by green color while lowest observed prevalence estimates are denoted by yellow colour. 133

Figure 5.5. Residual main spatial and spacetime interaction for Bayesian hierarchical spatiotemporal model of FGM among Kenyan girls 0-14 years born to women 15 to 49 years, between 2003 and 2014. 147

Figure 5.6. Residual main spatial and spacetime interaction for Bayesian hierarchical spatiotemporal model of FGM among Nigerian girls 0-14 years born to women 15 to 29 years, between 2008 and 2018. 148

Figure 5.7. Residual main spatial and spacetime interaction for Bayesian hierarchical spatiotemporal model of FGM among Senegalese girls 0-9 years born to women 15 to 35 years between 2010 and 2017. 149

Figure 5.8. Effects of Mother's and Girls' Age on FGM/C likelihood in Girl by country. 151

Figure 5.9. Effects of social normative influences operating at community level on FGM/C likelihood in a Girl by country. 152

Figure 5.10. Comparison of observed and predicted FGM/C prevalence risk by country 153

Figure 6.1. Geographic distribution of the 52 District Municipalities in South Africa by Province. . 173

Figure 6.2. Boxplot Distribution of Sample size for the 52 Districts. 174

Figure 6.3. Boxplot Distribution of the Coverage for the 52 Districts. 174

Figure 6.4. A comparison of the Predicted average Systolic Blood Pressure to the Observed data by NIDS Wave. 183

Figure 6.5. Observed Trajectory for the first 50 individuals in the sampled population. 183

Figure 6.6. Predicted Trajectory for the first 50 individuals in the sampled population. 184

Figure 6.7. Local trend plots of average systolic blood pressure in South African Adults for the 52 districts from the observed, direct, smoothed direct and HB random intercept linear mixed double measurement model. 189

Figure 6.8. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially-smoothed direct estimates for the 2008 NIDS Wave. 190

Figure 6.9. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially-smoothed direct estimates for the 2010 NIDS Wave. 191

Figure 6.10. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially-smoothed direct estimates for the 2012 NIDS Wave. 191

Figure 6.11. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially-smoothed direct estimates for the 2014/15 NIDS Wave. 192

Figure 6.12. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially-smoothed direct estimates for the 2017 NIDS Wave. 192

Figure A5.1. A plot of Observed versus Predicted prevalence risk for the best Bayesian model by country. 246

List of Abbreviations

BYM – Besag York Mollie model

DHS – Demographic and Health Survey

DIC – Deviance Information Criterion

FGM/C – Female Genital Mutilation/Cutting

HB – Hierarchical Bayes

KDHS – Kenya Demographic and Health Survey

LogCPO – Logarithm of the Conditional Predictive Ordinate

MCMC – Markov Chain Monte Carlo

NDHS – Nigeria Demographic and Health Survey

NIDS – National Income Dynamics Survey

PC-Prior – Penalized Complexity - Prior

PDF – Proximate Determinants Framework

PDF/ST-STAR – Proximate Determinants Framework/Spatial-Temporal STructured Additive Regression

POR – Posterior Odds Ratio

RM-LMM – Repeated measurement Linear Mixed Model

RMSE – Root Mean Square Error

SAE – Small Area Estimation

SBP – Systolic Blood Pressure

SDHS – Senegal Demographic and Health Survey

STAR – Structured Additive Regression

UN – United Nation

UNICEF – United Nations International Children Education Fund

WAIC – Watanabe Information Criterion

WHO – World Health Organization

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To my Parents, thank you for your steadfast support throughout my PhD. Your parental love is second to none.

Declaration

I declare that the work contained in this thesis has not been submitted for any other award and that it is all my own work. I also confirm that this work fully acknowledges opinions, ideas and contributions from the work of others. Any ethical clearance for the research presented in this thesis has been approved. Approval has been sought and granted by the Engineering & Environment Faculty Ethics Committee on 25/09/2017.

I declare that the word count of this Thesis is 55,642 words

Name: Glory O. Atilola

Signature: …….

Date: May 26, 2021

PUBLISHED WORK

Here, we discuss briefly highlights of published work that provided the basis for the research work presented in the thesis. The published work pertains to the first part of the research, namely the need for more reliable estimation of risk factor and determinants of female genital mutilation/cutting (FGM/C) among girls in space and time using complex survey designs. Here, we present two publications on spatial and spatiotemporal modelling of FGM/C among girls in Kenya and Nigeria (Kandala et al., 2019; Nnanatu et al., 2021). Both studies were undertaken as component of the "Evidence to End FGM/C: Research to help Women and Girls thrive" project, a Population Council-led consortium undertaken between 2018 and 2020 at Northumbria University. Detailed discussion on the methodological approaches utilized in both studies are summarized in chapter one and chapter three of the thesis. The overall objective of the current work on FGM/C is to address the methodological limitations of both studies and to provide a generalized framework to estimate risk factors, model and map geographic and temporal trends using complex surveys. Both papers are presented below.

Paper One

Kandala, N. B., Nnanatu, C. C., Atilola, G., Komba, P., Mavatikua, L., Moore, Z., Mackie, G., & Shell-Duncan, B. (2019). A Spatial Analysis of the Prevalence of Female Genital Mutilation/Cutting among 0-14-Year-Old Girls in Kenya.

Paper Two

Nnanatu CC, Atilola G, Komba P, Mavatikua L, Moore Z, Matanda D, et al. (2021) Evaluating changes in the prevalence of female genital mutilation/cutting among 0-14 years old girls in Nigeria using data from multiple surveys: A novel Bayesian hierarchical spatio-temporal model.

As a lead analyst and statistician on the project, I was responsible for retrieval, processing, and management of all secondary datasets utilized for both the descriptive and advanced statistical modeling and mapping of FGM/C in the project. In addition, I was responsible for descriptive analysis phase of the project required to understand bivariate association between FGM/C outcomes and various covariates, including geographic variation in FGM/C prevalence outcomes and trend mapping over time in Kenya (2003 to 2014), Nigeria (2003 to 2013) and Senegal (2010 to 2017). In addition, I contributed to discussion regarding statistical

formulations for the spatial and spatiotemporal models for FGM/C and implementation, evaluation, and interpretation of these models in the R statistical programming environment. I also made significant contribution to the preliminary and final manuscripts.

CHAPTER ONE

INTRODUCTION

1.1 Motivation for the study

Nationally representative surveys have played an important role in generating relevant data for monitoring and evaluation of health outcomes, notably since the early 1990s following the revolution in statistical computing. In such surveys, individuals, nested within georeferenced units are often sampled with unequal probabilities from a target population of interest; thus, inducing complexity in the structure of the survey data. National survey data have two features that make them particularly attractive to the modern statistical community. First, data are usually collected at individual-level by random selection of a representative units based on a predefined sampling design. Second, data are collected across geographically referenced units, and often repeatedly over time. These two features, combined, ensure that health outcome data and risk factors can be evaluated at individual level in a manner that quantifies the influence of geography, time, and the complex sampling design of the survey within a coherent statistical framework. This approach to modelling national survey data; motivated by the need for reliable estimation of risk factor effects on health outcomes, is currently lacking in the literature as reviewed in subsequent sections below. More so, little research work has been undertaken till date to develop small area estimation methodologies that account for the complexity often inherent in most nationally representative cross-sectional and longitudinal surveys. Therefore, the overall objective of the present work is to address these two methodological issues in two separate contexts. The first area of application seeks to identify important individual and community level predictors of female genital mutilation (FGM/C) likelihood in three African countries namely, Kenya, Nigeria and Senegal using Demographic and Health cross-sectional Surveys (DHS). The second area of application is the small area estimation of average systolic blood pressure (SBP) and local trends among South African adults using the National Income Dynamics Surveys (NIDS) with a cross-sectional and longitudinal sampling design.

1.2 Approaches to Modelling FGM/C risk factors using Complex Survey Data

Various statistical approaches have been utilized by various investigators to evaluate risk factors of FGM/C. This include conventional logistic regression models without random effect (Karmaker et al., 2011; Sakeah et al., 2018) and multilevel discrete time hazard model (Grose et al., 2019). The discrete time hazard model formulation was extensively employed by Yount and colleagues to test the feminist integrated theoretical framework in six African countries (Grose et al., 2019; Hayford et al., 2020; Yount et al., 2020).

The multilevel discrete hazard model presented by Yount and colleagues estimated the association of macro-level factors (community context) and individual-level variables (mother/daughter) with a girl's age-risk-set hazard of experiencing FGM/C using DHS complex sample. This class of model was first proposed by Barber et al. (2000) to address the problem of bias in hypothesis testing often associated with estimating hazard baseline function that fails to acknowledge the multilevel data structure of the complex survey in the statistical model framework.

A primary justification for such innovative sociological models is the need for estimation procedures for multilevel models of social behavior that account for the hierarchical data structure inherent in complex survey design (Barber et al., 2000). Therefore, in contrast to the classical statistical model assumption of independence of individual behavior, individuals within the same macro setting tend to behave more similarly than individuals from other settings. This emphasize the increasing influence and significance of neighborhood at finer levels of geographic interaction which must be accounted for within the statistical model formulation to improve estimation of change in individual-level risk behavior over time. Ignoring such multilevel data structures in a complex survey design setting also tend to increase the frequency of type 1 error rate (falsely rejecting the null hypothesis) (Barber et al., 2000).

In addition, accounting for the unobserved heterogeneity of the contexts as random intercepts within the hazard model statistical framework results in reduction in underestimation of the baseline hazard(Vaupel & Yashin, 1985). The greater the variability of the outcome across the macro context(s), the more appropriate the use of such multilevel models as observed in the case of a discrete FGM/C outcome. We describe the two-level discrete hazard formulation as presented in Yount et al.(2020) in equation 1 below:

$$\eta_{ijt} = \sum_{t}^{T} \gamma_t A_{ijt} + \gamma_F FGMC_{ij} + \gamma_N N_j + \gamma_O O_j + \gamma_{FN} FGMC_{ij} * N_j + \gamma_{FO} FGMC_{ij}, * O_j + u_j \quad (1.1)$$

where η_{ijt} is the predictor function for the conditional odds of a girl born to mother i in community j being cut at time t ($t =$ 0-1 years, 2-11 years, 12-16 years,17-20 years) given that she was not cut earlier; main exposure variables at individual and community level and their interactions; and random intercept community(cluster) -specific contribution u_j,which are assumed to have an independent and identically distributed error. $FGMC_{ij}$ denote the mother FGM/C attitudes and status, N_j is the community FGM/C social normative values (conventions and beliefs that govern rules of acceptable behavior within a specific community or people/ethnic group), and O_j the community extra-familiar opportunities for women. The γ_t identify the logit of baseline hazard A_{ijt} of cutting in a girl born to mother i in community j at time t for each age risk set. $\gamma_F, \gamma_N, \gamma_O, \gamma_{FN}$,and γ_{FO}, identify the effects associated with the exposures and their interactions. We note that the discrete hazard model formulation essentially treats time as a discrete factor by introducing one parameter γ_t for each possible age risks set.

More recently, structured additive regression (STAR) models have been considered for modelling FGM/C outcomes with the foray of statistical modelers into the FGM/C field. STAR models are a well-known class of flexible regression models with several applications across different fields of scientific inquiry and ever expanding presence in the field of global health and disease modelling (Kneib & Fahrmeir, 2006; Umlauf et al., 2015). STAR models provide a flexible framework for modelling nonlinear effects of continuous covariates, otherwise not possible within a generalized linear model framework (Lang & Brezger, 2004). The extensive application of this class of models have become attractive to investigators due to the remarkable flexibility of STAR models to describe a broad range of complex models (including spatial and temporal correlations) that are better able to capture existing variation in complex data in a realistic manner. Thus, improving the predictive performance of such models to forecast previously unknown information about a subpopulation, geographic location (small area) or future time point (Lang & Brezger, 2004).

STAR models, combined with the powerful Bayesian approach to statistical inference (itself made popular by breakthroughs in Markov Chain Monte Carlo (MCMC) simulation techniques in the field of Inferential Statistics), is therefore one of the most remarkable inventions in the late 20th century. We note two benefits of using the Bayesian approach to statistical inference.

First, all parameters (both fixed and random effects) are modelled as random with a prior distribution assigned to each parameter within the model framework. This ensures that inference is exact, and the full posterior conditional distribution of each parameter that can be obtained or sampled from using simulation techniques. Second, the hierarchical formulation of the model framework provides a means to capture varying degree of complexity inherent in modern data structures in a flexible manner, including, spatial, temporal, multilevel and longitudinal structures of national surveys. This gave applied researchers a wide range of options to collect increasingly more complex and realistic data and to analyse such data in a manner that better describes variability in the health or behavioural outcome of interest.

STAR models derived their name from a response variable with a distribution that belongs to the exponential family (e.g., a Normal, Binomial, or Poisson distribution) which depends on a set of covariates through a linear predictor η_i linked to a function of its mean with a link function $g(\mu_i)$ (e.g., Gaussian, logit or log respectively) (Kneib & Fahrmeir, 2006). A general formulation of the STAR is described in equation 2 below:

$$\eta_i = g(\mu_i) = f_1(\theta_{i1}) + f_2(\theta_{i2}), + \cdots + f_j(\theta_{ij}) + z'_i\boldsymbol{\beta} \tag{1.2}$$

Here,

- η_i denotes the linear predictor while i is the index for observations. $g(\mu_i)$ denotes the link function.
- The term f_j represents nonlinear (but not necessarily smooth) functions of continuous metric covariates denoted by θ_{ij} such as age and time, dependent and independent measures of spatial effects, and nonlinear temporal effects, among many other possible specifications. The use of the phrase "not necessarily smooth" implies that there are multiple nonlinear functions f_n which may be smoothed (with a dependent structure imposed on the smoothing parameters) or modelled simply as zero mean gaussian random variable.
- The vector of covariates z'_i was evaluated as fixed effects while $\boldsymbol{\beta}$ is the corresponding vector of unknown regression parameters.

The flexibility of STAR models within a Bayesian framework for modelling health outcome risk therefore implies that nonlinear effects of such covariates can be modelled using Bayesian penalized (P)splines or random walks while spatial dependence can be assumed to follow a Gaussian Markov Random Field prior (GMRF) (Lang & Brezger, 2004) as shown in subsequent chapters.

Over the past decade, the spatial and spatial-temporal formulations of the STAR class of models known as generalized linear additive regression models have been extensively employed to model FGM/C risk factors among women and girls in Africa (Achia, 2014; Kandala et al., 2009; Kandala & Shell-Duncan, 2019). More specifically, we note two recent FGM/C risk factor studies in which the researcher contributed to the model formulation and statistical analyses. The first study was conducted in Kenya (Kandala et al., 2019) with the objective to evaluate social normative influences on FGM/C likelihood and prevalence risk among Kenyan girls 0 to 14 years between 2003 and 2014. On the other hand, Nnanatu et al. (2021) evaluated changes in FGM/C prevalence risk among Nigeria girls aged 0-14 years between 2003 and 2016. Both studies assessed geographic variation and temporal changes in FGM/C risk using the spatial and spatial-temporal hierarchical Bayes logistic mixed regression model formulation. However, while Kandala et al. (2019) considered only one data source (the demographic and health surveys), Nnanatu et al. (2021) evaluated FGM/C changes by combining data from two sources (the demographic and health survey -DHS, and the multiple indicator cluster survey -MICS). We present detailed description of the FGM/C risk factor study conducted among Kenyan girls 0-14 years (Kandala et al., 2019) in Chapter 3. The model formulation for the probability that a girl i was cut denoted as fgm_i is presented in equation (1.3) below Nnanatu et al. (2021):

$$\begin{aligned} fgm_i = \eta_i = \text{logit}(\pi_{ist}) = \log\left(\frac{\pi_{ist}}{1-\pi_{ist}}\right) \\ = f_{str}(s_i) + f_{unstr}(s_i) + f_y(t) + f_1(Aged_i) + f_2(Agem_i) \\ + \beta_1 Rres_i + \beta_2 Educ_i + \cdots + \beta_p fgm_{i_{woman}} + Survey + \xi \end{aligned} \tag{1.3}$$

where**,**

- π_{ist} is the probability of girl i being cut in area s at time t

- $\boldsymbol{\beta} = (\beta_1, \dots \beta_p)$ are the regression coefficient parameters for the fixed effects of residence (rural-urban), mother's education and mother's FGM/C status. The fixed effects parameters $\boldsymbol{\beta}$ were assigned a diffuse prior such that, $\pi(\boldsymbol{\beta}) \propto constant$.
- The term $Survey$ is a fixed effect (an indicator variable) accounting for variation due to differences in the different survey methods with DHS used as the reference survey.
- The term ξ specifies the interaction effects between space (denoted as the state of residence) and time (survey year) which accounts for excess source of variability in FGM/C likelihood that varies simultaneously in space and time.
- The nonlinear functions $f_j(x_{ij}) = \{f_1, f_2, f_y, f_{str,} f_{unstr,} \xi\}$ are modelled as a linear combination of basis functions as shown in equation (5) below:

$$f_j(x_{ij}) = \sum_{m=1}^{M} \varphi_{jm} B_{jm}(x_{ij}) \; ; \tag{1.4}$$

The basis functions B_{jm} are defined only locally in the sense that they are nonzero only on a domain spanned by $2 + l$ knots (Brezger,2001). The unknown vector of basis regression coefficients $\boldsymbol{\varphi_{jm}} = (\varphi_1, \dots, \varphi_M)^{\mathbf{T}}$ are to be estimated such that we have $\boldsymbol{f_j}(\boldsymbol{X_j}\boldsymbol{\varphi_j})$, where $\boldsymbol{X_j}$ is an n $\times M$ design matrix with elements $X_j(i, m) = B_{jm}(x_{ij})$ where M is the number of knots specified (20 knots for age and 3 knots for year). To estimate the smooth functions, we used cubic splines which are twice continuously differentiable piecewise cubic polynomials. The spline can be written as a linear combination of B-spline basis functions $B_{jm}(x)$, the Bayesian version of the Penalized-Splines (P-Splines) proposed by Eilers & Marx (1996), such that $f_j(x_{ij}) = \sum_{m=1}^{l} \varphi_{jm} B_{jm}(x_{ij})$. In our approach, this corresponds to $2nd$ order random walks given by:

$$\varphi_{jm} = 2\varphi_{j,m-1} - \varphi_{j,m-2} + \mu_{j,m} \; ; \tag{1.5}$$

with Gaussian increments $\mu_{j,m} \sim N(0, \tau^2)$ and smoothness parameter τ estimated from data. A multivariate normal prior was assumed for the unknown regression parameters, such that:

$$\pi(\varphi_{jm}|\tau_j^2) \propto \exp\left(-\frac{1}{2\tau_j^2}\varphi'_{jm}K_{jm}\varphi_{jm}\right) ; \tag{1.6}$$

where K_{jm} is a frequentist penalty matrix that is rank deficient with $rank\ (K_{jm}) = m - 2$) for a second order random walk. The prior is improper and penalty matrices are not stochastic. The frequentist penalty matrix penalizes the basis spline function for additional model complexity. The variance parameter τ_j^2 determines the amount of smoothness imposed on the model. For a fully Bayesian inference the unknown variance parameter τ_j^2 are also considered as random and estimated simultaneously with the unknown φ_j. Hence, we assigned hyperpriors to them in an additional stage of the Bayesian hierarchical formulation by highly dispersed (but proper) inverse Gamma priors such that $\pi(\tau_j^2) \sim IG(a_j, b_j)$, where j is a generic subscript representing the random effects where a and b are hyperparameters.

Local Markov random field (MRF) prior (Rue et al., 2009) was utilized to model spatially structured spatial effect $f_{str}(s), s = 1, \dots, S$ which borrows strength from neighbouring areas to estimate average spatial effect in areas with sparse observations(small sample size). We note that the MRF is a spatial extension of random walk model with a first order neighbourhood structure given by:

$$f_{str}(s)|\{f_{str}(r); \tau_{str}^2 : r \neq s\} \sim N\left(\sum_{r \sim s} \frac{f_{str}(r)}{N_s}, \frac{\tau_{str}^2}{N_s}\right) \tag{1.7}$$

where N_s is the number of states that are contiguous (share border) to state s and $r \sim s$ denotes that state r is a neighbour of state s, and τ_{str}^2 is a variance parameter for the spatially structured random effect. On the other hand, a zero-mean independent and identically distributed Gaussian priors was assigned to the unstructured spatial effect $f_{unstr}(s)$ as shown below:

$$f_{unstr}(s)|\tau_{unstr} \sim N(0, \tau_{unstr}^2), \tag{1.8}$$

where τ_{unstr}^2 is the variance smoothing parameter for the unstructured spatial random effect. The interaction term ξ was modelled both as a smooth function: with a random walk of the

second order (RW2) prior assuming autocorrelation in time and space, and exchangeable with assumption of no autocorrelation in space and time: $\xi \sim N(0, \tau_{\xi}^{2})$.

To address the research question, six models were tested. The first two evaluated the unadjusted effects of a girl's geographical location on her likelihood of being cut adjusting for the variations due to the year of survey and type of survey. The second set of models evaluated the effects of geographical locations, social norms, mother's age, and other key covariates on a girl's likelihood of being cut adjusted for type of survey and potential spatial-temporal interaction. With respect to handling missing values, the bivariate descriptive analysis using Stata (version 14. 0 Stata Corps) and the Bayesian geo-additive regression models using R employed listwise deletion algorithm for observations with missing values.

The result of the spatial-temporal model showed that accounting for variations due to survey differences (DHS and MICS) did not provide any change suggesting that the methods used by the DHS and MICS were not significantly different in a statistical perspective.

Both studies reported substantial evidence for the influence of mother's FGM/C status and her support for the continuation of the practice on the likelihood of cutting her daughter adjusted for other factors. In addition, both studies found significant evidence of geographic variation in FGM/C risk for each consecutive survey time point evaluated. For instance, in Kenya, findings revealed North-Eastern as a significant hotspot for the practice compared to the low-risk regions in the western part of the country. This pattern was consistently observed across the 3 survey time points considered between the period 2003 and 2014. In Nigeria, geographic pattern of declining trend in the practice was found in the western region compared to increased presence of hotspots in the northern region between 2003 to 2016 (Kandala et al., 2019; Nnanatu et al., 2021). A stark contrast in temporal changes was also observed between the two countries. While evidence suggest a substantial decline in FGM/C risk among Kenyan girls between 2003 and 2014, the risk of a Nigerian girl being cut remained relatively the same between 2003 and 2016 (Kandala et al., 2019; Nnanatu et al., 2021). The two studies provide the basis for the present work.

While both studies evaluated spatial and temporal changes in FGM/C risk and risk factors over the years, the complexity of the survey sampling design was not accounted for in the model formulation. In addition, authors of the papers made little attempt to explicitly model and identify the structure of excess spatial-temporal variability due to unobserved risk factors operating in space and time. More so, the two studies did not account for community level

influence of social normative factors in the spatial-temporal formulation of the STAR framework.

We further note, that the objective of the study by Nnanatu et al.(2021) was to evaluate spatial and temporal changes in FGM/C risk in space and time, rather than to evaluate the effect of risk factors in space and time. Second, the authors' assumption of an independent space-time interaction effect may not be appropriate given that little attempt was made to evaluate the four possible types of space-time interaction effects(Blangiardo et al., 2013; Haining & Li, 2020; Knorr-Held, 2000).

In addition, we note that smoothing for prior knowledge of the spatial-temporal interaction inherent in the observed data can be incorporated into the model framework. To account for this prior knowledge, we considered the Knorr-Held (2000) specification with four possible types of space-time interaction for the non-separable space-time namely; type I, type II, type III and type IV space-time interaction effects. Type I interaction assumes no spatial and temporal structure in the observed response, hence modeled as zero mean Gaussian prior. In other words, observed risk or likelihood of the outcome is independent in space and time.

In type II space-time specification, prior model an assumption of interaction between the spatially unstructured effect and temporally structured effect. In other words, observed risk or likelihood is independent in space affected by neighboring time points, with the spatial component model as zero mean Gaussian prior and the temporal component modeled with a random walk of the first or second order. In the Type III space-time formulation, observed risk or likelihood is assumed to be dependent in space but independent in time. This implies that estimate observed in one area is affected by that observed in its neighboring regions (often of a first order). The most complex of the space-time specification is the type IV interaction effect. In this type of interaction, the observed risk or likelihood in an area is both dependent on observed value in neighboring areas in space and neighboring time points. Type IV interaction can be modeled using local Gaussian Markov random field (GMRF) prior for the structured spatial component and a random walk of second order for the temporal component. (Blangiardo et al., 2013; Haining & Li, 2020).

1.3 Small Area Estimation Methods for Complex Survey Data

In this section, we provide a background review to common approaches in the field of small area estimation (SAE) for complex survey data, a newly emerging field of modern statistics with wide applications in survey statistics, spatial statistics, and global public health. We then examined the three small area estimation methodologies that set the context for the present work, namely: The direct estimation (also known as the Horvitz-Thompson design-based estimator), the spatially-smoothed version of the deigns-based estimator proposed by Wakefield et al. (2020) and the class of linear mixed effects models within hierarchal Bayesian framework to produce small area estimates using complex longitudinal survey data.

The overarching objective of any small area estimation effort is to provide data-driven evidence base for monitoring and evaluation of policy-relevant indicators at local administrative level. A domain (usually an administrative tract) is defined as "small area" if the domain-specific sample size is not large enough to support direct estimates of adequate precision (Rao, 2003). Hence, the term "SAE" as used in this context, emphasizes the size of the sample rather than the size of the domain of interest. Small area can also be a socio-demographic domain of interest age, sex and race classification of the total population. Earliest adoption of small area statistics has been traced back to 11th century England and 17th century Canada (Ghosh & Rao, 1994).

The use of SAE procedure provides efficient method for obtaining reliable small area statistics for evidence-based policy formulation and targeting of limited allocation of resources to who and where they are most needed. SAE techniques combine multiple data sources to capitalize on the strengths of each data source. To implement a small area estimation technique, two types of data are required: survey data and auxiliary data. Survey data collect information on the target dependent indicator and additional variables related to the target indicator. On the other hand, auxiliary data (usually obtained from most recent census or reliable registry data), contain information for the covariates. Hence, SAE is a prediction problem that seeks to "borrow information" from auxiliary data through a set of covariates to improve estimation and explain observed variation between small areas (Rao, 2003).

There are two broad classifications of SAE techniques (Rao, 2003) developed to meet the growing demands for small area estimates in both public and private sectors, namely: the direct survey estimators and the indirect or model-dependent methods.

1.3.1. Direct Estimation Approaches

The direct estimation approach is so called because it employs the survey data only to obtain small area estimates such as means, proportions, or totals. A direct estimator is usually design-based in that it makes use of survey weights, and the associated inferences are based on the probability distribution induced by the sampling design while the population parameters are fixed. A direct estimate of an indicator of interest in a specific small area and time point only uses data on the variable collected from that area and time. Data collection is carried out by use of survey sampling, and individual units have unequal probability of inclusion in the sample survey. The inverse of this probability of inclusion is described as the sampling or design weights. In the case of a single stage sample survey, the sampling weight is obtained as the inverse of the unequal selection probability for very unit sampled. In multistage cluster sampling, however, the total weight is derived as the cross product of the inverse of inclusion probability across all stages (Wakefield et al., 2020).

In our study, we consider a design-based approach for the mean response y for individual i living in household j in cluster k and area s has an SBP measurement is given by:

$$\widehat{m}_s^{(HT)} = \frac{\sum_i \sum_j \sum_k w_{ijks} y_{ijks}}{\sum_i \sum_j \sum_k w_{ijks}} \tag{1.9}$$

where w_{ijks} is the design weight (defined as inverse of the probability of selection) for individual i living in household j in cluster k and area s. The design weights are included in the survey data for each time or multiple time points.

A key advantage of estimates obtained by the direct SAE approaches is that given a probability-based sampling design, the small area averages and variance estimators are design-unbiased and design consistent (Rao, 2003). An important consideration in the direct estimation approach is a valid measure of variability of estimates. Standard measures of achieving this include the coefficient of variation (CV), standard error or confidence interval. It has been suggested that a CV less than 20% provides a reliable and accurate estimates of the target small area mean (Molina & Marhuenda, 2015).

Despite its usefulness and wide applicability, a number of problems have been identified with the direct estimator of a small area domain. The design-based approach has been criticized on the grounds that the associated inferences, although assumption-free, refer to repeated sampling instead of just the particular sample that has been drawn. Direct estimators can lead to unacceptably large standard errors due to unduly small samples from the areas of interest. In fact, no sample units may be selected from some small domains leading to out-of-sample situation (Ghosh & Rao, 1994; Rao, 2003). This makes it necessary to find indirect estimators that increase the effective sample size and thus decrease the standard error. In addition, survey design often, do not account for competing interest regarding the targets of estimation, such as other risk factors that may be related to the response. In other instances, the problem of out-of-sample areas often arise, since not all domains of interest may be sampled. These limitations have led to developments of various model-assisted design-based methods that implicitly address such concerns. A well-known class is the generalized regression estimators (GREG estimators) that improve estimation by borrowing information form a set of auxiliary variables (often at the small area level) along with other calibration methods (Pfeffermann, 2002, 2013; Rao, 2003).

To obtain more reliable estimates in the domain of interest, it is often necessary to use model-based methods. Such method indirect estimation borrows information by using values of the target variable from related areas (and or time points, for instance, in the case of longitudinal or panel surveys) to increase the effective sample size. These values are brought into the estimation process through a model that provides a link to related areas with auxiliary information related to the outcome. Hence, small area estimates can be obtained for domains at a single time (often using cross-sectional survey data) or multiple time points (for instance, using longitudinal survey data). SAE techniques based on cross-sectional data can be further classified into area level and unit level models, while those that employ longitudinal survey data are generally known as mixed model approaches.

1.3.2. Model-based Estimation Approaches

Three common model-dependent (indirect) approaches to re three most used model-dependent methods to obtain prediction of small area estimates, namely: The frequentist approaches based on the theory of empirical best linear unbiased predictors (EBLUPs), the empirical Bayes approach (EB) and the Hierarchical Bayes approach (HB). The two methods have been shown to have distinct advantages over direct or other existing indirect estimators such as synthetic methods (Ghosh & Rao, 1994; Pfeffermann, 2013).

Model-dependent small area estimation techniques provide an effective alternative to address the limitations of the direct estimation methods. On the other hand, synthetic estimators provide a reliable direct estimator for the domain of interest (covering the small areas), is used to derive an indirect estimator for a small area under the assumption that the small areas have the same characteristics as the large area (for instance, the use of direct estimators at provincial level to derive estimate at district municipality level) (Rao, 2003). Unlike the synthetic estimators, the use of explicit models offers several advantages. First model diagnostics can be used to find suitable model(s) that fit the data well. Such model diagnostics include residual analysis to detect departures from the assumed model, selection of auxiliary variables for the model, and case-deletion diagnostics to detect influential observations. Second, area-specific measures of precision can be associated with each small area estimate, unlike the global measures (average over small areas) often used in synthetic estimates. Third, linear mixed models as well as nonlinear models, such as logistic regression models and generalized linear models with random area effects, can be entertained. Complex data structures, such as spatial dependence and time series structures, can also be handled. Fourth, recent methodological developments for random effects models can be utilized to achieve accurate small area inferences. Model-based approaches to SAE provide a means to account for additional random variation around the true area means in the direct estimation method. This excess variation can be accommodated(modeled) within a regression model framework in addition to more complex data structure including spatial and temporal dependence, two-fold nested regression and linear and generalized linear mixed models (Ghosh & Rao, 1994; Rao, 2003).

Model-dependent estimation methods can be formulated in a manner that relate the small area means to unit-level or area-specific auxiliary variables. The former specification is generally known as unit-level model and the latter as area-level of aggregate level model. Both alternative formulations provide a means to produce small area estimates based on available data, and

thereby maximizing efficient use of such data. The unit-level models are employed when individual -level survey data and auxiliary data are available for producing small area estimates (Ghosh & Rao, 1994). The first well known use case of such unit-level model formulation was the Battese, Harter and Fuller model (Battese et al., 1988). In the original formulation, it includes random area-specific effects to account for between area variation or explained variability between the small domains of interest. The use of unit-level data (mostly from national surveys or census) in such model specification improves model fit and reliability of small area averages and proportions. More so, area level or unit level auxiliary covariates can be utilized to improve model estimates for target domains of interest (Rao, 2003). However, given the difficulty in availability of unit-level data, in particular administrative records (for auxiliary data) due to privacy concerns, the area level model has become a viable alternative to produce useful small area estimates.

The basic Fay-Herriot model assumes independent and identically distributed small area effects (Fay & Herriot, 1979). However, in some applications it may be more realistic to entertain models that allow correlations among the area random effects. Spatial models are used when "neighboring" areas of each area can be defined. Such models induce correlations among the, for example, correlations that depend on geographical proximity in the context of estimating local disease and mortality rates. The area level variances can also be smoothed using generalized variance functions (Jiang & Lahiri, 2006) to obtain more stable estimates when then within area sample size is small.

Investigators in the field of small area estimates have, however, argued that such estimates obtained within an area-level framework may not be similar to that of unit-level SAE technique due to the obvious fact that the former is subject to ecological bias since actual observation on individual members of the population of interest was not made and hence correlated between outcome of interest and individual level covariates may not be accounted for (Gomez-Rubio et al., 2014). Alternatively, within a fully Bayesian framework a hierarchical structure can be imposed on both the small area means and variances to ensure that the sample variances are smoothed within a model framework and efficiency in precision estimates(Haining & Li, 2020).

1.3.2.1. Hierarchical Bayes Approach to Small Area Estimation

Early effort to implement small area estimation within the hierarchical Bayesian (HB) framework aimed to extend the Battese-Harter-Fuller model and the Fay-Herriot formulations in a manner that evaluate the full conditional probability distributions of all model parameters of interest given the observed data and an assumed prior distribution to produce the small area means (Datta & Ghosh, 1991). The conditional probability distribution of the observed data given the mean and model parameters (also known as the likelihood model) and the full conditional probability distribution of the small area random mean of interest given model parameters and hyperparameters (process model) is combined with a prior information on model parameters using the Bayes theorem to obtain an updated posterior distribution of the process of interest.

In fully Bayesian SAE techniques, inferences are based on the posterior distribution of the mean predictor and the variance components based on posterior variance estimates (Datta & Ghosh, 1991; Ghosh & Rao, 1994; Rao, 2003). The key advantage of HB approach is that inferences are exact in that the full conditional distribution of the mean response given the model parameters and prior information can be obtained. On the choice of prior information, informative prior may be considered in the light of available sufficient evidence on model parameters (for instance, from previous studies, surveys, or expert opinions). However, the difficulty in obtaining such evidence or ascertaining the reliability of subjective expert opinions often constrain Bayesian modelers to adopt an objective approach to inference using diffuse or vague or noninformative prior information (Gomez-Rubio et al., 2014). The choice of vague prior needs to be carefully considered given that some diffuse priors result in improper posteriors. The frequentist properties of estimates (such as relative bias of posterior means and variances) can also be evaluated. These properties are desirable within the context of small area estimation as it ensures that the design unbiasedness and consistency of estimates can be ascertained (Rao, 2003).

Of interest in Chapter 6 of the study is the utility of informative spatial, temporal, and spatial-temporal smoothing to improve model estimates and prediction. Such prior provides a means to account for spatial, temporal, and spatial-temporal knowledge of inherent space-time structure in the distribution of the observed data using smoothing techniques. Informative prior knowledge on the space-time structure provides an effective means to improve estimates and stabilize between area, between time and between area-time variances in the observed data.

The term “spatial smoothing” as used in the context of the present study considers a case of spatial heterogeneity in the spatial dependence structure. In this situation, the prior assumption is that localized patterns of spatial dependence exist between neighboring areas with different structures observed on different part of the domain of interest (Haining & Li, 2020). An additive combination of such spatially smoothed district effects with the unstructured (spatially uncorrelated) districts effects results in the well-known convolution model proposed by Besag, York and Mollie (BYM) (1991). A more recent reparameterization of the BYM model proposed by Riebler and Colleagues (2016) provides an additional spatial parameter which allows the spatial dependence to be quantified in a meaningful and interpretable way.

To model the effect of spatial correlation of the small area estimates, we considered an approach recently proposed by Wakefield et al. (2020). The proposed formulation provides a model-based adjustment to the design-based estimator via a logit link for binomial outcomes or Gaussian link for continuous outcomes within a hierarchical Bayesian framework. Hence, the regression allows for complex structure including spatial and temporal correlation to be accounted for to improve small area estimates. In Chapter 6, we considered a spatially smoothed design-based estimator of mean systolic blood pressure in which spatially structured and spatially unstructured random effects are accounted for within the Bayesian hierarchical framework. The general equation is given by:

$$\widehat{m}_s^{(smoothHT)} = \widehat{m}_s^{(HT)} + {1}\Big/{\sqrt{\tau_d}}\left(\sqrt{1-\emptyset}v_s + \sqrt{\emptyset}u_s\right) \tag{1.10}$$

where $\widehat{m}_s^{(smoothHT)}$ denotes the spatially smoothed estimate as a function of the designed based estimate $\widehat{m}_s^{(HT)}$ adjusted for spatially unstructured and structured effects v_s and u_s respectively. The degree of correlation across the spatial domain is quantified by the phi parameter $\emptyset$ while τ_d is the variance parameter.

Within the Bayesian hierarchical framework, common complex random effects specification such as spatial and temporal correlation, as well as correlated intercept and slope in the case of linear and generalized mixed models can be effectively accounted for. For instance, spatial correlation in the observed values of the population parameter of interest, can be modelled as a set of spatially structured effects, representing a set of unobserved risk factors shared by neighboring domains. In a similar manner, temporal structure may be induced as a result of

proximity of observed value in neighboring one or two more time points apart. Both spatial and temporal structured random effects components can be modeled using the conditional autoregressive prior (CAR) models (Beale et al., 2008; Besag et al., 1991; Best et al., 2005).

However, despite a robust attempt to account for the complex survey design of the NIDS sample data at each cross-sectional time point, we note three important limitations of the design-based and spatially smoothed design-based SAE approaches to modeling the NIDS sample data. First, both estimators do not account for the fact that two repeated measurements of SBP were taken for each survey participant at each wave. Not accounting for variability due to such repeated measurement may bias resulting small area estimates. Second, both SAE approaches do not account for the longitudinal features of the NIDS sample data given that repeated measurement of SBP was taken from individuals over time. As a result, within individual and between individual variability in SBP measurement are not captured. Third, is the need for a framework that allows borrowing of information to improve effective sample size in areas where sample size is mall or out-of-sample areas. To address the three important challenges, we reviewed the general linear mixed model-based approaches in the next section. We then propose a novel extension of the general linear mixed model formulation within a hierarchical Bayesian framework approach within this framework to address these challenges.

1.3.2.2. Linear mixed model Approach to Small Area Estimation

The basic unit-level approach proposed by Battese, Harter and Fuller (1988) can also be extended to account for additional individual level random effects components at a specific time and over time within a linear and generalized mixed effect model formulation. For instance, Saei and Chambers (2003) considered small area estimation under linear mixed model specification accounting for random area and time effects. The report was prepared as part of Southampton's involvement in the EURAREA "Enhancing SAE techniques to meet European needs" project. Saei and Chambers considered four special cases of the unit-level linear mixed models. The first was model with independent and identically distributed (IID) area time effects with normally distributed means and variances. The second was a model with IID area effects and autocorrelated time effects in which temporal correlation was accounted using the first order auto regressive (AR1) process. In the third formulation, they considered a model with time varying area effects, while the fourth was a model with spatial correlation, often induced by areas sharing common risk factors related to the outcomes of interest. In the fourth model

formulation, spatial correlated random effect was model was normally directed with mean zero and covariance matrix as a function of the distance between two areas.

The overall objective of such linear mixed model formulations is to utilize a statistical framework that allows all possible sources of variation (in the population characteristic of interest) in space and time to be accounted for simultaneously to improve the accuracy of the resulting small area means for a single time point of small rea trend for multiple time points. The possibility of accounting for complex data structures including spatial and temporal correlation has made such mixed effect approaches particularly attractive in the field of survey statistics and subfield small area estimation in recent times. The recent availability of nationally representative surveys has made it possible to produce such small area estimates using advanced statistical modelling techniques to quantify subnational trends of enormous policy and business applications as demonstrated by recent studies (Wandai et al., 2017).

However, the formulation by Saei and Chambers (2003) did not consider a case of potential correlation between the initial baseline observed value and the trajectory for each individual sampled unit of the population. As a result, their model formulations do not allow for modelling the impact of the correlation between the intercept and the slope on the estimated small area averages. Hence, a more robust statistical framework for the efficient utility of national household surveys with complex data structures can be implemented. More so, the inferences are obtained within the frequentist framework using the EBLUP procedures, and hence, inferences are not exact. The present work considered an implementation of linear mixed models with area and time random effects to produce small area averages within a fully Bayesian approach.

The present study considers an extension of the linear mixed model approach to producing small area estimates known as the double measurement hierarchical Bayes linear mixed effect model. In this formulation, double measurements y_1 and y_2 of a response y taken from an individual i at time point t follow a normal distribution with mean μ_{it} and variance σ_y^2 as shown in equation 1.11 below. The mean in turn depends on a set of fixed and random effects covariates parameters and a prior information. The general model formulation is given by:

$$y_{1,it}|\mu;\sigma^2 \sim N(\mu_{it}, \sigma_y^2) \tag{1.11}$$
$$y_{2,it}|\mu;\sigma^2 \sim N(\mu_{it}, \sigma_y^2)$$

where μ_{it} is the structural term on which a number of models can be specified, ranging from classical longitudinal models such as random intercept and slope to more complex specifications that account for spatial and temporal correlation; and σ_y^2 is the empirical variability of the two SBP measurements for all persons over the study time period.

The linear predictor of the mean response is given as:

$$\mu_{it} = \gamma_0 + \gamma_1 * (t-1) + b_{0i} + e_{it} \tag{1.12}$$

where γ_0 and γ_1 are the average SBP value at baseline (intercept) and change(slope) for the population. Also, i is a person indicator ($i = 1, \dots, N$) whose systolic blood pressure measurements $y_{1,it}$ and $y_{2,it}$ were taken at time t ($t = 1, \dots, T$). Also b_{0i} denotes individual-specific random intercept while e_{it} is the residual measurement error.

In Chapter 6 of the present study, we provide a detailed description of the small area methodology. We also present a Bootstrap procedure to obtain small area estimates of mean systolic blood pressure (SBP) for non-sampled individuals and average response for the total population within each small area at each time point of the longitudinal survey data.

1.4. Methodological Challenges

Evidence from previous studies including recent efforts to model health outcomes using nationally representative surveys, as number of important methodological challenges remain. We review some of these challenges in this section that provide the basis for the two strands of the present work. These challenges include the need to account for the complex sampling design inherent in most nationally representative household surveys, the need to account for spatio-temporal variability in modeling health outcomes in space and time and producing small area estimates using unit-level models with space and time random effects components.

The multistage cluster sampling approach employed by national surveys result in a situation whereby sample units are nested, for instance, within household and clusters which are in turn nested within regions in a two-stage or three-stage sampling design as often observed in most

surveys in developing countries (Wakefield et al., 2020). Such sampling scheme induced intra-cluster correlation among observations within the same cluster or households due to shared characteristics which may not be captured in the observed sample data. Consequently, the additional variability induced because the fact that observations are long longer independent (as in a simple random situation) must be accounted for. Failure to account for such variability may lead to less reliable and accurate risk factor estimates for FGM/C at individual level. Previous studies (Kandala et al., 2009, 2019; Kandala & Shell-Duncan, 2019; Nnanatu et al., 2021) have made little attempt to fully account for such complex sampling structure within a statistical model framework. One of the objectives of the present work is to address this important limitation and to evaluate its impact on FGM/C risk factor estimates.

Another important aspect of complex survey data for FGM/C modeling is the need to account for the excess spatio-temporal variability induced by unobserved factors interacting in space and time, in addition to the main spatial and temporal effects (Abellan et al., 2007, 2008). This is of a priority interest in the field of FGM/C given recent ambitious effort of the United Nations SDG groups to eliminate the practice across most affected countries in sub-Saharan Africa and Middle east by 2030 (WHO, 2012). Such excess spatio-temporal variability is expected to be induced by interplay of several factors such as spacetime variation in FGM/C interventions and effectiveness of FGM/C legislation as well as sheered demographic transition of a community, region or country from a highly practicing, to moderate, or low as a result of increasing education, urbanization and development (Williams-Breault, 2018). While there has been recent effort to account for such variability within FGM/C context in Kenya, Nigeria and Senegal (Kandala et al., 2019; Nnanatu et al., 2021), these studies did not separately quantify the additional influence of spacetime variability on risk factor estimates as well as its appropriateness given the choice of model formulation.

The third challenge is the lack of work to produce small area estimates for double measurements of systolic blood pressure and local trends based on unit-level data. Recent effort to produce estimates of geographic trend of blood pressure was conducted globally by the NCD Risk Factor Collaboration (NCD-RisC) group in a landmark study (Zhou et al., 2017). The investigators utilized a fully Bayesian framework to estimate 40-year trends in systolic and diastolic blood pressure between 1975 and 2015 across 200 countries. Notable findings from the study showed pattern of increasing trends in mean blood pressure across countries in sub-Saharan Africa and a decline in most western countries. However, estimates from the study were only obtained at national level for the respective countries, and therefore additional effort

to produce estimates of trends at small area level using recent country-specific nationally representative surveys are need across the region.

Governments around the world are now transitioning into a data-driven policy making practice across all subnational levels to leverage the power of data to understand policy priorities and identify areas where limited resources are most needed, and to effectively monitor progress and evaluate public health priorities at local administrative level. Classic examples of a countries where such effort has been effectively deployed over the years with much policy gains is widely applicable across several sector of governmental agencies include Canada through the Statistics Canada agency, United States Census Bureau and UK Office for National Statistics. Members of such agencies are also credited for shaping early development efforts and ongoing innovative advances in the methodological development and application of small area estimation techniques. While little attempt so far has been made in African countries to follow this innovative trend mostly due to inadequate quality data and limited expertise, recent availability of longitudinal or panel surveys that are nationally representative has made it possible to develop such innovative model-dependent SAE techniques.

1.5. Research Questions and Study Objectives

The objectives of the present study are motivated by the need to address five fundamental research questions.

First, what factors, operating at individual and contextual levels, explain observed prevalence trends in FGM/C among girls in Kenya, Nigeria, and Senegal between a specific period?

Second, does accounting for excess variability in FGM/C prevalence risk due to unmeasured risk factors interacting in space and time lead to observable changes in risk factor estimates?

Third, does accounting for the complex sampling design feature inherent in the Demographic and Health surveys result in observable changes in risk factor estimates?

Fourth, was there any significant change in the overall average systolic blood pressure among South African adults aged 18 years and older between 2008 and 2017?

Fifth, was there any observable geographic variation in average systolic blood pressure among South African adults aged 18 years and older at small area (district municipality) level in 2008, 2010, 2012, 2014/15 and 2017?

The study objectives are two folds. First, we seek to identify important individual and group level risk factors of FGM/C among girls 0-14 years in select African countries using a nationally representative survey data. The second objective is to produce subnational small area trend of mean SBP of South African Adult population for the period between 2008 and 2017. The overall aim of the methodological development is to capture the complex sampling design features of survey data to improve identification of important risk factors and to produce reliable trend estimates at small area level using unit-level data.

The study utilised two sources of nationally representative surveys data – The demographic and health survey (DHS) data on girls and their mothers collected cross-sectionally across three time points in 3 African countries – Kenya DHS sample datasets (2003, 2008, 2014), Nigeria DHS sample datasets (2008, 2013, 2018), and Senegal DHS sample datasets (2010, 2015, 2017). The second data source was the national income dynamics panel survey data collected every two years across 5 time points between 2008 and 2017 in South Africa. To address the first objective, we investigated changes to the influence of risk factor estimates on the likelihood of FGM/C among girls in Kenya and Nigeria and Senegal between the study period.

For the first objective, we implemented a non-separable Bayesian generalized additive mixed regression model guided by a conceptual proximate determinant framework for FGM/C. We evaluated changes to risk factors estimates by accounting for the complex sampling design features of the DHS data – stratification and cluster sampling. To account for the influence of geography and time on the outcome, we decomposed the spacetime variation into a main spatial effect, a main linear temporal effect and a spacetime interaction effect. We implemented the analysis using the integrated nested Laplace approximation (INLA) using the R-INLA package. Model comparison and evaluation was carried out using the deviance information criterion (DIC), Watanabe information criterion (WAIC) and logarithm of the conditional predictive ordinate (logCPO) and predictive performance was assessed using the root mean squared error. To address the second objective, we implemented a series of direct and model-based small area estimation methods - the direct estimation method, the spatially smoothed designed based estimation method, and Hierarchical Bayes linear mixed effect models. The HB models were implemented using MCMC simulation techniques with Gibb's sampling within WinBUGS.

1.6. Study Hypotheses

1. Overall variation in observed FGM/C prevalence among girls in space and time can be explained by factors operating at individual and community levels.
2. Accounting for excess variation in FGM/C due to space-time interaction provides improved estimation of risk factor influence on FGM/C likelihood in space and time.
3. Accounting for the complex sampling design feature of the DHS will result in observable changes in the influence of risk factors operating at both individual and community levels.
4. There was significant overall change in the mean systolic blood pressure among South African adults aged 18 years and older between 2008 and 2017.
5. Significant geographic variation existed at small area level in the observed average systolic blood pressure among South African adults in 2008, 2010, 2012, 2014/15 and 2017.

For the FGM/C study, we considered three countries in Africa. Each of the countries represents a distinct trend in the observed pattern of change in the FGM/C risk among girls. For instance, Kenya is the only country in Africa that has experienced dramatic decline in the FGM/C risk in the younger generation (girls 0-14 years) till date, while little to no gains have been made across most other countries (Kandala et al., 2018). The study therefore seeks to investigate factors that may explain observed trend in risk within a specific period. An important contribution of the study is to quantify changes in estimated influence of identified individual-level risk factors after accounting for the complex sampling design in the DHS. The study only considered daughters of women who have eared about the practice across all countries.

In this chapter, we introduced the recent availability of nationally representative surveys with complex sampling design as the primary motivation for the present work with a focus on health outcomes. We also provided a contextual background for the two important health outcomes of interest in the study and how the availability of such survey data can provide data driven insights using advanced statistical methods to address important research and policy question. In addition, we reviewed two statistical approaches: 1) spatial-temporal extension of the STAR models to model complex survey data and the linear mixed model within a hierarchical Bayesian formulation. The objective of the former is to quantify the influence of risk factors on the likelihood of FGM/C while the later provides a preliminary framework to produce small area estimates of average systolic blood pressure from two measurements using a longitudinal

survey data. An additional section provided a high-level summary of the important existing methodological challenges that remain to be addressed and therefore warrant further investigation in the light of recently conducted national surveys. These challenges include the need to account for the complex sampling design inherent in most nationally representative household surveys, the need to account for space time variation in health outcomes, and the need for subnational estimation of trend in risk of health outcomes for monitoring and evaluation of progress at local administrative level and policy relevant health indicators. Subsequent chapters address the research questions and demonstrate how advanced statistical methods can be utilized to generate invaluable insights from complex national household surveys.

CHAPTER TWO

BACKGROUND TO THE STUDY

2.1. Background to the Female Genital Mutilation Study

Female genital mutilation/cutting (FGM/C) is recognized worldwide as an important global health issue with at least 85% of the prevalence burden found among women and girls in Africa (UNICEF, 2020). The procedure involves the partial or total removal of external female genitalia or other injury to the female genital organs for non-medical reasons. According to the most recent report, at least 200 million girls and women have experienced the procedure across 31 countries predominantly in western and eastern Africa (UNICEF, 2020). FGM/C is mostly carried out on girls between infancy and age 15 (WHO, 2020). The procedure has been described as a serious violation of the rights of women and girls including their right to bodily integrity. While evidence of significant decline has been observed in a number of most affected countries, prevalence burden remains high in others. The target of the UN SDG goal 5.3 is to eliminate all forms of harmful practices, including FGM/C by the end of 2030 (UNFPA & UNICEF, 2020). Hence, effort to generate evidence to understand geographic pattern of risk and hotspots, evaluate subnational trends, and identify important individual and community level determinants of the observed trend is essential to measure progress towards abandonment of the practice in Africa by 2030.

Female Genital Mutilation/Cutting (FGM/C) is a harmful agelong traditional practice rooted in social norms and conventions of practicing tribal communities, in particular, in eastern and western Africa. Given the pervasiveness of the procedure across Africa and its disproportionate health consequences on women and girls, FGM/C has been enlisted as a key indicator of gender equality in the United Nations sustainable development programs. Hence, FGM/C is a useful measure of country progress on equality of women and men within the framework of sustainable development goal (SDG) 5 at national and subnational levels along with child marriage.

According to the United Nations report on SDG progress in 2019, evidence of significant decline in prevalence of FGM/C was found among girls aged 15 to 19 years across practicing countries from 51% in 1985 to 37% in 2019 (UNICEF, 2019). However, prevalence burden and absolute number of affected women and girls remain high especially in select countries in

western and eastern Africa. The same report noted a decline of one quarter between 2000 and 2018 across 30 countries where the practice persistently occurs (United Nations, 2019). Similar conclusions were observed in a meta-analysis of FGM/C among girls aged 0-14 years in 29 in low and middle-income countries (Kandala et al., 2018).

Six factors have been identified as drivers of persistence of FGM/C in most affected countries. This includes cultural traditions, marriageability, religion, sexual morals, health benefits, and male sexual enjoyment. The influence of one or combination of these factors, however, vary between countries, ethnic groups and communities (Berg & Denison, 2013). Studies have shown that FGM/C is a sensitive practice that is embedded within complex social and cultural systems of most practicing communities around the world especially in Africa. More so, is the varied motivations across affected countries and cultures. Evidence from studies and reports till date have consistently identified a complex web of interacting cultural, and religious factors operating at individual, household, and community levels as drivers of the practice in most affected countries (WHO, 2012). In West Africa, for instance, historical traditions promoted by older women within extended family households or women influencers within a community or social network play a central role in the persistence of the practice (Chidera, 2018; Okeke et al., 2012). Other motivations include: as a coming of age of a girl and her transition to womanhood, especially in eastern Africa (Abdelshahid & Campbell, 2015), as a symbol of social status within communities to earn respect of other women, especially in Senegal (Johnson-Agbakwu et al., 2014; Shell-Duncan et al., 2011), chastity and marriageability to ensure purity of girl before marriage, and to ensure cleanliness, hygiene and beauty as a symbol of cultural ideals of femininity and modesty (Chidera, 2018; Gruenbaum, 2006; Hellsten, 2004; C. Johnson & Nour, 2007; Okeke et al., 2012; Sakeah et al., 2018; Shakirat et al., 2020).

2.2. Existing Theories and Framework to explain FGM/C Persistence

Prominent researchers in the field of FGM/C and gender inequality have proposed important theories with the objective to better explain major drivers of FGM/C persistence in sub-Saharan Africa. These theories have contributed significantly to the design and effective deployment of intervention programs and formulation of legislative frameworks towards eliminating the practice in parts of affected countries. These theories include:

2.2.1. Social Norms and Conventions

The theory of social norms and conventions is the most influential and has been shown to explain a substantial amount of the variation observed at both individual and community levels by various investigators(Grose et al., 2019; Kandala et al., 2019; Kandala & Shell-Duncan, 2019). Social norms theory, a prominent framework for understanding FGM/C, posits that behaviours are influenced by social rules that are learned through social interactions with salient people in the community, commonly referred to as a reference group. Social norms are held in place by reciprocal expectations of those in a reference group. Hence, an individual's actions are not driven solely by their own preferences and attitudes; they are also influenced by perceived expectations of others and pressure to conform to existing norms and conventions. In a model first developed by political scientist Gerry Mackie, FGM/C was hypothesized to be a social norm that spread and became locked in place by interdependent expectations regarding marriageability (Mackie, 1996). In competition for marrying to higher social strata, FGM/C provided an advantage by signalling fidelity, and became a universal prerequisite for marriage. As a prerequisite to marriage, FGM/C became locked in place, since those opting out would pay the high price of foregoing marriage and legitimate childbearing (Mackie & LeJeune, 2009).

In the original application of this theory to FGM/C, Mackie also identified a second possible mechanism: peer pressure (Mackie, 1996). Ethnographical study by Shell-Duncan and colleagues (Shell-Duncan et al., 2011) in Senegambia showed that concerns over marriageability had eroded, but that FGM/C remained upheld by an inter-generational peer convention whereby the practice serves as a signal to other circumcised women that a girl or woman has been trained to respect the authority of her circumcised elders and is worthy of inclusion in their social network. Based on this finding, as well as a growth in scientific literature on social norms, Mackie and LeJeune (2009) expanded the original formulation of social norms theory, noting FGM/C may be held in place by a range of norms and associated meanings that may shift over time.

2.2.2. Religious Norms

Religious norms are often interwoven with construct of what is morally acceptable or not within a specific culture. Religious norms have a wider and ranging impact among members of practicing households and communities at all levels of influence. More so, is the critical role religious norms play in the collective decision of most African communities to reject or embrace a change (Hayford & Trinitapoli, 2011).

2.2.3. Gender Norms

Gender normative theory posits that there exists gender-based power relational dynamics between men and women within a household or community. This dynamic can often be explained by unwritten rules of acceptable behavior in relation to gendered roles and expectations that limit the capacity of women and girls to make or be involved in decisions that affect their own health (Cislaghi & Heise, 2019; Heise et al., 2019). An essential distinction between gendered normative and social normative influences is that while the former mostly operate at household level, the latter is more predominant at community level. Gender norms define what is appropriate behaviour for upholding ideals linked to masculinity or femininity in different social arenas—at home, in the community, in school or the workplace, and in interpersonal relationships. They are formed in the process of gender socialization and upheld by both internalized notions of gender-appropriate behaviours, as well as sanctions from both men and women within the community. Discriminatory gender norms are those that constrain girls' and women's power, educational and economic opportunities, and diminish their own goals and aspirations (Cislaghi & Heise, 2018).

2.2.4. Modernization Theory

Theory of modernization posits that the process of national development may have far-reaching effects, including reducing the demand for FGM/C (Boyle et al., 2002; Hayford, 2005; Modrek & Liu, 2013; Yount, 2002). This is thought to be possibly mediated by a number of factors, including; higher educational attainment, increased exposure to the media carrying international scripts about opposition to FGM/C, and economic development involving a shift to non-agricultural employment (Boyle et al., 2002; Modrek & Liu, 2013). A shift to an

industrialized economy may be accompanied by increased commerce and urban-rural migration. It is also posited that it may weaken traditional family values that previously emphasized collective responsibilities over individual rights and opportunities (Boyle et al., 2002; Hayford, 2005).

2.2.5. Feminist Theory

The Feminist theory dates to the feminist movement of the 1970s and their effort to create economic opportunities for women as a means to their freedom from patriarchal control. It is often perceived as a natural consequence of gender inequality, in turn, a result of imbalance power relation and roles over a long period of time (Cislaghi & Heise, 2019; Heise et al., 2019). Scholars have noted that economic development can have contradictory impacts on FGM/C, particularly if it does little to enhance women's autonomy or challenge patriarchal structures and women's economic dependency (Grose et al., 2019). The solution, from feminist perspectives, lies in part on reducing women's dependence on their husbands, creating avenues for women's future social security that lie beyond their role as a wife and mother, and challenging institutionalized policies and practices that limit choices and opportunities afforded to women. Thus, women's empowerment is considered an essential element to eliminate FGM/C. The Feminist theory points to a number of domains that may indicate gender inequalities. This includes women's agency, women's constraints, and opportunities, and more generally, gender norms.

2.2.6. Women Agency

The concept of women's agency encompasses the women's status, as reflected by household wealth, as well as structural inequalities that exist between men and women driven by educational attainment. Patriarchal societies impede women's agency by restricting their choices and their capacity for individualized action. It is posited to be linked to FGM/C based on the assumption that the practice serves to uphold men's position of dominance over women, and repress their sexuality (Cislaghi & Heise, 2019; Grose et al., 2019).

2.2.7. Women's Constraints and Opportunities

Women's constraints and opportunities reflect the gendered dimensions of bargaining power, and women's limited autonomy in decision-making (Cislaghi & Heise, 2019; Grose et al., 2019; Hay et al., 2019). With limited decision-making authority and limited economic or social autonomy, women lack the power and independence to challenge the practice of FGM/C.

2.2.8. Social Determinants of Health

Sociodemographic factors have long been regarded as underlying or contextual drivers of health-related outcomes across all cultural settings. According to the World Health Organization, the social determinants of health (SDH) are the factors that influence health. They include, social, economic, education, and environmental factors such as the built environment, neighbourhood effects, the wider political environment and prevailing policies and legislations. Altogether, they shape inequality in health outcomes and determine the everyday realities of individuals and populations (Donkin et al., 2018; WHO, 2010). They are the underlying cause of the causes (Braveman & Gottlieb, 2014), inequality in health outcomes, and access to safe treatment and affordable health care (Islam, 2019; O'Brien, 2019). More importantly in relation to FGM/C outcomes, they are the underlying determinants of whether a woman (or girl) is empowered enough to exercise her right to oppose the practice or submissively conform to existing harmful social norms and gender norms in her community for fear of being discriminated against or excluded from groups.

2.2.9. Geographic Location

An individual location residence determines the context in which they live, work, and play and influence of the social environment on their behavior. This may be due to factors operating within the immediate local community (normative influences) or at regional level (such as legislative policy). The effect of geographic location within FGM/C outcome often captures the role of unobserved risk factors whose influence is often accentuated by proximity in spatial location among practicing groups or communities (Kandala & Shell-Duncan, 2019; Shell-Duncan et al., 2011).

2.2.10. Media Exposure

Media exposure theory posits that accessibility to media, in particular international exposure to information about the harmful effects and consequences of FGM/C play a critical role in influencing whether a woman decided to cut her daughter or not. Women with increasing exposure to media such as newspapers, magazines, radio, or television, are therefore perceived to have decreased likelihood of cutting their daughters. This in turn translates to reduced prevalence at community level once a tipping point of media exposed women is reached. (Kandala et al., 2019; Kandala & Shell-Duncan, 2019). However, the dynamics of the direction of media exposure influence on FGM/C outcome varies from one country to another given the complexity of contextual factors (at household, community, and regional levels) that may influence the extent to which media information on FGM/C is made available and accessible to those who need it most.

2.2.11. Feminist social integrated theory

We also note the new gendered system framework recently proposed by Yount and Colleagues to assess the influence of individual and contextual factors on FGM/C risk in girls in low and middle-income countries described in the next (Grose et al., 2019; Young et al., 2019). This theory also doubles as a framework to understand community gendered influence of social and gender norms. Details of the framework is presented in next section.

2.3. Existing Frameworks to explain FGM/C risk Factors

A number of important frameworks have been developed to understand FGM/C outcomes. These include the social norms, gender norms and feminist theory as discussed in the previous section. The frameworks emerged in the past decade based on evidence from theoretically grounded quantitative studies by leading investigators in the field of FGM/C research. Such frameworks provide an evidence-driven and testable theoretical constructs to explain existence and persistence of the practice in relation to risk factor influence on observed outcome especially in developing countries. In addition to the theoretical constructs presented in the previous section, we describe a quantitative framework recently proposed below.

2.3.1. The Integrated Theoretic Framework

The objective of the integrated theoretic model is to explain and quantify influence of social norms and gender norms at individual and community levels. The framework tested if a daughter's risk of experiencing FGM/C was associated with living in a community with 1) norms that are less supportive of FGM/C; 2) more opportunities for women outside marriage, and 3) greater ethnic diversity. The second component tested if a mother's disapproval of FGM/C was more strongly associated with her daughter's FGM/C if the pair live in a community with 1) norms that are less supportive of FGM/C; 2) more opportunities for women outside marriage and 3) greater ethnic diversity. The integrated theory was tested across 5 countries with a varying prevalence burden among girls (Grose et al., 2019; Hayford et al., 2020; Yount et al., 2020). The objective was to assess the contribution of more favorable community-level gender systems and expanded opportunities for women outside the family in lowering FGM/C risk. An assessment of this theoretical model across the 5 African countries found strong support for the direct negative influence of maternal opposition and community gender norms that opposed FGM/C on FGM/C hazard in a girl in Egypt, Kenya, Burkina Faso, Cote d' Ivoire, and Mali. However, the influence of extra-familiar opportunities varied significantly across the five countries – positive influence in Kenya and Côte d'Ivoire (Grose et al., 2019; Hayford et al., 2020); Negative influence in Burkina Faso and Côte d'Ivoire (Hayford et al., 2020), and no influence in Egypt and Guinea (Hayford et al., 2020; Yount et al., 2020).

A summary of existing FGM/C theories and framework is presented in Table 2.1.

Table 2.1. Summary of FGM/C Theories and Frameworks

Study	Theory	Hypothesis	Level of analysis	Description	Important key Factors	Analysis year	Adjustment for complex design feature	Statistical Method
(Kandala et al., 2019) (Kenya)	Social norms, socio-demographic factors, Geographic location	Social normative influences significantly increase likelihood of cutting among girls 0-14 years in Kenya	Individual, community and regional	Assessed social normative influence on FGM/C in a girl	Social norms, ethnicity, religion, geographic location, ethnic fractionalization index (EFI)	2003-2014	No	Space and spacetime Hierarchical Bayesian logistic regression model
(Grose et al., 2019; Hayford et al., 2020b; Yount et al., 2020) (Kenya, Egypt, Mali, Guinea, Burkina Faso	Social norms, Gendered-based norms, Feminist theory	1) A daughter has a lower adjusted risk of experiencing FGM/C if she lives in a community with (a) norms that are less supportive of FGM/C; (b) more opportunities for women outside marriage; and (c) greater ethnic diversity. 2) A mother's disapproval of FGM/C is more strongly associated with her daughter's FGM/C if the pair live in a community with (a) norms that are less supportive of FGM/C;(b) more opportunities for women outside marriage; and (c) greater ethnic diversity.	Individual and community (inference at community level)	Proposed a feminist social-ecological theory that integrates norms-based and gender-based approaches to understanding daughters experience of FGM/C	Community opposition to FGM/C Maternal opposition to FGM/C Extra-familial opportunity	2014	Study compared single-level weight adjustment to unadjusted multilevel models but found no difference in estimated coefficient for fixed effects.	Multilevel discrete hazard model*
Present Study (Kenya, Nigeria, and Senegal)	Social determinants, Social norms. Gender norms, Religious norms, Feminist, Geographic location, time	1)Risk factors operate at individual and community levels to influence FGM/C outcome among girls 0-14 years. 2) Accounting for the complex survey design will modify individual level risk factor estimates	Individual, community, and region. Inference at individual level	The Proximate Determinants Framework (PDF) integrated approach to understand the roles of social norms, genders, social determinants, and geography in FGM/C outcome among girls and women in Africa	Social norms, Gender norms, Feminist,	Kenya: 2003-2014. Nigeria: 2008-2018. Senegal: 2010-2017	Study adjusted for cluster sample design	Spacetime Hierarchical Bayes logistic mixed regression model

2.4. Limitations of Existing FGM/C Frameworks

The contribution of the FGM/C theories to understanding FGM/C prevalence and persistence in research and programmatic context is an important advance. However, efforts to gain deeper insights into the interaction between the various theories in specific ecological context will provide a useful and integrated approach to understand FGM/C persistence within country-specific context. The integrated theoretic approach, on the other hand, provides an excellent framework to evaluate and theorize the influence of social and gender norms operating at multiple hierarchies including both individual and community levels within a country of interest. Hence, the term "integrated theoretic", as proposed by Grose and Colleagues in their recent articles (Grose et al., 2019; Hayford et al., 2020; Yount et al., 2020). The framework, however, does not allow excess variation in spatially structured and unstructured FGM/C risk at subnational, FGM/C prevalence trend over time and interaction between geography and time to be accounted for. More importantly, the strong leaning toward of the framework toward feminist gendered system to understanding FGM/C minimizes the contribution of social determinants of health which often provide the context that create and sustains social and gender norms in the first instance.

With regards to adjustment for the complex sampling design of the DHS, the authors of the integrated theoretic approach (Grose et al., 2019; Hayford et al., 2020) reported they considered a single-level weight adjustment but found no significant change to the regression coefficient of the fixed effect estimates. However, the tendency for bias to be introduced due to large excess variation observed at the primary sampling level unit (community level) - of which the analysis was implemented - is an issue of concern. While the authors reported the size of the bias introduced was minimal, the influence on their risk factor estimates could not be assessed. Accounting for the excess random variation at cluster level may, however, possibly change the observed risk factor estimates. Accounting for excess variation at the cluster level serves two purposes; to account for the unobserved factors at community level and to capture excess variation due to sampling/measurement error at cluster level.

Understanding the role of various risk factors at individual level offer the benefit of being able to evaluate and quantify the magnitude of risk among specific categories of member of the population. In addition, studies have shown that mother's educational attainment- an important measure of extrafamilial opportunity- is a necessary but not sufficient determinants of FGM/C outcome (Grose et al., 2019). This implies that women with high or low education

may be prone to cut their daughters depending on the community or region in which she lives and her group membership affiliation especially in African settings. For instance, in some countries (such as Kenya), high education protects while in others that cut for elitist status, it does not (such as Senegal). This pattern was also observed in the present study. Also, in some African countries, women with low education are easily reached with FGM/C interventions and influenced to participate in community abandonment effort especially with little financial incentive. Hence the observed influence is expected to vary across countries as reported in (Hayford et al., 2020).

In addition, accounting for the role of geography at subnational(regional) is often necessary to understand the geographic distribution of excess risk variation due to prevailing FGM/C policy and legislation which tend to affect all communities across the region (but to varying extent at community level).

2.5. The Proposed FGM/C Proximate Determinants Framework

In this section, we present a novel proximate determinant framework (PDF) to understand the distribution and determinants of FGM/C among women and girls in African populations. The proposed framework addresses two gaps in the FGM/C literature and quantitative research methodology. First, is the need for a framework to model and map observed prevalence and local trends of FGM/C among women and girls in Africa. Second is the need for a theoretically grounded and empirically driven framework to identify and quantify both known and unknown risk factors that drive observed prevalence and risk trends at individual and contextual levels. We believe such framework is better able to explain local variations and persistence, as well as where change is taking place in developing countries. The framework decomposed FGM/C risk into observable risk factors, and unobservable risk factors operating dependently and independently in space and in time as well as simultaneously in space-time.

The PDF provides a hypothesis-driven micro framework to generate evidence base for the ongoing monitoring and evaluation of individual and group level risk factors, geographic hotspots, and subnational trends. The PDF is an integrated ecologic approach to understanding how various components such as social norms, gender norms, and social determinants of health, operate at individual, household, community, and regional levels to influence FGM/C outcome among girls and women in Africa over time. Therefore, the novel contribution of the

framework is that it can provide deeper insight into evolution of risk and the spatial-temporal dynamics of FGM/C risk at local level, given that probability of observing an FGM/C event is subject to change based on contextual factors at play in a particular place and specific time point.

The PDF proposes there exist a set of underlying determinants that operate through intermediate and proximate determinants to influence FGM/C likelihood. Such framework is required given that social and gender norms often interact with other factors that sustain the practice of FGM/C (Cislaghi & Heise, 2019). More so, the observed influence of normative factors varies across subnational regions and over time (Kandala et al., 2019). It provides intuitive way to model, map and interpret the roles of various factors influencing FGM/C outcome within a specific context. Details of the framework is presented in Figure 2.1 below.

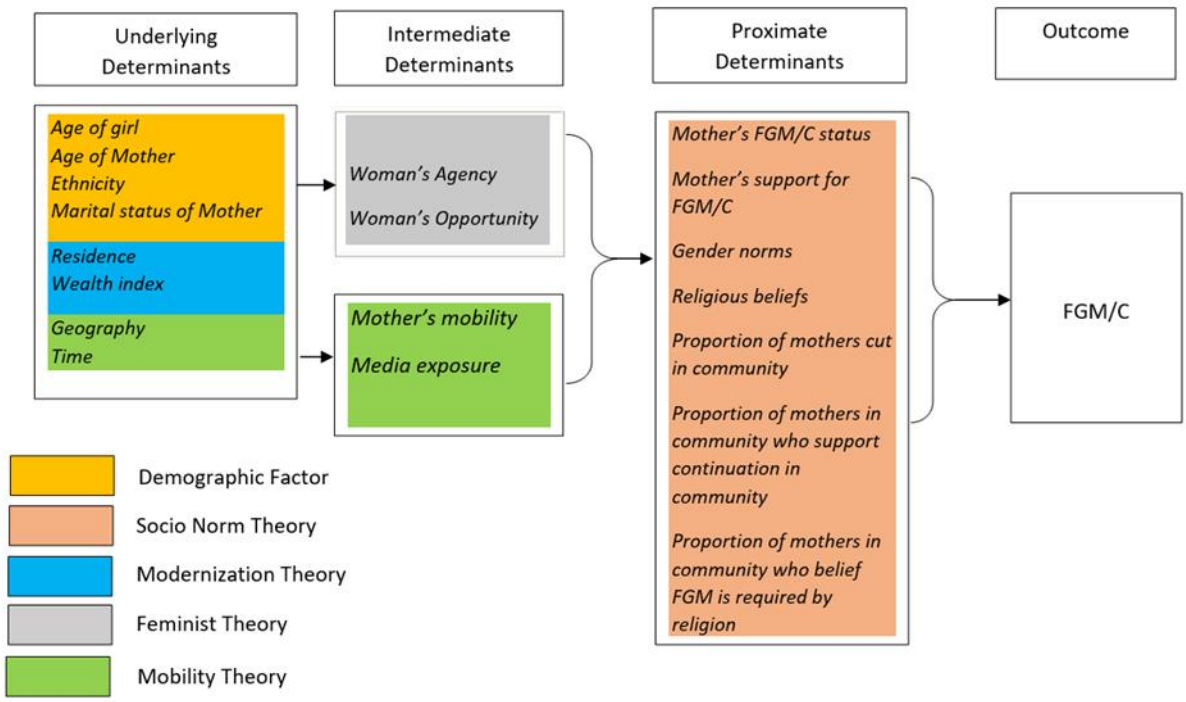


Figure 2.1. Proximate Determinants socio-ecological framework for Female Genital Mutilation among Girls aged 0-14 years in Sub-Saharan Africa.

The resulting implementation of the PDF within a hierarchical Bayesian spatio-temporal structured additive regression (PDF/ST-STAR) model framework provides a novel, robust and scalable approach to uncovering deeper insights into the nature of FGM/C persistence and progress towards abandonment by 2030 across several countries. Although the PDF framework is a pathway diagram that shows how a set of risk factors operate through others to influence probability of the outcome, the objective for the purpose of this study is largely "association" rather than "causal relations" and designed for ease of statistical model interpretation of association effects.

2.6. Background to the Blood Pressure Study

The increasing burden of raised blood pressure in sub-Saharan Africa in the past two decades has become a serious cause for global health and regional concern with estimated 11.1% rise in burden between 1990 and 2010 and a projected increase of 216.8 million affected individuals by 2030 from 130.2 million in 2010 (Adeloye & Basquill, 2014). Globally, high blood pressure accounts for at least 13% of all deaths and a leading risk factor for premature deaths due to cardiovascular diseases which in turn account for 17.3 million annual lives lost - that is more than total deaths due to tuberculosis, HIV and Malaria combined annually (WHO, 2017). In this region, the burden of raised blood pressure and cardiovascular disease mortality is highest in South Africa.

According to a recent study on hypertension among older adults in low and middle-income countries, South Africa has the highest rate of hypertension reported among persons 50 years and older for any country in the world, at any time in history with an estimated highest rate of 78% observed in South African ageing population (Lloyd-Sherlock et al., 2014). This sense of urgency led to the development of a National strategic plan for the prevention and control of chronic morbidities and co-morbidities across the population from 2013 to 2017 (DOH, South Africa, 2013) and from 2020 to 2025 (DOH, South Africa, 2019). As a result of this ambitious effort by the government which includes reduction of the hypertension burden by 20% and ensure regular physical activity in additional 10% of its population by 2020, various interventions have been rolled out to address this critical epidemic situation. Effort to assess geographic distribution and trends in blood pressure at small area level provides an important step to guide and monitor progress towards National targets and the global target of 25% reduction in the prevalence of raised blood pressure by 2025.

Availability of quality data sources across African countries to monitor trends and chronic disease risk factors has increasingly made it possible to conduct detailed spatial epidemiologic investigation to examine geographic trends to inform policy decision and evidence-driven public health. In South Africa, such data include the South Africa Demographic and Health Survey (SADHS), South Africa National Health and Nutrition Examination Survey (SANHANES) and National Income Dynamics Survey (NIDS). Each survey contains a comprehensive set of indicators for evaluating NCDs, risk condition and life style risk factors at population level (Wandai et al., 2017). Such data provide spatial epidemiologists and disease modelers a robust opportunity to investigate how underlying and behavioural factors shape individual and population level outcome of chronic disease conditions such as elevated blood pressure. However, SADH is a cross-sectional national survey with limited data collection (1998 and more recently 2003). Also, the SANHANES is a cross-sectional national survey that obtained data on blood pressure measurement on adults 18 to 40 years and hence, not nationally representative of the population. In addition, BP measurement was only taken once while a second measurement was only considered if the first BP was 140/90 mmHg or higher (Wandai et al., 2017).

On the other hand, the NIDS provides the first panel household survey that is nationally representative and obtained double measurements of BP on adults 18 years and older during the survey period (2008 to 2017). The availability of observed BP status for sampled individuals over time allows for evaluation of intervention programs in relation to chronic disease and risk and associated risk factors and assessment of longitudinal trends. More importantly, for the purpose of the present study, the stratification of the NIDS sample at district municipality level ensures that small area health indicators and local trends can be estimated and assessed at finer administrative geography. In Chapter 5, we demonstrate the utility of our novel approach to estimate average systolic blood pressure at small area level using the National Income Dynamics survey (NIDS).

CHAPTER THREE

PREVIOUS WORK ON FGM/C RISK FACTOR MODELLING

This chapter is a summary of a preliminary study undertaken and recently published on FGM/C risk factors among girls. The study laid the foundation for the present work on FGM/C risk factor estimation using complex surveys. The chapter has three objectives. First is to summarize the work and the analytical approach. Second, my contributions to each part of the work are highlighted. Lastly, we discussed in brief, the methodological limitations of the study on which the current study was predicated.

3.1. Summary of Methods and Findings

FGM/C is an important global health issue that affects women and girls. Despite remarkable gains achieved in the past two decades, the pace of progress towards FGM/C abandonment has been relatively slow across most affected countries in sub-Saharan Africa. Central to this persistence are FGM/C related social norms at play in specific contexts. The primary objective of the study was to evaluate the contribution of social norms and conventions to the observed prevalence pattern of FGM/C among girls 0-14 years in Kenya between 2003 and 2014. We assessed the influence of potential factors that contributed to FGM/C outcome, including geographic location of a girl and mapped subnational prevalence trend. The study considered the Kenya demographic and health surveys (KDHS) for four consecutive survey years between 1998 and 2014. We utilized a hierarchical Bayesian approach within a generalized additive mixed regression framework for model fitting. Parameter estimation was carried out using a Markov Chain Monte Carlo (MCMC) simulation technique. Model assessment and comparison were conducted using the deviance information criterion (DIC). Results showed substantial reduction in National prevalence from 9.9% in 1998 to 3% in 2014. Spatial analysis revealed socio normative influences - such as a mother's support for the continuation of the practice, her FGM/C status, and her belief that FGM/C is required by religion – were key drivers of FGM/C likelihood in a girl at individual and community levels. Other important risk factors identified include ethnic mixing within community, Muslim religious affiliation, and belonging

to Kisii and Somali ethnic extractions. The study was the first attempt to identify FGM/C risk factors in space and time, and to evaluate the role of FGM/C theories in FGMC outcome among girls 0-14 years. Findings provide important road map to evaluate progress and design tailored intervention to target most affected regions and communities in Kenya.

3.2. Introduction

FGM/C is an important health issue of global concern among women and girls (UNICEF, 2020). The procedure involves the removal of all or part of the female external genitalia or other injury to the female genital organs for non-medical reasons. As at the end of 2020, at least 200 million women and girls in 31 countries (with national prevalent data) have undergone FGM/C procedure in low and middle-income countries, with over 90% of cases reported in Africa (UNICEF, 2020).

FGM/C is a priority issue on the UN sustainable development agenda as a critical element of harmful traditional practices against women and girls targeted for elimination by 2030 (WHO, 2008). In line with this target, community-led intervention efforts have been deployed in most affected countries to achieve the 2030 elimination goal as observed in Kenya, Nigeria and Senegal (Diop & Askew, 2009; Mwendwa et al., 2020; The Girl Generation, 2013). A systematic review of effectiveness of FGM/C abandonment interventions in seven African countries, however found limited effectiveness of interventions evaluated, despite indications of positive changes in attitudes and knowledge in relation to FGM/C (Berg & Denison, 2013). The same study identified local FGMC traditions, religion and reduction in women's sexual desire as contextual drivers of FGM/C. More so, in countries that have experienced significant decline in FGM/C prevalence among women 15 to 49 years, subnational variation persists especially in certain ethnic communities (Shell-Duncan et al., 2017).

3.2.1. The Theory behind Normative Influences on FGM/C

A number of theories have been proposed to explain reason for persistence of FGM/C in developing countries. The most important of this is the social norm/convention theory which has been a core element of most successful FGM/C abandonment interventions. According to the theory, patterns of behaviors are influenced by unwritten rules and expectations acquired by constant interaction with key members of the community. These members, also known as

the reference group, are often perceived as the gatekeepers of community culture and traditions. Hence, the actions of individuals are influenced by such expectations to avoid being sanctioned or ostracized from group or community membership (Mackie & LeJeune, 2009; Shell-Duncan et al., 2011; Shell-Duncan, 2016; Yount, 2004; Yount, 2002). According to the first proponent of the theory, FGM/C was hypothesized to be a social norm, that spread and became locked in place by inter-dependent expectations in relation to marriageability (Mackie & LeJeune, 2009). Hence, a young woman having undergone the procedure is considered fit for marriage especially into a high social status family and will show fidelity to her marriage partner. In other instances, studies have shown that FGM/C is a prerequisite for inclusion in all-women group membership especially in countries where it has persisted such as in western Africa (Shell-Duncan et al., 2011). However, social norms have been the least tested within a statistical framework to estimate associated FGM/C risk in Kenya.

Apart from social norms, other identified norms that influence the risk of cutting include gender norms (Cislaghi & Heise, 2018) and unfounded beliefs that it is a religious requirement (Hayford & Trinitapoli, 2011). Previous studies on spatial patterns and significant influence of normative influences on observed FGM/C likelihood among women 15 to 49 years in Kenya and Senegal (Achia, 2014; Kandala & Shell-Duncan, 2019) elicited two questions: 1) Do we find similar trends among the younger generation in Kenyan girls 0-14 years old, and 2) are there similar strong associations between normative influences and a girl's FGM/C status? Another important question is the role of geographic location in which a girl or her mother resides.

The study therefore assessed how social norms influenced spatial variation in risk among Kenyan girls. It sought to test the prediction of socio norms/convention theory, by examining trends in prevalence of FGM/C among girls. The study also assessed the effect of geographic location and time on observed prevalence. We employed advanced statistical methods that allow for the effects of multiple factors operating at individual and community levels to be evaluated simultaneously within a unified hierarchical Bayesian (HB) regression framework. While HB has been extensively applied in disease mapping (Best et al., 2005), its potential in FGM/C risk factor studies has only begun to be explored. For instance, spatial geo-additive regression model was utilized by (Kandala et al., 2009) and later by (Achia, 2014) to understand spatial patterns and FGM risk factors among women of reproductive age in Nigeria and Kenya respectively. More recently (Kandala & Shell-Duncan, 2019) employed similar Bayesian geo-additive mixed regression approach to examine FGM/C risk factors among women in Senegal

in 2010 and 2015. The present study is the first to model and map FGM/C prevalence patterns, trends, and the role of social normative influences on FGM/.C likelihood among girls 0-14 years in Kenya.

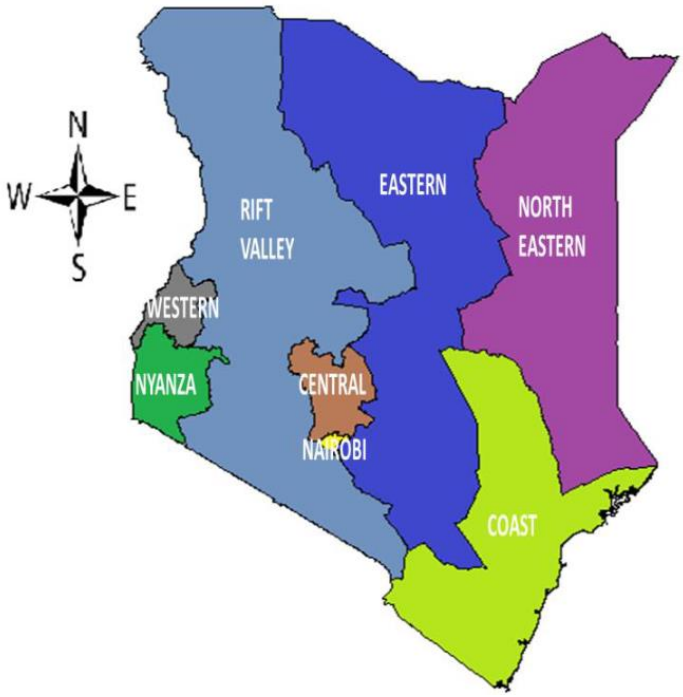


Figure 3.1. Map of Kenya showing the eight administrative regions.

3.3. Methods

3.3.1. Data

The study utilized data obtained from four successive Kenya demographic and health surveys (KDHS) conducted in 1998, 2003, 2008 and 2014. Data was obtained from a set of responses on FGM/C using household questionnaire administered to women of reproductive age group (15 to 49 years). The FGM/C module included a set of questions on history of cutting in both women and their daughters (if the daughter was still alive as at the time of the survey). Another important question asked was whether she would support continuation of the practice in her community. Different methods were used to elicit information on FGM/C status of daughters in each survey. Information was obtained on eldest daughter in the 1998 and 2003 KDHS; on most recently circumcised daughter in 2008 KDHS and all girls aged 0-14 years in 2014 KDHS. All surveys employed a stratified, two-stage cluster sampling design in which the entire

country was stratified based on a combination of type of residence (rural-urban) and region of residence (eight administrative regions in total as shown in Figure 1). Subsequently, a two-stage sampling of primary unit, knows as clusters, followed by sampling of households within selected clusters was conducted. For the study, we extracted data for girls aged 0 to 14 years across all survey years to ensure trend estimates are comparable over time using the 1998, 2003, 2008 and 2014 KDHS.

3.3.2. Study Variables

3.3.2.1. Outcome Variable

We defined the outcome variable of interest as a binary indicator of whether a girl aged 0 to 14 years was cut or not across the four survey years.

3.3.2.2. Exposure Variables

The primary exposure variables are proximate determinants measures of social normative influences such as FGM/C status of mother, her support for FGM/C continuation, and her believe that FGM/C was a religious requirement at individual level of measurement. In addition, the proportion of each exposure variable was also assessed at community level as indicators of prevalence burden within community. Another important exposure variable is the geographic location effect which captured excess variation and neighborhood effects due to interaction among unknown risk factors at the regional level. Additional variables include underlying determinants such as measure of socio-demographic characteristics of mother and girl - age of mother, age of girl, ethnicity, religious affiliation, marital status, household wealth quintile, as well as intermediate determinants such as mother's decision-making power within household, and ethnic fractionalization index to assess ethnic mixing within community.

3.3.3. Statistical Analysis

We present the preliminary descriptive and evaluation of bivariate associations between the main outcome of the study – FGM/C among Kenyan girls 0-14 years and mother/daughter covariate characteristics for the survey years 1998, 2003, 2008 and 2014 as shown in Table A3.1. Subsequently, we utilized a class of generalized additive mixed regression models (GAMMs), to estimate the effects of different covariates on the observed data. Unlike the standard regression framework, which assumes strictly linear relationship between the covariates and the response variable, GAMMs provide a flexible alternative in that they allow evaluation of nonlinear relationships. Hence, complex structures such as spatial and temporal dependence in the data can be assessed within a unified regression framework (Kammann & Wand, 2003; Kneib & Fahrmeir, 2006).

3.3.4. Notation and Model Specification

We denote the outcome variable of whether girl i was cut or not by fgm_i such that $fgm_i = 1$ if girl i was cut and $fgm_i = 0$ if otherwise. The random variable fgm_i hence follows a Bernoulli distribution with parameter π_{ist}. Given the logit link function, the linear predictor η_{ist} of the fully adjusted model for the pooled data is given in (3.1) as:

$$\begin{aligned}\eta_{ist} = \text{logit}(\pi_{ist}) &= \log\left(\frac{\pi_{ist}}{1-\pi_{ist}}\right) \\ &= \beta_0 + z'_i\beta + f_1(agem_i) + f_2(aged_i) + f_3(efi_i) + f_4(cut_i) \\ &+ f_5(req_i) + f_6(sup_i) + f_t\,(year) + f_{str}(s) + f_{unstr}(s) \\ &+ f_{st}(s,t)\end{aligned} \tag{3.1}$$

where,

- π_{ist} is the probability of cutting girl i in region s at time t.
- $f_j = \{f_1(.), \dots, f_6(.), f_t\,(year), f_{str}(s), f_{unstr}(s), f_{st}(s,t)\}$ is the smoothed functions of metric covariates, such as age of girl and time.
- β_0 is the intercept, $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)'$ are unknown coefficients of other class of covariates, $z_i's$.
- $s_i = 1, \dots, S_i$, where s_i is the geographic reference location of girl i.

- $f_{str}(.)$ and $f_{unstr}(.)$ denote the structured and unstructured spatial effects, respectively.
- $f_t\ (year)$ is the smooth function of the temporal effect common to all the regions, and $f_{st}(s,t)$ is the region-specific temporal smooth function.

The fixed effects parameters $\theta = \{\beta_0, \boldsymbol{\beta}\}$, are given diffuse priors such that, $\pi(\theta) \propto constant$ while metric covariates such as age and time are modelled using random walk of the second order (RW2) as described in the previous chapter.

We utilized a fully Bayesian inferential approach via Markov Chain Monte Carlo (MCMC) simulation algorithm using metropolis-Hastings sampling from the posterior distribution using the R implementation of the BayesX package. To account for spatial dependence in the observed response, we "borrowed information" from neighboring regions by assigning a Markov random field (MRF) prior:

$$f_{str}(s)|\{f_{str}(r), \tau_{str}^2\}; r \neq s \sim N\left(\sum_{r\sim s} \frac{f_{str}(r)}{N_s}, \frac{\tau_{str}^2}{N_s}\right) \tag{3.2}$$

where $r\sim s$ indicates the neighborhood relationship between area s and r while "$r \neq s$" indicates that area r is not the same as s; N_s denotes the summation of the spatial weight matrix defined as the spatial proximity of neighboring regions to region s, $\tau_{str}^2 > 0$ is the variance parameter for the spatially structured random effects of geographic(regional) location. The variance parameter term τ_{str}^2 of the spatial random effect is divided by the number of its neighbours N_s and not the total number of areas in the study domain N_S. This in turn allows for local smoothing of the area-specific random effect in area s which in turn depends on the sample size in area s and the variability of the information in its neighbouring regions. Consequently, if N_s is small then, the conditional variance parameter for area s will be large and the area-specific mean will be further away from the average of its neighbours. The reverse is true for areas will larger number of neighbours (N_s) with mean estimates closer to average of their neighbours and smaller conditional variance. The term τ_{str}^2 is an unknown conditional variance parameter that controls the amount of local smoothing for the study domain in the ICAR model specification. Consequently, the larger the variance parameter τ_{str}^2, the larger the

conditional variances for all the areas in the study domain (Haining & Li, 2020). The first component captures the conditional spatial dependence of $f_{str}(s)$ which is defined as a weighted average of its neighbors while the second captures the variance components. The dependence introduced via the MRF prior ensures that information is shared among neighboring regions. In other words, MRF priors allows information borrowing to improve effective sample size especially in low or out-of-sample regions. In addition, a computational advantage is gained from the sparseness introduced by the conditional independence structure of the MRF in that the full conditional distribution of each structured spatial component can be obtained. Spatial heterogeneity $f_{unstr}(s)$ was modeled as independent and identically distributed with a zero mean Gaussian prior:

$$f_{unstr}(s)|\tau_{unstr} \sim N(0, \tau_{unstr}^2) \tag{3.3}$$

Where $\tau_{unstr}^2 > 0$ is variance parameter for the spatially unstructured random effect of geographic location.

We model the continuous variables assumed to be non-linear(smooth) functions using Bayesian P(enalised)-splines (Lang & Brezger, 2004) which are the Bayesian analogue of the P-splines developed by Eilers and Marx (Eilers & Marx, 1996). These continuous metric covariates include; time in years $f_y(year_i)$, mother's age ($f_1(agem_i)$, girl's age ($f_2(aged_i)$, space-time interaction term $f_{st}(s_i, t_i)$, ethnic fractionalization index $f_3(efi_i)$, proportion of cut women in the community $f_4(cut_i)$, proportion women in the community who believed that FGM/C was a religious requirement $f_5(req_i)$ and proportion of women who supported FGM/C continuation $f_6(sup_i)$. The smooth function $f_j(x_{ij})$, is expressed as a linear combination of n B-spline basis functions as:

$$f_j(x_{ij}) = \sum_m \varphi_{jm} B_{jm}(x_{ij}) \tag{3.4}$$

The interaction term function $f_{st}(x_{is}, x_{it})$ is modelled using the tensor product of two one-dimensional B-splines as:

$$f_{st}(x_{is}, x_{it}) = \sum_{k=1}^{n}\sum_{j=1}^{m} \varphi_{stjk} B_{sj}\,(x_{is}), B_{tk}(x_{it}) \tag{3.5}$$

The choice of priors for $\varphi_{st} = (\varphi_{st11,} \dots, \varphi_{stmn})'$ are based on the conditional autoregressive priors which is defined by specifying the conditional distributions of φ_{stjk} given neighboring parameters and the variance component τ_{st}^2 (Lang, 2003; Besag & Kooperberg, 1995). For instance, prior specification based on the 4 nearest neighbors can be defined as:

$$\varphi_{stjk}|. \sim N\left(\frac{1}{4}\left(\varphi_{stj-1,k} + \varphi_{stj+1,k} + \varphi_{stj,k-1} + \varphi_{stj,k+1}\right), \frac{\tau_{st}^2}{4}\right) \tag{3.6}$$

For $j = 2, \dots, m-1$ and $k = 2, \dots, n-1$ and appropriate changes for corners and edges. For example, for the upper left corner we obtain $\varphi_{st11}|. \sim N\left(\frac{1}{2}(\varphi_{st12} + \varphi_{st21}), \frac{\tau_{st}^2}{2}\right)$. For the left edge we get $\varphi_{st1k}|. \sim N\left(\frac{1}{3}\left(\varphi_{st1,k+1} + \varphi_{st1,k-1} + \varphi_{st2,k}\right), \frac{\tau_{st}^2}{3}\right)$. This prior is a direct generalization of a first order random walk in one dimension. An alternative of prior specification for φ_{st} can be formulated based on the Kronecker product $K_{st} = K_s \otimes K_t$ of penalty matrices of the main effects (Clayton,1996). We consider the four alternative specifications of this choice of prior as proposed by Knorr-Held (2000) in Chapter 4.

Furthermore, we assigned $inverse\ Gamma$ prior distribution, to the variance parameters, that is, $\tau_l^2 \sim \mathrm{IG}(a_l, b_l)$, where a and b are hyperparameters. Parameter estimation procedures were carried out using Markov Chain Monte Carlo (MCMC) simulation using R implementation of an advanced statistical software, BayesX. (Umlauf et al., 2015). We considered the choice of a=1, b=0.0005(sensitivity analysis showed no sensitivity to this choice of prior for the variance parameters) and drew N$(= 2 \times 10^4)$ samples from the parameter space $\theta = \left\{\beta_0, \{\beta_j\}, \{f_{str}(.)\}, \{f_{unstr}(.)\}, \{f_{st}(.)\}, \{\varphi_{jm}\}, \{\varphi_{stjk}\}, \{p_i\}\right\}$ as well as the hyperparameters space $\emptyset = \{\tau_{str}^2, \tau_{unstr}^2, \tau_{st}^2\}$. We used a combination of thinning and Burn-in to improve the posterior estimates by sampling every 50th sample after discarding the first 2000 iterations as burn-in. Model comparison was carried out using deviance information criterion (DIC). The DIC compares two models by assessing how well the model describes the data (using the deviance) relative to the complexity of the model (using the effective number of parameters).

Smaller DIC (by at least 5 points) indicates a better model, while a larger effective number of parameters indicates a better model. We report results obtained from the posterior distribution of model parameters in tables, graphs, and maps.

In addition, we calculated a measure of ethnic diversity within a community using the ethnic fractionalization index (EFI) using the normalized Herfindahl-Hirschman Index (Posner, 2004) as shown in the equation 6 below:

$$EFI_i = 1 - \sum_{k=1}^{n_i} e_{k_i}^2 \tag{3.7}$$

where e_{k_i} is the proportion of the kth ethnic group in the ith community with $n_i \geq 2$ ethnic groups. A higher value (close to 1) indicates a multi-ethnic community and hence greater diversity in which all the available ethnic groups are fairly equal in size. A lower value (close to 0) indicates a community with fewer ethnic mixing or monoethnic (if zero).

3.4. Results

The eight administrative regions of Kenya are shown in Figure 1 below. The objective is to understand the geography of FGM/C prevalence among girls 0-14 years across the regions using the KDHS samples.

3.4.1. Descriptive Analysis

We obtained a combined dataset of 27,746 total records of girls (as reported by their mothers) from 1998 (N=4,069), 2003 (N=4,048), 2008 (N=7,195), and 2014 (N=12,434). Results showed a rapid decline in national prevalence of FGM/C among Kenya girls 0-14years from 9.9% in 1998 to 3% in 2014. Significant variation, however, existed at subnational level and by characteristics of mother as shown in Table A3.1. Prevalence was substantially higher in daughters of cut women at 20% in 1998, followed by a reduction to 9.9% in 2014. However, a marginal drop of 0.1% was observed in girls born to uncut women between the same period. Similar pattern was noted in relation to girls born to women who supported FGM/C continuation.

3.4.2. Regional distribution of FGM/C Prevalence from 2003 to 2014

We present the geographic distribution in the crude FGM/C prevalence among Kenyan girls 0-14 years for the four consecutive survey years in Figure 3.2. Results showed that while the majority of the regions experienced significant reduction between 1998 and 2014 (2003 to 2014 for North-Eastern region), prevalence remained relatively high in North-Eastern region at 42% as well as 11% in Nyanza.

Table 3.1. National prevalence and girl's female genital mutilation/cutting (FGM/C) prevalence by normative influence variables across the four selected Demographic and Health Surveys (DHS) surveys in Kenya, Kenya Demographic and Health Surveys (KDHS) 1998 to 2014.

Factor	Level	1998 KDHS (n = 4069, FGM/C = 9.9%)	2003 KDHS (n = 4048, FGM/C = 9.4%)	2008 KDHS (n = 7195, FGM/C = 7.6%)	2014 KDHS (n = 12,434, FGM/C = 3.0%)
Mother's FGM/C status	*Cut*	22.0	23.5	21.5	9.9
	Uncut	0.3	0.4	0.1	0.2
Mother's support for FGM/C continuation	*Continued*	29.2	–	41.8	23.1
	Undecided	5.1	–	4.0	1.1
Mother's belief that FGM/C is required by religion	*Required*	–	–	46.7	27.8
	Not required	–	–	4.5	1.4

Noted: The percentages are not complementary and thus did not add up to 100% since what is shown is the percentage of women in the given category whose daughters were cut.

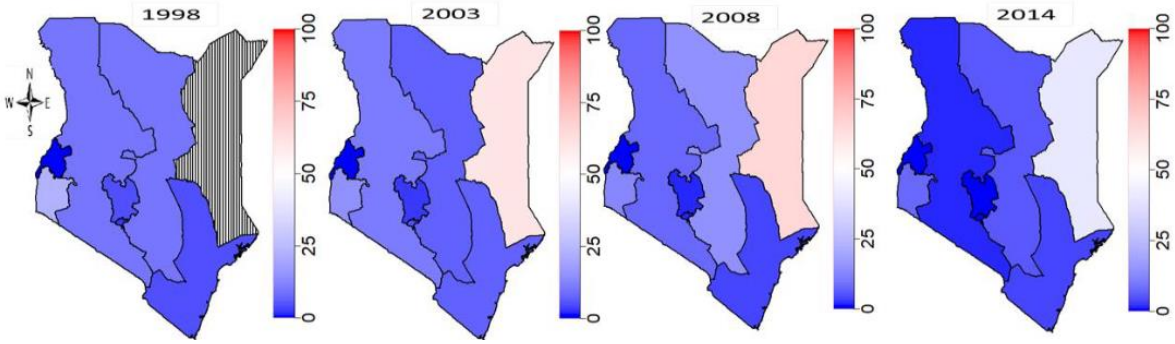


Figure 3.2. Evolution of FGM/C prevalence among 0-14 years old girls in Kenya from 1998 to 2014. Note that in 1998, there were no surveys in the Northeastern region hence the black-white stripes. Across the years, red regions had highest prevalence which decreased in magnitude as it fades through red to deep blue.

3.4.3. Bayesian hierarchical geo-additive Logistic Regression

The descriptions of the models fitted to the datasets along with the corresponding fit indices are given in Table 3.2. Three separate regression models were fitted to the most recent (2014 KDHS) and poled survey (2003-2014 KDHS). In the spatial analysis, the first model (model A) was an unadjusted model for indicators of normative influence at individual and community level - mother's FGM/C status, proportion of cut women, proportion of women who supported the continuation of the practice, as well as the proportion of women who believed FGM/C was a religious obligation. In the second model, we fitted the space-adjusted model (Model B) which accounted for the unobserved effects of spatial locations and normative influences simultaneously. The third model (Model C) adjusted for the effects of other potential risk factors of the observed influence of social norms variables. Similar modelling procedure utilized for the spatiotemporal analysis of the pooled data with excess variation in time and interaction between space and time accounted for in the fully adjusted model. We also note that only the influence of FGM/C status of mother was assessed in the spatiotemporal formulation. This is because information on a woman's support for FGM/C continuation and her belief that FGM/C was a religious requirement were not obtained in 2003. We present the results for both strands of the study in the next section.

3.4.3.1. Spatial Analysis

Results of the model comparison for the spatial regression analysis is presented in Table 2 below (top panel). Findings showed that Model C (fully adjusted for other individual-level covariates) returned the smallest DIC with a difference of 87 DIC points relative to the model of normative influence variables and spatial effects only (Model B). Findings of Model C are presented for the spatial regression analysis of the 2014 Kenya demographic and health survey (2014 KDHS).

Analyses from the spatial regression model (for the 2014 KDHS) revealed important results. We found significant evidence for social normative influences as key drivers of the FGM/C likelihood in a Kenyan girl 0-14 years both at individual level and community level in 2014 (See Table A3.2). The likelihood of cutting in a girl increased by 3 times if her mother supported FGM/C continuation (POR: 3.08; 95%CI: 1.76, 5.55). A similar pattern of dominant

influence of a woman's support for the continuation of the practice on FGM/C in her daughter was observed at the community level (Figure 3.3). Accounting for other potential confounders in Model 3 substantially reduced the influence of FGM/C status of mother (POR: 1.97; 95%CI: 0.69, 6.01). Also, evidence for the negative influence of ethnic diversity (at 0.5 or higher) in lowering likelihood of FGM/C in a girl was found.

Other important risk factors that contributed to FGM/C likelihood in a Kenyan girl include Muslim religious affiliation of mother compared to Christians (POR: 5.5; 95%CI: 2.65, 10.60), and belonging to Kisii ethnicity (POR: 11.73; 95%CI: 3.69, 37.38). Findings also suggest that exposure to radio increase the likelihood of a girl being cut in 2014. (POR: 1.66; 95%CI: 1.15, 2.37). We found no support for the protective effect of residence type and household wealth quintile. In addition, we also found little support for gender normative influences as evaluated by a woman's decision-making power within the household and indicators of gender-based violence (justification of wife beating).

Furthermore, findings seemed to show a negative support for the Feminist theory as indicated by lower likelihood of cutting in girls born to women with no occupation compared to those with former occupation (POR: 0.62: 95%CI: 0.3, 1.28). Little evidence of excess variation in risk was observed after accounting for other potential confounders (except significantly low risk observed in Nyanza region) as shown in Figure 3.4.

Table 3.2. Deviance information criterion (DIC), Effective sample size (pD) and mean deviance (Dbar) from the three models fitted on the 2014 KDHS data and the combined 2003 to 2014 data.

Data	Model	Description	DIC	pD	Dbar
2014 KDHS	**Model A**	Normative influence variable only(mother cut)	3551.4	19.7	3531.7
	Model B	Normative influence variable and total space	1805.3	62.6	1742.7
	Model C	Normative influence variable, space and other individual-level covariates	1718.6	117.1	1601.5
2003 to 2014 Pooled Data	**Model I**	Normative influence variable only	8104.9	8.0	8096.9
	Model II	Normative influence variable, space without time and space-time interaction	8108.1	9.7	8098.4
	Model III	Normative influence variable, space without time and space-time interaction and other individual-level covariates	6501.4	44.4	6457

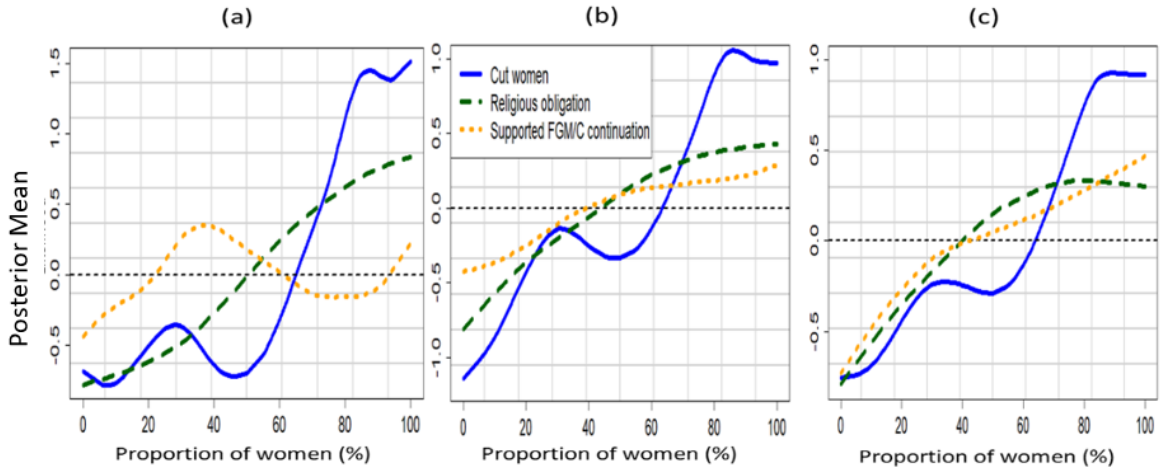


Figure 3.3. Non-linear effects of the proportions of women in a girl's community who were cut(blue), who supported the continuation of FGM/C (orange), and who believed that FGM/C was a religious obligation for (a) Model A, (b) Model B and (c) Model C. Evidence from the 2014 KDHS.

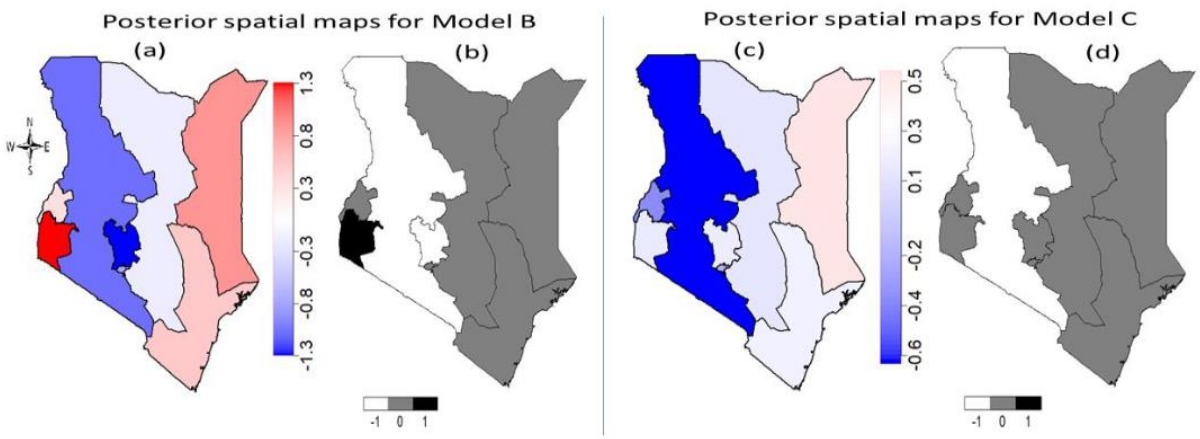


Figure 3.4. Posterior risk maps [(a) and (c)] of Kenyan 0-14 years old-girls' FGM/C with the corresponding 95% (right) [(b) and (d)] posterior significance maps for Model B (left panel) and Model C (right panel). Deep blue to red corresponds to low risk to high risk. Black colour indicates significantly high-risk regions, white colour indicates significantly low risk regions and grey colour indicates nonsignificant regions.

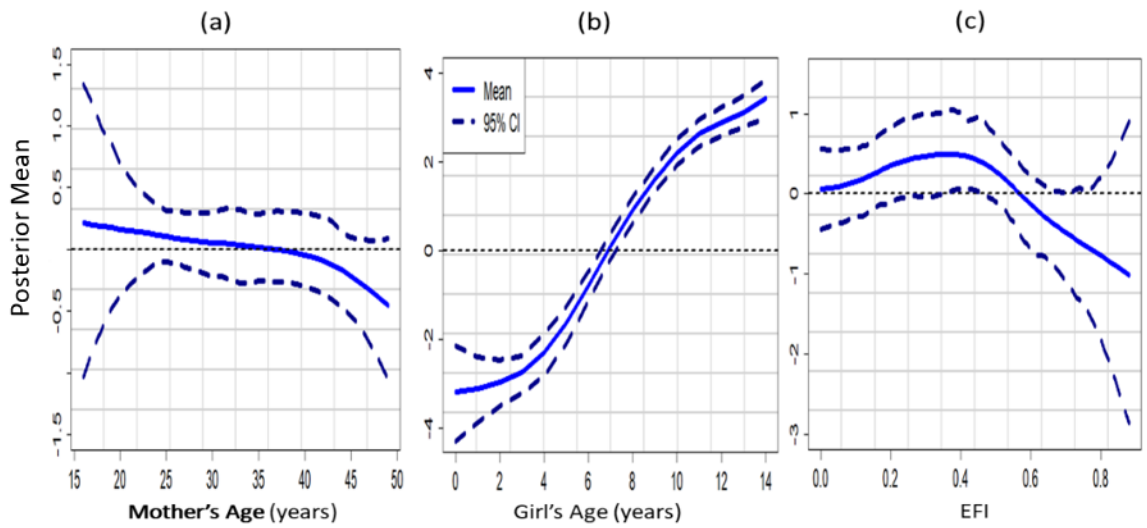


Figure 3.5. Non-linear effects on a girl's likelihood of experiencing FGM/C of mother's age (a); girl's age (b) and ethnic fractionalization index (EFI) (c). Evidence from the 2014 KDHS Model C.

3.4.3.2. Spatiotemporal Analysis

The study further evaluated the average effects of social normative influences on FGM/C likelihood in a Kenya girl aged 0-14 years between 2003 and 2014 accounting for 4 additional social and demographic characteristics of the mother – Marital status, ethnicity, educational attainment, and occupation as presented in Table A3. Estimates from the model comparison for the spatial-temporal regression analysis (Table 2, bottom panel) showed that Model III (fully adjusted for other individual-level covariates) provided a substantial improvement to the model fit by a difference of 1,607 DIC points despite Model III exhibited 4.6 times more complexity compared to model with normative influence variables, space without main time effect and space-time interaction only (Model B). Subsequently, we therefore provide additional interpretation of Model III below.

We found substantial influence of FGM/C status of mother estimated at 27 times higher likelihood (POR: 27.29; 95%CI: 24.62, 30.38). Findings did not provide evidence of rural-urban differential in FGM/C likelihood among Kenyan girls (POR: 1.17; 95%CI: 0.92, 1.51), while Muslim religious affiliation was significantly associated with FGMC likelihood in a girl (POR: 2.48; 95%CI: 1.77, 3.35). Increased likelihood of cutting in a girl was also significantly

associated with the ethnicity of her mother. Highest likelihood was observed in daughters born to women who belonged to Kisii ethnicity.

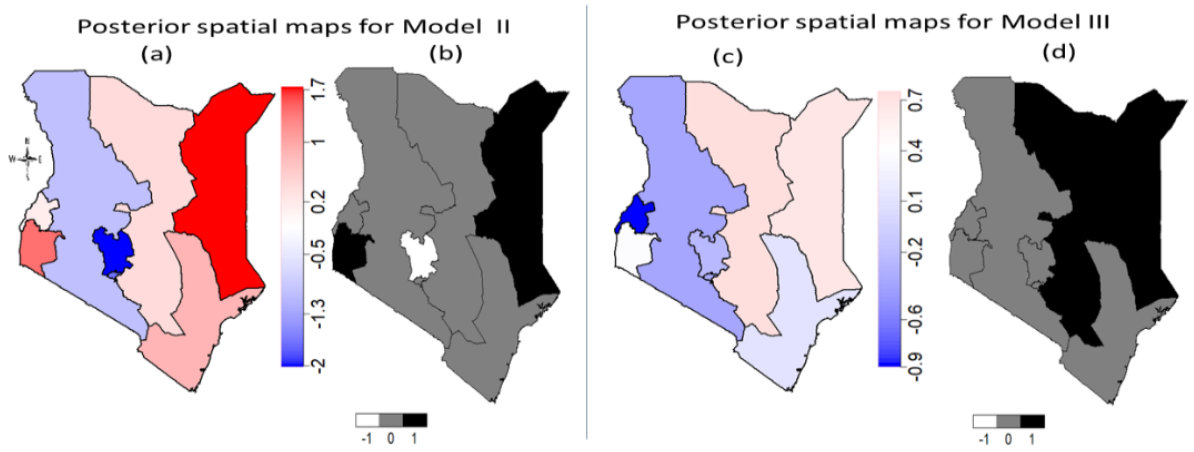


Figure 3.6. Posterior risk maps ((a) and (c)) of Kenyan 0-14 years old girls' FGM/C with the corresponding 95% (right (b) and (d)) posterior significance maps for Model II (left panel) and Model III (right panel). Deep blue to red corresponds to low risk to high risk. Black colour in (b) and (d) indicates significantly high-risk regions, white colour indicates significantly low risk regions and grey colour indicates nonsignificant regions. Evidence from the pooled data 2003 to 2014 KDHS.

In the spatiotemporal model formulation, we found support for the feminist theory in the increased likelihood of cutting in girls born to women with no education (POR: 5.78: 95%CI: 3.27, 10.71), but little support for occupational advantage. The posterior risk maps revealed North-eastern and Eastern as regions with significant excess risk of FGM/C in girls between the study period (Figure 3.6). The posterior mean prevalence estimates showed a pattern of consistently high prevalence in North-eastern and Nyanza in 2003, 2008 and 2014. However, an overall decline was observed in 2014 despite that prevalence remained relatively high in Northeast region at 41%. (Figure 3.7). A steady decline in the likelihood of a girl being cut was also found between 2003 and 2014, while a positive association was found with increasing age of her mother (Figure 3.8).

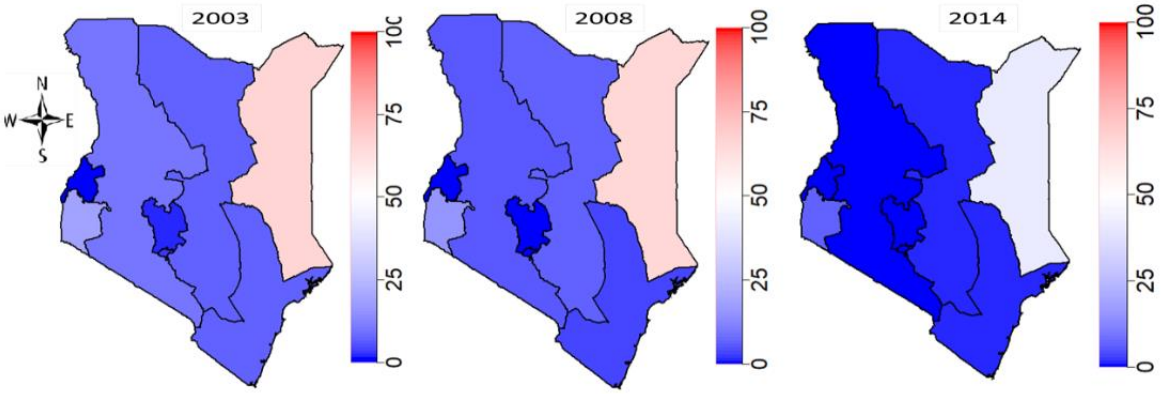


Figure 3.7. Predicted fully adjusted FGM/C prevalence among 0-14 years old girls in Kenya from 2003 to 2014 from the best fit model (Model III) of the pooled 2003 to 2014 data. Across the years, red regions had highest prevalence, while deep blue regions had lowest prevalence.

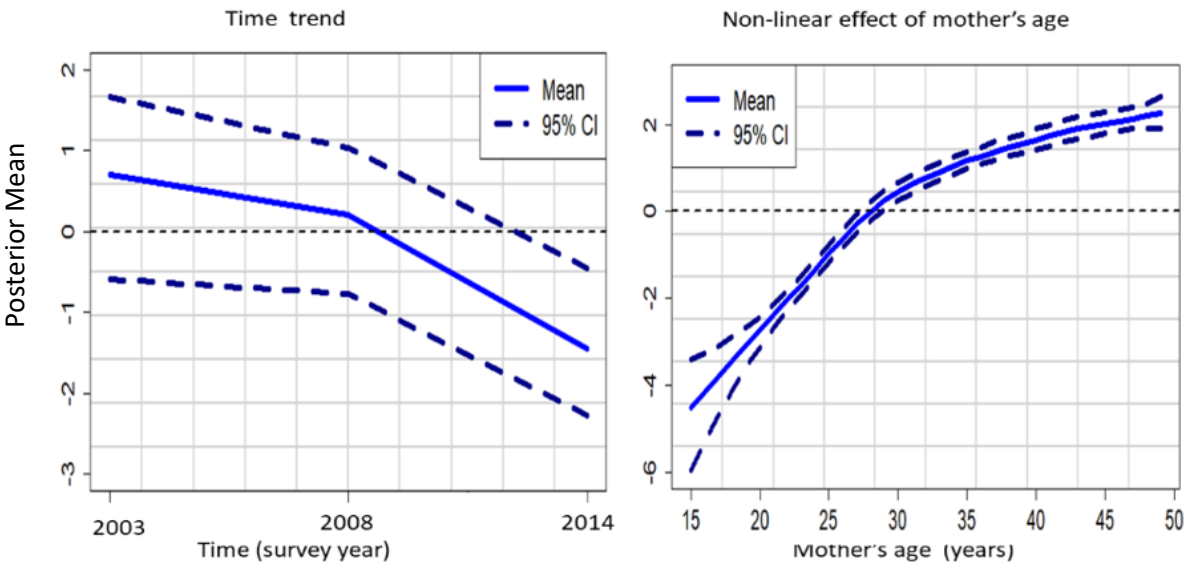


Figure 3.8. Time trend (left panel) and non-linear effect of mother's age (right panel). Evidence from the KDHS 2003 to 2014 pooled data Model III.

3.5. Discussion

In this study, we assessed the effects of social normative influence and other risk factors on FGM/C likelihood among Kenyan girls 0-14 years. Evidence of substantial influence of social norms and conventions was found at individual and community levels. The study revealed social normative influences as key drivers of FGM/C in Kenya between 2003 and 2014. Having a circumcised mother, living in a community with a high proportion of cut women, or high proportion of women who supported FGM/C continuation, and high proportion of women who believed FGM/C was a religious obligation, increased the chances of a girl being cut. The findings provide additional contribution to recent efforts to quantify the contextual influence of social normative factors on observed FGM/C prevalence trend in sub-Saharan Africa (Grose et al., 2019; Kandala & Shell-Duncan, 2019; Yount et al., 2020).

In addition, the use of Bayesian spatial modelling to account for this relationship is an important contribution to a robust evidence base, which highlights the importance of community-level influences on FGM/C related outcomes. More importantly, this methodological approach, rarely used in the ecological research on FGM/C, adds additional evidence to the more recent body of research testing the prediction of social norms theory in countries such as Senegal and the Gambia (Shell-Duncan et al., 2011).

Additional evidence from the study provided support for the contribution of other risk factors such as Muslim religious affiliation, Kisii and Somali ethnicity and geographic location in the Northeastern or Nyanza regions as important risk factors of FGM/C among Kenyan girls 0-14 years. We also found that the likelihood of a girl experiencing FGM/C decreased as the ethnic fractionalization index EFI increased. This finding supports the concept of assimilative change (Mackie & LeJeune, 2009). As a result, women and girls have the opportunity to shift their reference group within a community to other groups of different ethnic origin that opposed or do not discriminate against those who opposed the practice. Findings suggest a mixed effect of mother's education as we found education to be protective on the average between the study period but little evidence of its beneficial effect was observed in the most recent survey. This may be due to the observed low level of national prevalence at which stage effect of education may be minimal.

Finally, the study highlights the important connection between geographic location and members of certain ethnic communities as observed in high prevalence among girls born to women of Somali ethnic predominantly in the North-eastern region and among Kisii girls in

the Nyanza region. Findings therefore provide greater insight into patterns and dynamics change in observed FGM/C prevalence among Kenyan girls 0-14 years. The findings are robust enough to target interventions to who (ethnic communities) and where (region) they are most needed in Kenya.

3.6. Study Limitations

We reported two limitations in the study. First, the data was obtained based on self-reporting for all women selected in the KDHS and therefore claims of cutting could not be verified clinically or by other more reliable means (Shell-Duncan, 2016). However, other studies have shown a high degree of agreement between self-reported FGMC status and actual FGM/C status of women interviewed in the DHS (Bjälkander et al., 2013; Elmusharaf et al., 2006). Despite this, some women may withhold their status for fear of being sanctioned by the government if found out, hence the need for caution in the interpretation of results(Shell-Duncan, 2016). The second has to do with the study population of girls and definition of the outcome variable FGM/C status of a Kenyan in earlier DH surveys.

3.7. Methodological Limitations of the study that provided the basis and justification for the present work

Despite the important methodological contribution of the study to the use of spatiotemporal additive mixed models to assess FGM/C risk factors among Kenyan girls, four important methodological limitations have been identified. First, is the need to assess the influence of complex survey design on estimated risk factors at individual-level. Given the stratified two-stage cluster sampling design of the DHS data, a high degree of intra-cluster correlation is often observed, at the primary cluster sampling stage. Hence, the influence of the complex survey design – stratification and or cluster design effect, need to be evaluated within a statistical modeling framework to ensure reliable estimation of risk factor effects on FGM/C outcome at one time point or multiple timepoints.

Second, the study did not account for community level influence of socio normative factors in the spatiotemporal formulation of the risk factor model - hence the observed large point estimates observed in the average effect of mother's FGM/C status at individual level.

Therefore, we hypothesize a substantial reduction in the individual level influence of mother's FGM/C status given that its influence is predominantly observe at the community level, rather than individual. Quantifying the amount of influence observed at both levels within a statistical modeling framework is an essential step to understand the role of social norms at individual and community levels.

Third, the spatiotemporal model formulation also did not assess the separate influence of variation in unobserved FGM/C risk due to interaction between space and time after accounting for known risk factors, as well as the main spatial and temporal residual variation and as presented for the spatial regression formulation.

Fourth, given that a substantial amount of observed spatially structured effects of social norms operate at the community level and not at regional level (neighborhood effect is more likely to be observed between members of two communities than between members of two regions), effort to model spatially structured and unstructured random effects at regional level need to identify and separate out community level influence of social normative factors. We hypothesize that separating out the influence of social normative factors operating predominantly at community level will significantly reduce or eliminate spatially structured risk factors at regional level.

CHAPTER FOUR

METHODOLOGY FOR THE FEMALE GENITAL MUTILATION/CUTTING STUDY

In this chapter, we present the proposed unified hierarchical Bayesian framework for statistical modelling of female genital mutilation/cutting (FGM/C) risk factors in space and time using complex national household surveys. The chapter is organized as follows. Section 1 provides a brief description of the demographic and health survey (DHS) data samples utilized for the present study and the sampling design features. In Section 2, we describe the main outcome and exposure covariates considered in the study. The section demonstrates how known exposure covariates (potential risk factors to be evaluated separately for each country) act as proxy measures for different components of the proximate determinants framework (PDF) proposed in Chapter 1. In Section 3, we discuss limitations of the use of the DHS data in relation to measuring FGM/C outcome and additional evidence for reliability and quality of DHS data sample. Section 4 presents a working statistical definition for the term "complex survey design" as implemented in the proposed unified framework. To obtain preliminary understanding of the DHS data, we conduct descriptive analysis, spatial exploratory analysis, and assessment of nonlinear trends separately for the three countries under investigation as presented in Section 5. In Section 6, we reviewed the limitations of existing methodological approaches for modelling FGM/C using survey data both in space and in space-time. The objective here is to highlight how the current work fills an important gap in the FGM/C statistical methodology literature. The overarching goal is to improve estimation of risk factor influence at a single time point and impact over a specific period. In Section 7, we presented the main inferential algorithm for the current study - the integrated nested Laplace approximation (INLA) for approximate Bayesian inference. The INLA methodology provides a fast computational alternative to Markov chain Monte Carlo (MCMC) simulation techniques for the class of latent Gaussian models. In Section 8, we present the statistical modelling framework and model formulation for the proposed hierarchal space-time models accounting for complex design features along with the choice of prior distributions for model parameters and hyper-parameters. Model assessment procedure and evaluation of prediction accuracy are discussed in Section 9. We conclude the chapter with a summary of the methodology presented.

4.1. Description of Survey Sample Data

The data samples utilized for modeling risk and determinants of FGM/C evaluated in this study are successive waves of the Demographic and Health Surveys (DHS) for three African countries (Kenya, Nigeria, and Senegal) between specific periods. The DHS is a nationally representative household cross-sectional survey conducted across developing countries to monitor country progress on development indicators ranging across a wide number of themes such as health, sexual and reproductive health, maternal and child nutrition, harmful traditional practices among others.

Detailed methodology of the sampling design approach for the DHS has been extensively discussed elsewhere (Elkasabi et al., 2020). Briefly, the DHS is a nationally representative population-based survey of a complex multi-stage sampling design conducted across low and middle-income countries over the past four decades. To obtain a representative sample of the target population, the DHS randomly samples units from an existing sampling frame. The existence of such list allows a probability-based selection of individual units of the survey from a target finite population. Sampling is implemented in a stratified two-stage cluster design in which a random selection of primary sampling units (PSUs) or clusters is carried out at the first stage. For our study, each of these clusters represents a community (defined as a group of households within a local geographical setting). In the second stage, a systematic selection of households from a complete listing of all households within each selected PSU is carried out. Members of selected households are eligible to participate in the survey wave. Initial interview of a household respondent is often first conducted to obtain relevant information about the household as one unit and separate from other households in the neighborhood. This is then followed by interview of eligible women and men within selected households. The result of this sampling design is a nested data structure, with women, men or households at level-1, PSUs at level-2 and the region of residence at level 3 (Elkasabi et al., 2020).

In addition, sampled units are usually stratified into subgroups of homogenous units made up of individuals with similar characteristics than members of other strata. Stratification procedure ensures reduction in sampling variability within each stratum of the DHS samples. This is particularly important given the significant disparity expected in rural versus urban households across health and related indicators of interest. The DHS apply the stratification procedure only at the first stage followed by a systematic sample of households at the second stage. A multilevel stratification procedure by place of residence level (rural versus urban) and region

level is usually implemented in most DHS surveys. The FGM/C module provides information about the prevalence of the practice in both women and their living daughters.

Datasets for the study populations of interest (girls below 15 years) were subsequently extracted from successive household surveys of the three countries of interest – Kenya, Nigeria and Senegal as presented in Tables 4.1 to 4.3.

Table 4.1. Total number of samples (girls aged 0-14 years) and cluster size by region and survey year for Kenya.

ID	2003 DHS		2008 DHS		2014 DHS	
	Sample(n)	Cluster(n)	Sample(n)	Cluster(n)	Sample(n)	Cluster(n)
1	586	55	658	49	958	173
2	424	45	793	50	1,388	195
3	467	56	997	54	2,043	262
4	414	50	438	52	264	55
5	237	25	637	27	965	90
6	485	55	1,006	58	1,703	206
7	687	64	1,284	60	3,928	457
8	492	50	916	48	1,172	139
Total	**3,792**	**400**	**6,729**	**398**	**12,421**	**1,577**

Table 4.2. Total number of samples (girls aged 0-14 years) and cluster size by region and survey year for Nigeria.

ID	2008 DHS		2013 DHS		2018 DHS	
	Sample(n)	Cluster(n)	Sample(n)	Cluster(n)	Sample(n)	Cluster(n)
1	141	23	105	22	43	19
2	126	23	95	21	145	31
3	120	22	123	22	55	27
4	139	23	119	22	116	33
5	103	19	230	24	352	39
6	225	22	247	23	32	17
7	124	22	68	20	142	31
8	373	24	178	20	142	32
9	159	23	163	23	48	21
10	146	23	152	22	81	25
11	174	23	188	23	144	33
12	163	23	114	22	57	24
13	107	22	125	23	53	24
14	68	20	128	23	49	23
15	88	20	86	19	87	27
16	99	18	145	18	116	25
17	85	22	130	23	84	25
18	33	15	430	24	383	38
19	74	17	228	23	278	38
20	454	32	789	40	280	48
21	134	23	286	24	28	13
22	99	17	201	21	214	33
23	25	12	39	16	55	24
24	161	21	203	22	107	29
25	158	31	178	37	66	31
26	91	22	72	18	25	9
27	27	9	103	17	118	30
28	121	18	77	20	41	15
29	113	22	125	22	55	24
30	148	24	152	24	65	25
31	205	24	186	24	43	19
32	39	16	14	7	33	15
33	107	21	121	20	64	26
34	83	19	518	24	34	17
35	70	17	270	22	182	30

36	96	19	323	21	290	35
37	66	16	440	23	239	31
Total	**4,744**	**767**	**7,151**	**819**	**4,346**	**986**

Table 4.3. Total number of samples (girls aged 0-9 years) and cluster size by region and survey year for Senegal.

	2010 DHS		2015 DHS		2017 DHS	
ID	Sample(n)	Cluster(n)	Sample(n)	Cluster(n)	Sample(n)	Cluster(n)
1	428	34	203	20	432	44
2	620	31	305	16	548	28
3	452	28	258	14	497	28
4	267	21	210	14	443	24
5	574	27	317	14	622	26
6	514	29	388	16	385	25
7	587	27	391	16	583	27
8	506	28	221	14	477	30
9	464	26	275	14	575	26
10	549	26	344	14	602	24
11	418	29	202	16	466	30
12	597	27	303	14	637	27
13	568	31	293	18	539	34
14	332	26	188	14	355	27
Total	**6,876**	**390**	**3,898**	**214**	**7,161**	**400**

4.2. Study Variables

4.2.1. Outcome Variable

The outcome variable of interest in the present study is a binary indicator of whether a girl was cut (yes) or not (no) as reported by mothers whose daughters were still alive as at the time of the survey in the three respective countries.

4.2.2. Exposure Variables

We considered a carefully selected set of known FGM/C risk factor covariates based on theoretically driven quantitative studies reported by previous investigators (Achia, 2014; Grose et al., 2019; Kandala et al., 2009; Kandala & Shell-Duncan, 2019; Young et al., 2019). This allows the investigation of the role of social normative influences operating at both individual and community levels as well as the contribution of other measurable individual level characteristics. Exposure variables include proxy measures of social normative influences such as mother's FGM/C status, her support for continuation, and her belief that FGM/C was a religious requirement at individual level. We derived a community level set of predictors (from corresponding individual level covariates) to assess the influence of social norms and conventions operating at community level, namely: proportion of mothers cut within a community, proportion of mothers who supported continuation of FGM/C, and proportion of mothers who believed FGM/C was required by religion.

In addition, we considered relevant social and demographic characteristics of mother and girl such as age of mother, age of girl, ethnicity, religious affiliation, marital status, type of residence, household wealth quintile, mother's educational attainment, employment status, justification of wife beating by her partner, mother's decision-making power within household and media exposure to newspaper, radio and television. Each of these variables aims to measure a particular construct in the FGM/C proximate determinants framework (PDF) to provide deeper understanding into the underlying processes that shape FGM/C likelihood within a specific population. Another important exposure variable of interest is the role of geographic location which captures excess variation and neighborhood effects induced by interaction among unknown (unmeasured) risk factors operating at various levels of geographical influence. Within our framework, the geographic location (region or state) and cluster effects

(at community level) both aim to capture excess variability due to such unmeasured risk factors unaccounted for within the statistical model framework. A summary of the exposure variables is presented in Table 4.4 below with proxy measures classified under relevant component of the PDF framework.

Table 4.4. Description of study variables by the FGM/C Proximate Determinants Framework.

Demographic	Social Norm	Gender Norm	Feminist Theory	Exposure/Mobility
1). Age of girl ***(continuous)***	1). FGM status of mother ***(binary)*** **and** 2). Proportion of mothers cut in community	1). Beating justified if mother denies father sex	1). Mother's occupation ***(categorical)***	1). Frequency of reading newspaper/magazine ***(categorical)***
2). Age of mother ***(continuous)***	3). Mother support FGM ***(categorical)*** **and** 4). Proportion of mothers who supported continuation in community	2). Expenditure of mother's earning decided by mother or jointly ***(categorical)***	2). Mother's level of education ***(categorical)***	2). Frequency of listening to radio ***(categorical)***
3). Religion ***(categorical)***	5). Mother cut for religious reasons ***(binary)*** **and** 6). Proportion of mothers that cut for religious reasons in community			3). Frequency of watching television ***(categorical)***
4). Ethnicity of mother ***(categorical)***				4). Geographic location **(fixed/random)**
5). Marital status of mother ***(categorical)***				Time ***(fixed/random)***
Modernization 1). Type of residence ***(categorical)*** 2). Wealth index ***(categorical)***				
OUTCOME VARIABLE: FGM/C; CUT=1; UNCUT=0				

4.3. Limitations of DHS Data on FGM/C

In this section, we discuss limitations of the demographic and health surveys in measuring FGM/C indicators among women and girls in low and middle-income countries as highlighted by various investigators in the field of FGM/C (Askew, 2005; Shell-Duncan, 2016) . First, self-reported data on FGM/C needs to be treated with caution as inaccuracies may arise due to a number of reasons. For instance, given the sensitivity of FGM/C related topics in many affected countries in Africa, women may be unwilling to disclose their true status if they had been cut. Furthermore, women may be unaware of whether they had been cut or the extent (severity) of the cut.

A well-known problem often associated with cross-sectional self-reported surveys is recall bias which may occur when survey participants have difficulty in reporting events that happened in distant past. FGM/C often takes place during infancy or early childhood in many African countries. The longer the time span between the time of event and time of reporting, the greater the chance of a recall bias. However, we expect the impact of recall bias to be minimal in the present study given that information on FGM/C was elicited from mothers of the girls (rather than directly from the girls who might not have memory of such event). In addition, the translation of survey questions may also lead to ambiguity and the choice of wording may influence which types of cutting are understood to be FGM/C. However, since we considered all forms of FGM/C for the purpose of risk factor estimation in our study, this is of minimal concern in the present context.

In addition, other studies have attempted to determine the reliability of self-reports of FGM/C status by verifying them through clinical examinations. Even though clinically determined FGM/C status is regarded as the gold standard, studies that have investigated the validity of self-report versus clinical examination have shown that self-reporting is a reliable and valid approach. However, concurrence between the two approaches varies depending on context (Elmusharaf et al., 2006; Morison et al., 2001; Odujinrin et al., 1989; Snow et al., 2002). More so, in Sudan, investigators reported complete agreement (100%) between what women and girls reported regarding their FGM/C status and what was found by inspection of genitals (Elmusharaf et al., 2006).

A community-based study conducted in the Gambia indicated a 97% concurrence in FGM/C status between self-reports and clinical examination(Morison et al., 2001). Another Egyptian fertility care study also indicated 94% concurrence (Population Council, 1996) while a separate

study conducted in Nigeria showed 79% concurrence (Snow et al., 2002). In contrast to these findings, a study conducted in rural Tanzania showed inconsistency between self-reported and clinically determined FGM/C status with authors highlighting that both women and clinicians might incorrectly report women's FGM/C status (Klouman et al., 2005).

The reliability of survey data before and after passage of laws concerning FGM/C is also noteworthy especially in the past one decade since the declaration of the UN 2030 elimination goal (WHO, 2008). As a result, legislative measures that prohibit the practice of FGM/C have been put in place in countries where survey data have been collected both before and after enacting criminal laws. Observed changes across surveys in FGM/C practices and attitudes may therefore, result from deterrence or alternatively, reflect unwillingness to honestly disclose FGM/C status or views due to fear of punishment or courtesy bias (Shell-Duncan, 2016). It is therefore important to be cognizant of the limitations of self-reported FGM/C status especially in contexts where FGM/C is conducted early during infancy and is less severe such as observed in many ethnic communities across Nigeria and Senegal. (Elmusharaf et al., 2006; Klouman et al., 2005; Snow et al., 2002).

For the purpose of the present study, the 2003 Nigeria DHS and 2005 Senegal DHS were excluded from the space-time model since the data was collected prior to the revision and standardization of the FGM/C module in 2010 by DHS and UNICEF (Shell-Duncan, 2016). However, we have considered 2003 and 2008 Kenya DHS as they are two of the three (3) most recent surveys in Kenya.

4.4. Working Statistical definition of Complex Survey Design

In this section, we provide a working statistical definition of complex survey design as implemented in the present study. The hierarchical structure of the DHS data is a result of the fact that individuals - stratified across region and type of residence, are nested within households which are in turn nested within clusters and clusters within regions or states. For the study, we defined each of these clusters as a community that provides the local context in which FGM/C risk factors operate. This stratified multistage hierarchical structure of the data is what we defined as the term "complex" that must be accounted for in a multilevel statistical modelling framework to provide reliable estimation of risk factor covariate effects on the outcome at the individual level.

Various studies have considered the inclusion of the sampling weights in the regression model framework (Sheffel et al., 2019; Winship & Radbill, 1994). In these studies, the objective was to assess whether accounting for the unequal probability of selection of individual sample units would lead to better model fit and estimation of model parameters. Sheffel and Colleagues (2019) found that estimates adjusted for the sampling weights were less biased (i.e., closer to the true values) while estimates without sampling weights were less variable.

In a separate work (Carle, 2009), additional guidance was provided on accounting for the design weights within a multilevel model framework using national surveys. The study evaluated the performance of scaled-weighted (recommended for weighted regression) and unweighted estimates across a series of multilevel models. Findings suggest minimal differences in both approaches and did not lead to significant change in conclusion. However, the assessment was conducted using the National Survey of Children with Special Health Care Needs (NSCSHN) in the USA, and not on a nationally representative household survey often conducted in developing countries, such as the DHS. In addition, the sampling design, study population, and collection of the NSCSHN differ from that of the DHS. The NSCSHN was a cross-sectional telephone survey of households with at least one resident child aged 0 to 17 years at the time of the interview: with stratification by state and sample type (landline or cell phone) and with clustering of children within households. Hence, the observed minimal influence of the sampling weight was not surprising given that clustering effect was observed at household level, rather than at enumeration area (EAs) or community level typical in DHS samples (NSCSHN, 2020).

Also, Skinner and Wakefield (2017) suggested the need to account for the survey sampling design in a model-based regression framework. For instance, in the case of surveys with a stratified two-stage cluster sampling design, they suggested that statistical modellers should consider accounting for the stratification variables as a fixed effect and the nested structure at household and cluster levels as random effects. Their recommendation is given in general and applicable to surveys with such complex sampling design. We followed their advice by including stratification variables (type of residence and region) as fixed covariates and the clusters were modelled as random effects. The present work attempts to fill this gap within a spacetime generalized regression framework and to evaluate the performance of such hierarchical models in risk factor estimation at individual level compared to more parsimonious alternatives.

Further, studies in the field of complex survey modelling have attempted to model the risk of outcomes in space and time in a manner that accounted for survey design features. For instance, Mercer and Colleagues (2015) proposed a Bayesian spacetime modelling of under 5 child mortality that combined data from complex household surveys and demographic surveillance sites. Their approach combined designed-based approach and model-based spacetime smoothing. The study is a notable contribution to the field of spacetime modelling of complex surveys. The objectives of such studies, however, was not to explain covariate/exposure effects on the outcome at individual level, but rather, to develop a reliable estimation (prediction) of outcome risk by smoothing the risk surface in space and time (Mercer et al., 2015). We took a specific statistical modelling approach with the objective to improve reliable estimation of risk factor influences and impact by accounting for both the influence of complexity induced by survey design features and local context (neighbourhood at cluster level).

4.5. Preliminary Analysis

4.5.1. Descriptive Analysis

Descriptive and bivariate analyses were conducted to characterize the study population and evaluate bivariate associations between the outcome of interest and the explanatory variables. Results obtained are presented in tables, graphs, and maps.

4.5.2. Exploratory Spatial Analysis

The goal of exploratory spatial analysis is to assess the data for evidence of spatial autocorrelation effects. We describe spatial autocorrelation as an event in which the FGM/C outcome is correlated with values of itself observed in another location within the spatial domain of interest. The occurrence of spatial autocorrelation more often may be induced by unmeasured risk factors, missing confounders, group effect, or neighbourhood effect. Group effect is often induced in samples that preserve the structure of the natural population as is often the case in national surveys with complex sampling designs. This is because members of a group (for instance, ethnicity or religious affiliation) tend to exhibit geographic proximity due to shared similar values and cultural norms that may impact on their preferential disposition

towards a culturally embedded practice such as FGM/C. As a result, neighbourhood effect may be induced given that the occurrence of events among individuals in one location may influence occurrence among their nearest geographic neighbours with similar cultural inclination**.** In Africa, this is often the case as individuals with shared ethnicity and cultural norms tend to reside in closely knit geographic clusters. This spatially structured arrangement is observed across diverse ethnic groups in Kenya, Senegal, and Nigeria. Spatial autocorrelation, therefore, provides a statistical tool to quantify such spatial dependency due to shared unobserved risk factors.

For FGM/C prevalence outcome $\boldsymbol{y} = (y_1, \dots, y_n)$ observed in n regions, we want to know if y_k is correlated with values observed in nearby regions (Anselin, 2002; Tobler, 1979; Tsai et al., 2009). We therefore utilize the global Moran's I statistic to quantify the extent of spatial autocorrelation in the FGM/C prevalence data as described below:

$$I = \frac{N \sum_{k=1}^{n} \sum_{l}^{n} w_{kl}(y_k - \bar{y})}{(\sum_{k=1}^{n} \sum_{l=1}^{n} w_{kl}) \sum_{k=1}^{n} (y_k - \bar{y})^2} \tag{4.1}$$

where w_{kl} defines an element within an adjacency matrix to denote how n areal units are spatially located relative to each other. The term $(y_k - \bar{y})^2$denotes the square deviation of the observed values of y in location k from the mean.

We obtained a spatial weight matrix $\boldsymbol{W}$ to summarize the spatial relations between the n spatial units, commonly known as the neighbourhood matrix. Here, each spatial weight, w_{kl}, typically reflects the "spatial influence" of area l on area k. Following standard convention, we exclude "self-influence" by setting w_{kk} to 0 since an area cannot be a neighbour to itself. Hence, this results in a 0 diagonal adjacency matrix. We considered a spatial weight matrix based on polygon boundaries typically used to model spatial dependence in irregular lattice data. In this context, therefore, the boundaries shared between the areal units play an important role in determining the extent of "spatial influence".

Based on the contiguity binary weight matrix, two regions are defined as neighbours if they share a common boundary such that $w_{kl} = 1$ if k and l are neighbours and $w_{kl} = 0$ otherwise.

We compared the performance of two commonly employed contiguity specifications – the first order queen contiguity weight and the rook contiguity weight. The queen contiguity weight allows the possibility that spatial units share only a single boundary point with their neighbours. On the other hand, the rook contiguity weight imposes a stricter condition in that some positive portion of the boundary length between immediate neighbouring units must be shared. While both specifications provided similar estimates in the present study, we employed the first order rook contiguity matrix throughout the study. We present a simple illustration of the resulting neighbourhood binary weight matrix for Kenya with eight (8) administrative regions in Table 4.5 below.

Table 4.5. First order rook contiguity matrix for Kenya with eight (8) administrative regions.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	0	0	1	1	0	0	1	0
2	0	0	1	0	1	0	1	0
3	1	1	0	1	1	0	1	0
4	1	0	1	0	0	0	1	0
5	0	1	1	0	0	0	0	0
6	0	0	0	0	0	0	1	1
7	1	1	1	1	0	1	0	1
8	0	0	0	0	0	1	1	0

In the presence of spatial autocorrelation, the implication of defining the neighbourhood matrix is that if $w_{kl} = 1$, then the observed data in area k will be modelled as conditionally independent, given the set of its neighbours resulting in a local Markovian property (Blangiardo et al., 2013). On the other hand, if $w_{kl} = 0$, they will be modelled as conditionally independent. In addition, the sparse precision matrix resulting from the nonzero patterns in the neighbourhood structure of the process also provides great computational benefits (pairwise Markov property). This Gaussian Markov Random Field (GMRF) principle (Rue et al., 2009) provides the basis for the statistical formulation of the conditionally independent autoregressive model employed to account for spatial correlation in the study (as described in the next section). If the data are positively spatially autocorrelated, then the numerator in equation 4.1 above will have positive values, which implies that high risk (low-risk) areas tend to share geographic proximity with other high-risk (low-risk) areas anywhere across the spatial domain. The reverse is the case when a negative spatial autocorrelation is observed. Moran's I statistic takes the same set of values as any correlation coefficient (between -1 and 1). For instance, a value of 1

indicates evidence of a high positive spatial dependence in the observed data, and should be accounted for (quantified) within the regression framework formulation to obtain reliable risk factor estimates.

For this study, we assessed the significance of the observed global Moran's I statistic using a statistical test under a null hypothesis (H_0) of no spatial dependence in the observed FGM/C prevalence among the regional units. An alternative hypothesis (H_a) of some spatial dependence was assessed. Under the alternative hypothesis, spatial correlation can either take a positive value (I > 0) or a negative value (I < 0). The p value against independence is computed via a Monte Carlo permutation test as follows. First, compute the Moran's I statistic for the data. Then randomly reassign the data values to areas and recompute Moran's I for the random assignment. This is expected to return a value close to zero under the null hypothesis. This step is repeated 10,000 times to obtain 10,000 values of Moran's I statistic generated under independence. The p value essentially quantifies how extreme the observed value of Moran's I is from the real data compared to 10,000 values generated under independence from the randomly generated data.

Findings of the spatial exploratory analysis are presented in Figure 4.1 along with the neighborhood structure for the three countries under investigation. Results showed no statistically significant spatial autocorrelation in observed FGM/C prevalence among the 8 regions in Kenya. In contrast however, statistically significant evidence of spatial autocorrelation in FGM/C prevalence was observed among states in Nigeria; at 0.2 in 2008 and 0.33 in 2018. The highest degree of positive spatial autocorrelation was observed in Senegal; at 0.5 in 2010, 2015 and 2017. This implies strong evidence that regions with high observed FGM/C prevalence are more likely to be surrounded by regions with similarly high values. This in turn, provides strong indication of neighborhood effect in the observed data which we further explored within the modelling framework.

Parameter	2003	2008	2014
Statistic	-0.08	-0.00	0.03
Variance	0.02	0.02	0.02
P-value	0.32	0.15	0.09

Parameter	2008	2013	2018
Statistic	0.20	0.09	0.33
Variance	0.010	0.010	0.10
P-value	0.009	0.118	<0.001

Parameter	2010	2015	2017
Statistic	0.54	0.53	0.49
Variance	0.03	0.03	0.03
P-value	<0.001	<0.001	<0.001

Figure 4.1. Neighborhood structure and Global Moran's I statistics by country at regional level (Kenya-top panel; Nigeria-middle panel; Senegal-bottom panel).

4.5.3. Assessment of Nonlinear Trends

Another aspect of the exploratory analysis was the assessment of nonlinear trends between proportion of girls cut in Kenya, Nigeria and Senegal and continuous covariates observed at individual and community levels. This includes age of mother and age of girl (at individual level), proportion of mothers cut, proportion of mothers that supported continuation of FGM/C and proportion of mother that cut for religious reasons (at community level).

In Kenya, a general pattern of increasing proportion of cut girls was observed with increasing age of mother and age of girl (Figure 4.2). The pattern suggests that older women and girls were more likely to be cut. A strong positive correlation pattern was consistently observed in 2003 and 2008 for age of mother and girl. This correlation pattern was however, in general moderate in 2014 (was relatively stronger for the age of girl). In addition, communities with

higher proportions of cut mothers also tend to show a pattern of high proportion of cut girls in 2003, 2008 and 2014. (Figure 4.2).

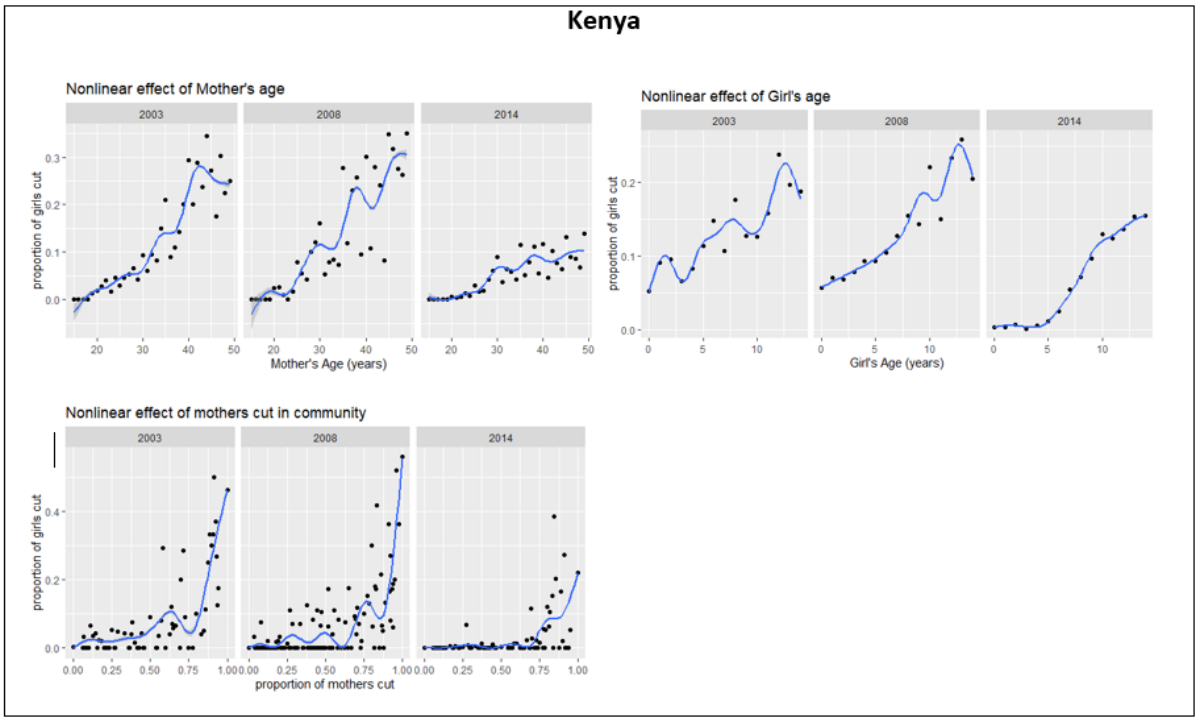


Figure 4.2. Exploratory nonlinear trend in Age of mother (top left panel), Age of girl (top right panel) and proportion of mothers cut within community (bottom panel) in Kenya from DHS 2003, 2008 and 2014.

In Nigeria, an overall pattern of linear trend was observed, notably in community level variables. Results, however, showed weak correlation of FGM/C proportion in girls with increasing age of mother in the first two surveys and a strong negative correlation in 2018. On the other hand, while a similar trend of weak correlation was observed between proportion of girls cut and age of girl within the first ten (10) years of life, result suggest a strong correlation pattern between proportion of cut girls in older girls in 2008 and 2013. Proportion of cut girls appeared to be relatively stable across all age groups in 2018, although at a higher proportion relative to the two previous surveys. A general pattern of strong positive correlation was observed between proportion of girls cut and proportion of cut mothers within community and mothers that continuation of the practice. Religious motivation for cutting was most positive correlated with proportion of cut girls in 2013 and less so in 2018. (Figure 4.3).

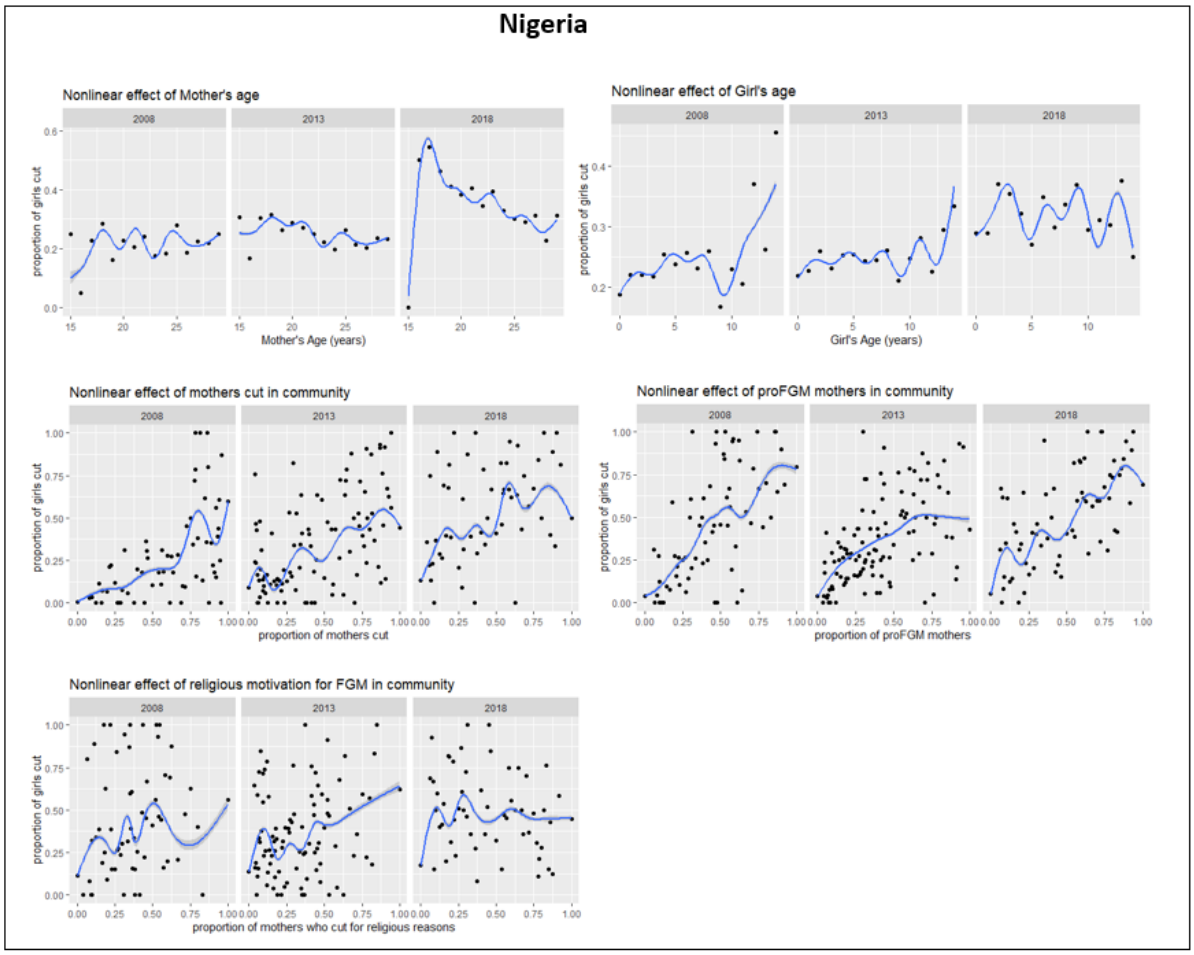


Figure 4.3. Exploratory nonlinear trend in Age of mother (top left panel), Age of girl (top right panel), proportion of mothers cut (middle left panel), proportion of mothers that support continuation of FGM/C (middle right panel) and proportion of mothers that cut daughters for religious reasons(bottom) within community in Nigeria from the DHS 2008, 2013 and 2018.

A similar pattern of overall linear trend was also observed in Senegal, with varying degree of correlations between variables and across survey years. Results suggest a strong positive linear trend was observed between proportion of girls cut with increasing age. This implies that older girls were more likely to be cut in 2010, 2015 and 2017. With respect to community level factors, findings suggest that proportion of cut girls increased with increasing proportion of cut mothers and proportion of mother that supported FGM/C continuation and proportion of mothers that cut for religious reasons within a community (Figure 4.4).

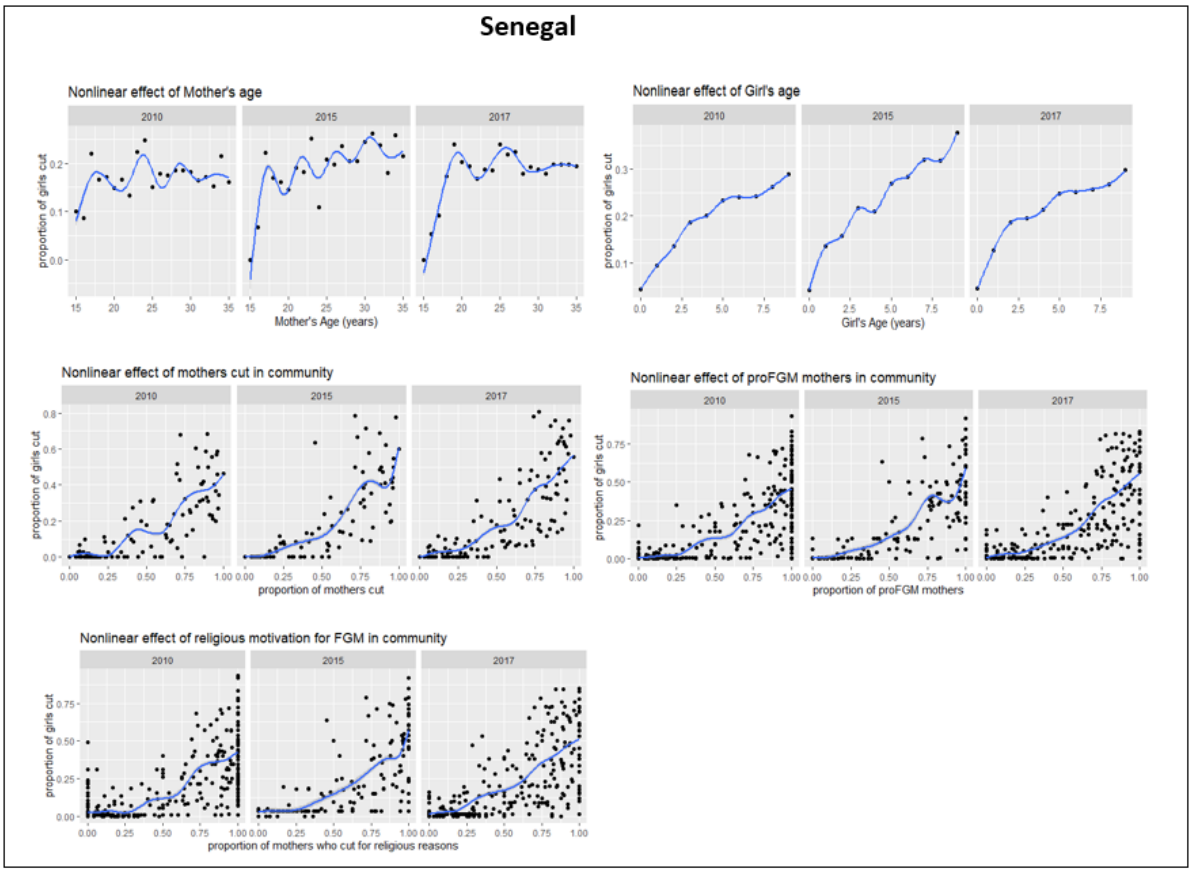


Figure 4.4. Exploratory nonlinear trend in Age of mother (top left panel), Age of girl (top right panel), proportion of mothers cut (middle left panel), proportion of mothers that support continuation of FGM (middle right panel) and proportion of mothers that cut daughters for religious reasons (bottom panel) within community in Senegal from the DHS 2010, 2015 and 2017.

4.6. Limitations of Existing Approaches for Modelling FGM/C using Complex Surveys in non-separable Space and Time

Over the past few years, studies have been conducted to identify risk factors of FGM/C among women and girls (Achia, 2014; Kandala et al., 2009; Kandala & Shell-Duncan, 2019; Nnanatu et al., 2021). However, while these studies acknowledged geographic variation in risk by accounting for the spatial dependence in the regression model framework, all studies were conducted at a single time point. Study by Kandala and Shell-Duncan (2019) attempted to investigate the risk of FGM/C among women in Senegal in 2005 and 2010, by conducting

separate analysis for both survey years. Of interest in the present study is that none of these studies (conducted at a single time point) accounted for the sampling survey design intrinsic in nationally representative household surveys commonly utilized to implement such modelling exercise.

We also note a recent study (Kandala et al., 2019) assessed risk factors of FGM/C among Kenyan girls aged 0-14 years in nonseparable spacetime using a fully Bayesian generalized linear additive mixed model framework. In the model formulation, the authors decomposed the residual spacetime variability into a main spatially structured (modeled as Gaussian Markov random field prior) and unstructured random effects (modelled as exchangeable with mean Gaussian prior), a nonlinear time effects (modelled using Bayesian penalized spline) and a spacetime interaction effect modeled as a tensor product of one-dimensional B-spline basis function (See Chapter 3 for detail).

In a similar study, changes in prevalence of FGM/C among girls 0-14 years in Nigeria between 2003 and 2016 using nationally representative data from two different but similar surveys (Nnanatu et al., 2021). The innovative addition of modelling data from two sources in the Nigeria study allows statistical modelling to account for random variation due to the source of data. However, the objective of the spacetime formulation was to assess geographic and temporal trends and to obtain improved prediction of FGM/C prevalence at state level rather than individual-level risk factor estimation. Hence, limited covariates were considered. We provided a number of limitations of the study by Kandala et al. (2019) in the previous chapter most of which are also applicable to the study by Nnanatu et al. (2021). Of interest is that the authors did not account for the sampling survey design in both the spatial and spacetime model formulations. Apart from this study, we are not aware of any other study undertaken till date to produce reliable estimates for the influence of FGM/C risk factors at individual level in space and time in a manner that account for the complexity of the survey design.

4.7. Bayesian inference for Latent Gaussian Models using Integrated Nested Laplace Approximation (INLA)

Bayesian hierarchical modelling techniques provides an elegant alternative inferential framework to the classical frequentist paradigm. The Bayesian framework formalizes the statistical modelling procedure into three components, namely, the data model, the process model, and the parameter model. Under the Bayesian hierarchical framework, all model

parameters are treated as random with uncertainty associated with the estimated parameters fully propagated. The objective of a statistical modelling exercise within a Bayesian paradigm is then to learn about a process along with the associated unknown parameters, conditional on the observed data, thus accounting for the three sources of uncertainties (data, process and parameter) (Haining & Li, 2020). This principle allows for joint inference on the conditional distribution of the process and unknown parameters to be modelled as the product of conditional distribution of the data (given the process and parameter), the conditional distribution of the process (given the parameter) and, the conditional distribution of the unknown parameters consistent with the Bayes Theorem.

Such statistical model hierarchical formulation provides a flexible framework to address two important challenges often encountered in spatial and spatiotemporal statistics namely, dependence (e.g., clustering of high-risk regions) and heterogeneity (e.g. variation in observed FGM/C prevalence outcome across the regions) (Haining & Li, 2020). The principles of fully Bayesian inference combines the probability of observing a data (likelihood) with a set of prior information specified on model parameters and hyperparameters to obtain a posterior density distribution with all uncertainties fully accounted for. The natural flexibility of implementing the Bayesian inferential approach for complex nested model hierarchy is what makes it particularly attractive for the objective of the present study.

The Bayesian inferential paradigm has seen a significant increase in its statistical applications over the past three decades following the development of the MCMC simulation techniques to draw sample from the posterior distribution of a target parameter of interest. Common MCMC-based sampling algorithms include: Gibbs sampling (Gelfand & Smith, 1990; Wakefield et al., 1994), the Metropolis-Hastings algorithm (Chib & Greenberg, 1995), and the Hamiltonian Monte Carlo (Betancourt, 2018; Neal, 2012). The BUGS implementation of the Gibbs sampling technique has made Bayesian inference accessible and intuitive to a wide range of applied researchers. The Bayesian mode of inference by design, ensures that the full posterior distributions can be sampled from the posterior density, and the interpretation is consistent with natural probability of real-world events. The Bayesian hierarchical modelling framework can effectively handle data with complex or nested structures, including correlation in space and time and their potential interaction. (Aswi et al., 2018; Knorr-Held, 2000; Knorr-Held & Besag, 1998; Knorr-Held & Raßer, 2000; Sahu & Mardia, 2005). For the present study, we considered an implementation of Bayesian inference within a generalized regression framework in discrete space (at region or state level), and discrete time (in years).

The computational complexity often associated with MCMC simulation for complex models (considered in the present study) has led to the development of approximation technique to Bayesian inference such as the integrated nested Laplace approximation (INLA) (Rue et al., 2009). The INLA is a powerful technique to approximate posterior marginals of the hyperparameters using only a modest number of evaluations of the joint posterior distributions of the hyperparameters without any need for numerical integration. The INLA inferential procedure provides much gain in greater computational advantage to performing numerical integration on class of latent Gaussian models (LGMs). INLA makes use of deterministic nested Laplace Approximations (LAs) as an algorithm tailored to the class of LGMs. It provides a faster and more accurate alternative to simulation-based MCMC schemes (Martins et al., 2013; Rue et al., 2009). Studies have also shown that the INLA procedure provides remarkable accuracy similar to simulation-based MCMC procedure for modeling spatio-temporal data within a Bayesian inferential framework (Fong et al., 2010; Schrödle & Held, 2011).

In the present study, we further demonstrate the utility of the INLA algorithm to model nationally representative survey data in space and time, with additional accounting for complex design features.

4.8. Statistical Modelling Framework and Model Formulation

For the study, we evaluated five competing Bayesian hierarchical structural additive regression models in increasing complexity as described follows:

4.8.1. Model 1 – Model with individual level Covariates only

The first model adjusted for the effects of covariates observed at individual level only as shown in equation 2 below:

$$logit(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f_1(b1_{i1}) + f_2(b2_{i2}) \tag{4.2}$$

where, the regression models include:

a) Logit link function $logit\left(\frac{\pi_{ijkt}}{1-\pi_{ijkt}}\right)$ where π_{ijkt} is the probability of FGM/C in individual girl i=1,…,N, in cluster $\boldsymbol{j}$ =1,…,J, in area $\boldsymbol{k} = 1, \ldots, K$ at survey time point $\boldsymbol{t}$ =1,…,T

b) An overall intercept term α_0. The intercept α_0 was assigned a flat prior: $p(\alpha_0) \propto constant(1)$, where p indicates probability

c) $X_{ijkt}\beta$ is the vector of covariates matrix $\mathbf{X}$ ($\boldsymbol{X} = X_1, X_2, \ldots X_p$) along with their regression coefficients $\boldsymbol{\beta}$ where ($\boldsymbol{\beta} = \beta_1, \beta_2, \ldots \beta_p$) for the fixed effects of known risk factors of FGM/C among girls. The $\boldsymbol{\beta}$ for fixed effects and intercept terms were assigned Normal priors. $\beta \sim N(0,1000)$

d) The nonlinear effects of age of mother and girl, denoted as $f_j(b_j) = \{b1, b2\}$, are modeled non-parametrically using second order random walk prior distribution with mean Gaussian prior : $f_j(b_j) \sim N(2\varphi_{b_{j-1}} - \varphi_{b_{j-2}}, \tau_j^2)$. The inverse of the variance parameter $1/\tau_j^2$ (also known as the precision) is modeled with a $\log(1/\tau_j^2) \sim \log\mathrm{Gamma}(1,0.01)$ prior. (Martins et al., 2013; Rue et al., 2009).

The primary objective of this model is to evaluate the effect of individual level covariates on FGM/C likelihood in a girl. Key components of this model include measures of social norms and social conventions such as FGM/C status of mother and her support for continuation of the practice. These two factors are two major and well-established determinants of FGM/C in a girl. Evaluating their influence at individual and community levels within a unified statistical framework will provide greater insight into the strength of their operation within the context of other demographic and social factors in the community within which a girl lives. Other types of norms such as gender norms and religious norms are also important determinants of FGM/C outcomes, given the central roles religion and patriarchy play in the lives of populations across the three countries. Hence the need to estimate their influence on the likelihood of cutting over a specified period.

4.8.2. Model 2 – Model with individual and community level covariates

In this formulation, we extended the individual-level covariates model in equation 4.2 to account for the influence of social norms at community level, a critical element of context in which FGM/C takes place. This formulation allows us to partition social norms influence between individual level and community level, and hence quantify how much of the influence is attribute able to both, an essential element of missing in previous studies (Grose et al., 2019; Kandala et al., 2019; Yount et al., 2020). Hence, using primary sampling clusters as proxy definition of a community, we adjusted for the community level influence of three proxy measures of social normative influence, namely: proportions of mothers cut within the community, proportion of mothers that supported FGM/C continuation within community and proportion of mothers that cut daughters for religious reasons as shown in equation 4.3 below:

$$logit(\pi_{ij}) = \alpha_0 + X_{ij}\beta + f_1(b1_{i1}) + f_2(b2_{i2}) + f_3(p1_{ij3}) + f_4(p2_{ij4}) + f_5(p3_{ij5}) \quad (4.3)$$

where community level effects such as: proportion of mothers cut in community, denoted as $f_3(p1_{ij3})$, proportion of mothers that supported continuation of FGM/C within community, denoted as $f_4(p2_{ij4})$ and proportion of mothers within community that cut for religious reasons, denoted as $f_5(p3_{ij5})$ are modelled non-parametrically using second order random walk prior: $f_3(p1_{ij3}) \sim N\left(2p1_{p-1} - p1_{p-2}, {}^{1}/_{\tau_{p1}}\right)$, $f_4(p2_{ij4}) \sim N\left(2p2_{p-1} - p2_{p-2}, {}^{1}/_{\tau_{p2}}\right)$, $f_5(p3_{ij5}) \sim N\left(2p3_{p-1} - p3_{p-2}, {}^{1}/_{\tau_{p3}}\right)$ where $\tau_{p1}, \tau_{p2}, \tau_{p3}$ are the precisions terms for the 3 community level effects with precision parameters modelled as $\log(\tau_{p1}) \sim \text{logGamma}(1,0.01)$, $\log(\tau_{p2}) \sim \text{logGamma}(1,0.01)$ and $\log(\tau_{p3}) \sim \text{logGamma}(1,0.01)$ respectively. We considered a 25 knots specification given that increasing the knots beyond this specification did not provide any additional improvement to the model.

4.8.3. Model 3 – Model with individual and community level covariates and residual main spatial effect, main temporal effect, and spacetime interaction effect

We extended the covariates model in equation 3 to model dynamics of unobserved risk factors in space and time. This we achieved by decomposing the excess variation in FGM/C risk in space-time into main spatially structured and unstructured random effect denoted as u_k and v_k respectively, main linear and nonlinear temporal effect denoted as bt and γ_t respectively, and space-time interaction denoted as δ_{kt} as shown in the general formulation in equation 4.4 below:

$$logit(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\boldsymbol{\beta} + f_1(b1_{i1}) + f_2(b2_{i2}) + f_3(P1_{ij3}) + f_4(P2_{ij4}) + f_5(P3_{ij5}) + v_k + u_k + bt + \gamma_t + \delta_{kt}\ ; \quad (4.4)$$

where α_0 is the intercept; $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)'$ is the vector of fixed regression coefficients for fixed covariates X_{ijkt}; $f_j(.) = f_1(x_1) + \cdots f_p(x_p)$ are the functions of metrical covariates modelled nonparametrically as smoothed or non-smoothed functions. The terms bt, γ_t, and δ_{kt} are the linear temporal and nonlinear effects of time (in year) and the non-separable space-time interaction between geography and time.

Different specifications of the main spatial and temporal are considered for the three countries. The main spatial effect is decomposed into spatially structured random effects, denoted as u_k to account for structured unobserved spatial random effects in the likelihood of FGM/C between neighboring regions and spatially unstructured random effects, and the spatially uncorrelated random effects which accounted for region-specific heterogeneity in unobserved FGM/C risk denoted as v_k.

As part of rigorous sensitivity analysis, we evaluated six (6) different types of prior specifications to explain various assumptions imposed on the dependence structure of the area-specific parameters and whether information was shared (borrowed) globally and or locally. This includes, an Exchangeable hierarchical model; the Intrinsic Conditional AutoRegressive (ICAR) model (Besag et al., 1991); the proper ICAR model; an alternative version of the proper ICAR model; the Convolution or Besag-York-Mollie (BYM) model; and a reparameterization of the BYM model with a penalized complexity prior.

The first model specification modelled area-specific parameters hierarchically based on the exchangeable assumption in which information is borrowed globally (across the study domain). This implies the assumption that all areas within the study domain of interest are similar with a common prior probability distribution whose parameters are unknown. An important consequent of the information borrowing principle within the Bayesian hierarchical modeling framework is that estimate of area-specific parameter utilizes available information from both the area and equally from other areas across the study domain which results in shrinkage (smoothing) of point estimate (towards the global mean in this case).

The degree to which smoothing is carried out is a function of the weighted average of the sample mean and the global mean such that the resulting parameter estimate for each area lies between the sample mean and the global mean. By weighted average, this implies the degree to which information is borrowed (globally or locally) is a function of how much sample is available in each area and variances of the variable of interest (Haining & Li, 2020). The exchangeable random effect is modelled as independent and identically distributed with zero mean Gaussian prior as shown below:

$$v_k \sim N(0, \sigma_v^2) \tag{4.5}$$

In contrast to the exchangeable assumption for the dependency structure above, the ICAR model specification ensures that the conditional mean for each n areas can be modeled as spatially structured (Besag et al., 1991) as presented below:

$$u_k | \boldsymbol{u}_{-k} \sim N\left(\mu_k + \sum_{l=1}^{n} p_{kl}(u_l - \mu_l), \frac{\sigma_u^2}{N_k}\right) \tag{4.6}$$

where μ_k is the mean for the area k and σ_u^2 is the variance parameter that controls the amount of variation between the spatially structured random effects. The term $\frac{\sigma_u^2}{N_k} = s_k^2$, is the variance for the same area k which depends on the number of neighbors its N_k. The larger the number of neighboring areas, the smaller the variance and more information is available to estimate the area-specific random effect in the presence of strong spatial correlation (Blangiardo et al.,

2013). Therefore, the conditional mean μ_k is pulled towards the mean of the parameters of the neighboring areas μ_l such that the parameters are similar locally(smoothing). Also, the larger the sample size in an area, the less local smoothing will be imposed on its parameter (Haining and Li, 2020). The quantity p_{kl} denotes the spatial proximity of neighboring areas to area k and can be calculated as $\phi \times W_{kl}$, where $W_{kl} = {}^{w_{kl}}/_{N_k}$, where $w_{kl} = 1$ if areas k and l are neighbors, and 0 otherwise ($w_{kk} = 0$ since an area cannot be its own neighbor). The scalar parameter ϕ controls the properness of the distribution (integrate to 1) of the area-specific parameters. For the joint distribution of the spatially structured random effect to be proper (integrate to 1) and positive definite, the precision matrix $\boldsymbol{Q} = (\boldsymbol{I} - \phi\boldsymbol{W})$ needs to be invertible such that the covariance matrix $(\boldsymbol{I} - \phi\boldsymbol{W})^{-1}$ exist. As a result, the values of ϕ is constrained to lie between the range of ${}^{1}/_{min_{k=1,\dots,n}} \rho_k$ and ${}^{1}/_{max_{k=1,\dots,n}} \rho_k$ with ρ_k indicating the minimum and maximum eigenvalues of $\boldsymbol{W}$ (Cressie, 1993). Hence, this symmetric restriction on $\boldsymbol{W}$ implies that the ICAR model assumes a spatial model in which the influence of area k on its neighbor l is the same as the influence of area l on k. Thus, the proper conditional autoregressive $\boldsymbol{u}$ is a multivariate Normal random variable as shown below:

$$\boldsymbol{u} \sim \text{MVNorm}(\boldsymbol{\mu}, (\boldsymbol{I} - \phi\boldsymbol{W})^{-1}\boldsymbol{S}^2) \tag{4.7}$$

where $\boldsymbol{\mu} = \{\mu_1, \dots, \mu_n\}$ is the mean vector, $\boldsymbol{I}$ is the identity matrix, and $\boldsymbol{S}^2$ is the area-specific variance parameters with diagonal matrix $\boldsymbol{S} = \text{dia}(s_1, \dots, s_n)$. The scalar parameter ϕ measures the strength of the spatial autocorrelation such that a value of ϕ close to 0 indicates weak or absence of spatial dependence, ϕ value less than 0 indicates negative spatial autocorrelation and ϕ value greater 0 indicates positive spatial autocorrelation. Hence, the conditional distribution of the spatially structured random effects under the proper CAR specification is given as:

$$u_k | \boldsymbol{u}_{-k} \sim N\left(\mu_k + \phi \sum_{l=1}^{n} \frac{w_{kl}(u_l - \mu_i)}{N_k},\ \frac{\sigma_u^2}{N_k}\right) \tag{4.8}$$

Hence, the correlation between areas k and l depends only on ϕ and spatial weight matrix $\boldsymbol{W}$. We considered a binary spatial contiguity matrix in the present study as explained above.

In a simpler formulation of the ICAR model, the ϕ parameter is set to 1 which results in the well-known intrinsic conditional autoregressive (iCAR) with a nonpositive definite covariance matrix and improper conditional distribution for u_k as specified below:

$$u_k|\boldsymbol{u}_{-k} \sim N\left(\mu_k + \sum_{l=1}^{n} \frac{w_{kl}(u_l - \mu_l)}{N_k},\ \frac{\sigma_u^2}{N_k}\right) \tag{4.9}$$

For identifiability purpose, a sum to zero constraint must be imposed on the area-specific parameters ($\sum_{k=1}^{n} u_k = 0$). When μ_k is assumed to be 0 for each k, then the conditional distribution reduces to:

$$u_k|\boldsymbol{u}_{-k} \sim N\left(\sum_{l=1}^{n} \frac{w_{kl}(u_l)}{N_k},\ \frac{\sigma_u^2}{N_k}\right) \tag{4.10}$$

In many instances in the field of FGM/C spatiotemporal modelling, the distribution of FGM/C prevalence in a country is such that it contains both spatial structure (arising from spatially positive autocorrelation between areas with similar FGM/C prevalence) and a certain degree of random variation (heterogeneity with no intrinsic spatial structure in FGM/C prevalence) distributed across the entire domain. For the model to provide a good basis for inference, it needs to account for both sources of variability simultaneously within a unified statistical framework (Haining & Li, 2020). To achieve this objective, the iCAR (which borrows information locally), can be combined with the exchangeable model (which borrows information globally), which results in the so called Besag-York-Mollie (BYM) model (Besag et al., 1991) specified as:

$$\theta_k = \alpha + u_k + v_k \tag{4.11}$$

where θ_k is the area-specific parameter (i.e., risk of FGM/C among girls). The model term α is an intercept included because of the sum-to-zero constraint on the spatially structured component u_k modeled as iCAR and the prior 0 mean in the spatially unstructured component v_k model as exchangeable random effect.

However, we considered a recent reparameterization which addressed the nonidentifiable and scaling issue of the BYM model (Riebler et al., 2016). This ensures the spatial correlation parameter denoted as ω, is interpretable and therefore, facilitates the assignment of meaningful penalized complexity prior. The prior model utilizes a scaled version of the spatially structured component $\boldsymbol{u}^*$ and an unstructured component $\boldsymbol{v}$ as presented below, where $\boldsymbol{Q}_*$ is the scaled precision matrix for Besag model:

$$\mathbf{b} = \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\emptyset}\,\boldsymbol{v} + \sqrt{\emptyset}\,\boldsymbol{u}^*\right) \tag{4.12}$$

Where $\mathbf{b}$ is the overall spatial component, τ_b is the marginal precision with a covariance matrix:

$$\mathrm{Var}(\mathbf{b}|\tau_b, \emptyset) = \tau_b^{-1}((1-\emptyset)\mathbf{I} + \emptyset\boldsymbol{Q}_*^{-}) \tag{4.13}$$

We should note that, both $\boldsymbol{v}$ and $\boldsymbol{u}^*$ are standardized to have variances equal to 1(Riebler et al., 2016). The precision parameter $\tau_b > 0$ controls the marginal variance contribution of the weighted sum of the spatially unstructured and spatially structured effects. The mixing parameter $0 \leq \emptyset \leq 1$ measures the proportion of the marginal variance explained by the spatially correlated effect u_s. Thus, this reparameterization of the convolution model is equal to the intrinsic CAR model when $\emptyset = 1$, and spatially independent random effect when $\emptyset = 0$ (Riebler et al., 2016). Unlike the original BYM in which priors are specified separately for τ_u and τ_v, prior beliefs can be expressed in terms of total variability of the model. The PC prior framework allows the total variance to be distributed to the modified BYM model. The construction of the PC priors follows four principles as presented in Simpson et al. (2015). This includes (1) Occam's razor – simpler models should be preferred until there is enough support for a more complex model, (2) Measure of complexity – The Kullback-Leibler distance (KLD) is used to measure increased complexity, (3) constant-rate penalization – The deviation from the simpler model is penalized using a constant decay rate and (4) User-defined scaling – The user has an idea of a sensible size of the parameter of interest (Riebler et al., 2016).

Penalized complexity priors penalize the model complexity in terms of deviation of the flexible model from the base model with constant relative risk across all areas. Hyperpriors were

defined in two levels. First, a prior for τ_b is defined, which will control the marginal variance contribution of the weighted sum of $\boldsymbol{v}$ and $\boldsymbol{u}^*$. Second, the marginal variance is distributed to the components $\boldsymbol{v}$ and $\boldsymbol{u}^*$ by defining an appropriate prior for the mixing parameter $\emptyset$. The PC prior will automatically shrink towards $\emptyset = 0$ which implies no spatial smoothing.

We considered the principles of the PC framework to penalize model complexity in terms of a measure of information-theoretic deviation from the flexible model to the base model which is a function of the Kullback Leibler divergence (KLD). Following the recommendation of Simpson et al. (2017), we considered the type-2 Gumbel distribution to obtain prior for the τ_b parameter as specified below:

$$\pi(\tau_b) = \frac{\theta}{2}\tau_b^{-3/2}\exp\left(-\theta\tau_b^{-1/2}\right) \tag{4.13}$$

This prior corresponds to an exponential prior with rate θ for the standard deviation $1/\sqrt{\tau_b}$. To deduce θ we use the probability statement

$P\left(\left(\frac{1}{\sqrt{\tau_b}}\right) > U1\right) = \alpha 1$, which gives $\theta = -\log(\alpha)/U$, where U is the upper bound of the parameter to be estimated (in this case $U1 = 1$) and α is the probability weight imposed which we set to be very minimal ($\alpha 1 = 0.01$) for an assumed probability of 0.99 of a residual relative risk smaller than 2. Similarly, for the spatial dependence parameter, we specified a probability statement $P(\emptyset > U2) = \alpha$, where set $U2 = 0.5$ and $\alpha 2 = 2/3$, which corresponds to a 67% chance that more than 50% of the total variation of the district random effect has spatial structure (Wakefield et al., 2020).

The log of marginal precision τ_b has the distribution $\log(\tau_s) \sim \text{logGamma}(1,0.01)$ and $\emptyset$ is denoted as $\text{logit}(\emptyset) = \text{loggamma}(0.5,0.5)$. The unstructured spatial random effect is modeled as independent and identically distributed with zero mean Gaussian prior. $v_s \sim N(0, \tau_v)$ and precision parameter $\log(\tau_v) \sim \text{loggamma}(1,0.01)$.

For INLA implementation we considered the proper CAR prior proposed by Bivand et al. (2015) with a conditional distribution of the spatial random effects shown below:

$$u_k | \boldsymbol{u}_{-k}, \sigma_u^2 \sim N\left(\frac{\sum_{l=1}^{n} w_{kl} u_l}{N_k + d}, \frac{\sigma_u^2}{N_k + d}\right) \qquad \text{for } k \neq l \tag{4.14}$$

where σ_u^2 is the variance parameter for spatially structured random effects $\left(\sigma_u^2 = {}^{1}/_{\tau_u}\right)$ that controls the amount of local smoothing in the study domain, while τ_u is the precision. The variance parameter is conditional on the number of neighbours N_k that share border with area k. The larger the number of neighbours, the smaller the variance parameter and the closer the mean estimate of area k to the average of its neighbouring regions. The term $N_k = \sum_{l=1}^{n} w_{kl}$, denotes the sum of the elements in the kth row. The term d is a positive quantity to make the distribution of the covariance matrix proper (i.e. integrated to 1) as explained previously. A log-gamma prior distribution is assigned to logarithms of τ_u and d such that $\log(\tau_u) \sim \text{logGamma}(a, b)$ and $\log(\text{d}) \sim \text{logGamma}(1,1)$. A more general approach is obtained with the precision matrix:

$$\boldsymbol{Q} = \left(\boldsymbol{I} - \frac{\omega}{\lambda_{max}}\boldsymbol{W}\right) \tag{4.15}$$

where $\boldsymbol{I}$ is the identity matrix and λ_{max} is the maximum eigenvalue of the spatial weight matrix $\boldsymbol{W}$. A Gaussian prior is assigned on $\log(\omega/(1-\omega))$. This specification ensures that ω takes a value between 0 and 1 such that $\log(\omega/(1-\omega)) \sim N(0,0.45)$.

In addition, we considered an alternative formulation of the proper CAR model defined with the precision matrix $\tau_u((1-\omega)\boldsymbol{I} + \omega\boldsymbol{W})$. The six alternative formulations implemented are summarized in Table 4.6 along with the DIC and WAIC values. The smaller the DIC and the WAIC, the better the model fit.

From the Table 4.6, results showed no additional improvement to the model by imposing a spatial dependence parameter on the area-specific random effects in Kenya and Senegal. Hence, we modeled the area-specific effect as independent and identically distributed with mean Gaussian prior and τ_v precision parameter, such that $\log(\tau_v) \sim \text{logGamma}(1,0.1)$. In contrast, however, findings provide support for a substantial evidence of spatial dependence effect operating among neighboring states in Nigeria ($\omega = 0.4$). Hence, we modelled the residual spatial effects as the sum of spatially structured effects and spatially unstructured random effects in Nigeria. Also, we note that the observed spatial dependence in Nigeria may

in fact be as a result of larger number of spatial subdomains (n=37 states) compared to that observed in Kenya (n=8 regions) and Senegal (n=14 regions).

Table 4.6. Summary of Spatial model formulation evaluated for the area random effect.

Model	Description	Specification	Prior	DIC	WAIC
Exchangeable	Area-specific random effect	$N(0, \sigma_v^2)$	$\log(\tau_v) \sim$loggamma(1,0.01)	6387[k]; 9288[n]; 8010[s]	6390[k]; 9290[n]; 8011[s]
iCAR	Area-specific effects due to spatial dependence between neighbouring areas	iCAR (0,σ_u^2)	$\log(\tau_u) \sim$loggamma(1,0.01)	6387[k]; 8009[s]	6390[k]; 8010[s]
pCAR1	Spatial dependence random effect with a positive definite covariance matrix	iCAR + a positive quantity, d	log $(\tau_u)\sim$loggamma(1,0.0)1) $\log(d)\sim$loggamma(1,1)	6388; 9253; 8009	6391; 9255; 8010
pCAR2	A re-parameterization of properCAR with an additional spatial dependence parameter specified on	$\tau_u((1-\omega)\boldsymbol{I} + \omega\boldsymbol{W})$	$\log(\tau_u) \sim$loggamma(1,0.01) $\text{logit}(\omega)\sim N(0,0.45)$	6387;9254; 8009	6390; 9256; 8010

	the structure matrix				
BYM	A convolution of the IID and the iCAR model with a sum to zero constraint on u_s	$\alpha + u_k + v_k$	$\log(\tau_u) \sim \text{loggamma}(1,0.01)$ $\log(\tau_v) \sim \text{loggamma}(1,0.01)$	6386; 9253; 8010	6389; 9255; 8010
BYM2	A reparameterization of the BYM model with penalized complexity prior on both the precision parameters and spatial dependence hyperparameter	$\frac{1}{\sqrt{\tau_s}}\left(\sqrt{1-\emptyset} + \sqrt{\emptyset}\, u_s\right)$	$\log(\tau_s) \sim \text{loggamma}(1,0.01)$ $\log\left({}^{\omega}/_{1-\omega}\right) \sim \text{loggamma}(1,0.01)$	6387; 9254; 8010	6390; 9256; 8010

Note that the superscripts k, n, and s denote the three countries of interest – Kenya, Nigeria and Senegal. The Besag only could not be fitted to the Nigeria data, hence not added to the table.

This key finding supports our preliminary hypothesis in that we expect a significant reduction in the observed spatial dependence at area level after accounting for key FGM/C risk factors operating at community level, including prevalence of FGM/C in community and/or prevalence of support for continuation of the practice in such a community. This is the case, given that a substantial amount for the spatial dependence occurs at the cluster/community level of interaction as a results of strong neighborhood influence of FGM/C as a socially coordinated norm as eloquently presented by Mackie in his seminal paper (Mackie, 1996) and confirmed by several studies more recently (Kandala & Shell-Duncan, 2019; Shell-Duncan et al., 2011).

The main temporal effect was modeled as both linear fixed effects bt and correlated random effects γ_t , modeled via a first order random walk (Khana et al., 2018). This component assumes

that the values for a given district at a specific time point depend upon the values observed for that district in the previous year plus a residual. The correlated temporal random effect, γ_t, which has a random walk prior distribution with precision τ_{γ_t}; where $\gamma t \sim N(\gamma_{t-1}, \frac{1}{\tau_{\gamma_t}})$. The conditional precision of the structured random time effect was assigned $\tau_{\gamma_t} \sim \text{loggamma}(1,0.1)$ prior.

The spacetime interaction term, δ_{kt}, was considered to account for any deviation in space and time from the main spatial or temporal trends (Knorr-Held, 2000; Knorr-Held & Besag, 1998). In other words, the assumption here is that the change in the risk of FGM/C in a girl living in region k at a specific time point t is independent of the observed risk in neighboring regions and observed risk in the preceding surveys. This type of interaction assumes that, after accounting for spatial and temporal main effects, the residuals do not have structure in space and time. This additional spacetime interaction term was implemented in equation 4.16 to quantify the excess risk of FGM/C in a girl due to spacetime interaction in the observed FGM/C patterns along with the Bayesian posterior probability of such risk and implemented in INLA (Blangiardo et al., 2013). The space-time interaction effect was assumed to be independently and identically distributed with zero mean Gaussian prior; $\delta_{kt} \sim N(0, \frac{1}{\tau_{\delta kt}})$. The conditional precision of the unstructured random effect was assigned $\log(\tau_{\delta kt}) \sim \text{loggamma}(1,0.001)$ prior.

In addition to the space-time type I interaction, we also evaluated the prior assumptions of a type II, type III, and type IV residual space-time interactions in the observed FGM/C prevalence separately for each country. Type I interaction assumes that the unstructured spatial random effects and unstructured temporal random effect interact, hence, no spatial or temporal structure is imposed on the observed space-time residual variation in FGM/C prevalence among the study regions and are assumed to be independent and identically distributed in space and time. In type II interaction, the structured main temporal effects (specified as a random walk of order 1 in our study) and the unstructured spatial effect interact (specified as mean Gaussian prior). This leads to the assumption that for the kth area the parameters vector $\{\delta_{i1}, \dots, \delta_{iT}\}$ has an autoregressive structure on the temporal component, which is independent from other areas. Type III space-time interaction combines the main unstructured temporal effect and the spatially structured main effect (modelled through the conditional autoregressive prior). Here, the assumption is that the parameters of the time point $\{\delta_1, \dots, \delta_n\}$ have a spatial structure independent from previous or subsequent time points. (Blangiardo et al., 2013; Knorr-

Held, 2000). In this case, the observed FGM/C is assumed to be spatially structured by independent in time.

Type IV is the most complex interaction, which assumes that spatially structured and temporally structured random effects operating in space and time interact. The structure matrix can be written as the Kronecker product of the structure matrix $R_\delta = R_u \otimes R_\gamma$ and has a rank of (T-1)(n-1) for a random walk of order 2. It assumes that the temporal dependency structure for each area is dependent on the temporal pattern of its neighbors.(Blangiardo et al., 2013; Knorr-Held, 2000). Within the context of the current study, this implies that the observed FGM/C prevalence at one time point in an area k is simultaneously dependent on observed FGM/C prevalence at proximal time points and that of neighboring areas. We present the results for the four specifications of spacetime interaction in Table 4.7 below along with the DIC and WAIC estimates for model comparison. Therefore, given that the assumption of type I space-time interaction provided the best fit to the data, we considered this specification in subsequent model formulation to account for the complex survey design features in subsequent sections and interpretation of results in Chapter 5.

Table 4.7. Summary of the four types of space-time interaction specification evaluated.

Model	Interacting main effects	Prior specification for space-time cell parameters	Rank	DIC	WAIC
Type I	$v_k + \lambda_t$	$v_k \sim N(0, \sigma_v^2)$ $\lambda_t \sim N(0, \sigma_\lambda^2)$	nT	5595[k]; 8867[n]; 7879[s]	5599[k]; 8866[n]; 7879[s]
Type II	$v_k + \gamma_t$	$v_k \sim N(0, \sigma_v^2)$ $\gamma_t \sim rw1(0, \sigma_\gamma^2)$	n(T-1)	8220; 9202; 9572	8195; 9204; 9550
Type III	$u_k + \lambda_t$	$u_k \sim iCAR(0, \sigma_u^2)$ $\lambda_t \sim N(0, \sigma_\lambda^2)$	n-1(T)	8226; 9925; 9578	8202; 9893; 9559

Type IV	$u_k + \gamma_t$	$u_k \sim iCAR(0, \sigma_u^2)$ $\gamma_t \sim rw1(0, \sigma_\gamma^2)$	(n-1)(T-1)	5595; 9943; 7881	5600^k; 9903^n; 7883^s

Note that the superscripts k, n, and s denote the three countries of interest – Kenya, Nigeria and Senegal

4.8.4. Model 4 – Model with individual and community level covariates, and residual main spatial effect, main temporal effect, spacetime interaction effect and stratification design effect

We extended the model formulation in equation 4.7 to account for the first key component of the DHS sampling design – stratification. For the procedure for stratification was similar across the three countries with stratification implemented by region and type of residence (rural versus urban) resulting in a specific number of strata for each country across the 3 survey years– 48 in Kenya, 222 in Nigeria and 84 in Senegal. For the purpose of this study, we modelled the stratification as fixed effect as recommended (Skinner & Wakefield, 2017). The result is the model formulation in equation 4.16 below:

$$logit(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f_1(b1_{i1}) + f_2(b2_{i2}) + f_3(P1_{ij3}) + f_4(P2_{ij4}) + f_5(P3_{ij5}) + v_k + u_k + bt + \gamma_t + \delta_{kt} + \vartheta_{strata} \quad (4.16)$$

where the additional term, ϑ_{strata}, denotes the stratification design effect variable, modelled by accounting for type of residence and region as fixed effect covariates. We compared the performance of the model with stratification variables (equation 4.16) to model with space-time interaction only (see equation 4.4).

4.8.5. Model 5 – Model with individual and community level covariates, and residual main spatial effect, main temporal effect, spacetime interaction effect and cluster design effect

In this model formulation, we assessed the effect of incorporating the second component of the complex survey design - cluster sampling design effect. As highlighted in the previous chapter, the use of cluster sampling approach in household surveys introduced extra amount of variability, hence bias, into the observed data. Therefore, clustering of individuals violates the

independence assumption of these individuals. This in turn has an impact on how the data from these correlated/dependent individuals are used for estimation. All surveys considered a two-stage cluster design sampling with a first stage random selection of clusters (from a master list of enumerations areas) independently drawn from each stratum and a subsequent random selection of representative households from each cluster in the second stage. We considered the need to account for extra variability at the cluster design stage given that a larger proportion of the variability is observed among girls and women at the community level compared to a relatively low amount variability within household. Another motivation for accounting for the cluster design effect is to capture unexplained FGM/C risk factors (including other social normative influences) operating within a specific community in the statistical model formulation. The model specification for the cluster design effect is given in equation 4.17 below:

$$\begin{aligned}\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + f(P2_{ijkt}) \\ + f(P3_{ijkt}) + v_k + u_k + bt + \gamma_t + \delta_{kt} + \sigma_j\end{aligned} \quad (4.17)$$

where the cluster design effect is denoted as σ_j and are assumed to be independently and identically distributed with zero mean Gaussian prior: $\sigma_j \sim N(0, \tau_{\sigma_j})$ given that clusters from a survey year were independently sampled from clusters from other time points. The precision parameter was denoted with a log gamma prior: $\log(\tau_{\sigma_j}) \sim \text{loggamma}(1,0.001)$. Model performance was compared to model with spacetime interaction effect. A summary of the DHS surveys, sampling design, model formulation for the three countries is presented in Table 4.6.

Table 4.8. Summary of Model specification for Kenya, Nigeria and Senegal.

Country	Model	Model Description	Specification
KENYA	1	Individual level covariates only	$\text{logit}(\pi_i) = \alpha_0 + X_i\beta$
	2	Individual and cluster level covariates	$\text{logit}(\pi_{ij}) = \alpha_0 + X_i\beta + f(Age1_{ij}) + f(Age2_{ij}) + f(P1_{ij})$
	3	Individual and cluster level covariates and main spatial, main temporal, and space-time interaction	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + v_{kt} + u_{kt} + bt + \delta_{kt}$
	4	Individual and cluster level covariates and main spatial, main linear temporal, and space-time interaction effects and stratification design effects	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + v_{kt} + u_{kt} + bt + \delta_{kt} + \varphi_{strata}$
	5	Individual and cluster level covariates and main spatial, main linear temporal effect, and space-time interaction effects and cluster design effects	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + v_{kt} + u_{kt} + bt + \delta_{kt} + \sigma_j$
NIGERIA	1	Individual level covariates only	$\text{logit}(\pi_i) = \alpha_0 + X_i\beta$
	2	Individual and cluster level covariates	$\text{logit}(\pi_{ij}) = \alpha_0 + X_i\beta + f(Age1_{ij}) + f(Age2_{ij}) + f(P1_{ij}) + f(P2_{ij}) + f(P3_{ij})$
	3	Individual and cluster level covariates and main spatial, main linear and nonlinear temporal effects, and space-time interaction	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + f(P2_{ijkt}) + f(P3_{ijkt}) + v_{kt} + u_{kt} + bt + \gamma_t + \delta_{kt}$
	4	Individual and cluster level covariates and main spatial, main linear and nonlinear temporal effects, and space-time interaction effects and stratification design effects	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + f(P2_{ijkt}) + f(P3_{ijkt}) + v_{kt} + u_{kt} + bt + \gamma_t + \delta_{kt} + \varphi_{strata}$
	5	Individual and cluster level covariates and main spatial, main linear and nonlinear temporal, and space-time interaction effects and cluster design effects	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + f(P2_{ijkt}) + f(P3_{ijkt}) + v_{kt} + u_{kt} + bt + \gamma_t + \delta_{kt} + \sigma_j$
SENEGAL	1	Individual level covariates only	$\text{logit}(\pi_i) = \alpha_0 + X_i\beta$
	2	Individual and cluster level covariates	$\text{logit}(\pi_{ij}) = \alpha_0 + X_i\beta + f(Age1_{ij}) + f(Age2_{ij}) + f(P1_{ij}) + f(P2_{ij}) + f(P3_{ij})$
	3	Individual and cluster level covariates and main spatial, main linear temporal effect, and space-time interaction effect	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + f(P2_{ijkt}) + f(P3_{ijkt}) + v_{kt} + u_{kt} + bt + \delta_{kt}$
	4	Individual and cluster level covariates and main spatial, main linear temporal effect, and space-time interaction effects and stratification design effects	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + f(P2_{ijkt}) + f(P3_{ijkt}) + v_{kt} + u_{kt} + bt + \delta_{kt} + \varphi_{strata}$
	5	Individual and cluster level covariates and main spatial, main linear temporal, and space-time interaction effects and cluster design effects	$\text{logit}(\pi_{ijkt}) = \alpha_0 + X_{ijkt}\beta + f(Age1_{ijkt}) + f(Age2_{ijkt}) + f(P1_{ijkt}) + f(P2_{ijkt}) + f(P3_{ijkt}) + v_{kt} + u_{kt} + bt + \delta_{kt} + \sigma_j$

4.9. Model Assessment and Prediction Accuracy

To compare the five alternative Bayesian model formulations described in Table 4.6 above, and evaluate their predictive performance, we considered three measures of model fit commonly used in Bayesian inferential procedures – the deviance information criterion (DIC) (Spiegelhalter et al., 2002), the Watanabe information criterion (WAIC)(Watanabe, 2013) and logarithm of the conditional predictive ordinate (Gelman et al., 2014).

The DIC and WAIC give approximately unbiased estimates of elppd by starting with something like lppd and then subtracting a correction for the effective number of parameters:

$$\widehat{\mathrm{elpd}_{\mathrm{DIC}}} = \log p\left(y \middle| \hat{\theta}_B\right) - \ p_{\mathrm{DIC}} \tag{4.18}$$

where p_{DIC} is the effective number of parameters, defined as:

$$p_{\mathrm{DIC}} = 2\left(\log p\left(y|\hat{\theta}_B\right) - \mathrm{E}_{\mathrm{post}}(\log p\left(y|\theta\right)\right) \tag{4.19}$$

where the expectation in the second term is an average of θ over its posterior distribution. Expression (8) is calculated using simulations $\theta^s = 1, \dots, S$ as:

computed $p_{\mathrm{DIC}} = 2\left(\log p\left(y|\hat{\theta}_B\right) - \frac{1}{S}\sum_{s=1}^{S} \log\ p(y|\theta^s)\right)$

The quantity known as DIC is defined in terms of the deviance rather than the log predictive density as:

$$\mathrm{DIC} = -2\log p\left(y \middle| \hat{\theta}_B\right) + 2P_D \tag{4.20}$$

The DIC, therefore combines the goodness of fit (first term) and a penalty term that is based on the complexity of the model (second term) within a Bayesian regression framework to evaluate alternative models. Here, the first term log $p\left(y \middle| \hat{\theta}_B\right)$ is the deviance, which denotes the posterior expectations of the latent effects $\boldsymbol{\theta^{par}} = \{u_k, v_k, \gamma_t, \delta_{kt}\}$ and hyperparameters $\boldsymbol{\theta^{hyp}} = \{\tau_u, \tau_v, \delta_{kt}, \emptyset\}$. The term P_D is the effective number of parameters which penalizes the model for complexity. It is defined as:

$$P_D = \left(2(\log p\left(y\middle|\hat{\theta}_B\right) - \mathrm{E}_{\mathrm{post}}(\log p(y|\theta))\right) \tag{4.21}$$

Since the deviance is expected to decrease with increasing number of parameters given a model, the P_D term compensates for this effect by favoring models with a smaller number of parameters. INLA uses the posterior means of the latent field but the posterior mode of the hyperparameters because these may be very skewed. Regarding application to model selection, the DIC favors models with lower values, indicating better fit of such models to the observed data. In the present study, a DIC point difference of 5 is adjudged to provide significant improvement.

The WAIC, also known as widely applicable information criterion, provides an alternative approach to estimating the expected log pointwise predictive density (Watanabe, 2013). Although similar to the DIC, WAIC is computed based on the posterior variance of the log predictive density as defined below:

$$\widehat{\mathrm{elpd}_{\mathrm{WAIC}}} = \widehat{\mathrm{lppd}} - p_{WAIC} \tag{4.22}$$

where p_{WAIC} is the bias correction factor estimated by summing over the posterior variance as shown below:

$$p_{WAIC} = \sum_{i=1}^{n} var_{post}(\log p(y_i|\theta)) \tag{4.23}$$

However, compared to the DIC, the WAIC is a more fully Bayesian approach for estimating out-of-sample expectation. It also has the desirable property of averaging over the posterior distribution rather than conditioning on a point estimate. This is especially relevant in a predictive context as it evaluates the prediction that are being used for new data in a Bayesian context.

To evaluate the predictive performance of the alternate space-time model formulations, we considered a commonly used leave-one-out cross validation procedure for approximate Bayesian inference within the INLA framework known as the conditional predictive ordinate (CPO). CPOs are a cross-validatory criterion for model assessment that is computed for each observation as:

$$CPO_i = \pi(y_i|y_{-i}) \tag{4.24}$$

Hence, for each observation, its CPO is the posterior probability of observing that observation when the model is fit using all data but y_i. Large values indicate better fit of the model to the data, while small values indicate a poor model performance. The log average sum of the CPO is a measure that summarizes CPO for all observations in the data and returns the logarithmic score which provides a predictive measure of how well the models fit the data as shown below:

$$\sum_{i=1}^{n} \log (CPO_i) \tag{4.25}$$

Unlike the CPO however, the lower the sum of log CPO, the better the mode fit to the data. The two later procedures are also more applicable to estimate pointwise out-of-sample prediction accuracy from a Bayesian hierarchical model using the log-likelihood evaluated at the posterior predictive distribution of the parameter values. (Vehtari et al., 2017).

The predicted risk of outcome (proportion of cases) for each study is presented along with the predictive measure of model fit. A comparison of observed and predicted risk of FGM/C was conducted separately for each survey to evaluate the accuracy of the best model and evaluated using the R-squared and the root mean squared error (RMSE). The estimated marginals of the coefficients of the fixed effects and the estimated marginals of the precisions of the prior variances for all the random components from the best model are presented along with the posterior means and 95% Bayesian credible intervals.

In discussion, in this chapter, we present in detail our proposed framework for modeling FGM/C using nationally representative survey data with complex sampling design in space and time. More specifically, we described the statistical methodology to model FGM/C prevalence risk in space and time using the proximate determinant framework (PDF) within a hierarchical Bayesian formulation. The proposed framework provides a structured and data-driven approach to test the seven (7) most prominent theories to explain FGM/C persistence especially in sub-Saharan Africa including: Social normative influences, Demographic factors, Gender norms, Feminist theory, Modernization theory, Media exposure and geographic mobility. The flexibility of the framework ensures that the role of neighborhood(context) and spatial-temporal dynamics of the practice can also be tested and quantified. We considered five (5) different model formulations to identify the set of risk factors that best explain the observed FGM/C prevalence patterns within a specific country context. In the first model, we evaluated the influence of individual level covariates (proxy measures for theoretical constructs). In the second model formulation, we quantified the additional effects of social normative influences

operating within community such the prevalence of FGM/C among women and their support for continuation of the practice.

In the third model, we decomposed the spatial-temporal dynamics of unobserved FGM/C risk factors into main spatial, main temporal and space-time interaction effects. Six different alternative model formulations were evaluated to identify the best choice of prior assumption for spatial smoothing of prevalence risk across the three African countries of interest. This include the IID, the Besag, the Besag proper, the Besag proper with additional spatial dependence parameter, the convolution model, and the convolution model penalized for complexity. Findings showed that the convolution model (un)penalized for model complexity provided the best fit for the data across the three countries. Similarly, four (4) different types of priors for the space-time interaction effect as proposed by Knorr-Held (2000). This include Type I, Type II, Type III and Type IV spacetime interaction each with its specific prior assumption in relation to the nature of the space-time interaction terms. Our findings showed that the Type I space-time formulation with unstructured space and time effects provided the best fit for the data across the three countries.

Furthermore, we evaluated the additional benefits to modelling the complexity of the survey design features: Stratification design (modeled as a fixed effect) in the fourth model and the cluster sampling design (model as independent and randomly distributed) in the fifth model. In conclusion, the first 3 models provide a statistical to evaluate Hypothesis 1 of this study which is identify FGM/C risk factors operating at individual and community levels in space and time. Model 3 provides a statistical framework to quantify excess variability in FGM/C risk due to unobserved risk factors operating simultaneously in space and time (Hypothesis 2). More importantly, Model 4 and Model 5 provides a statistical framework to evaluate accounting for the survey design complexity will result in observable changes to the influence of identified FGM/C risk factors (Hypothesis 3). In the next chapter, we present the results of the Bayesian analyses, compared estimates across the three (3) countries and discuss implications of the results in the context of existing FGM/C literature.

CHAPTER FIVE

RESULTS AND DISCUSSION FOR THE FEMALE GENITAL MUTILATION/CUTTING STUDY

5.1. Introduction

In this chapter, we present the results of the hierarchical Bayesian space-time modeling of female genital mutilation (FGM/C). In addition, we evaluated evidence of statistical support for the various FGM/C theories separately for the study populations in the three African countries of interest. The structure of the chapter is organized as follows: in Section 1, we present descriptive analysis of FGM/C national prevalence for the study population and prevalence by exposure variable categories separately for the three countries. We present the geographic distribution of the observed FGM/C prevalence among girls for each country by survey year in Section 2. Results of the hierarchical Bayesian spatio-temporal models are presented in Section 3. Here, the objective is to evaluate changes in risk factor estimates on FGM/C likelihood after accounting for complex survey design features – i.e. stratification and clustering. In Section 4, we present the results of geographic variation in residual risk as observed in the main spatial effects. Additional attempt was made to quantify excess variability in FGM/C risk due to unobserved risk factors interacting simultaneously in space and time in Section 5. We assessed the effects of individual level and community level covariates in Section 6. We evaluated predictive performance of the best fitting model in comparison to the observed data in Section 7. A comprehensive effort was made to discuss study findings in the context of existing FGM/C risk factor literature in Section 8. We conclude the chapter with a summary of key findings and future direction for the study.

5.2. Descriptive Analysis

In this section, the descriptive characteristics of the study participants across the three surveys are presented separately for the three countries as shown in Table 5.1 – Table 5.3 below. The geographic distributions of the administrative level (region or state) of interest is also shown for the three respective countries in Figures 5.1 to 5.3 below.

In Kenya, the estimated weighted prevalence of FGM/C in the study sample was highest in 2003 at 9.3% followed by a rapid decline to 3% in 2014. In addition, prevalence differed by exposure characteristics. For instance, the average age of girls who were cut was higher than uncut girls, with a relative increase in average age at cutting observed over the years. Similarly, mothers of cut girls were older on the average by at least 4 years across the 3 surveys. A significantly higher proportion of cut girls were born to mothers who were cut. Mothers of cut girls were three times more likely to be cut compared to mothers of uncut girls. Mothers of cut girls were also more likely to report not working or occupationally engaged than uncut girls with increasing differential observed over time.

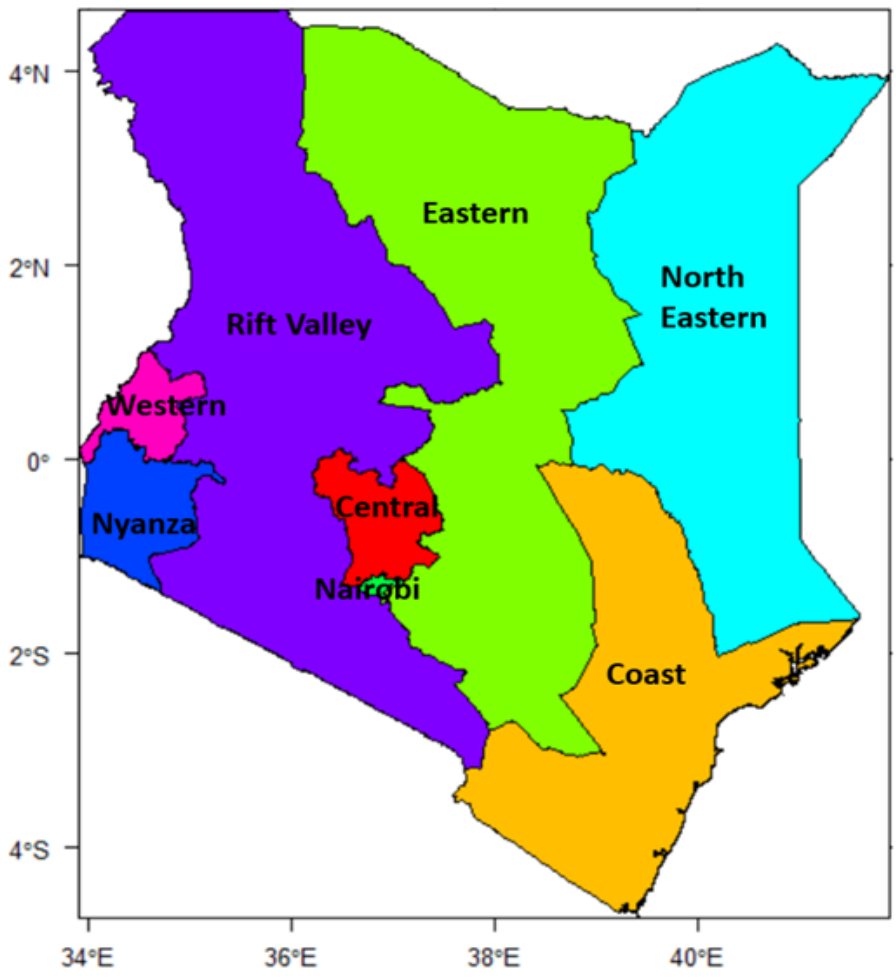


Figure 5.1. Map of Kenya showing the eight (8) Administrative regions.

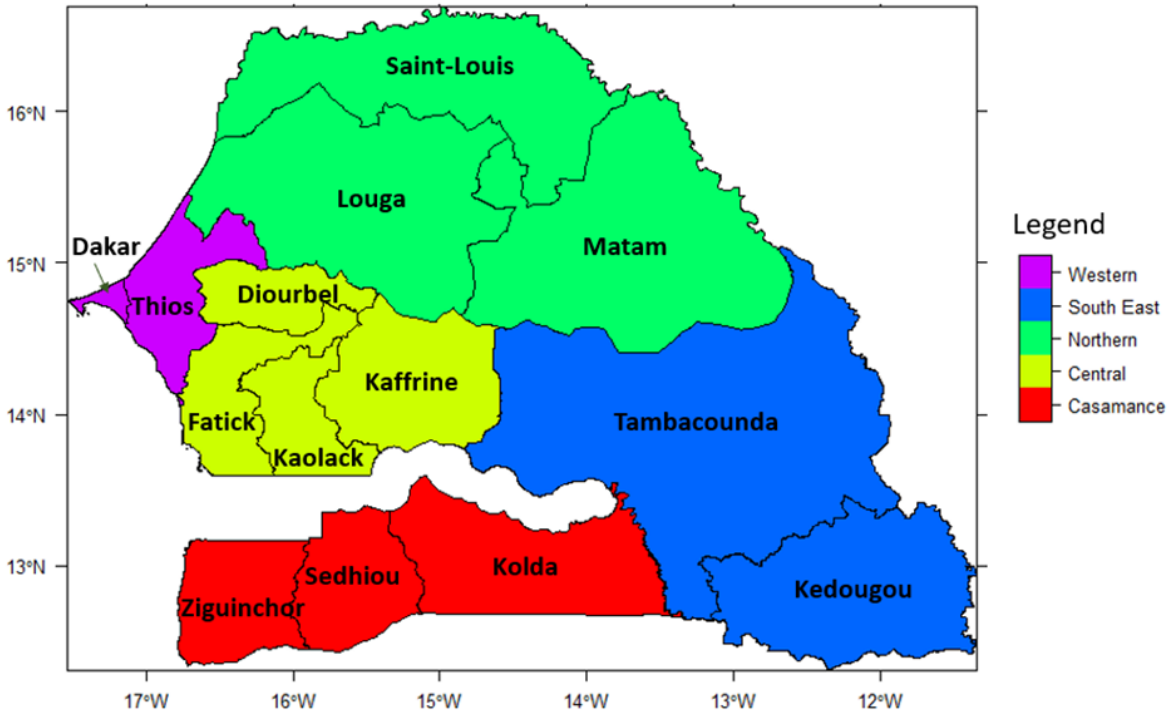


Figure 5.2. Map of Senegal showing the 14 Administrative regions.

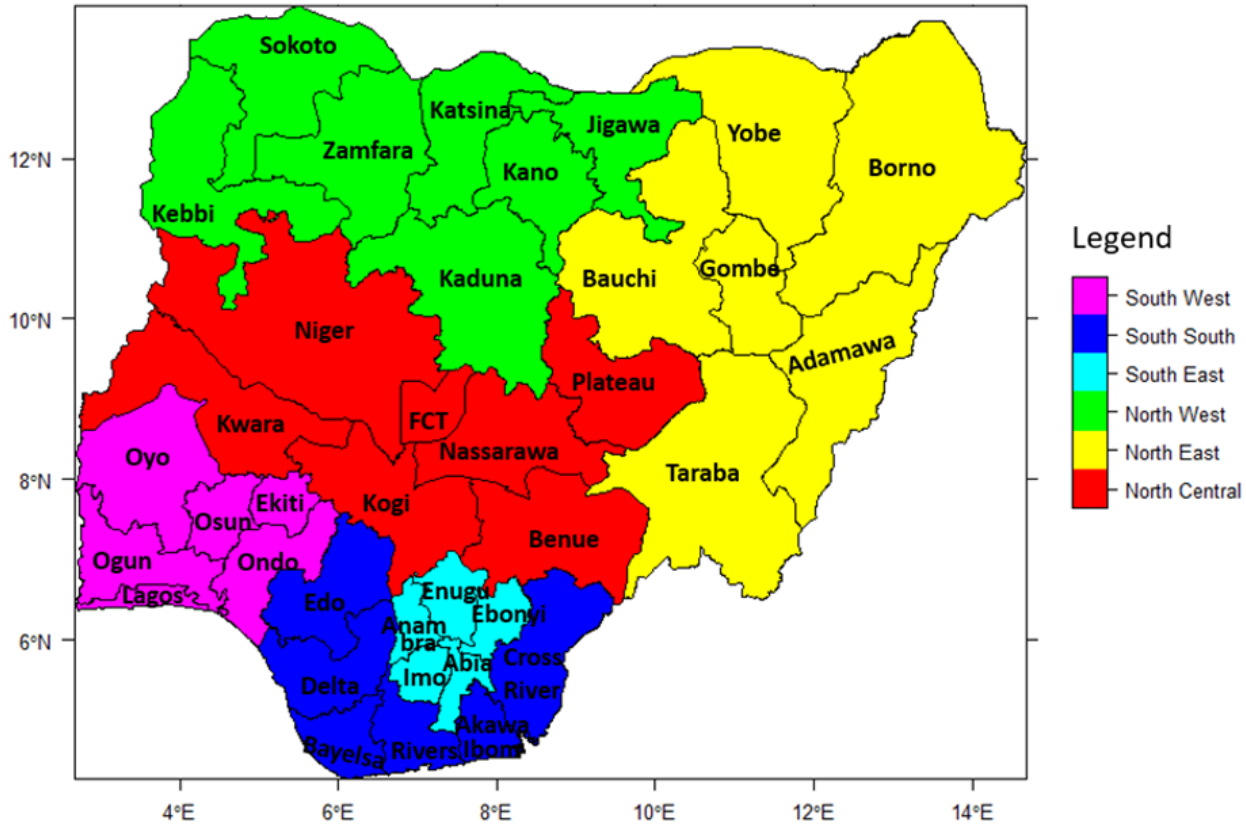


Figure 5.3. Map of Nigeria showing the 36 Administrative States and the Federal Capital Territory (FCT).

Table 5.1. National prevalence of female genital mutilation/cutting (FGM/C) among girls 0-14 years born to women 15 to 49 years who have heard of FGM/C and prevalence by study variables across the three selected Demographic and Health Surveys (DHS) surveys in Kenya.

Variable	2003 DHS N=3,792 (Weighted Prevalence = 9.3%)		2008 DHS N=6,729 (Weighted Prevalence = 8.0%)		2014 DHS N=12,421 (Weighted Prevalence = 3.0%)	
	FGM N=414 n (%)	No FGM N=3,378 n (%)	FGM N=878 n (%)	No FGM N=5,851 n (%)	FGM N=733 n (%)	No FGM N=11,688 n (%)
Mean age girls (SD) (p<0.0001)	6.3(4.3)	4.6(4.0)	8.3(4.1)	6.2(4.2)	10.5(2.7)	6.4(4.1)
Mean age of mothers (SD) (p<0.0001)	37.0(6.8)	30.7(7.5)	36.7(6.6)	31.6(7.2)	35.8(6.1)	32.3(7.1)
Place of residence	p=0.002		p=0.000		p=0.131	
urban	92(22.2)	1,003(29.7)	95(10.8)	1,416(24.2)	207(28.2)	3,611(30.9)
rural	322(77.8)	2,375(70.3)	783(89.2)	4,435(75.8)	526(71.8)	8,077(69.1)
Marital Status	p=0.000		p=0.000		p=0.000	
never married	4(1.0)	221(6.5)	11(1.3)	284(4.8)	3(0.4)	483(4.1)
currently married	351(84.8)	2,754(81.5)	802(91.3)	4,866(83.2)	675(92.1)	9,764(83.6)
formerly married	59(14.2)	403(11.9)	65(7.4)	701(12.0)	55(7.5)	1,441(12.3)
Mother's Education	p=0.000		p=0.000		p=0.000	
none	236(57.0)	489(14.5)	581(66.2)	816(14.0)	524(71.5)	2,145(18.4)
primary	143(34.5)	1,943(57.5)	236(26.9)	3,575(61.1)	146(19.9)	6,760(57.8)
secondary	32(7.3)	724(21.4)	54(6.2)	1,107(18.9)	52(7.1)	2,161(18.5)
higher	3(0.7)	222(6.6)	7(0.8)	353(6.0)	11(1.5)	622(5.3)
Wealth Quintile	p=0.000		p=0.000		p=0.000	
poorest	152(36.7)	627(18.6)	530(60.4)	1,311(22.4)	458(62.5)	3,528(30.2)
poorer	92(22.2)	597(17.7)	130(14.8)	1,067(18.2)	97(13.2)	2,535(21.7)
middle	74(17.9)	589(17.4)	94(10.7)	1,110(19.0)	73(10.0)	2,166(18.5)
richer	53(12.8)	634(18.8)	83(9.5)	1,108(19.0)	68(9.3)	1,947(16.7)
richest	43(10.4)	931(27.6)	41(4.7)	1,255(21.5)	37(5.1)	1,512(12.9)
Ethnicity	p=0.000		p=0.000		p=0.000	
Embu	4(1.0)	25(0.7)	7(0.8)	75(1.3)	1(0.1)	101(0.9)
Kalenjin	29(7.0)	299(8.9)	48(5.5)	734(12.5)	11(1.5)	1,941(16.6)
Kamba	16(3.9)	362(10.7)	35(4.0)	477(8.2)	5(0.7)	1,101(9.4)
Kikuya	24(5.8)	784(23.2)	10(1.1)	933(16.0)	0(0.0)	1,532(13.1)
Kisii	85(20.5)	109(3.2)	144(16.4)	203(3.5)	128(17.5)	596(5.1)
Luhya	4(1.0)	612(18.1)	0(0.0)	1,053(18.0)	5(0.7)	1,421(12.2)
Luo	5(1.2)	391(11.6)	1(0.1)	806(13.8)	1(0.1)	1,097(9.4)
Maasai	40(9.7)	69(2.0)	34(3.9)	101(1.7)	10(1.4)	385(3.3)
Meru	9(2.2)	153(4.5)	10(1.1)	290(5.0)	1(0.1)	509(4.4)
Mijikenda/Swahili	3(0.7)	263(7.8)	3(0.3)	496(8.5)	2(0.3)	578(5.0)
Somali	173(41.8)	134(4.0)	453(51.6)	247(4.2)	417(56.9)	618(5.3)
Taita-taveta	12(2.9)	42(1.2)	16(1.8)	88(1.5)	3(0.4)	158(1.4)
Other	0(0.0)	55(1.6)	117(13.3)	348(6.0)	36(4.9)	191(1.6)
Religion	p=0.000		p=0.000		p=0.000	
Christian	231(55.8)	2,952(87.4)	333(37.9)	4,932(84.3)	194(26.5)	9,973(85.3)
Muslim	175(42.3)	326(9.7)	535(60.9)	733(12.5)	536(73.1)	1,494(12.8)
Other	8(1.9)	98(2.9)	10(1.1)	186(3.2)	3(0.4)	219(1.9)
Region	p=0.000		p=0.000		p=0.000	
Central	17(4.1)	569(16.8)	7(0.8)	651(11.1)	1(0.1)	957(8.2)

Coast	28(6.8)	396(11.7)	35(4.0)	758(13.0)	55(7.5)	1,333(11.4)
Eastern	33(8.0)	434(12.9)	163(18.6)	834(14.3)	103(14.1)	1,940(16.6)
Nairobi	19(4.6)	395(11.7)	3(0.3)	435(7.4)	0(0.0)	264(2.3)
North-Eastern	143(34.5)	94(2.8)	427(48.6)	210(3.6)	404(55.1)	561(4.8)
Nyanza	85(20.5)	400(11.8)	141(16.1)	865(14.8)	130(17.7)	1,573(13.5)
Rift Valley	85(20.5)	602(17.8)	102(11.6)	1,182(20.2)	37(5.1)	3,891(33.3)
Western	4(1.0)	488(14.5)	0(0.0)	916(15.7)	3(0.4)	1,169(10.0)
FGM status of Mother	p=0.000		p=0.000		p=0.000	
uncut	13(3.1)	2,290(67.8)	9(1.0)	4,024(68.8)	20(2.7)	7,452(63.8)
cut	401(96.9)	1,087(32.2)	869(99.0)	1,826(31.2)	713(97.3)	4,232(36.2)
Mother's occupation	P=0.000		P=0.000		P=0.000	
formal	93(22.5)	887(26.3)	219(24.9)	2,544(43.5)	78(10.6)	1,881(16.1)
informal	138(33.3)	1,458(43.2)	124(14.1)	1,327(22.7)	194(26.5)	6,472(55.4)
not working	183(44.2)	1,033(30.6)	534(60.8)	1,962(33.5)	461(62.9)	3,279(28.1)
Expenditure of mother's earning decided by mother or jointly	p=0.000		p=0.000		p=0.000	
Mother	99(23.9)	1,106(32.7)	66(7.5)	1,015(17.4)	89(12.1)	2,394(20.5)
Mother and Partner	44(10.6)	484(14.3)	56(6.4)	1,160(19.8)	48(6.6)	2,004(17.2)
Partner/Someone else	20(4.8)	171(5.1)	29(3.3)	183(3.1)	13(1.8)	497(4.3)
Beating justified if mother denies father sex	p=0.000		p=0.000		p=0.000	
no	206(49.8)	2,261(66.9)	448(51.0)	4,274(73.1)	474(64.7)	8,849(75.7)
yes	208(50.2)	1,117(33.1)	343(39.1)	1,472(25.2)	243(33.2)	2,681(22.9)
Read Newspaper	p=0.000		p=0.000		p=0.000	
not at all	362(87.4)	2,075(61.4)	813(92.6)	3,847(65.8)	697(95.1)	8,781(75.1)
less than once a week	27(6.5)	645(19.1)	30(3.4)	1,042(17.8)	16(2.2)	1,821(15.6)
at least once a week	25(6.0)	658(19.5)	32(3.6)	956(16.3)	20(2.7)	1,083(9.3)
Listen to Radio	p=0.000		p=0.000		p=0.000	
not at all	201(48.6)	567(16.8)	462(52.6)	1,067(18.2)	459(62.6)	2,973(25.4)
less than once a week	38(9.2)	294(8.7)	101(11.5)	497(8.5)	89(12.1)	1,538(13.2)
at least once a week	175(42.3)	2,517(74.5)	315(35.9)	4,285(73.2)	185(25.2)	7,177(61.4)
Watch Television	p=0.000		p=0.000		p=0.000	
not at all	343(82.9)	2,213(65.5)	752(85.7)	3,642(62.3)	650(88.7)	7,477(64.0)
less than once a week	26(6.3)	296(8.8)	56(6.4)	612(10.5)	36(4.9)	1,539(13.2)
at least once a week	45(10.9)	869(25.7)	69(7.9)	1,596(27.3)	46(6.3)	2,668(22.8)

Furthermore, overall prevalence of FGM among girls 0-14 years in Nigeria increased from 27.8% in 2008 to 36.6% in 2018. On the average, no difference was observed in age between cut and uncut Nigerian girls and a negligible difference in age was observed in the mean age of mothers (Table 5.2). In addition, a substantial higher proportion of cut girls were born to cut mothers compared to their uncut counterparts, a differential of more than 90% consistently observed across the 3 consecutive survey years. Higher prevalence was also consistently observed in cut girls born to women who supported FGM/C continuation and believed FGM/C was required by religion.

Table 5.2. National prevalence of female genital mutilation/cutting (FGM/C) among girls 0-14 years born to women 15 to 29 years who have heard of FGM/C and prevalence by study variables across the three selected Demographic and Health Surveys (DHS) surveys in Nigeria.

Variable	2008 DHS N=5,139 (Weighted Prevalence=27.8%)		2013 DHS N=7,457 (Weighted Prevalence=26.8%)		2018 DHS N=4,485 (Weighted Prevalence=36.6%)	
	FGM N=1,431 n (%)	No FGM N=3,709 n (%)	FGM N=1,997 n (%)	No FGM N=5,460 n (%)	FGM N=1,640 n (%)	No FGM N=2,845 n (%)
Mean age girls (SD)	p=0.006		p=0.088		p=0.464	
	4.0(3.3)	3.7(3.2)	3.9(3.2)	3.8(3.2)	4.0(3.2)	3.9(3.2)
Mean age of mothers (SD)	p=0.535		p=0.001		p=0.000	
	25.2(3.0)	25.1(3.0)	24.8(3.2)	25.0(3.0)	24.6(3.2)	25.2(2.9)
Place of residence	p=0.427		p=0.016		p=0.000	
urban	507(35.5)	1,454(39.2)	592(29.7)	2,083(38.1)	386(23.6)	1,190(41.8)
rural	923(64.5)	2,254(60.8)	1,405(70.3)	3,378(61.9)	1,254(76.4)	1,654(58.2)
Marital status	p=0.004		p=0.004		p=0.003	
never married	12(0.8)	123(3.3)	22(1.1)	132(2.4)	6(0.4)	78(2.7)
currently married	1,371(95.9)	3,469(93.5)	1,932(96.7)	5,127(93.9)	1,596(97.3)	2,668(93.8)
formerly married	47(3.3)	116(3.1)	43(2.2)	202(3.7)	39(2.4)	99(3.5)
Mother's Education	p=0.000		p=0.000		p=0.000	
No education	590(41.2)	1,103(29.7)	1,227(61.4)	2,463(45.1)	1,042(63.5)	1,088(38.3)
primary	413(28.9)	923(24.9)	333(16.7)	944(17.3)	220(13.4)	479(16.8)
secondary	387(27.1)	1,475(39.8)	387(19.4)	1,755(32.1)	341(20.8)	1,083(38.1)
higher	41(2.9)	207(5.6)	50(2.5)	299(5.5)	38(2.3)	195(6.9)
Wealth Quintile	p=0.234		p=0.000		p=0.000	
lowest	206(14.4)	544(14.7)	599(30.0)	1,236(22.6)	584(35.6)	608(21.4)
second	338(23.6)	623(16.8)	551(27.6)	1,175(21.5)	427(26.0)	588(20.7)
middle	255(17.8)	733(19.8)	334(16.8)	966(17.7)	333(20.3)	597(21.0)
higher	339(23.7)	942(25.4)	331(16.6)	1,018(18.6)	207(12.6)	617(21.7)
highest	293(20.5)	867(23.4)	182(9.1)	1,065(19.5)	90(5.5)	436(15.3)
Ethnicity	p=0.000		p=0.000		p=0.000	
Hausa	624(43.7)	588(15.9)	1,232(61.7)	2,103(38.5)	1,085(66.1)	811(28.5)
Igbo	185(13.0)	663(17.9)	183(9.2)	652(12.0)	87(5.3)	431(15.2)
Yoruba	390(27.3)	641(17.3)	272(13.6)	585(10.7)	75(4.5)	323(11.3)
Other	231(16.1)	1,802(48.6)	310(15.5)	2,120(38.8)	393(24.0)	1,280(45.0)
Religion	p=0.000		p=0.000		p=0.000	
Muslim	1,013(70.8)	1,519(41.0)	1,670(83.6)	3,381(61.9)	1,482(90.4)	1,653(58.1)
Christian	403(28.2)	2,122(57.2)	314(15.7)	1,992(36.5)	157(9.6)	1,175(41.3)
Other	11(0.8)	64(1.7)	6(0.3)	44(0.8)	1(0.1)	17(0.6)
Region	p=0.000		p=0.000		p=0.000	
north central	88(6.2)	313(8.4)	69(3.5)	366(6.7)	71(4.4)	385(13.6)
north east	34(2.4)	643(17.4)	111(5.6)	1,029(18.9)	394(24.0)	700(24.6)
north west	653(45.6)	590(15.9)	1,351(67.7)	2,144(39.3)	1,010(61.6)	751(26.4)
south east	146(10.2)	533(14.4)	177(8.9)	522(9.6)	74(4.5)	342(12.0)
south south	113(7.9)	846(22.8)	31(1.6)	674(12.3)	23(1.4)	310(10.9)
south west	396(27.7)	783(21.1)	257(12.9)	726(13.3)	69(4.2)	357(12.6)
FGM status of Mother	p=0.000		p=0.000		p=0.000	
uncut	72(5.0)	2,591(69.9)	464(23.2)	4,052(74.2)	581(35.4)	2,302(80.9)
cut	1,358(95.0)	1,117(30.1)	1,379(69.1)	1,065(19.5)	957(58.4)	443(15.6)
Mother support FGM	p=0.000		p=0.000		p=0.000	

stopped	214(15.0)	2,940(79.3)	497(24.9)	3,958(72.5)	280(17.1)	2,187(76.9)
continued	889(62.1)	331(8.9)	1,249(62.5)	738(13.5)	1,213(73.9)	366(12.9)
don't know/depends	322(22.5)	436(11.8)	252(12.6)	764(14.0)	148(9.0)	292(10.3)
Mother believes FGM is required by religion	p=0.000		p=0.000		p=0.000	
no	587(41.1)	2,956(79.7)	872(43.7)	3,871(70.9)	911(55.5)	2,312(81.3)
yes	476(33.2)	335(9.1)	696(34.8)	572(10.5)	689(42.0)	394(13.9)
Mother's occupation	p=0.064		p=0.095		p=0.765	
formal	783(54.7)	2,309(62.3)	1,029(51.5)	2,805(51.4)	909(55.4)	1,369(48.1)
informal	233(16.3)	434(11.7)	329(16.5)	677(12.4)	91(5.6)	121(4.3)
not working	409(28.6)	949(25.6)	636(31.9)	1,943(35.6)	528(32.2)	849(29.8)
Expenditure of mother's earning decided by mother or jointly	p=0.001		p=0.300		p=0.000	
Mother	692(48.4)	1,318(35.5)	1,006(50.4)	2,323(42.6)	868(52.9)	999(35.0)
Mother and Partner	102(7.2)	424(11.4)	172(8.6)	514(9.4)	106(6.4)	333(11.7)
Partner/Someone else	106(7.4)	305(8.2)	86(4.3)	201(3.7)	32(1.9)	169(5.9)
Beating justified if mother denies father sex	p=0.758		p=0.003		p=0.134	
no	1,086(75.9)	2,776(74.8)	1,444(72.3)	4,291(78.6)	1,195(72.8)	2,174(76.4)
yes	345(24.1)	933(25.2)	530(26.5)	1,079(19.8)	445(27.1)	652(22.9)
Read Newspaper	p=0.004		p=0.001		p=0.000	
Not at all	1,230(86.0)	2,905(78.3)	1,810(90.6)	4,607(84.4)	1,565(95.4)	2,515(88.4)
Less than once a week	114(8.0)	428(11.5)	112(5.6)	502(9.2)	61(3.7)	245(8.6)
At least once a week	87(6.1)	376(10.2)	66(3.3)	310(5.7)	15(0.9)	85(3.0)
Listen to Radio	p=0.033		p=0.005		p=0.014	
Not at all	278(19.4)	975(26.3)	801(40.1)	1,937(35.5)	855(52.1)	1,309(46.0)
Less than once a week	261(18.2)	592(16.0)	559(28.0)	1,293(23.7)	313(19.1)	739(26.0)
At least once a week	892(62.4)	2,141(57.7)	632(31.7)	2,205(40.4)	473(28.8)	796(28.0)
Watch Television	p=0.013		p=0.000		p=0.000	
Not at all	759(53.1)	1,594(43.0)	1,205(60.3)	2,803(51.3)	1,196(72.9)	1,495(52.5)
Less than once a week	122(8.5)	474(12.8)	369(18.5)	855(15.7)	233(14.2)	555(19.5)
At least once a week	550(38.4)	1,641(44.2)	414(20.7)	1,779(32.6)	211(12.9)	796(28.0)

In Senegal, an overall slight increase in FGM/C prevalence was observed among girls aged 0-9 years born to women 15 to 35 years, from 12.5% in 2010 to 13.6% in 2017 (Table 5.3). The mean age of cut girls was higher than uncut girls while no difference was observed in the age of mothers of cut and uncut girls. Results also showed that a significantly higher proportion of cut girls were born to mothers; who were cut, supported FGM/C continuation and believed FGM/C was a religious obligation (Table 5.3).

Table 5.3. National prevalence of female genital mutilation/cutting (FGM/C) among girls 0-9 years born to women 15 to 35 years who have heard of FGM/C and prevalence by study variables across the three selected Demographic and Health Surveys (DHS) surveys in Senegal.

Variable	2010 DHS N=6,876 (Weighted Prevalence=12.5%)		2015 DHS N=3,898 (Weighted Prevalence=14.4%)		2017 DHS N=7,161 (Weighted Prevalence=13.6%)	
	FGM N=1,211 n (%)	No FGM N=5,665 n (%)	FGM N=825 n (%)	No FGM N=3,073 n (%)	FGM N=1,408 n (%)	No FGM N=5,753 n (%)
Mean age girls (SD)	p=0.000		p=0.000		p=0.000	
	5.0(2.5)	3.6(2.8)	5.1(2.6)	3.5(2.8)	5.0(2.6)	3.7(2.8)
Mean age of mothers (SD)	p=0.8923		p=0.0027		p=0.9595	
	27.6(4.7)	27.6(4.8)	28.3(4.4)	27.8(4.6)	28.1(4.4)	28.1(4.5)
Place of residence	p=0.000		p=0.000		p=0.000	
urban	239(19.7)	1,882(33.2)	148(17.9)	991(32.3)	215(15.3)	2,242(39.0)
rural	972(80.3)	3,783(66.8)	677(82.1)	2,082(67.8)	1,193(84.7)	3,511(61.0)
Marital status	p=0.015		p=0.075		p=0.000	
never married	17(1.4)	162(2.9)	12(1.5)	88(2.9)	10(0.7)	158(2.8)
currently married	1,153(95.2)	5,319(93.9)	786(95.3)	2,888(94.0)	1,340(95.2)	5,347(92.9)
formerly married	41(3.4)	184(3.3)	27(3.3)	97(3.2)	58(4.1)	248(4.3)
Mother's Education	p=0.000		p=0.000		p=0.000	
No education	1,019(84.2)	4,117(72.7)	664(81.3)	2,047(66.6)	1,040(73.9)	3,638(63.2)
primary	159(13.1)	1,165(20.6)	123(14.8)	708(23.0)	244(17.3)	1,272(22.1)
secondary	33(2.7)	371(6.6)	37(3.8)	293(9.5)	122(8.7)	753(13.1)
higher	0(0.0)	12(0.2)	1(0.1)	25(0.8)	2(0.1)	90(1.6)
Wealth Quintile	p=0.000		p=0.000		p=0.000	
lowest	537(44.3)	1,560(27.5)	337(40.9)	876(28.5)	600(42.6)	1,515(26.3)
second	325(26.8)	1,398(24.7)	250(30.3)	737(24.0)	447(31.8)	1,403(24.4)
middle	241(19.9)	1,197(21.1)	167(20.2)	660(21.5)	277(19.7)	1,339(23.3)
higher	83(6.9)	928(16.4)	52(6.3)	503(16.4)	72(5.1)	920(16.0)
highest	25(2.1)	582(10.3)	19(2.3)	297(9.7)	12(0.9)	576(10.0)
Ethnicity	p=0.000		p=0.000		p=0.000	
diola	45(3.7)	187(3.3)	43(5.2)	74(2.4)	45(3.2)	156(2.7)
wolof	14(1.2)	2,118(37.4)	2(0.2)	1,212(39.4)	7(0.5)	2,130(37.0)
poular	771(63.7)	1,612(28.5)	517(62.7)	880(28.6)	846(60.1)	1,591(27.7)
serer	3(0.3)	803(14.2)	3(0.4)	381(12.4)	3(0.2)	853(14.8)
mandingue	216(17.8)	364(6.4)	146(17.7)	269(8.8)	333(23.7)	490(8.5)
soninke	34(2.8)	92(1.6)	18(2.2)	32(1.0)	40(2.8)	82(1.4)
other Senegalese	83(6.9)	363(6.4)	35(4.2)	143(4.7)	65(4.6)	155(2.7)
non-Senegalese	45(3.7)	126(2.2)	61(7.4)	82(2.7)	69(4.9)	296(5.2)
Religion	p=0.000		p=0.020		p=0.000	
Muslim	1,199(99.0)	5,500(97.1)	811(98.3)	2,974(96.8)	1,397(99.2)	5,594(97.2)
Christian	12(1.0)	165(2.9)	14(1.7)	99(3.2)	11(0.8)	159(2.8)
Region	p=0.000		p=0.000		p=0.000	
Dakar	28(2.3)	400(7.1)	2(0.2)	201(6.5)	11(0.8)	421(7.3)
Diourbel	2(0.2)	618(10.9)	0(0.0)	305(9.9)	1(0.1)	547(9.5)
Fatick	0(0.0)	452(8.0)	4(0.5)	254(8.3)	1(0.1)	496(8.6)
Kedougou	36(3.0)	231(4.1)	58(7.0)	152(5.0)	169(12.0)	274(4.8)
Kaffrine	15(1.2)	559(9.9)	4(0.5)	313(10.2)	12(0.9)	610(10.6)
Kaolack	2(0.2)	512(9.0)	21(2.6)	367(11.9)	5(0.4)	380(6.6)
Kolda	230(19.0)	357(6.3)	175(21.2)	216(7.0)	175(12.4)	408(7.1)

Louga	24(2.0)	482(8.5)	0(0.0)	221(7.2)	4(0.3)	473(8.2)
Matam	198(16.4)	266(4.7)	154(18.7)	121(3.9)	324(23.0)	251(4.4)
Sedhiou	272(22.5)	277(4.9)	150(18.2)	194(6.3)	227(16.1)	375(6.5)
Saint-Louis	96(7.9)	322(5.7)	62(7.5)	140(4.6)	121(8.6)	345(6.0)
Tambacounda	239(19.7)	358(6.3)	117(14.2)	186(6.1)	258(18.3)	379(6.6)
Thios	5(0.4)	563(9.9)	0(0.0)	293(9.5)	8(0.6)	531(9.2)
Zinguichor	64(5.3)	268(4.7)	78(9.5)	110(3.6)	92(6.5)	263(4.6)
FGM status of Mother	p=0.000		p=0.000		p=0.000	
uncut	12(1.0)	3,893(68.7)	17(2.1)	2,147(69.9)	22(1.6)	4,178(72.6)
cut	1,199(99.0)	1,772(31.3)	808(97.9)	926(30.1)	1,386(98.4)	1,575(27.4)
Mother support FGM	p=0.000		p=0.000		p=0.000	
stopped	199(16.4)	4,503(79.5)	161(19.5)	2,410(78.4)	207(15.9)	4,650(80.8)
continued	964(79.6)	838(14.8)	646(78.3)	554(18.0)	1,165(81.7)	822(14.3)
don't know/depends	48(4.0)	324(5.7)	18(2.2)	109(3.6)	36(2.4)	281(4.9)
Mother believes FGM is required by religion	p=0.000		p=0.000		p=0.000	
no	352(29.1)	4,391(77.5)	365(44.2)	2,572(83.7)	523(37.1)	4,679(81.3)
yes	798(65.9)	883(15.6)	418(50.7)	346(11.3)	829(58.9)	651(11.3)
Mother's occupation	p=0.000		p=0.000		p=0.000	
formal	318(26.3)	1,699(30.0)	136(16.5)	686(22.3)	187(13.3)	1,487(25.9)
informal	304(25.1)	900(15.9)	403(48.9)	1,237(40.3)	595(42.3)	2,016(35.0)
not working	589(48.6)	3,066(54.1)	283(34.3)	1,1340(36.9)	612(43.4)	2,192(38.1)
Expenditure of mother's earning decided by mother or jointly	p=0.055		p=0.000		p=0.000	
Mother	331(27.3)	1,576(27.8)	243(29.5)	990(32.2)	331(23.5)	2,010(34.9)
Mother and Partner	51(4.2)	196(3.5)	34(4.1)	167(5.4)	44(3.1)	239(4.2)
Partner/Someone else	24(2.0)	188(3.3)	15(1.8)	128(4.2)	64(4.6)	210(3.7)
Beating justified if mother denies father sex	p=0.000		p=0.000		p=0.000	
no	431(35.6)	2,477(43.7)	289(35.0)	1,361(44.3)	540(38.4)	2,900(50.4)
yes	780(64.4)	3,188(56.3)	536(65.0)	1,712(55.7)	868(61.6)	2,853(49.6)
Read Newspaper	p=0.000		p=0.000		p=0.000	
Not at all	1,156(95.5)	5,130(90.6)	806(97.7)	2,864(93.2)	1,352(96.0)	5,086(88.4)
Less than once a week	48(4.0)	309(5.5)	15(1.8)	123(4.0)	35(2.5)	430(7.5)
At least once a week	7(0.6)	226(4.0)	4(0.5)	86(2.8)	21(1.5)	237(4.1)
Listen to Radio	p=0.000		p=0.002		p=0.000	
Not at all	238(19.7)	1,067(19.2)	190(23.0)	564(18.4)	331(23.5)	935(16.3)
Less than once a week	346(28.6)	1,281(22.6)	209(25.3)	918(29.9)	514(36.5)	1,825(31.7)
At least once a week	627(51.8)	3,317(58.6)	426(51.6)	1,591(51.8)	563(40.0)	2,993(52.0)
Watch Television	p=0.000		p=0.000		p=0.000	
Not at all	597(49.3)	2,111(37.3)	416(50.4)	1,141(37.1)	671(47.7)	1,596(27.7)
Less than once a week	258(21.3)	867(15.3)	163(19.8)	576(18.7)	380(27.0)	1,279(22.2)
At least once a week	356(29.4)	2,687(47.4)	246(29.8)	1,356(44.1)	357(25.4)	2,878(50.0)

5.3. Geography of FGM/C prevalence by country and survey year

We present the geographic distribution of FGM/C prevalence among Kenyan girls 0 to 14 years born to women 15 to 49 years in Figure 5.1(top panel) in 2003, 2008 and 2014. An overall spatial pattern of high prevalence in Northeastern region and low prevalence in other regions was observed. In Northeastern Kenya, prevalence estimate ranged from 60.3% in 2003 with an increase to 66.5% in 2008 followed by a reduction to 42% in 2014. Nyanza in western Kenya had the next higher prevalence of 17.5% in 2003 followed by a rapid decline to 7.8% in 2014.

Observed geographic distribution of FGM/C prevalence among Nigerian girls 0 to 14 years born to women 15 to 29 years is presented for the survey years 2008, 2013 and 2018 respectively (Figure 5.1). Overall, the results showed a clear geographic pattern across the six regions. For instance, a pattern of decline in intensity of cut girls over the years was observed in southwestern Nigeria. In contrast, however, an increasing pattern in both intensity and spread to neighboring States was observed in the northwest and north central. Highest observed prevalence ranged from 84% in Kano in 2008 to 63% in Jigawa in 2013 and 81% in Kaduna in 2018. In addition, while a general pattern of decreasing trend was observed in states such as Osun, Oyo and Kwara states in the southwest, an increase in prevalence intensity was observed in others such as Bauchi, Jigawa, Kaduna, Niger and Yobe states.

Similarly, the observed evolution of FGM/C prevalence among Senegalese girls 0-9 years born to women 15 to 35 years is presented in Figure 5.1(bottom panel). The result showed that in 2010, highest prevalence of 50% of cut girls in Sedhiou, 43% in Matam and 40% in Tambacounda was observed. Highest prevalence of 56% was observed in Matam in subsequent surveys. Over the years, prevalence remained high in the southern regions such as Kolda, Sedhiou and Zinguichor. We also noted a pattern of decline in prevalence trend between 2015 and 2017 in Zinguichor and Kolda, and increasing trend in Kedougou and Tambacounda between the same period.

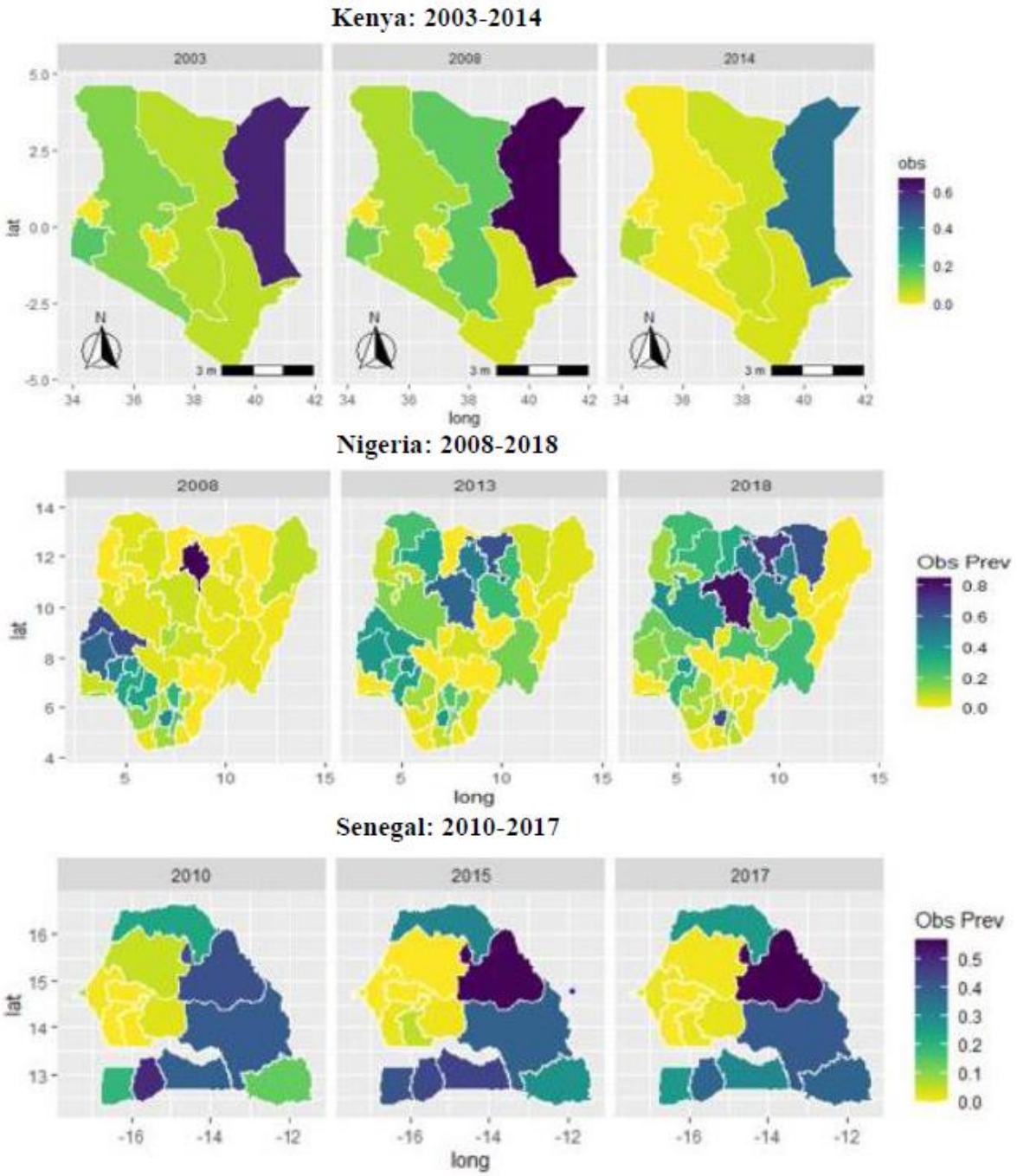


Figure 5.4. Geographic distribution of observed FGM/C prevalence proportion among girls in Kenya (top panel), Nigeria (middle panel) and Senegal (bottom panel) for each survey year under study. Highest observed prevalence proportion estimates are denoted by green color while lowest observed prevalence estimates are denoted by yellow colour.

5.4. Spatiotemporal analysis of FGM/C risk factors

In this section, results from the five fitted Bayesian hierarchical nested models are presented for the purpose of evaluating changes in risk factor estimates from the simpler model (Model 1) after accounting for community level factors (Model 2), space-time interaction effects (Model 3), stratification design effect (Model 4) and clustering design effect (Model 5). Here, the objective is to quantify the impact of changes in the risk factor estimates on the response likelihood for the respective girl populations across the three countries. In each section below, we present the findings and compared the observed changes between the countries. We employed the deviance information criterion (DIC) and Watanabe information criterion (WAIC model) model comparison tools to compare estimates from the five models as presented in Table 5.7. In general, we note a substantial improvement in the overall fit of the model adjusted for cluster design effect across the three countries, and to varying extent changes in risk factors estimates (see Tables 5.4 to 5.6). Country-specific findings are presented in the subsections below.

5.4.1. FGM/C risk factors in Kenya

Bayesian spatiotemporal evaluation of risk factor estimates among Kenyan girls showed that accounting for community level variables (in Model 2) and cluster design effect (Model 5) significantly improved the model estimation by 147 DIC points (relative to Model 1) and 294 DIC points (relative to Model 3) respectively. On the other hand, while accounting for the stratification design (in Model 4) showed no improvement to the type 1 space-time interaction model (Table 5.4). We therefore present findings of the space-time interaction model adjusted for the cluster design effect as the best fitting model for FGM/C risk factor estimate among Kenyan girls between 2003 and 2014.

Table 5.4. DIC comparison for Bayesian models by Country.

Model	KENYA					NIGERIA					SENEGAL				
	pD	DIC	WAIC	logCPO	#failure	pD	DIC	WAIC	logCPO	#failure	pD	DIC	WAIC	logCPO	# failure
1	50	6561	6563	0.143	0	44	10966	10968	0.338	0	46	8409	8410	0.234	0
2	51	6414	6415	0.140	0	54	10554	10555	0.325	0	49	8076	8077	0.225	0
3	70	5594	5599	0.122	0	126	8872	8872	0.273	0	74	7877	7877	0.220	0
4	72	5595	5600	0.122	0	130	8874	8876	0.273	0	77	7875	7876	0.220	0
5	322	5300	5305	0.116	0	657	7644	7618	0.235	0	314	7408	7410	0.207	0

Model 1*: individual level covariates only;* ***Model 2****: Model 1 adjusted for community level covariates;* ***Model 3****; Model 2 adjusted for main spatial, main temporal, and space-time interaction effect;* ***Model 4****: Model 3 adjusted for stratification design;* ***Model 5****: Model 3 adjusted for cluster design. # failure indicates the number of failed cross validated prediction of observed data points using the best model as obtained by DIC and WAIC values.*

Findings showed support for the contribution of ethnicity and religion as important demographic factors that influenced FGM/C likelihood in Kenyan girls between the study period (Table 5.5). For instance, girls born to women of Kisii ethnicity were 7.7 times (95%CI:4.33, 13.8) more likely to be cut compared to girls from Embu ethnic extraction. Girls from other ethnic groups such as Maasai and Somali also had significantly increased likelihood of being cut (Table 5.4). In addition, a girl born to a Muslim mother had 4.4 times higher likelihood (95%CI:2.75, 7.16) to be cut compared to her counterpart born to a Christian mother. With respect to modernization, girls across all wealth index categories had higher likelihood of being cut compared to girls from affluent Kenyan households. Despite initial protection of rural dwelling observed in the space-time model (in Model 3), we found no support after accounting for the cluster design effect between the study period. Findings, however, showed significant support for the significant contribution of a woman's agency to increased FGM/C likelihood consistently across all models, with little improvement observed after accounting for cluster design effect (Model 5)

Furthermore, results showed a pattern of increased FGM/C likelihood by 3.7 times (95%CI:1.86,7.71) in girls born to mothers with no formal education compared to girls born to women with a higher education (Table 5.5). Findings showed social norm as a key driver of FGM/C in Kenyan girls as measured by FGM/C status of the mother and prevalence of cut mothers within the community. We noted that accounting for the proportion of mothers that were cut within community significantly reduced the observed individual level risk factor estimate of FGM/C status of mother from 19.8 (in Model 1) to 5.5 (in Model 2). This corresponds to a 74% reduction in the observed influence of mother's FGM/C status operating at community level. This is an important finding as it clearly partitions the observed effect of a socio normative indicator into those operating at individual level and those operating at the

community level. Hence, in Kenya, it is therefore evident that a substantial component of the contribution of mother's FGM/C status to the likelihood of cutting her daughter can be explained by the proportion of cut women in the community in which she lived and much less so from her personal motivations or decision.

Findings also showed support for gender normative influences as positively associated with higher likelihood of a girl being cut, in particular when decision regarding expenditure of mother's earnings was made by father alone (OR:1.90; CI: 1.23, 2.90). With respect to media exposure, a significantly lower likelihood of cutting was observed in daughters of women who read newspaper or magazine less than once a week, but not more frequently. This finding is rather surprising, and therefore the beneficial effect of such exposure in reducing FGM/C likelihood is inconclusive at best. Between 2003 and 2014, an overall linear trend of significant decline in FGM/C risk (by 147%) was observed among Kenyan girls 0 to 14 years. (Table 5.5)

Table 5.5. Posterior odds ratios (POR) and associated 95% credible interval (CI) from the Hierarchical Bayes space-time generalized additive mixed Models of FGM/C among Girls ages 0–14 years across exposure covariates in Kenya (for the 2003, 2008 and 2014 combined survey data).

PDF CATEGORY	Variable	Model 1 POR (95%CI)	Model 2 POR (95%CI)	Model 3 POR (95%CI)	Model 4 POR (95%CI)	Model 5 POR (95%CI)
DEMOGRAPHIC	Ethnicity					
	emb(ref)	1.00	1.00	1.00	1.00	1.00
	kalenjin	0.65(0.46,0.92)	0.88(0.62,1.25)	0.53(0.33,0.85)	0.58(0.36,0.94)	0.60(0.34,1.09)
	kamba	1.45(0.97,2.16)	2.47(1.63,3.74)	0.54(0.33,0.89)	0.51(0.31,0.84)	0.39(0.19,0.76)
	kikuyu	0.43(0.27,0.67)	0.83(0.51,1.32)	0.32(0.16,0.62)	0.40(0.20,0.78)	0.27(0.13,0.57)
	kisii	12.64(9.09,17.69)	10.73(7.7,15.11)	6.64(4.23,10.52)	6.86(4.30,11.05)	7.70(4.33,13.80)
	luhya	0.77(0.34,1.64)	1.62(0.69,3.53)	0.70(0.27,1.73)	0.89(0.32,2.32)	0.64(0.23,1.67)
	luo	1.09(0.43,2.49)	2.14(0.82,5.04)	0.73(0.27,1.84)	0.74(0.27,1.87)	0.54(0.18,1.50)
	masaai	2.16(1.50,3.10)	2.16(1.50,3.12)	1.77(1.08,2.92)	1.95(1.17,3.24)	2.31(1.24,4.31)
	meru	0.57(0.33,0.96)	0.73(0.42,1.24)	0.16(0.08,0.29)	0.15(0.08,0.27)	0.13(0.06,0.29)
	mijk/swahili	0.29(0.12,0.59)	0.67(0.28,1.44)	0.13(0.05,0.31)	0.12(0.05,0.29)	0.11(0.04,0.30)
	somali	5.73(4.33,7.62)	5.74(4.32,7.66)	1.95(1.19,3.20)	1.88(1.12,3.16)	2.35(1.26,4.41)
	taitaiveta	3.34(1.99,5.54)	5.22(3.04,8.83)	1.48(0.74,2.91)	1.34(0.66,2.67)	1.54(0.64,3.66)
	others	3.21(2.33,4.43)	3.35(2.42,4.65)	1.09(0.74,1.62)	1.08(0.73,1.61)	0.98(0.58,1.65)
	Marital stat					
	never	1.00	1.00	1.00	1.00	1.00
	currently	1.01(0.57,1.89)	1.04(0.57,1.97)	1.27(0.64,2.64)	1.27(0.64,2.64)	1.24(0.61,2.66)
	formerly	0.77(0.42,1.47)	0.82(0.44,1.59)	0.99(0.48,2.11)	0.99(0.49,2.12)	0.97(0.46,2.14)
	Religion					
	chri(ref)	1.00	1.00	1.00	1.00	1.00
	mus	3.13(2.31,4.25)	2.81(2.06,3.85)	3.65(2.52,5.31)	3.48(2.39,5.08)	4.44(2.75,7.16)
	oth	0.77(0.45,1.27)	0.70(0.40,1.15)	0.65(0.36,1.13)	0.65(0.36,1.13)	0.71(0.37,1.32)
MODERNIZATION	Residence					

	urban(ref)	1.00	1.00	1.00	1.00	1.00
	rural	1.46(1.20,1.78)	1.36(1.11,1.66)	0.79(0.63,0.99)	0.79(0.63,0.99)	0.78(0.56,1.07)
	Wealth ind					
	highest	1.00	1.00	1.00	1.00	1.00
	lowest	1.15(0.80,1.65)	0.76(0.52,1.10)	1.47(0.98,2.22)	1.44(0.96,2.18)	1.48(0.91,2.41)
	second	1.33(0.92,1.93)	0.93(0.64,1.36)	1.33(0.88,2.02)	1.31(0.86,1.98)	1.46(0.90,2.36)
	middle	1.46(1.02,2.09)	1.07(0.74,1.56)	1.44(0.96,2.17)	1.42(0.94,2.13)	1.56(0.98,2.49)
	higher	1.38(0.99,1.93)	1.10(0.78,1.55)	1.34(0.92,1.96)	1.31(0.90,1.92)	1.47(0.95,2.26)
WOMEN'S AGENCY	Mother's Ed					
	higher	1.00	1.00	1.00	1.00	1.00
	none	6.21(3.44,11.58)	5.89(3.21,11.15)	3.99(2.11,7.83)	4.04(2.13,7.92)	3.72(1.86,7.71)
	primary	3.23(1.84,5.86)	3.38(1.90,6.22)	2.61(1.43,4.96)	2.64(1.45,5.03)	2.39(1.24,4.79)
	secondary	2.11(1.20,3.83)	2.19(1.22,4.04)	1.69(0.92,3.23)	1.71(0.93,3.28)	1.42(0.73,2.87)
WOMEN'S OPPORTUNITY	Mother's occ					
	formal(ref)	1.00	1.00	1.00	1.00	1.00
	informal	0.48(0.40,0.59)	0.50(0.41,0.60)	0.96(0.76,1.21)	0.97(0.77,1.22)	0.97(0.75,1.25)
	not working	0.72(0.59,0.88)	0.73(0.59,0.90)	0.97(0.78,1.22)	0.97(0.78,1.22)	0.94(0.74,1.21)
SOCIAL NORMS	Mother's cut					
	no(ref)	1.00	1.00	1.00	1.00	1.00
	yes	19.81(13.43,30.16)	5.37(3.45,8.57)	5.20(3.28,8.47)	5.33(3.36,8.68)	5.89(3.61,9.73)
GENDER NORMS	Sex					
	no(ref)	1.00	1.00	1.00	1.00	1.00
	yes	1.38(1.21,1.58)	1.38(1.20,1.58)	1.14(0.98,1.32)	1.14(0.99,1.33)	1.14(0.96,1.34)
	Expenditure of moth. earnings					
	mother	1.00	1.00	1.00	1.00	1.00
	moth n father	0.73(0.57,0.93)	0.75(0.58,0.95)	0.80(0.61,1.04)	0.80(0.61,1.04)	0.76(0.56,1.01)
	father	1.55(1.08,2.21)	1.65(1.14,2.36)	1.73(1.16,2.55)	1.75(1.17,2.58)	1.90(1.23,2.90)
MEDIA EXPOSURE	Newspaper					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1 week	0.64(0.48,0.86)	0.64(0.47,0.86)	0.58(0.42,0.80)	0.58(0.42,0.79)	0.58(0.41,0.82)
	≥ 1 week	1.08(0.77,1.51)	1.12(0.79,1.57)	0.89(0.61,1.28)	0.88(0.61,1.27)	0.86(0.57,1.28)
	Radio					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1 week	0.92(0.74,1.14)	0.91(0.73,1.14)	1.00(0.79,.1.27)	1.00(0.79,1.27)	1.00(0.77,1.30)
	≥ 1 week	1.01(0.85,1.20)	1.03(0.87,1.23)	0.95(0.78,1.15)	0.95(0.78,1.15)	0.90(0.73,1.11)
	Television					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1 week	0.86(0.66,1.12)	0.88(0.67,1.14)	1.06(0.79,1.41)	1.06(0.80,1.41)	1.08(0.79,1.48)
	≥ 1 week	0.73(0.55,0.95)	0.73(0.55,0.96)	0.84(0.62,1.12)	0.85(0.63,1.13)	0.86(0.63,1.19)
TIME	Year(mean)			-1.32(-1.67, -0.97)	-1.37(-1.73, -1.00)	-1.47(-1.85, -1.10)

Model 1: Individual level Covariates only; Model 2: Individual and Community level Covariates; Model 3: Model 2 adjusted for main spatial, main temporal, and space-time interaction; Model 4: Model 3 adjusted for stratification design effect; Model 5: Model 3 adjusted for clustering design effect

5.4.2. FGM/C risk factors in Nigeria

Table 5.6 shows the results of the Bayesian spatiotemporal evaluation of risk factors on the likelihood of FGM/C among Nigeria girls 0-14 years born to women 15 to 29 years for the period 2008 to 2018. Similar to the pattern observed in Kenya, accounting for the community level influence of proportion of mothers, who were cut, supported FGM/C continuation and believed FGM/C was a religious obligation (in Model 2), substantially improved the model fit to the observed data (by 412 DIC points) (Table 5.6). Further, we found substantial improvement in model fit (by 1228 DIC points relative to model 3 with type 1 space-time interaction) after accounting for the cluster design effect in model 5(Table 5.4.). On the other hand, modelling variables of the stratification design (region and rural versus urban) as fixed effect in model 4 provided poor fit to the observed data (Table 5.6).

Results showed that underlying risk factors of FGM/C among Nigerian girls 0-14 years between 2008 and 2018 include ethnicity, marital status of mother and her religious affiliation (Table 5.5). For instance, a girl was two times more likely to be cut (95%CI:1.08,3.31) if her mother was currently married compared to girls born to women who were never married. Also, a significantly higher likelihood of cutting was observed in girls born to mothers of Igbo extraction, with 2.6 times (95%CI:1.44, 4.58) greater likelihood of being cut than Hausa girls. A 56% lower likelihood (OR:0.44; 95%CI: 0.32,0.60) of cutting was also observed among Christian girls compared to Muslim girls. In contrast to the observed pattern in Kenya, however, we found a reversed support for the influence of modernization on FGM/C likelihood among Nigerian girls between the study period. Findings revealed that girls from affluent households were more likely to be cut relative to girls born to poorer or middle- class Nigerian households. Significance of this finding only emerged after accounting for the cluster design effect in Model 5. This suggests, a possible link between elitism and FGM/C cutting in Nigeria and therefore a beneficial effect of modernization to the persistence of the practice among women and girls in the upper echelon of the Nigerian society. Evidence provided a mixed support for the feminist theory as observed in Kenya. For instance, mothers with low educational attainment were more likely to cut their girls (OR:1.73;95%CI:1.13, 2.66), while extra-familiar opportunities outside the household as measured by occupation had no effect on FGM/C likelihood between the study period.

Social normative influences including, FGM/C status of mother, mother's support of FGM/C continuation and her belief that FGM/C was a religious requirement, were found to be

substantial drivers of FGM/C among Nigeria girls between 2008 and 2018 at both individual and community levels. We noted a significant improvement in the model fit (by 412 DIC points) after adjusting Model 1 for community level prevalence of the three social normative influences with significantly lowered observed influence of FGM/C status of mother by 54%, and mother's support for FGM/C continuation by 32% (Model 2). In addition, results showed substantial increase in the influence of social normative factors after accounting for excess variability due to cluster design effects (by 1228 DIC points) relative to Model 3 with Type 1 space-time interaction effect. For instance, girls born to cut mothers were 13 times (OR:13.15;95%CI:10.74,16.15) more likely to be cut, while girls born to mothers that supported continuation of the practice were 19 times (95%CI:15.69, 22.91) more likely to be cut (Table 5.6). Findings therefore strongly suggest the true observed influence of social normative factors were significantly underestimated when the clustering survey design effect is ignored in the hierarchical model specification.

We found additional support for the contribution of gender normative influence to FGM/C outcome in a Nigeria. However, contrary to the patriarchal influence in Kenya, observed pattern in Nigeria showed that decision making by both mother and father on spending her earnings significantly contributed to increased likelihood of cutting in her daughter (OR:1.34;95%CI:1.04, 1.73). This important finding suggests that both parents may be involved in decision making in relation to whether a girl is cut or not, rather than the mother only. We found no support for the influence of media exposure on FGM/C likelihood in a Nigerian girl. Between 2008 and 2018, an overall positive linear temporal trend of 38% increase in FGM/C risk was found among girls 0-14 years born to women 15 to 29 years in Nigeria. (Table 5.6)

Table 5.6. Posterior odds ratios (POR) and associated 95% credible interval (CI) from the Hierarchical Bayes space-time generalized additive mixed Models of FGM/C likelihood among Girls ages 0–14 years across exposure covariates in Nigeria (for the 2008, 2013 and 2018 combined survey data).

PDF CATGEORY	Variable	Model 1 POR (95%CI)	Model 2 POR (95%CI)	Model 3 POR (95%CI)	Model 4 POR (95%CI)	Model 5 POR (95%CI)
DEMOGRAPHIC	Marital status					
	never	1.00	1.00	1.00	1.00	1.00
	currently	1.80(1.18,2.79)	1.75(1.15,2.71)	1.40(0.88,2.26)	1.37(0.86,2.21)	1.87(1.08,3.31)
	formerly	1.82(1.10,3.03)	1.68(1.02,2.81)	1.09(0.63,1.91)	1.07(0.61,1.87)	1.59(0.82,3.11)
	Ethnicity					
	Hausa(ref)	1.00	1.00	1.00	1.00	1.00
	Igbo	0.69(0.55, 0.87)	0.66(0.52,0.83)	1.94(1.26,2.97)	2.09(1.34,3.23)	2.58(1.44,4.58)
	Yoruba	0.47(0.39, 0.56)	0.43(0.35,0.52)	1.09(0.77,1.56)	1.09(0.76,1.57)	1.53(0.93,2.52)
	Other	0.36(0.31, 0.40)	0.39(0.34,0.45)	0.74(0.62,0.89)	0.76(0.64,0.92)	0.83(0.65,1.07)
	Religion					
	Muslim (ref)	1.00	1.00	1.00	1.00	1.00
	christian	0.26(0.22,0.31)	0.26(0.22,0.31)	0.55(0.43,0.69)	0.56(0.44,0.71)	0.44(0.32,0.60)
	other	0.07(0.04,0.13)	0.07(0.03,0.12)	0.28(0.13,0.56)	0.29(0.14,0.58)	0.36(0.14,0.89)
MODERNIZATION	Residence					
	urban(ref)	1.00	1.00	1.00	1.00	1.00
	rural	1.31(1.15,1.49)	1.23(1.08,1.40)	1.13(0.97,1.32)	1.14(0.97,1.33)	1.19(0.91,1.56)
	Wealth index					
	highest	1.00	1.00	1.00	1.00	1.00
	lowest	1.06(0.83,1.35)	1.00(0.78,1.28)	0.82(0.61,1.09)	0.81(0.61,1.08)	0.63(0.43,0.91)
	second	0.95(0.75,1.19)	0.86(0.68,1.09)	0.78(0.59,1.02)	0.77(0.59,1.02)	0.63(0.44,0.89)
	middle	0.95(0.77,1.17)	0.87(0.70,1.08)	0.79(0.62,1.01)	0.79(0.62,1.00)	0.63(0.46,0.86)
	higher	0.99(0.83,1.19)	0.97(0.81,1.17)	0.89(0.73,1.10)	0.89(0.73,1.10)	0.77(0.60,1.00)
WOMEN'S AGENCY	Mother's Education					
	higher	1.00	1.00	1.00	1.00	1.00
	none	1.11(0.80,1.55)	1.16(0.83,1.62)	1.34(0.94,1.93)	1.34(0.94,1.94)	1.59(1.02,2.49)
	primary	1.07(0.78,1.48)	1.05(0.76,1.45)	1.34(0.95,1.90)	1.36(0.96,1.93)	1.73(1.13,2.66)
	secondary	1.07(0.80,1.44)	1.08(0.81,1.46)	1.13(0.82,1.55)	1.13(0.83,1.55)	1.30(0.89,1.92)
WOMEN'S OPPORTUNITY	Mother occupation					
	formal(ref)	1.00	1.00	1.00	1.00	1.00
	informal	1.17(1.00,1.37)	1.13(0.96,1.32)	1.09(0.91,1.31)	1.09(0.91,1.31)	1.12(0.89,1.39)
	not working	0.91(0.81,1.03)	0.94(0.83,1.05)	0.87(0.76,0.99)	0.86(0.75,0.98)	0.88(0.75,1.03)
SOCIAL NORMS	Mother's cut					
	no(ref)	1.00	1.00	1.00	1.00	1.00
	yes	11.73(10.40,13.24)	5.36(4.58,6.28)	8.03(6.72,9.60)	8.17(6.83,9.78)	13.15(10.74,16.15)
	Mother supp FGM					
	stop(ref)	1.00	1.00	1.00	1.00	1.00
	continued	11.07(9.82,12.50)	7.49(6.48,8.68)	10.67(9.06,12.59)	10.79(9.15,12.74)	18.94(15.69,22.91)
	don't know	3.04(2.63,3.51)	2.72(2.34,3.15)	2.62(2.22,3.10)	2.61(2.21,3.09)	3.00(2.45,3.68)
	FGM required by religion	1.00	1.00	1.00	1.00	1.00
	no(ref)	1.32(1.16,1.49)	1.49(1.27,1.75)	1.51(1.26,1.81)	1.51(1.26,1.81)	1.65(1.34,2.02)
	yes					
GENDER NORMS	Sex					
	no(ref)	1.00	1.00	1.00	1.00	1.00
	yes	0.88(0.79,1.00)	0.96(0.85,1.09)	0.87(0.76,1.01)	0.87(0.75,0.98)	0.88(0.73,1.05)

	Expenditure of mother earnings					
	mother	1.00	1.00	1.00	1.00	1.00
	moth n father	1.32(1.09,1.58)	1.35(1.12,1.63)	1.43(1.16,1.76)	1.44(1.17,1.77)	1.34(1.04,1.73)
	father	0.83(0.66,1.04)	0.81(0.64,1.03)	1.06(0.81,1.38)	1.06(0.81,1.39)	1.12(0.81,1.55)
MEDIA EXPOSURE	Newspaper					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1 week	1.03(0.83,1.27)	1.04(0.83,1.29)	0.97(0.77,1.23)	0.98(0.77,1.24)	1.07(0.80,1.42)
	≥ 1 week	0.89(0.67,1.18)	0.93(0.70,1.24)	0.83(0.61,1.13)	0.83(0.61,1.13)	0.95(0.66,1.36)
	Radio					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1 week	1.30(1.13,1.50)	1.37(1.18,1.58)	1.32(1.12,1.56)	1.33(1.12,1.57)	1.20(0.98,1.47)
	≥ 1 week	1.04(0.92,1.19)	1.04(0.91,1.18)	1.03(0.88,1.20)	1.02(0.88,1.19)	0.98(0.82,1.17)
	Television					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1 week	0.88(0.74,1.04)	0.80(0.67,0.95)	0.88(0.73,1.07)	0.88(0.73,1.07)	0.90(0.71,1.14)
	≥ 1 week	0.91(0.77,1.08)	0.85(0.72,1.02)	0.92(0.76,1.11)	0.92(0.76,1.11)	1.02(0.81,1.29)
TIME	Year(mean(95%CI))			0.30(-0.18,0.78)	0.29(-0.19,0.76)	0.38(-0.11,0.88)

Model 1: Individual level Covariates only; Model 2: Individual and Community level Covariates; Model 3: Model 2 adjusted for main spatial, main temporal, and space-time interaction; Model 4: Model 3 adjusted for stratification design effect; Model 5: Model 3 adjusted for clustering design effect

5.4.3. FGM/C risk factors in Senegal

Table 5.7 shows the results of the Bayesian spatiotemporal evaluation of risk factors on the likelihood of FGM/C among girls 0-9 years born to women 15 to 35 years in Senegal during the period 2010 to 2017. Similar to the pattern observed in Kenya and Nigeria, accounting for the community level influence of proportion of mothers, who were cut, supported FGM/C continuation and believed FGM/C was a religious obligation, significantly improved model fit to the observed data (by 333 DIC points) (see Model 2 in Table 5.7). Further, we found substantial improvement in the overall fit of the type 1 space-time interaction model to the observed data (by 469 DIC points) after accounting for the cluster design effect in Model 5 (although to a lower extent compared to Nigeria and Kenya) (Table 5.4). Incorporating the stratification design in Model 4 did not improve the fit of the model to the data as observed in the two previous countries.

Analysis results revealed that the three demographic factors evaluated, namely, marital status, ethnicity and religious affiliation were not important risk factors of FGM/C among girls in Senegal between the study period (Table 5.7). This finding is in sharp contrast to the pattern observed in Kenya and Nigeria in which case demographic factors played significant roles in influencing observed FGM/C outcomes. Findings suggest a mixed support for the influence of modernization on FGM/C likelihood in a Senegalese girl. Specifically, girls who were resident

in rural areas were more likely to be cut (OR:1.71;95%CI:1.33, 2.21) compared to their urban counterparts. On the other hand, no support was found for the influence of household wealth quintile on FGM/C outcomes. In addition, evidence also provides a mixed support for the feminist theory in Senegal with a rather unexpected pattern of significantly lower likelihood of cutting found in daughters of women with no education (OR:0.81:95%CI:0.68, 0.96) compared to women with higher education. We note also that this trend was consistently observed across all competing models (Table 5.7). Accounting for both stratification design (Model 4) and cluster design features (Model 5) had no effect on the observed influence of education attainment from the type 1 space-time interaction model (Model 3). This finding, therefore, suggests a possible link between elitism and FGM/C likelihood in Senegal as a potential explanation for the persistence of the practice. On the other hand, however, extra-familiar opportunity, such as formal employment, showed a protective influence on reducing FGM/C likelihood in a Senegalese girl.

Furthermore, findings revealed that the single most important driver of FGM/C likelihood in a Senegalese girl is her mother's FGM/C status, and to a lesser extent her support for continuation of the practice and her belief in FGM/C as a religious requirement (Table 5.7). Evidence also suggests that about 50% of the observed risk factor influence of FGM/C status of the mother; 24% of her support for FGM/C and 13% of her belief in FGM/C as a religious requirement operated at community/contextual level as shown in Model 2 (Table 5.7). Between 2010 to 2017, result further showed that a girl was 20 times more likely to be cut if her mother was cut, and 5 times more likely if she supported FGM/C continuation in the cluster design effect adjusted model (Model 5). Religious motivation for cutting had little influence on FGM/C likelihood in a Senegalese girl between the study period.

In addition, we found additional support for the contribution of gender normative influence to a Senegalese girl being cut. The observed risk factor in Senegal was justification of wife beating by a girl's mother, a departure from the observed gender normative risk factor observed in Kenya and Nigeria. Hence, a girl was more likely to be cut if her mother justified wife beating by her husband for sex refusal (OR:1.29; 95%CI:1.13, 1.47). We also found a strong support for the influence of media exposure on FGM/C likelihood in a Senegalese girl. Findings showed that women who listened to radio had an increased likelihood of cutting their daughters with increasing frequency of exposure. Similar to the observed trend in Nigeria, an overall pattern of upward trend in FGM/C likelihood was observed with 16% increase observed during

the study period. Variance components for the competing models fitted separately for each country are presented in Tables A5.1 to A5.3.

Table 5.7. Posterior odds ratios (POR) and associated 95% credible interval (CI) from the Hierarchical Bayes space-time generalized additive mixed Models of FGM/C likelihood among Girls ages 0–9 years across exposure covariates in Senegal (for the 2010, 2015 and 2017 combined survey data).

PDF CATEGORY	Variable	Model 1 POR (95%CI)	Model 2 POR (95%CI)	Model 3 POR (95%CI)	Model 4 POR (95%CI)	Model 5 POR (95%CI)
DEMOGRAPHIC	Ethnicity					
	Diola	1.00	1.00	1.00	1.00	1.00
	Wolof	0.24(0.14,0.41)	0.47(0.26,0.82)	0.50(0.27,0.91)	0.50(0.27,0.91)	0.49(0.25,0.95)
	Poular	1.38(1.05,1.82)	1.55(1.16,2.07)	1.47(1.04,2.07)	1.47(1.04,2.09)	1.48(0.98,2.24)
		0.20(0.09,0.41)	0.32(0.14,0.68)	0.43(0.18,0.95)	0.49(0.20,1.10)	0.43(0.17,1.01)
	SererMandingue	1.00(0.75,1.34)	0.99(0.74,1.34)	1.14(0.80,1.61)	1.18(0.83,1.67)	1.06(0.70,1.62)
		1.30(0.86,1.96)	1.62(1.06,2.46)	1.63(1.02,2.59)	1.67(1.04,2.67)	1.35(0.76,2.40)
	Soninke	0.93(0.66,1.32)	0.98(0.68,1.39)	1.15(0.77,1.72)	1.18(0.79,1.77)	1.20(0.75,1.92)
	Other Sen	0.87(0.62,1.21)	0.94(0.66,1.33)	1.13(0.76,1.66)	1.14(0.77,1.69)	1.06(0.67,1.69)
	Non-Sen					
	Marital status					
	never	1.00	1.00	1.00	1.00	1.00
	currently	1.51(1.00,2.33)	1.52(1.00,2.36)	1.56(1.02,2.43)	1.58(1.03,2.45)	1.55(0.99,2.48)
	formerly	1.47(0.90,2.43)	1.49(0.91,2.49)	1.45(0.88,2.43)	1.45(0.88,2.43)	1.45(0.85,2.51)
	Religion					
	christian (ref)	1.00	1.00	1.00	1.00	1.00
	muslim	1.01(0.62,1.61)	1.10(0.67,1.76)	1.15(0.70,1.86)	1.13(0.69,1.84)	1.50(0.86,2.57)
MODERNIZATION	Residence					
	urban(ref)	1.00	1.00	1.00	1.00	1.00
	rural	2.15(1.85,2.50)	1.64(1.40,1.93)	1.64(1.39,1.93)	1.67(1.42,1.97)	1.71(1.33,2.21)
	Wealth index					
	highest	1.00	1.00	1.00	1.00	1.00
	lowest	1.18(0.80,1.75)	0.80(0.53,1.21)	0.96(0.63,1.47)	0.97(0.63,1.50)	0.79(0.49,1.28)
	second	1.20(0.82,1.77)	0.79(0.53,1.19)	0.91(0.60,1.39)	0.92(0.61,1.41)	0.79(0.50,1.25)
	middle	1.41(0.98,2.04)	0.96(0.66,1.42)	1.07(0.72,1.60)	1.08(0.72,1.62)	0.95(0.62,1.48)
	higher	1.22(0.82,1.81)	1.05(0.70,1.60)	1.13(0.74,1.72)	1.14(0.75,1.73)	1.07(0.68,1.70)
WOMEN'S AGENCY	Mother Education					
	none	1.00	1.00	1.00	1.00	1.00
	primary	0.74(0.64,0.86)	0.78(0.67,0.91)	0.80(0.69,0.94)	0.80(0.69,0.94)	0.81(0.68,0.96)
	secondary	0.99(0.77,1.27)	1.04(0.80,1.34)	1.09(0.83,1.41)	1.09(0.84,1.42)	1.14(0.86,1.51)
	higher	0.85(0.19,3.14)	1.02(0.23,3.77)	0.98(0.21,3.77)	0.99(0.21,3.82)	0.85(0.17,3.67)
WOMEN'S OPPORTUNITY	Mother's occ					
	formal(ref)	1.00	1.00	1.00	1.00	1.00
	informal	1.46(1.25,1.71)	1.47(1.25,1.72)	1.48(1.25,1.75)	1.48(1.25,1.75)	1.47(1.22,1.77)
	not working	1.34(1.15,1.55)	1.29(1.10,1.51)	1.30(1.11,1.52)	1.30(1.11,1.53)	1.22(1.02,1.46)
SOCIAL NORMS	Mother's cut					
	no(ref)	1.00	1.00	1.00	1.00	1.00
	yes	31.47(23.15,43.63)	16.16(11.67,22.78)	16.97(12.24,23.92)	17.02(12.28,24.00)	20.35(14.47,29.12)

	Mother support FGM					
	stop(ref)	1.00	1.00	1.00	1.00	1.00
	continued	5.49(4.82,6.25)	4.17(3.63,4.79)	4.48(3.89,5.17)	4.50(3.90,5.20)	5.30(4.56,6.18)
	don't know	1.46(1.09,1.95)	1.30(0.96,1.75)	1.43(1.05,1.94)	1.43(1.05,1.93)	1.53(1.08,2.11)
	FGM required by religion					
	no(ref)	1.00	1.00	1.00	1.00	1.00
	yes	1.72(1.53,1.94)	1.49(1.30,1.71)	1.47(1.28,1.68)	1.46(1.27,1.67)	1.53(1.32,1.77)
GENDER NORMS	Sex					
	no(ref)	1.00	1.00	1.00	1.00	1.00
	yes	1.26(1.12,1.41)	1.34(1.19,1.51)	1.36(1.20,1.53)	1.36(1.21,1.54)	1.29(1.13,1.47)
	Expenditure of moth. earnings					
	mother	1.00	1.00	1.00	1.00	1.00
	moth n father	1.10(0.83,1.45)	1.18(0.89,1.57)	1.23(0.92,1.64)	1.23(0.92,1.64)	1.28(0.94,1.75)
	father	0.79(0.58,1.07)	0.77(0.56,1.05)	0.80(0.58,1.10)	0.80(0.58,1.10)	0.77(0.54,1.08)
MEDIA EXPOSURE	Newspaper					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1 week	1.10(0.81,1.51)	1.09(0.79,1.49)	1.14(0.83,1.56)	1.14(0.82,1.56)	1.11(0.79,1.57)
	≥ 1 week	0.96(0.57,1.59)	0.93(0.54,1.57)	0.91(0.52,1.55)	0.90(0.52,1.54)	0.97(0.53,1.74)
	Radio					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1wk	1.21(1.04,1.41)	1.24(1.06,1.46)	1.26(1.07,1.49)	1.26(1.07,1.48)	1.43(1.19,1.71)
	≥ 1 week	1.32(1.14,1.52)	1.39(1.20,1.61)	1.41(1.21,1.65)	1.41(1.21,1.65)	1.61(1.36,1.92)
	Television					
	not at all	1.00	1.00	1.00	1.00	1.00
	< 1 week	1.18(1.02,1.37)	1.13(0.97,1.31)	1.14(0.97,1.33)	1.14(0.98,1.33)	1.11(0.93,1.31)
	≥ 1 week	0.97(0.82,1.14)	0.96(0.81,1.14)	0.99(0.83,1.17)	0.99(0.83,1.18)	0.88(0.72,1.06)
TIME	Year(mean)			0.21(-0.07,0.49)	0.21(-0.29,0.72)	0.16(-0.15, 0.46)

Model 1: Individual level Covariates only; Model 2: Individual and Community level Covariates; Model 3: Model 2 adjusted for main spatial, main temporal, and space-time interaction; Model 4: Model 3 adjusted for stratification design effect; Model 5: Model 3 adjusted for clustering design effect

5.5. Evaluating the impact of modeling complex survey design features on risk factor estimates

In Kenya, results showed that modelling the cluster design feature (Model 5 in Table 5.4) had varied impact on risk factor estimates. For instance, there was an increase in the positive influence of certain ethnic groups such as Kisii (12%), Somali (25%) and Masaai (18%) and further reduction in the protective influence of others such as Kamba (24%), Kikuyu (33%) and Luhya (28%). Additional changes were observed in increased positive association between Muslim religious affiliation and FGM/C likelihood. Also observed was a slight reduction in the estimated negative influence of education on FGM/C likelihood in a Kenyan girl after accounting for cluster design effect. On the other hand, accounting for the cluster design

features had no impact on estimated effects of occupation, social normative influence as measured by FGM/C status of mother and frequency of a girl's mother exposure to media.

In Nigeria, we found notable changes in the influence of the estimated influence of social norms, ethnicity, education, religion, and household wealth index. For instance, a substantial increase in the positive influence of social normative factors was observed after accounting for cluster design effect, with a doubling observed in the estimated effects FGM/C status of a girl's mother and her support for the continuation of the practice within her community. In addition, we observed an increase in the positive influence of currently married status (33%), Igbo ethnic extraction (33%) and low educational attainment (29%) on daughter FGM/C likelihood. We further noted an increase in the estimated negative influence of Christian religious affiliation (20%) and lower household wealth index (23%). On the other hand, accounting for the complex design feature had no observable change on the influence of type of residence, occupational status, gender normative influences and media exposures (except in the reduction in the negative influence of listening to radio less than once a week which was no longer significant after accounting for the cluster design effect (Model 5 in Table 4.5).

In contrast to the observed pattern in Nigeria, the overall impact of accounting for the cluster design feature was minimal on estimated influence of risk factor of FGM/C among girls 0-9 years in Senegal (Table 5.6). However, compared to the spacetime interaction model, there were notable reduction in the influence Soninke ethnicity of girl's mother, (17%), positive increase in the influence of Muslim religious affiliation of mother (30%). A 15% lower likelihood of FGM/C was observed in mothers with higher education after accounting for cluster design effects relative to the space-time interaction model. Accounting for complex design feature had minimal impact on social normative risk factors was found in Senegal with minimal for instance, a change of 20% in the influence of FGM/C status of mother, 18% increase in the influence of her support for FGM/C continuation was found, suggesting that the influence of unobserved variability at cluster level and cluster sampling error was minimal relative to the substantial influence observed in Nigeria. Additional increase in the positive influence of listening to radio was observed in Model 5, which suggests the possible role of contextual factors at play (Table 5.6).

5.6. Geographic variation in residual FGM/C risk

In this section, we present geographical distribution in spatial residual variation in probability that a girl is cut in Kenya, Nigeria and Senegal as shown in Figure 5.5 - 5.7. Across the three countries, little to no evidence of spatially structured random effect due to unobserved risk factors at regional level was found compared to region specific residual effect. This is not surprising, given that spatial correlation in the observed data operated between neighboring community rather than neighboring regions. Therefore, accounting for community level influences of social normative factors substantially eliminated a large percentage of excess risk due to neighborhood effects. Hence, adjusting for spatial correlation provided no improvement to the more parsimonious model with spatial heterogeneity only. An additional explanation for this observed trend includes fewer regions across the study domains with minimal cross-regional interaction taking place. The greater the intensity of the residual spatial (regional) effect, the higher the influence of unobserved risk factors operating within the region but not explained by observed covariates in the Bayesian hierarchical spacetime regression model.

In Kenya, spatial residual variation in FGM/C risk was very low across the eight regions with highest influence of unobserved risk factors found in North-eastern region and its two neighboring regions (Eastern and Coast) to the east and Nyanza to the west along with a high Bayesian posterior probability (> 0.8) as shown in Figure 5.5 below (top panel).

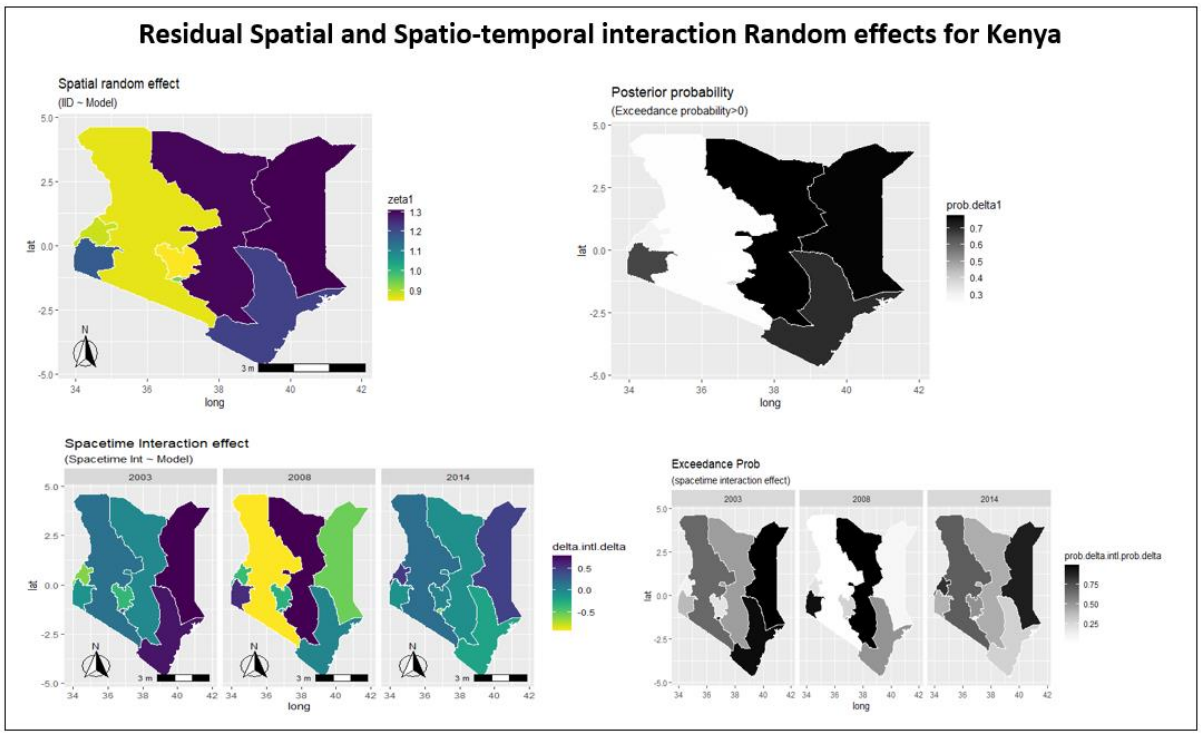


Figure 5.5. Residual main spatial and spacetime interaction for Bayesian hierarchical spatiotemporal model of FGM among Kenyan girls 0-14 years born to women 15 to 49 years, between 2003 and 2014.

In Nigeria, influence of spatial residual risk of FGM/C among girls was generally partitioned into high excess FGM/C risk in the Northern regions (in particular in the Northwestern States) and relatively low excess risk in the Southern regions (Figure 5.6 top panel left). Hence, between 2008 and 2018, highest excess FGM/C risk due to unobserved risk factors was found in Kano at 16 times greater risk than the national average and to a lesser but significant extent across its neighboring States including, Kaduna to the south, Jigawa to the northeast and Bauchi to the southeast. The Bayesian posterior probability of these estimates was very high (>0.8) (Figure 5.6 top panel right). Other states, such as Taraba in the northcentral, Sokoto to northwest, Ondo in southwest and Imo in the southeast also showed significantly elevated latent unobserved effects but to lesser extent compared to the four states in northcentral Nigeria.

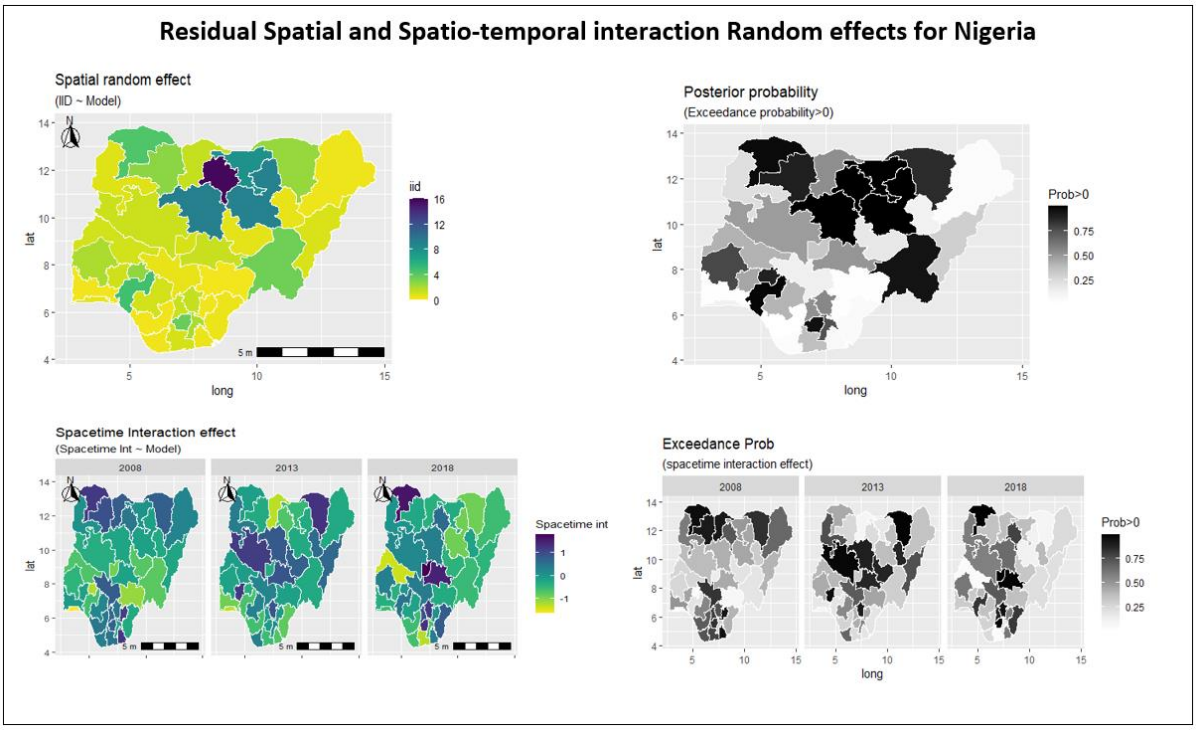


Figure 5.6. Residual main spatial and spacetime interaction for Bayesian hierarchical spatiotemporal model of FGM among Nigerian girls 0-14 years born to women 15 to 29 years, between 2008 and 2018.

Geographic variation in latent regional risk of FGM/C among Senegalese girls across the 14 regions of Senegal is presented in Figure 5.7 (top panel). In general, we note that excess risk due to the influence of unobserved risk factors that are spatially-structured (related especially in neighboring regions or states) was generally low in Kenya and Senegal compared to Nigeria. Therefore, between the period 2010 and 2017, highest excess FGM/C risk across the regions varied from 1.6 in Matam region (in the northeast) to 0.6 in Fatick region (in the west). Other regions with relatively high residual spatially-structured effects due to unobserved risk factors include Saint Louis to the north, Kolda to the south, as well as Tambacounda to the southeast, both of which shared border with higher risk regions with high posterior probability (Figure 5.7 top panel).

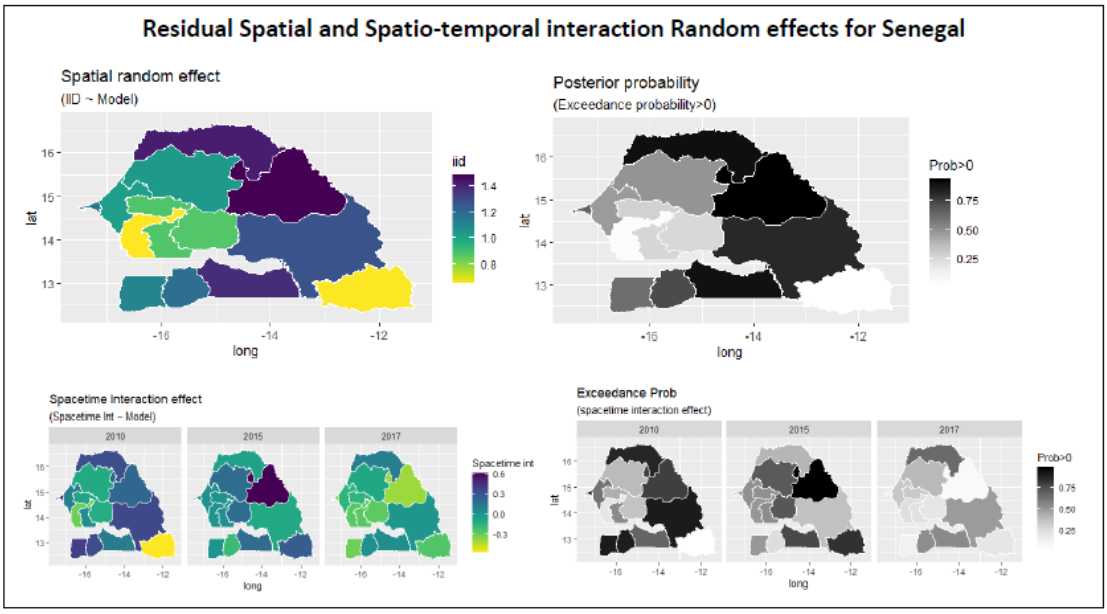


Figure 5.7. Residual main spatial and spacetime interaction for Bayesian hierarchical spatiotemporal model of FGM among Senegalese girls 0-9 years born to women 15 to 35 years between 2010 and 2017.

5.7. Non-separable spatiotemporal interaction in residual FGM/C risk

In this section, we discuss evidence for the detection of interaction between space and time from the best-fitting model across the three countries, results of which are presented in Figures 5.5 to 5.7 along with the Bayesian posterior probability (bottom panel). Hence, the resulting spacetime structure matrix for 3 time points is of size; 8×3 =24 parameters in Kenya; 37 × 3=111 parameters in Nigeria, and 14 × 3 = 21 parameters in Senegal. The underlying hypothesis therefore is the assumption of independent and identically distributed excess variation in FGM risk in a specific region and at a specific time point. In other words, observed excess risk in a location at a particular point in time is not affected by its neighboring areas or previous time point.

Findings from our study revealed significant evidence of non-separable spacetime interaction. In comparison to the separable space-time model formulation (a version of Model 3 without space-time interaction, not shown), accounting for the extra variation in risk due to interaction between space and time (Model 3) significantly improved model performance as measured by the DIC – by 54 points in the Kenya study, 339 points in the Nigeria study and 104 points in the Senegal study. The objective of the non-separable spacetime model formulation is to

account for residual local trends due to additional unobserved influence of interaction between space and time on the observed FGM/C outcome. For instance, this may arise as a result of locally targeted FGM/C interventions in some regions over time but not in others. This scenario is rife regarding FGM/C local and international interventions across the three countries. A second possible reason may be due to spacetime variation in the effectiveness of FGM/C legal framework and policies related to domestic violence and gender equity in certain regions or states but not in others. A third reason may be due to the emergence of a localized contextual risk factor, among specific women groups or communities in some regions but not in others. For instance, influx of FGM/C practicing refugees into a region or country at a particular time point as commonly observed among migrants in developed countries across the world or cross-border migration from neighboring countries such as in SeneGambia and among Somali ethnic communities in both Northeast Kenya and Somalia. Such sudden increase may often warrant further investigation beyond the identification of excess latent risk as typically implemented in a statistical framework.

Results showed evidence of residual space-time interaction effect across the 3 countries with observed geographic patterns differing for each time point. In Kenya, elevated risk was observed in northeast and coast regions in 2003, Eastern and Nyanza in 2008 and to a lesser extent Northeast and Nyanza in 2014 as shown in Figure 5.5(bottom panel). In Nigeria, study revealed substantial evidence of spacetime interaction with each distinct spatial pattern observed in 2008, 2013 and 2018. Increasing pattern of elevated risk of FGM/C observed across the six regions (Figure 5.6 bottom panel). Moderately elevated risk was observed in the North-West and Southern States in 2013. Elevated risk was observed in Niger and Yobe, Sokoto in Northwest, the Federal Capital Territory (FCT) and Nasarawa in North-Central, and Imo, cross river and Enugu in South-Eastern Nigeria in 2018.

In addition, evidence of excess variation in FGM/C risk due to spacetime interaction was detected in Senegal between 2010 and 2017 as shown Figure 5.7 (bottom panel left). Results showed that regions such as Matam and Saint Louis to the north and Sedhiou and Zinguichor to the south exhibited elevated excess spacetime risk in 2010; only Matam exhibited significantly higher risk in 2015 as measured by the posterior probability. On the other hand, little evidence of excess spacetime risk was observed in 2017.

5.8. Effects of continuous covariates

5.8.1. Individual level covariates

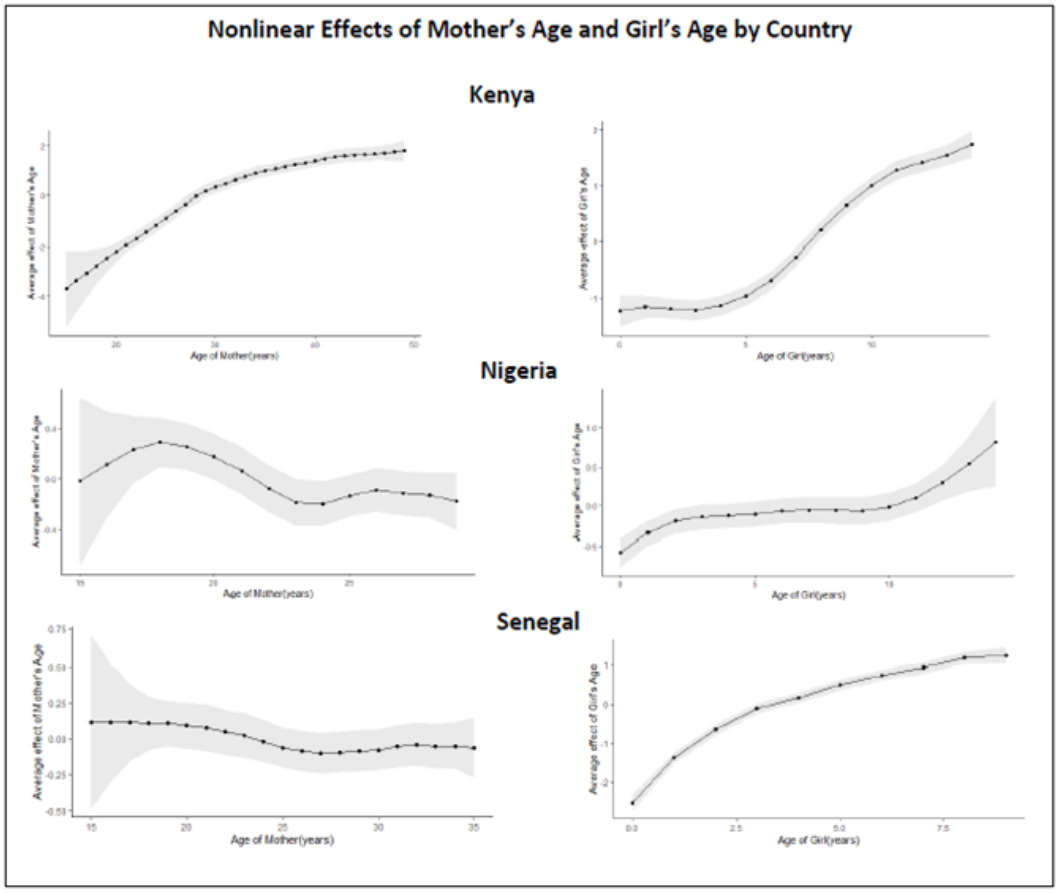


Figure 5.8. Effects of Mother's and Girls' Age on FGM/C likelihood in Girl by country.

5.8.2. Community level covariates

An overall linear pattern was observed in the effects of all community level variables on the risk of FGM in a girls across the three countries, implying an increasing risk of FGM in a girl with increasing proportion of women that were cut in her mother's community (in Kenya, Nigeria and Senegal) and proportion of women that support continuation of the FGM related practices in her mother's community (Nigeria and Senegal) and to a less extent proportion of women that are motivated to cut their daughters as a religious obligation. (Figure 5.9).

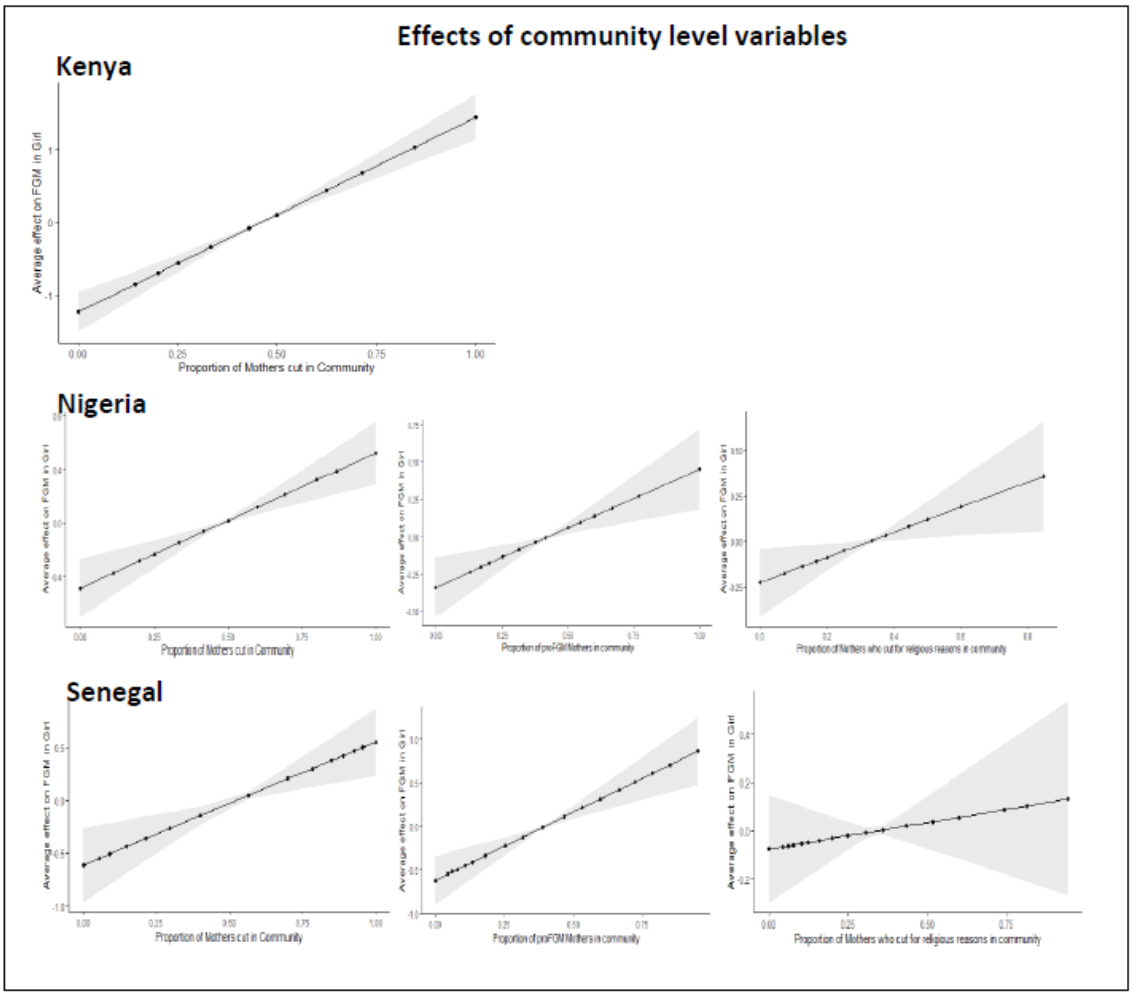


Figure 5.9. Effects of social normative influences operating at community level on FGM/C likelihood in a Girl by country.

5.9. Evaluation of model performance

We assessed performance of the best-fitting model by comparing the predicted value of the FGM/C prevalence in each region to the observed values. At individual level, we measured the predictive performance of all models using the WAIC and the logCPO (see Table 5.4). At regional or aggregate level, we considered the root mean square error (RMSE) and the adjusted R squared as presented Tables B1 to B3 (see Appendix B). Results of the WAIC and logCPO clearly showed significant improvement to model fit for the model that accounted for survey cluster design in addition to spatial-temporal interaction across the three countries. Additional information for the predicted values obtained at each location along with the 95% confidence interval of estimates across the three countries are also shown. Plots of the predicted values

against the observed values of FGM/C prevalence is shown in Figure 5.10 and Figure B1. separately for Kenya (top panel), Nigeria (middle panel) and Senegal (bottom panel). Subnational predicted estimates of FGM/C prevalence across the three countries showed good performance and adequate fit to the data. At the area (regional or state) level, the standard deviation of the residuals (prediction error between the predicted and observed prevalence data) as a measured by the root mean squared error was very low (<0.1 for the three countries) while the adjusted R-squared showed that model-based predicted prevalence estimates explained a near 100% variability in the observed prevalence data for the three countries.

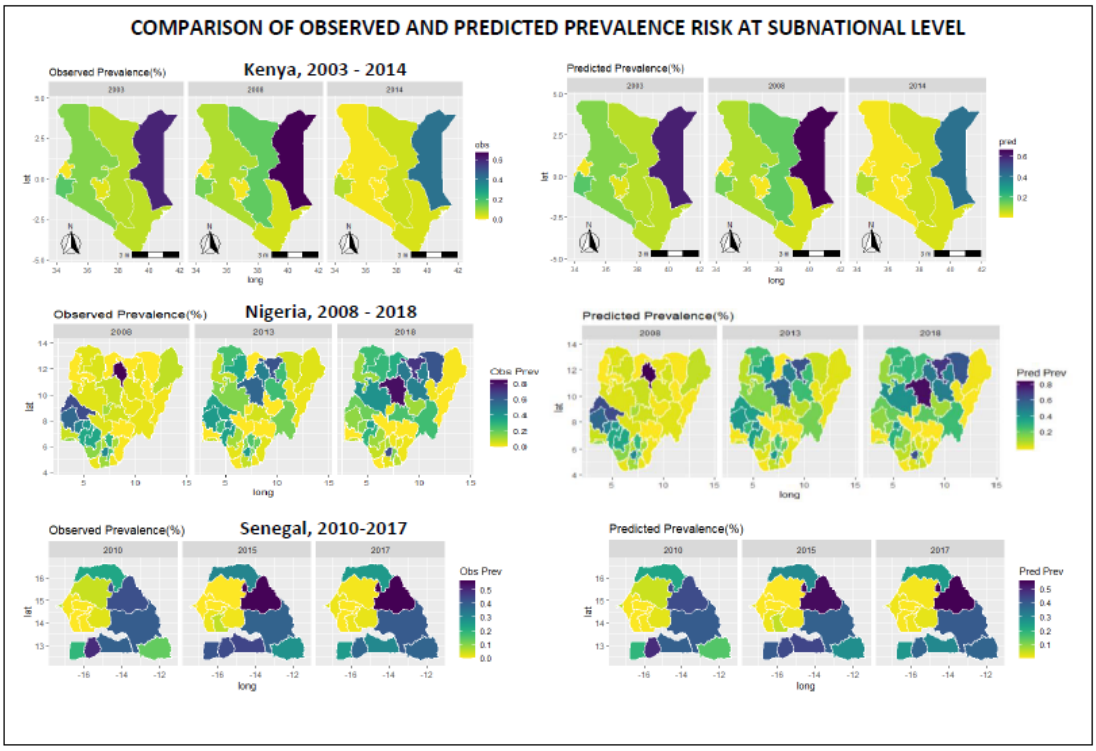


Figure 5.10. Comparison of observed and predicted FGM/C prevalence proportion by country

In conclusion, the most notable changes due to the impact of modeling the cluster sampling design features in the space-time hierarchical model was observed in risk factor estimates on FGM/C likelihood among Nigerian girls. This was in particular the case, as evident in substantial increase in the influence of social normative influences. Other important changes were observed in the influence of certain ethnic groups, Muslim religious affiliation, education and household wealth index across the three countries. The highest impact of cluster design effect on media exposure was observed with respect to exposure to radio in Senegal. Results

showed no meaningful change in risk factor estimates after accounting for the stratification design across three countries.

5.10. Discussion

This study evaluates important risk factors of FGM/C among girls by modelling and mapping successive waves of complex national survey data in space and time separately for Kenya (2003 to 2014), Nigeria (2008 to 2018) and Senegal (2010 to 2017). The objective of the study was to provide more precise estimates of the individual-level effects of key determinants of FGM/C between specific time period for each country using the proposed proximate determinants framework (PDF).

In more specific terms, we quantified the roles of socio-demographic factors identified as the underlying determinants; the roles of woman's agency and extra-familiar opportunities outside the household identified as the intermediate determinants, and most importantly the roles of social and gendered normative influences operating at both individual and community levels, identified as proximate determinants, in FGM/C outcomes among girls. Additional attempt was made to explore geographic variation and temporal trends in the practice and the excess risk due to unobserved risk factors whose influences are independent in space and time. These questions were addressed using a hierarchical Bayesian generalized mixed modeling approach which simultaneously accounted for both linear and nonlinear predictors, and the inherent spatial, temporal and spatio-temporal trends in the observed complex survey data.

Results showed that FGM/C prevalence among girls under 15 years varied geographically and temporally between countries and within countries at subnational level over the study period. For instance, a general pattern of substantial decline in prevalence was found among girls 0 to 14 years in Kenya between 2003 and 2014, especially in the western regions, with highest prevalence rate (24%) observed in Northeast in 2014. In Nigeria, prevalence pattern was partitioned into a decreasing trend in southern regions and increasing trend in the northern regions with highest prevalence observed in northern States of Kaduna (81%) and Jigawa (71%) in 2018. Similar geographic pattern in the distribution of FGM/C among girls 0-14 years was reported in a recent study that considered multiple sources to evaluate subnational changes in prevalence in Nigeria between 2003 and 2016 (Nnanatu et al., 2021). In Senegal, the highest

prevalence was observed in Matam region at 56% in 2017. Highest increase in prevalence was observed in Kedougou (from 29% to 38%) and reduction observed in Zinguichor (from 40% to 27%). These findings are consistent with similar studies conducted in these countries. (Kandala et al., 2017, 2019, 2020).

Findings suggest significant variation with respect to the influence of age of a girl and that of her mother on her FGM/C likelihood across three countries. In Kenya, a positive pattern of increased likelihood of cutting was found with increasing age of a girl and her mother, suggesting that older girls were more likely to be cut in Kenya; and in particular, girls born to older women. This finding was expected and consistent with the well-known tradition of FGM/C procedure as an important rite of passage for pubescent girls transitioning into womanhood in practicing Kenyan communities (Chege et al., 2001; Prazak, 2007). However, attempts have been made over the past ten years to implement alternative rites of passage, without FGM/C (Droy et al., 2018; Graamans et al., 2019), and may in part, explain observed decline in prevalence over the years. A pattern of low risk of cutting was observed in Kenyan girls under 5 years, reflecting observe decline in the practice in recent time. The observed influence of mother's age was, however, weak in Nigeria, with evidence suggesting that younger women had increased probability of cutting their daughters and older girls were more likely to be cut.

Similar study between a different time period (2003 to 2016) also found a weak association between age of mother and FGM/C likelihood in Nigeria with evidence of higher likelihood of cutting girls among younger women (Nnanatu et al., 2021). The weak association between FGM/C likelihood and age of a girl or her mother in Nigeria suggest that factors beyond age have stronger influences on FGM/C outcomes, most important of which are the ethnic extraction and locality of residence of a woman as found in our study. In Senegal, results showed strong positive association between the age of a girl and her likelihood of being cut, with older girls having increased likelihood of cutting, as reported by previous studies (Kandala et al., 2020; Kandala & Shell-Duncan, 2019). The observed trend of strong influence of girl's age and weak influence of mother's age may be because women are usually cut during infancy in Nigeria and Senegal or in late girlhood (usually between age 9 and 14 years) in Kenya.

Other important demographic factors identified in the study include ethnicity and religion in Kenya and Nigeria as well as marital status in Nigeria. In Kenya, women from Kisii and Somali ethnicity had the highest likelihood of cutting their girls, hence, the disproportionate burden of

observed FGM/C prevalence observed in the northeast region and Nyanza where they are most predominant. Similar findings have been reported by other investigators (Kandala et al., 2017, 2019). The persistence of FGM/C among women of Kisii extraction may be explained by the fact that FGM/C is usually a private family affair and conducted without attracting public attention. More so, cut girls in Kisii communities are adequately rewarded with gifts and social acceptance, and considered more worthy for marriage while uncut girls and women are subjected to stigmatization and social exclusion. (Oloo et al., 2011).

In Nigeria, highest FGM/C likelihood was found among girls of Igbo extraction compared to Hausa and Yoruba girls between 2008 and 2018. However, findings from our study contrast that of Nnanatu et al.(2021) in which ethnicity of a girl's mother had no influence on her likelihood of being cut. We note however, that in Nnanatu et al. (2021), the role of ethnicity was only considered for the 2016 survey year, rather than its influence over a specific time period as evaluated in our study. Previous studies have suggested that while type I and II FGM/C are predominantly practiced by the Yoruba, and type III by the Hausa, the Igbo tend to practice all the three types with a strong sense of communal traditions which may further strengthen likelihood and persistence of the practice (Kandala et al., 2009).

Our study also identified Muslim religious affiliation as an important risk factor of FGM/C among girls in Kenya and Nigeria. Previous quantitative studies have also established Muslim religious affiliation as an important determinant of whether a woman would cut her daughter or not in some parts of Africa. (Hayford & Trinitapoli, 2011); and more recently in Kenya and Nigeria within a spatial and spatiotemporal multilevel regression model framework.(Kandala et al., 2009, 2019). More so, studies in south east Asia have also reported predominance of the procedure across Muslim communities where 87% of participants in a study believed FGM/C was required by Islamic faith (Rashid & Iguchi, 2019). However, leading Islamic scholars have shown that FGM/C has no connection with the Islamic religion. Rather, it is a practice deeply rooted in pre-Islamic cultural and traditional norms and poses health risk to women and girls (Birge & Serin, 2019; Gomaa, 2013). However, effective cooperation with pro-FGM/C clerics should be considered for any FGM/C intervention to work in most affected communities, given their influential role in decision making regarding what is considered morally right or wrong. (Gomaa, 2013).

In addition, the association of FGM/C with marital status among married women in Nigeria has important implications for married women who cut their daughters and their motivations

for doing so. Recent reviews have reported such motivations to include, the need to preserve sexual purity, family honor, and marriageability of the girl into a respectable family(Awolola & Ilupeju, 2019; Okeke et al., 2012). The intimate connection between family, marriage and preservation of sexual purity of a girl in both northern and southern Nigeria require a deeper exploratory study as this may be a key explanation to the persistence of the practice especially among young married women.

Results showed substantial contribution of social normative influences operating at both individual and contextual level to FGM/C likelihood among girls in Kenya, Nigeria and Senegal. Our study is the first attempt to separate and quantify the two influences in a manner that accounted for regional and temporal variations in risk. These findings provide strong support for social normative influences as important drivers of persistence of FGM/C in Nigeria for the period 2008 and 2018 and Senegal for the period 2010 to 2017. This notable observation was made in comparison to the remarkably low influence of social norms in Kenya where significant decline in FGM/C prevalence was observed between 2003 to 2014. The varying influence of social normative factors operating at both individual and community levels across the three countries indicates the significance of context in shaping individual woman's decision to cut her daughter and the observed FGM/C outcome in a girl, as reported by previous studies. (Grose et al., 2019; Hayford et al., 2020; Kandala et al., 2019). Adequate understanding of such context-specific normative influences that underly a woman's decision to support continuation of the practice and to have her girl cut is a critical element to design effective intervention successful strategies. (Cislaghi & Heise, 2018, 2019). More so, a woman may support continuation of the practice simply because she is not the key decision maker regarding observance of traditional norms within the family hierarchy or community. Hence, support for continuation of the practice does not necessarily imply a woman would cut her daughter, and thus separating the two influences. (Shell-Duncan et al., 2011; Wander & Shell-Duncan, 2020).

An important aspect of our findings is the varying extent of social normative influences as proxy measures of contextual factors, on the decision of a woman to cut her daughter in Nigeria and Senegal between the study period as previously demonstrated in a recent study in 4 West African country (Hayford et al., 2020). For instance, in Nigeria, of the three indicators of social normative influences observed, the FGM/C status of a woman and her support for continuation of the practice both had a substantial impact on her decision to cut her daughter between 2008 and 2018. On the other hand, in Senegal, FGM/C status of a woman had the single greatest influence on her decision to cut her daughter, four times, relative to her support for continuation

of the practice. Such evidence-driven insight can be factored into a deeper understanding of underlying contextual motivations for the practice in each country; a critical step in country-specific intervention design.

A number of reasons why people comply to social norms have been elucidated by various investigators, many of which are socially coordinated within a specific context and varies from one locality and or ethnic groups to another (Kandala & Shell-Duncan, 2019; Shell-Duncan et al., 2011; Wander & Shell-Duncan, 2020). Motivations for cutting at the individual level, may include desire of a woman to preserve the virginity of her daughter and family honor, and hence ensures her marriageability. This is still an important motivation for the practice especially in Nigeria as recently reported by various studies and report. (Chidera, 2018; Okeke et al., 2012). Another reason is for respectability and worthy of inclusion into exclusive women groups as observed in Senegal and Gambia (Shell-Duncan et al., 2011). This motivation may possibly explain the positive association between higher educational attainment and FGM/C among girls in Senegal between the study period. Other women may simply support continuation of the practice as an internalized sense of what is morally right to do without any obvious explanation for doing so.

The social coordination norm (SCN) model remains the most effective construct to understand how social normative influences drive the persistence of the practice as recently tested by a study conducted in the Senegambia (Wander & Shell-Duncan, 2020). The SCN model of FGM/C attributes the persistence to high costs for uncut women and girls including social exclusion and harassment by cut women and girls. It argues that household decision to cut or not cut are shaped by anticipated benefits and cost. Interventions based on the social coordination norm model seek to minimize social consequences for uncut women and girls by coordinating decision not to cut among a critical mass of families within a reference group (such as locality, ethnic or religious groups), this making abandonment, viable within this group. Once a threshold, or “tipping point” of abandoning families is reached, it is predicted that a rapid shift from a cutting to non-cutting convention will take place and becomes the new normal. (Mackie & LeJeune, 2009). These interventions are often community-based and community-led and have been shown to yield significant results in Kenya, western regions of Senegal and south western Nigeria (Denison et al., 2009; Ekundayo & Robinson, 2019; Mwendwa et al., 2020).

Findings of our study showed support for gender normative influences as measured by household decision making on a woman's expenditure of her income, by mother alone (in Kenya), and by both mother and father (in Nigeria), and her justification of wife beating if she refused her husband/partner sex (in Senegal) between the study period. The observed mixed influence of household decision making on expenditure of mother's earning in Kenya and Nigeria may suggest the participation of the father in household decision making to cut a girl in Nigeria, rather than mother alone in Kenya. On the other hand, justification of wife beating for sex refusal in Senegal may indicate the underlying influence of gendered based norms and domestic violence on the probability that a girl is cut as recently argued by scholars (Cislaghi & Heise, 2018, 2019).

In our study, we found support for the benefit of extra-familiar opportunities, such as educational attainment of a woman, in reducing the likelihood of FGM/C in a girl in Kenya and Nigeria, but a rather increased likelihood of cutting with higher education in Senegal. Our finding in Kenya and Nigeria is consistent with reports from other studies which have demonstrated the significance of education in women empowerment as a pathway to facilitate socio norm change and hence, FGM/C abandonment (Grose et al., 2019; Hayford et al., 2020; Kandala et al., 2019; Kandala & Shell-Duncan, 2019). On the other hand, the observed increase in cutting among girls born to women with higher education in Senegal may have possible link to observations that FGM/C is associated with access to social network of older women (Shell-Duncan et al., 2011). FGM/C may therefore be an important measure of social acceptability or worthiness among women elite group especially in the Northeastern and southern part of Senegal where the practice is most rife. In our study, we evaluated women agency (formal education attainment) and opportunities (as measured by occupation status) as intermediate components within the proximate determinant framework given their role in shaping social-behavioral outcome of a woman in the household and locality (Cislaghi & Heise, 2019). They determine whether she is empowered enough to make personal decision to cut her girl (beyond influences from family and community ties) or support continuation of the practice within her community based on personal preferences. The dynamics of the two factors operating as intermediate determinants (between underlying and proximate risk factors) would therefore shape multiple social and gender related outcomes.

With respect to modernization, study provided little support for modernizing influence, as assessed by type of residence of woman and the wealth quintile of household, on FGM/C

likelihood among girls in Kenya. Similar finding was obtained by Kandala et al. (2019) in the spatio-temporal component of their model formulation. In Nigeria, however, we found negative support for the influence of household wealth index, as study showed that girls from affluent households were more likely to be cut than girls from poorer households between the study period. Findings our study was consistent with the study conducted by Kandala et al. (2009) among eldest daughters of Nigeria women using the 2003 NDHS, while recent study by Nnanatu et al, (2021) found no significant influence of household wealth index on the probability that a girl was cut in 2016. We note however note that results of both studies are not directly comparable to our study given that influence of household wealth was only assessed at a single time point.

The study therefore suggest that FGM/C may often be practiced among wealthy Nigerian households, thus providing additional support for desire to preserved virginity of a girl and her marriageability (Chidera, 2018). The fact that the practice is therefore stull rife among elite households in both northern and southern Nigeria may warrant further focused inquiry into the nature and dynamic of the practice within specific reference groups (defined by ethnicity and religion). However, we note the significant progress made in South West Nigeria primarily as a combination of effective legislation in south western States and a number of intervention programs (Awolola & Ilupeju, 2019). In Senegal, findings showed that girls residing in rural areas were more likely to be cut between 2010 and 2017. The higher likelihood of rural girls to be cut in Senegal with no evidence for the influence of increased household wealth suggest that contextual factors rooted in ancestral traditions including respect for elders and proper behavior within community (Shell-Duncan et al., 2011; Wander & Shell-Duncan, 2020) may play an important role in the persistence of the practice.

Media exposure to radio was found to play an important role in FGM/C likelihood among Senegalese girls, but not in Kenya and Nigeria. We found this positive association between listening to radio and increase likelihood of cutting quite interesting and rather unexpected. Media exposure has been described as an important source of information and communication about harmful consequences of FGM/C and existing legislation that criminalize the practice in Senegal. However, the observed positive link may warrant further inquiry given that a significant proportion of the population (at least 40%). This is the first study to explore this possible link. We hypothesize that the observed positive association may be related to local programs encouraging (or not denouncing) the practice. However, this requires additional

investigation. On the other hand, exposure to newspaper or magazine in Kenya, had significant influence on the decrease likelihood of FGM/C in a girl between 2003 and 2014. No support was found for the influence of media exposure in Nigeria.

Further, a significant aspect of our findings in this study is the separation of influences of social norms operating at community level from region effects. This we modelled by accounting for and quantifying excess variability due to unobserved contextual factors operating within local community and measurement error across clusters separately from the main spatially structured and unstructured unobserved risk factors at regional or state level. By so doing, we found substantial evidence that the observed spatial clustering (correlation) of FGM/C risk in the study population data occurred at community level. After accounting for sample correlation at cluster level, we found no evidence of spatial clustering of unobserved risk factors among neighboring regions or state, while the average spatially unstructured effects of unobserved risk factors (specific to each region or state) remained significant. Hence, findings showed that observed spatially structured random effect at regional level was in fact due to clustering of shared contextual effects among closely related women and girls, especially along the line of proximity in locality(community) and ethnicity.

This approach to separately quantifying clustering behavior of FGM/C risk at community and regional/state level is a radical departure from previous approaches commonly employed in spatial and spacetime FGM/C modelling (Kandala et al., 2009, 2019; Nnanatu et al., 2021). Across the three studies, there is an implicit assumption that spatial clustering in FGM/C risk or prevalence occur at regional or state level. By eliminating the influence of clustering and variability at community level, we found that the only source of variability at larger geographic level were mainly due to unobserved region or state specific factors. This includes existing FGM/C legislation and policy framework prioritizing gender-based and domestic violence towards women and girls, and most importantly availability and effectiveness of FGM/C interventions based on contextual understanding of the practice within the state.

A strong support for spatial clustering at community level was found across the three (3) countries. This is expected given that the fundamental principles of clustering require geographic proximity at the finest possible resolution appropriate for the outcome of interest. In this case members of neighboring communities are likely to interact and share common risk factors (perceived benefits or health risk) associated with the FGM/C than members of neighboring regions or states. Further evidence of FGM/C clustering at community level is also

supported by two recent studies conducted in West Africa that demonstrated significant clustering of FGM/C prevalence at community level. For instance, study by Wander and Shell-Duncan(2020) provided strong support for FGM/C as a social coordination norm with significant clustering in prevalence between zero or one and a bimodal distribution consistent with the social coordination norm model (Mackie & LeJeune, 2009; Shell-Duncan et al., 2011). The study also found that communities where the perceived benefits of cutting outweigh the health risk are more willing to support continuation of the practice (observed as high prevalent communities). The reverse is the case in low prevalent communities (Wander & Shell-Duncan, 2020).

In a separate study by Howard and Gibson (2017) across five west African countries using the DHS sample dataset, evidence suggested FGM/C behavior is frequency-dependent. Hence, the probability girls are cut varies in proportion to the frequency of practice among member of their reference group - extended household or ethnic extraction, both of which are component of the fabric within which the practice takes place in the community (Howard & Gibson, 2017). Another important finding of the study demonstrated the implications of FGM/C practice for evolutionary adaptation, survival and fitness for women and girls resident in such communities. (Howard & Gibson, 2017; Wander, 2017). This may, therefore, well explain persistence of the practice across West Africa and Northeast African countries.

CHAPTER SIX

SMALL AREA ESTIMATION OF SYSTOLIC BLOOD PRESSURE AMONG SOUTH AFRICAN ADULT POPULATION USING CROSS-SECTIONAL AND LONGITUDINAL SURVEY DATA

In this chapter, we present a preliminary attempt to produce small area estimates of mean systolic blood pressure (SBP) derived from a nationally representative cross-sectional and longitudinal survey data using hierarchical Bayes (HB) model-based formulation. Here, the objective is to obtain small area estimates of mean SBP among South African adults and evaluate trends at national and local levels between the period 2008 and 2017. We propose a hierarchical Bayes repeated measurement linear mixed model, a novel approach to obtain the small area mean estimate. We utilized the national income dynamics survey (NIDS) – the first nationally representative household panel survey conducted in South Africa (Branson and Wittenberg,2019), to realize this objective. Estimates derived from the proposed HB approach is subsequently compared to direct and smoothed-direct methods based on cross—sectional analysis of the NIDS survey data. We discuss the key findings and the implications of our preliminary findings for future extension of the proposed small area estimation methodology to evaluate local trends using complex longitudinal survey data in sub-Saharan Africa.

6.1. Introduction

Raised blood pressure is an important risk factor for cardiovascular disease outcomes with increasing epidemiological burden in sub-Saharan Africa in recent years. The burden of raised blood pressure (hypertension) and cardiovascular disease mortality in sub-Saharan Africa is highest in South Africa (Lloyd-Sherlock et al., 2014). Recent study on raised blood pressure among older adults in low and middle-income countries, has shown that South Africa has the highest rate of raised blood pressure reported among persons 50 years and older for any country in the world, at any time in history, with an estimated highest rate of 78% (Lloyd-Sherlock et al., 2014). This sense of urgency led to the development of a National strategic plan for the prevention and control of chronic morbidities and co-morbidities across the population from 2013 to 2017 (DOH, South Africa, 2013) and from 2020 to 2025 (DOH, South Africa, 2019).

To provide the basis for the present study, we reviewed relevant methodologies developed till date to obtain small area estimates, and to utilize such estimates to understand geographic disparity and trend in average systolic blood pressure and other health outcomes in sub-Saharan Africa.

Small area estimation (SAE) is a newly emerging field of modern statistics in the late 20th century with wide applications across many sectors. Such applications are often driven by the increasing demands from national agencies for appropriate data to drive public health, policy decisions and equitable allocation of limited resources at small area level. More recently, it has seen an increasing role in producing official statistics and relevant indicators at regional, national and global levels as observed for cardiovascular disease outcomes (Roth et al., 2017; Roth Gregory A. et al., 2020). To meet the data need, efforts have been invested by various governments in the collection of national surveys. Such surveys are representative of the target population at various administrative geographies and may be collected repeatedly over time.

Furthermore, SAE plays an important role in modern epidemiology and global health endeavors. First, it reveals disparities in geographic distribution of various indicators of health and well-being at various administrative levels which allows the monitoring of progress with regards to indicators of interest. Second, it provides the evidence base to formulate initial hypothesis that may inform additional inquiry into the true nature and causal explanation for the observed inequality between low risk and high-risk small area profile and to subsequently address them. We note however, that most significant development and applications (including at global scale) in the field of small area statistics have been developed in western countries (Forouzanfar et al., 2017; C. O. Johnson et al., 2019; Rao, 2003; Reitsma et al., 2017). More recently, the use of complex multistage household surveys has been considered for producing small area estimates and subnational trends in low and middle-income countries in a manner that account for the complex design features. Such estimates have been shown to provide good predictive performance for precision public health in sub-Saharan Africa (Li et al., 2019; Wakefield et al., 2020). A part explanation for this trend is due to the lack of adequate population statistics collected at regular time points and poor data quality where they are available.

Therefore, the need to provide estimates for small domains (such as geography) has led to methodological development in two directions. On one hand, survey statisticians utilize efficient survey designs that can produce domain estimates of adequate precision within the

standard design-based mode of inference commonly referred to as design-based estimates first proposed by Horvitz and Thompson (1952). For such estimates to be reliable, sample must be obtained across all small areas of interest. However, given the constraints on cost of obtaining adequate sample size, data obtained at finer geographic scale are often sparse and may be missing. The former may often result in unstable direct estimates with large precision while the later renders the direct estimate non-applicable to obtain estimates at out-of-sample areas. Therefore, the need to address the problem of low precision and out-of-sample data have led to extensive developments of indirect estimation approaches, together referred to as model-based approaches. These methods have been developed to be robust and more efficient in addressing the problems associated with the direct estimator.

The objective of all model-based approaches is the use of data available at the small area level, obtained across the domains or areas of interest at a specific or multiple time point to produce small area estimates of spatial and spatial-temporal patterns and trends in the target indicator of interest(s). Two types of model-based methods have been extensively developed to address the problem of data sparsity often encountered at finer geographic resolution and to improve precision of direct estimates: the area level and the unit-level models. Most small area estimation endeavors utilize either of the two approaches. Two of the early proponents of a model-based approach to estimate small area statistics were Fay and Herriot (1979). They proposed an area level regression model to account for the probability of unequal sampling in producing small area estimates of a population characteristic at area level. An important subsequent development in the field allowed individual-level information (microdata) to be modelled, popularly known as unit level model. The first form of this model was proposed by Battese and Fuller (1988) in their “so called” nested error model (or one fold nested regression model given that error variances at individual level are nested within the area random effects one fold up). A popular form of the nested error regression is the two-fold nested regression in which error variance are nested within clusters which are in turn nested within domains (Rao, 2003). The two-fold nested regression has been extensively used by World Bank to obtain small area estimate of poverty in developing countries (Marhuenda et al., 2017; Stukel & Rao, 1997).

Various estimation approaches exist for model-based estimates. The empirical best unbiased linear predictors (EBLUPS) provide a frequentist approach to obtain small area prediction by replacing fixed and random effects parameters with their estimators from the fitted model parameters. This is followed by obtaining a subsequent prediction of the small area target mean

of interest along with the mean square error of the estimates. The empirical Bayes (EB) derives prior evidence for Bayesian updating from the observed data. The third approach is the hierarchical (fully) Bayes (HB) that combines prior information (from previous studies or expert opinions) with the likelihood of the observed data to obtain a posterior distribution for all model parameters of interest (Datta & Ghosh, 1991; Ghosh & Rao, 1994; Rao, 2003). Implicit in fully Bayesian estimation procedure is shrinkage in terms of prior, in which the posterior estimates of the prior mean are shifted from the sample mean towards the prior mean, resulting in smoothing of extreme values, and reduction in variance (Haining & Li, 2020).

A key advantage of HB approach is that inferences are exact. In other words, the exact conditional probability distribution of the response (given model parameters and the data likelihood), can be obtained. The choice of prior often needs to be carefully considered depending on the objective of inference. For the purpose of small area estimation, Rao (2003) argued for the use of a diffuse or "vague" prior. The use of diffuse prior offers two advantages in that estimates of the posterior distribution are proper and the frequentist properties of estimates (such as relative bias of posterior means and variances) can be assessed (Rao, 2003).

Furthermore, the basic unit-level approach proposed by Battese, Harter and Fuller (1988) can also be extended to account for additional individual-level random effects components within a nonspatial, spatial and spatial-temporal linear mixed model formulation. For instance, Saei and Chambers (2003) considered a case of unit-level linear mixed model with random variations in space and time in four different formulations using a frequentist approach. The first formulation was a model with independent and identically distributed (IID) area-time effects with normally distributed means and variances. The second formulation was a model with IID area effects and autocorrelated time effects in which temporal correlation was accounted for using the first order auto-regressive (AR1) process (Saei and Chambers, 2003). In the third formulation, they considered a model with time varying area effects, while the fourth was a model with spatial correlated random effects. While their estimation procedure was implemented within a frequentist approach, our study seeks to consider a fully Bayesian formulation of their models.

In addition, model-based SAE techniques have been applied extensively to produce small area estimates of health outcomes at various spatial disaggregation level ranging from global to national, subnational domains. At global or regional level, Reitsma et al. (2017) obtained country-level trends in prevalence of smoking in 195 countries and territories from 1990 to

2015 using a spatiotemporal Gaussian process regression (ST-GPR). Similarly, Johnson et al (2019) reported global regional and national burden of stroke between 1990 and 2016 using an ensemble process. At a regional level, Li et al. (2019) utilized complex household surveys to evaluate changes in the spatial distribution of the under 5 mortality rate(U5MR) in thirty-five(35) African countries. The region-time specific estimates are smoothed using a Bayesian, space-time model at a one-year scale. The resulting estimated distributions of the U5MR are summarized and employed to evaluate subnational progress toward the MDG 4 target of two third reduction in U5MR from 1990 to 2015. At county level, a novel application of the demographic and health surveys (DHS) data was utilized to produce design-based and model-based estimates of education in Kenya for women age 20 to 29 at finer geographic resolution in Kenya in a manner that accounted for the complex design of the survey (Paige et al., 2019).

Further, the application of small area techniques to produce small area estimates of SBP has attracted notable interest given that raised blood pressure is an important risk factor for cardiovascular diseases and all-cause mortality in both developed and developing countries. Two recent studies are noted. The first was conducted by Zhou et al. (2017) with the objective to estimate global, regional, and country-level trends in blood pressure from 1975 to 2015. The second was conducted by Forouzanfar et al. (2017) to examine global burden of hypertension and systolic BP between 1990 and 2015. In the first study, countries were organized into 21 regions based on geography and national income, and further aggregated into 9 “super regions”. This presents a hierarchical structure in which estimates for each country and year were informed by country data across the years or other neighboring countries in similar period. Thus, the hierarchical formulation allowed information borrowing by space, time, and age across available studies. The model incorporated non-linear time trends and age patterns. The model allowed the age association of blood pressure to vary across populations, and the rise in means and prevalence over age to be steeper where blood pressure was higher. The model also accounted for variations in type and levels of studies, rural-urban differentials and important covariate predictors of blood pressure. The second study, however utilized a spatiotemporal Gaussian process regression (ST-GPR) to produce estimates of average blood pressure accounting for variance in age, sex, country and year. The ST-GPR is a 3-step modelling approach that allows linear prior to be refined by weighting and addition of residuals in space and time, followed by subsequent Gaussian process regression. Both studies reported increased burden in low and middle-income countries (including sub-Saharan Africa) in mean systolic blood pressure for the two study periods.

However, no studies, till date have considered the use of repeated measurements within a linear mixed model framework to produce small area estimation of population health outcome to evaluate geographic variation and local trends. The present study we seek to fill this important gap using South Africa – the country with the highest burden of raised blood pressure in the African region, as a case study. Effort to produce estimates of average SBP at small area level will provide invaluable evidence base to monitor country progress and evaluate geographic inequality in systolic blood pressure at a single and or multiple time points.

6.2. Methodology

In this section, we present the statistical procedure we utilized to analyze the national income dynamic survey (NIDS) data cross-sectionally and longitudinally. The overarching goal is to obtain small area estimation of geographic patterns and trends in SBP separately for the 52 district municipalities of South Africa from 2008 to 2017. We present model formulation for the four different types of approach that we considered in the study namely, small area estimates from the unweighted observed data direct estimator for the observed data, the direct (design-based) estimator, the spatially smoothed design-based estimator and the proposed repeated measurement hierarchical Bayes (HB) linear mixed model. The section is organized as follows. First, we present the description of the NIDS cross-sectional panel survey and the sampling technique employed. Second, we describe the statistical methodology and model formulation for the four types of SAE techniques considered. Third, we describe a bootstrap procedure for the computation of the uncertainty of the HB model-based estimates. In the discussion section, we discuss our findings and implications for future extension of the proposed linear mixed model framework. We conclude the chapter by highlighting plans for further extensions of the repeated measurement HB linear mixed effect model to produce small area estimates from complex national household panel surveys.

6.2.1. Description of the National Income Dynamic survey (NIDS)

In 2006, the South African government embarked on an intensive effort to track changes in the well-being of South Africans by closely following about 28,000 people over time. The national income dynamics study (NIDS) was the first national panel household survey to document change in the dynamic structure of a sample of household members in South Africa and changes in their incomes, expenditures, assets, access to services, education, health, and other dimensions of well-being. Key feature of the panel study is its ability to follow people as they moved out of their original 7,305 households. The first baseline wave was conducted in 2008 with subsequent waves conducted every two years on average. A total of 5 waves was completed between 2008 and 2017. Thus, providing a rich source of data to understand the health dynamics of the south African population using a representative national survey. The panel data is invaluable for the purpose of evaluating and monitoring the effective implementation of national policies and health interventions at small area level.

A stratified two-stage cluster design was employed in sampling eligible households in the baseline study. In the first stage, 400 primary sampling units (PSUs) were selected from Statistics South Africa's (Stats SA) 2003 Master Sample of 3000 PSUs. This Master Sample was the sample used by Stats SA for its Labour Force Surveys and General Household Surveys between 2004 and 2007 and for the 2005/06 Income and Expenditure Survey. A PSU is defined as a geographical area that consists of at least one Enumeration Area (EA) or several EAs from the 2001 Census, when the originally selected EA was found to have less than 74 households. In some cases, it has been necessary to add EAs to the original EA to meet the requirement of a minimum of 74 households per PSU. The EA or EAs added to the original EA has to be of the same settlement type as the original EA. An EA is the smallest portion of land that the country was demarcated into for the purpose of census enumeration. Each of these PSUs is called a "cluster". Each cluster has an average of 240 households ranging from 6 and 513 households per cluster.

The target population for NIDS was private households in all nine provinces (Figure 6.1) and residents in worker's hostels, convents, and monasteries. The sampling frame excludes other collective living quarters such as students' hostels, old age homes, hospitals, prisons, and military barracks. The sample of PSUs for NIDS is a subset of the Master sample. The explicit strata in the Master sample are the 52 districts councils (DCs). The NIDS sample was proportionally allocated to the strata based on the Master DC PSU allocation. A total of 400

PSUs were randomly selected across the 52 strata (each stratum is allocated a certain proportion based on the master sample. The proportion allocated to each stratum determines the number of NIDS clusters randomly selected from within it, a total of which sums to 400 clusters over the 52 districts. This was the case for the first four waves. However, due to low baseline response rate among White and Indian neighbourhoods, additional top-up sampling was conducted in wave 5 to increase the number of white, Indian, and high-income survey participants and to ensure the sample was nationally-representative. A summary of average distribution of households per cluster is presented for each wave in Table 6.1.

In addition, the geographic location of each of the 400 clusters is known. It should be noted that all waves were calibrated by adjusting the survey design weight in each wave for the age-gender-race total population across the 52 districts resulting in the calibrated weights (with the oldest three age categories for Indian males and Indian females: 75-79, 80-84, & 85+, combined) (Chinhema et al., 2016). The calibrated weights were utilized for the cross-sectional analysis of the small area estimate of average systolic blood pressure in this study using the design-based and spatially smoothed design approaches. At the time that the Master Sample was compiled, 8 non-overlapping samples of dwelling units were systematically drawn within each PSU. Each of these samples is called a "cluster" by Stats SA. These clusters were then allocated to the previous surveys conducted by Stats SA between the period 2004 and 2007. However, two clusters in each PSU were never used by Stats SA and these were allocated to NIDS. We compare the distribution of the PSUs that are in the NIDS sample against those that are in the Master Sample in Table 6.2. It can be seen from the table that sample spread per province is quite similar between the two samples. Thus, the selected sample was deemed adequate.

Table 6.1. Summary of average distribution of households per cluster by Wave

Wave	Sample Size	Ave Household per cluster (std)	Range (min, max)	Total cluster (PSU)
2008	15,201	248(77)	17, 513	400
2010	16,324	249(78)	17, 513	400
2012	17.651	247(77)	17 ,513	400
2014/15	19.503	248(77)	17,513	400
2017	21.452	212(99)	6, 513	532

All resident household members at selected dwelling units were included in the NIDS panel, provided that at least one person in the household agreed to participate in the study. In addition, non-resident members that were not available at the time of the survey also became NIDS sample members. These two groups constituted the permanent sample members (PSMs). An initial sample of 9600 households was drawn with the expectation of realizing 8000 successful interviews. However, a response rate of 69% (7305 out of 10,642 households visited) was achieved in the first wave and varied from 76% in Black Africans households to 36% in Whites households. Three types of non-response are noted in the NIDS data – the household nonresponse, the non-respondents within responding households (with over 88% response at baseline) and item non-nonresponse (Chinhema et al., 2016).

Table 6.2. Comparing the distribution of the PSUs per province

	NIDS sample		Master sample	
Province	Frequency	Percent	Frequency	Percent
Western Cape	52	13.0	385	12.8
Eastern Cape	53	13..3	396	13.2
Northern Cape	27	6.8	207	6.9
Free State	31	7.8	245	8.2
Kwazulu-Natal	86	21.5	640	21.3
North West	35	8.8	259	8.6
Gauteng	48	12.0	353	11.8
Mpumalanga	30	7.5	233	7.8
Limpopo	38	9.5	282	9.4
RSA	400	100	3000	100

(Source: Chinhema et al,2016- NIDS User panel manual)

A key issue with such survey is the loss to follow up of survey participants between waves, a phenomenon known as attrition. In NIDS, attrition between waves is defined by comparing the number of successful interviews in a wave to the number preceding wave. The sample used to determine attrition contains those respondents that are present in both waves and alive at the beginning of the wave of interest. Reasons for attrition include refusal to participate in the survey (most common among Whites and Asians), non-contact of a participant (not tracked, not located or moved outside South Africa), a common reason among Africans. In addition, a

participant in previous wave(s) may be deceased at the beginning of the next wave. The population groups with the highest attrition rates were White and Asian/Indian respondents. A summary of the attrition rate for the NIDS is presented in Table 6. 3 below

Table 6.3. Reasons for Attrition.

	Reason	Refusal	Non-Contact	Deceased	Total
Wave 2	Number	2425	2890	876	6191
	Percent	39	47	14	100
Wave 3	Number	2481	2276	708	5465
	Percent	45	42	13	100
Wave 4	Number	2294	2400	882	5576
	Percent	41	43	16	100
Wave 5	Number	3481	3040	784	7305
	Percent	48	42	11	100

(Source: NIDS Panel User Manual, Release 2018: version 1)

6.2.2. Sample weights calculation in NIDS survey data

This is essentially a two-stage procedure. In the first stage, the design weights were calculated as the inverse of the probability of inclusion. In the second, the weights were calibrated to the midyear population estimates for the respective waves. Two sets of wave specific weights are thus provided, the design weights and the post-stratification weights (Leibbrandt et al., 2009). The basis for the calculation of the design weights is a two-stage sampling process from the Master sample. Two sets of calculations were necessary in deriving the design weights. First, there is a calculation of the probability of sampling each PSU, and second, is the probability of inclusion of each household in each PSU in the NIDS sample (corrected for household nonresponse). The second set of weights are the post-stratification weights. These weights adjust the design weights such that the age-sex-race marginal totals in the NIDS data match the population estimates produced by Stats SA for the mid-year Population estimates for each year (Leibbrandt et al., 2009).

Furthermore, a constraint was imposed that the population distribution by provinces should correspond to that released in those population estimates and that the total weights should add

up to the estimated total population, for instance, 48,687,000 for 2008. A final constraint of constant weight within households was imposed, hence persons from the same household have the same weight. The third type is the panel weights which adjusted for both individual and household characteristics that are predictive of attrition and has been rescaled to sum to the population total since the last wave. It is important to note that a sample top-up was conducted in wave 5 (2017) to correct for the low response rate among Whites and Indian households in previous waves (Leibbrandt et al., 2009). For the purpose of the SAE study, we considered the calibrated weights and the calibrated weights (with top-up sample for wave 5). Given that blood pressure varies with age, gender and race, the use of calibrated weights is more likely to accurately measure the mean estimates for target small areas.

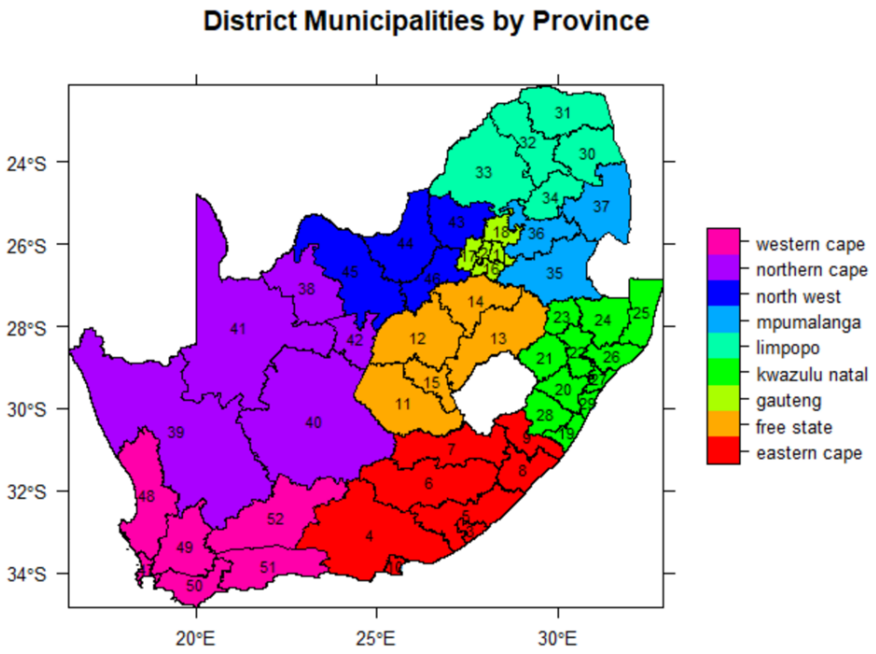


Figure 6.1. Geographic distribution of the 52 District Municipalities in South Africa by Province.

District names: 1-Ekurhuleni, 2-City of Johannesburg, 3-Buffalo City, 4-Cacadu, 5-Amathole, 6-Chris Hani, 7-Joe Gqabi, 8-O.R.Tambo, 9-Alfred Nzo, 10-Nelson Mandela Bay, 11-Xhariep, 12-Lejweleputswa, 13-Thabo Mofutsanyane, 14-Fezile Dabi, 15-Mangaung, 16-Sedibeng, 17-West Rand, 18-City of Tshwane, 19-Ugu, 20-Umgungundlovu, 21-Uthukela, 22-Umzinyathi, 23-Amajuba, 24-Zululand, 25-Umkhanyakude, 26-Uthungulu, 27-iLembe, 28-Harry Gwala, 29-eThewini, 30-Mopani, 31-Vhembe, 32-Capricorn, 33-Waterberg, 34-Sekhukhune, 35-Gert Sibande, 36-Nkangala, 37-Ehlanzeni, 38-John Taolo Gaetsewe, 39-Namakwa, 40-Pixley ka Seme, 41-Z F Mgcawu, 42-Frances Baard, 43-Bojanala, 44- Ngaka Modiri Molema, 45-Dr Ruth Segomotsi Mompati, 46-Dr Kenneth Kaunda, 47-City of Cape Town, 48-West Coast, 49-Cape Winelands, 50-Overberg, 51-Eden, 52-Central Karoo

Table 6.4. Summary of Sample size and Coverage by Wave for the 52 Districts.

Wave	Sample size Mean (std)	Sample size Median (min, max)	Coverage Mean(std)	Coverage Median (min, max)
2008	324(106)	321(67,564)	0.00094(0.001)	0.00064(0.00013,0.00673)
2010	400(150)	393(96,744)	0.00109(0.001)	0.00076(0.00017,0.00696)
2012	414(155)	391(95,812)	0.00108(0.001)	0.00075(0.00017,0.00739)
2014/15	496(214)	477(116,1213)	0.00122(0.001)	0.00083(0.00021,0.00801)
2017	547(282)	480(150,1573)	0.00127(0.001)	0.00086(0.00027,0.00798)

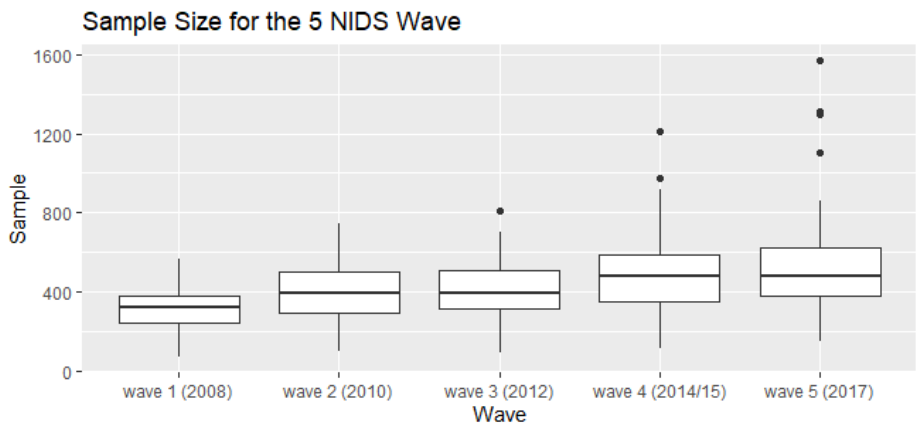


Figure 6.2. Boxplot Distribution of Sample size for the 52 Districts.

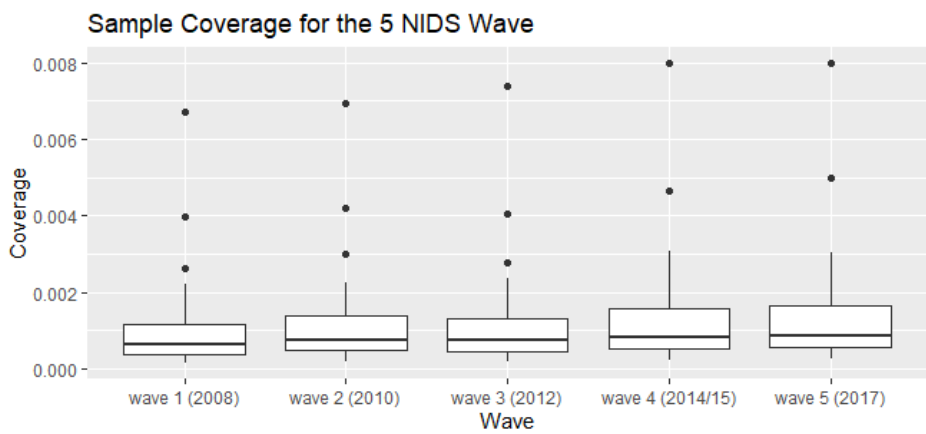


Figure 6.3. Boxplot Distribution of the Coverage for the 52 Districts.

6.2.3. Statistical methods

In this section, we describe the model formulation for the various SAE techniques considered to estimate the mean of blood pressure measurement at small area level for 5 NIDS waves. These include: the direct estimator (unweighted); direct estimator (design-based) as proposed by Horvitz and Thompson (1952); the spatially smoothed direct estimator (Wakefield et al., 2020) and the Hierarchical Bayes general linear and varying coefficient regression models (Datta and Ghosh, 1991). One important distinction between the direct methods and the HB models is the that the former considered the NIDS survey as a cross-sectional single time point data while the HB models account for the longitudinal design feature as well as the spatial and temporal correlation in the NIDS panel data. Each SAE approach is described below. The distributions of the sample size and coverage for the small area estimation study are summarized in Table 6.2 and Figures 6.2 and 6.3 above. In our SAE study, it is important to note that the number of participants was allowed to vary from one wave to another in the cross-sectional analysis (design-based and spatially smoothed design-based estimators). In contrast, the number of participants is assumed to be constant over waves in the longitudinal analysis.

6.2.3.1. Notation and overview

We will let s index the areal units for which estimation is required, with m areas in total. Assume there are N_s individuals in the population with responses y_{is}, $i = 1, \dots, N_s$, in area s. We let D_s represent the set of indices of the selected individuals in area s, with $n_s = |D_s|$ the number sampled in area s. In this case, n_s, is non-random given that the small areas of interest are the strata in the NIDS sample, which is the 52 districts. As target of inference, the empirical mean of the response value of a finite population characteristic, is described in equation 6.1 below:

$$m_s = \frac{1}{N_s} \sum_{i=1}^{N_s} y_{is} \tag{6.1}$$

Given the two-stage sampling design of the NIDS survey, a list of households in each selected 400 PSUs was constructed, usually by mapping the cluster and listing every household within the cluster. A fixed number of households are then drawn using simple random sampling (SRS)

6.2.3.2. Small Area Estimation Methods

6.2.3.2.1. Direct Estimator (observed data)

We also considered a direct estimator from the observed data for each area, that excludes the sampling weight. This estimate was included for comparison with model-based based HB methods which similarly do not account for the sampling design. It also provides a basis to evaluate by how adjusting for the calibrated weight change the estimates. Hence, we assume sampling weight free estimate for individual i living in household j in turn nested in cluster k within area s, whose response is y_{ijks} is given as:

$$\widehat{m}_s = \frac{\sum_i \sum_j \sum_k y_{ijks}}{\sum_i \sum_j \sum_k n_{ijks}} \tag{6.2}$$

6.2.3.2.2. Design-based Estimator (weighted observed data)

A key element in the direct(design-based) approach to inference are the design weights (Rao, 2003). Design weights are the reciprocal of the inclusion probabilities for every sampled individual (nested within a household and in turn within a district) that corresponds to the number of persons in the general population a sampled individual represents in the survey. This ensures the data is adequate to infer population characteristics of interest using appropriate statistical procedures. A direct estimate of a quantity in a specific area and time only uses data on the variable of interest from that area and time period. In this case, we assumed that strata correspond to the small areas of interest (the 52 DCs in South Africa) and that the weights are simply the reciprocal of the inclusion probabilities which are already included in the NIDS data. For the purpose of cross-sectional analysis of the NIDS sample, we considered the calibrated weights which ensures the sample was representative of the age, sex, and race structure of the total population at each time point. We index the areas by s, and let w_{is} be the design weight associated with individual i living in household j in cluster k in area s, whose response is y_{ijks}. Within area s, the design-based estimator is given in equation 6.3 below:

$$\widehat{m}_s^{(HT)} = \frac{\sum_i \sum_j \sum_k w_{ijks} y_{ijks}}{\sum_i \sum_j \sum_k w_{ijks}} \tag{6.3}$$

Where $w_{ijks} = {}^{1}/_{\pi_{ijks}}$, satisfies the design unbiasedness and consistent condition and leads to the well-known Horvitz-Thompson (H-T) estimators (Rao, 2003). And its variance estimates may be calculated using Jackknife or bootstrap estimation procedure. The design-based small area mean, and the associated variance of estimates are both design unbiased and consistent. However, model-based enthusiasts have criticized on the grounds that the associated inferences, although assumption-free, refer to repeated sampling instead of simply the sample that has been drawn.

6.2.3.2.3. Spatially-smoothed Design-based Estimator

In this section, we consider a formulation in which the estimated design-based small area mean of systolic blood pressure (SBP|) was spatially smoothed to stabilize excess variance between the areas well as unobserved spatially structured effect of unobserved risk factors. This approach to model-based adjustment to the design-based estimator was first proposed by Wakefield et al.(2020b). We considered the discrete spatial model, using a revised parameterization of the convolution model proposed by Riebler et al. (2016). as specified below:

$$\widehat{m}_s^{(smoothHT)} = \widehat{m}_s^{(HT)} + {}^{1}\Big/_{\sqrt{\tau_d}}\left(\sqrt{1-\emptyset}\boldsymbol{v} + \sqrt{\emptyset}\boldsymbol{u}\right) \tag{6.4}$$

where $\boldsymbol{v} = (v_1, \dots, v_s)$ and $\boldsymbol{u} = (u_1, \dots, u_s)$ are spatially unstructured and spatially structured random effect components (Besag et al., 1991) . τ_d is the overall variance parameter for d. The precision parameter τ_d>0 controls the marginal variance contribution of the weighted sum of the spatially unstructured and spatially structured effects. The mixing parameter $0 \leq \emptyset \leq 1$ measures the proportion of the marginal variance explained by the spatially correlated effect u_s. We considered a penalized complexity(PC) prior (Daniel Simpson et al., 2017) for both the spatial dependence parameter $\emptyset$ and the precision parameter. The PC priors provide a simple yet powerful and interpretable framework to evaluate evidence of support for a more flexible model over a simple model known as the base model. The PC priors obey the principle of parsimony and thus favours the simpler model unless sufficient exist to favour the more complex model. Transformation of the prior back to the original parameter scale ensures interpretability of the posterior estimates, a key advantage over the Besag formulation.

Therefore, unlike the convolution model(Besag et al., 1991) with a single parameter (precision), the convolution model with penalized complexity prior has two components: the precision and an additional spatial dependence parameter denoted as $\emptyset$ in equ(8) above. It is important to note that priors are assigned to "distances" between the base and flexible models, rather than to the parameters while the increased complexity introduced by the flexible model is evaluated using the Kullback-Leibler Discrepancy (KLD) (Simpson et al., 2017)

To specify the PC prior, we considered the probability statement $P\left(\left(\frac{1}{\sqrt{\tau_s}}\right) > U1\right) = \alpha 1$ and $P(\emptyset > U2) = \alpha 2$, where $U1$ and $U2$ are the upper bounds of the precision and spatial dependence parameters respectively (in this case $U = 1$) while $\alpha 1$ and $\alpha 2$ are the probability weight imposed on the priors. (in this case we set $\alpha = 0.01$).. Following Wakefield et al.(2020c), for the overall precision parameter in the spatially-smoothed model, we set $U1 = 1$ and $\alpha 1 = 0.01$ which gives a corresponding prior probability of 0.99 of having residual odds ratios smaller than 2. For the spatial dependence parameter, we set $U2 = 0.5$ and $\alpha 1 = 2/3$, which corresponds to a 67% chance that more than 50% of the total variation of the district random effect has spatial structure. Additional details for the derivations of the PC prior for the reparametrized convolution model can be found in Riebler et al.(2016). The log precision τ_d has a prior distribution of $\log(\tau_d) \sim \mathrm{pc.prec}(1,0.01)$ and $\emptyset$ was assigned $\mathrm{logit}(\emptyset) = \mathrm{pc}(0.5,0.67)$. (Wakefield et al., 2020).

A sum to zero constraint was applied to the ICAR term for identifiability purpose. We compared the geographic distribution of mean SBP obtained from the spatially smoothed design-based approach to the design-based (HT) estimates.

We implemented the direct estimation approaches in the R programming environment and obtained weighted estimates and variances, and coefficient of variation, for the small areas using the survey package (Lumley, 2004). In addition, the spatially smoothed model was implemented using the SUMMER package (Li et al., 2019) and using the INLA to obtain fast computation of model parameters via Bayesian inference procedure (Rue et al., 2009).

6.2.3.2.4. Unit-level Hierarchical Bayes Longitudinal approach

In this section, we proposed a hierarchical Bayes (HB) approach to produce small area estimates of average systolic blood pressure (SBP) from a double measurement at each repeated time point of a longitudinal survey data. Therefore, in contrast to the cross-sectional analysis of the NIDS survey data considered in the direct and smoothed-direct approaches in the previous sections, the objectives of the HB longitudinal model formulation are to acknowledge the double measurement of SBP on each individual at each wave and also account for the longitudinal design features of the observed data – i.e., repeated SBP measurement over time for sampled members of the South African adult population. In addition, a comparison of the NIDS data to the DHS data (examined in the previous chapters) reveals some important commonalities and differences. While both survey data are obtained at repeated time point, the DHS is cross-sectional panel in design (different individuals were sampled at each time point), while NIDS is a repeated longitudinal panel (individuals were followed up every two years on average once enrolled in the survey). Also, while both surveys obtained geographically referenced data at subnational level, the DHS is designed to be representative at regional level (first administrative level) while the NIDS is representative at the district level (second administrative level defined as the small area of interest in this study).

In addition to these key distinctions between the two surveys, the NIDS exhibits data sparsity problem at spatially disaggregate level of small area of interest (district municipality) given that less than 0.1% of the population in each area(district) were sampled (Table 6.4). This presents a unique challenge to obtaining reliable small area estimate using direct approaches. Therefore, we propose a unit-level model-based approach to obtaining reliable small area estimates (SAE) for double measurement of SBP from a longitudinal panel survey data using a HB approach. In subsequent section, we describe a Bootstrap method to quantify the uncertainty interval associated with the small area mean. While the HB mixed effect model formulation has been shown to be well suited for producing SAE as reviewed in the previous sections above, the unique features of our proposed model formulation is the estimation of the average blood pressure from a repeated measurement at each specific time point from the panel data and a bootstrap approach to quantify associated uncertainty interval.

6.2.3.2.4.1. The Repeated Measurement Hierarchical Bayes Linear Mixed Model

The model formulation for the proposed repeated measurement HB linear mixed model (RM-LMM) follows the classical three-stage model specification – the observed data or likelihood model, the process model and the parameter model (Haining & Li, 2020). In the first stage, we specified the likelihood model for the observed SBP repeated double measurements y_1 and y_2 for individual i at time point(wave) t. We assumed y_1 and y_2 are independent realizations of a normal random variable Y which denotes the true SBP value for each individual at specific time point, with common mean μ_{it} and variance σ_y^2 as presented in equation 6.5 below:

Stage 1: Observed data model

$$y_{1,it}|\mu_{it};\sigma_y^2 \sim N(\mu_{it},\sigma_y^2) \qquad (6.5)$$
$$y_{2,it}|\mu_{it};\sigma_y^2 \sim N(\mu_{it},\sigma_y^2)$$

Where: $i =$ person indicator ($i = 1, \dots, N$); $t =$ wave indicator ($t = 1, \dots, T$); $\mu_{it} =$ structural term on which a number of models can be specified; and $\sigma_y^2 =$ which accounts for the empirical variability of the two SBP measurements for all persons over the study time period. This was estimated by obtaining the standard deviation (SD) of the difference between the two measurements. Attempt to estimates this variance jointly with other model parameters resulted in non-convergence of the model. We note that this might be due to the fact that variance estimation for the distribution of two set of measurements may be particularly challenging within a Bayesian framework. Nevertheless, we acknowledge that the choice of plugging in a value for the measurement error variance ignores the uncertainty of this parameter. But given that this single variance parameter is estimated using a lot of measurements over the waves and the national representativeness of the survey sample, this uncertainty is expected to be small.

In the second stage, we specified the process model along with the priors for the model parameters. Throughout the model formulation, we assigned diffuse priors to model parameters to ensure that posterior inferences are primarily derived from the sampled data (Haining & Li, 2020). Specifically, a normal distribution with zero mean and large variance (1000000) is used as a vague prior for the fixed effects parameters (global intercept and slope). The Gamma distribution, which is the inverse of the variance, with parameter values of 0.001 – Gamma (0.001,0.001) is assigned to the precision of the random intercept. We considered the Gamma distribution given that the support of a Gamma distribution prior and posterior is on the positive

real line, a feature that satisfies the requirement of a variance parameter, which must be strictly positive.

As a proof of concept, we considered a random intercept repeated measurement HB linear mixed model in which the underlying mean which the two SBP measurements attempt to capture is specified as a linear function of an overall population average intercept and slope denoted as γ_0 and γ_1, and individual-specific intercept b_0 and residual measurement error e_{it} with zero mean Gaussian error and variance σ_e^2 as presented below:

Stage 2: Process model $$\mu_{it} = \gamma_0 + \gamma_1 * (t-1) + b_{0i} + e_{it} \quad (6.6)$$

Prior Specification

$$\gamma_0 \sim N(0,10000001)$$
$$\gamma_1 \sim N(0,10000001)$$
$$b_{0i} \sim N(0, \sigma_{b0}^2)$$
$$e_{it} \sim N(0, \sigma_e^2)$$

Where: $\gamma_0 =$ population average SBP at baseline for the entire South African adult population assumed to be normally distributed with a diffuse prior

$\gamma_1 =$ population average change in SBP between the study period assumed to be normally distributed with a diffuse prior

$b_{0i} =$ individual -specific random intercept assigned an exchangeable Gaussian prior with mean 0 and variance σ_{b0}^2. By exchangeability here, the assumption is that each of the individual-specific random intercept parameters $b_{01}, \dots, b_{0N}$ follows a common prior probability distribution. However, the parameters of this common prior distribution ae unknown and are therefore assigned a hyperprior (eq 11)

$e_{it} = r$esidual measurement error in estimating the true mean SBP with a zero mean Gaussian prior and variance σ_e^2

In the third stage, we specified the parameter mode in which the prior variance hyperparameters for the random intercept and residual error are specified inverse variance (precision).

Third stage: Parameter model $$1/_{\sigma_{b0}^2} \sim Gamma(0.001,0.001) \quad (6.7)$$

$$1/_{\sigma_e^2} \sim Gamma(0.001,0.001)$$

6.2.4. Parameter estimation for the RM-LMM

Given that it is not feasible to draw independent samples from the joint posterior densities of the model parameters because the denominator is intractable, we implemented Markov Chain Monte Carlo (MCMC) Simulation method using the Gibbs sampling algorithm (Gelfand & Smith, 1990; Geman & Geman, 1984) to estimate model parameters within WinBUGS. Two MCMC chains were constructed with different initial values and subsequently executed for a total of 80,000 MCMC iterations thinning every 10th iteration to ensure convergence and efficiency of the MCMC samples. Convergence, (as evaluated by diagnostic history plot and the Brooks-Gelman-Rubin (BGR) summary statistic), was attained after the first 5000 iterations and were discarded as burn-in while the remaining 75,000 samples were utilized for posterior inference. To assess efficiency, we considered the Monte Carlo standard error (defined as the standard error of the mean based on the MCMC samples as an estimate of the true posterior mean). The efficiency for a parameter is met when the MC error is less than 5% of the posterior standard deviation of that parameter. Results showed a general pattern of convergence (BGR=1 for all parameters) and efficient sampling (MC error <5% for all model parameters with a few parameters at the borderline of 5%). Individual-specific predicted mean estimates from the random intercept repeated measurement HB linear mixed model were further compared with the observed average values as shown in Figure 6.4 to 6.6 below.

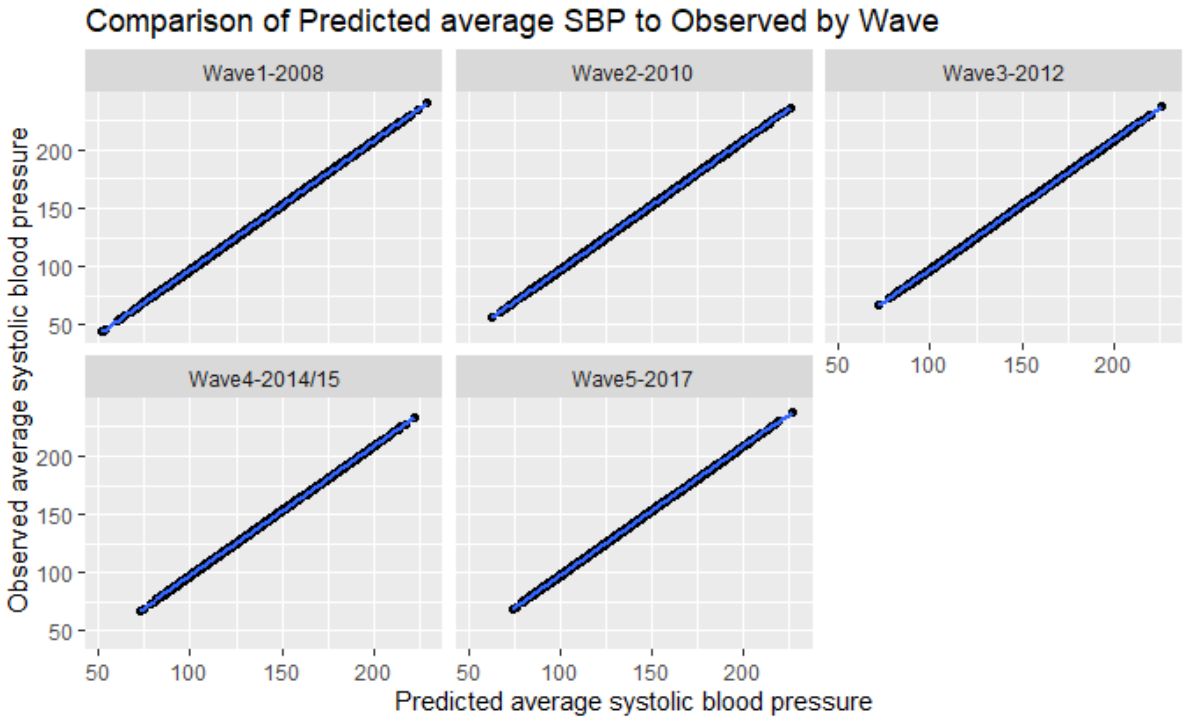


Figure 6.4. A comparison of the Predicted average Systolic Blood Pressure to the Observed data by NIDS Wave.

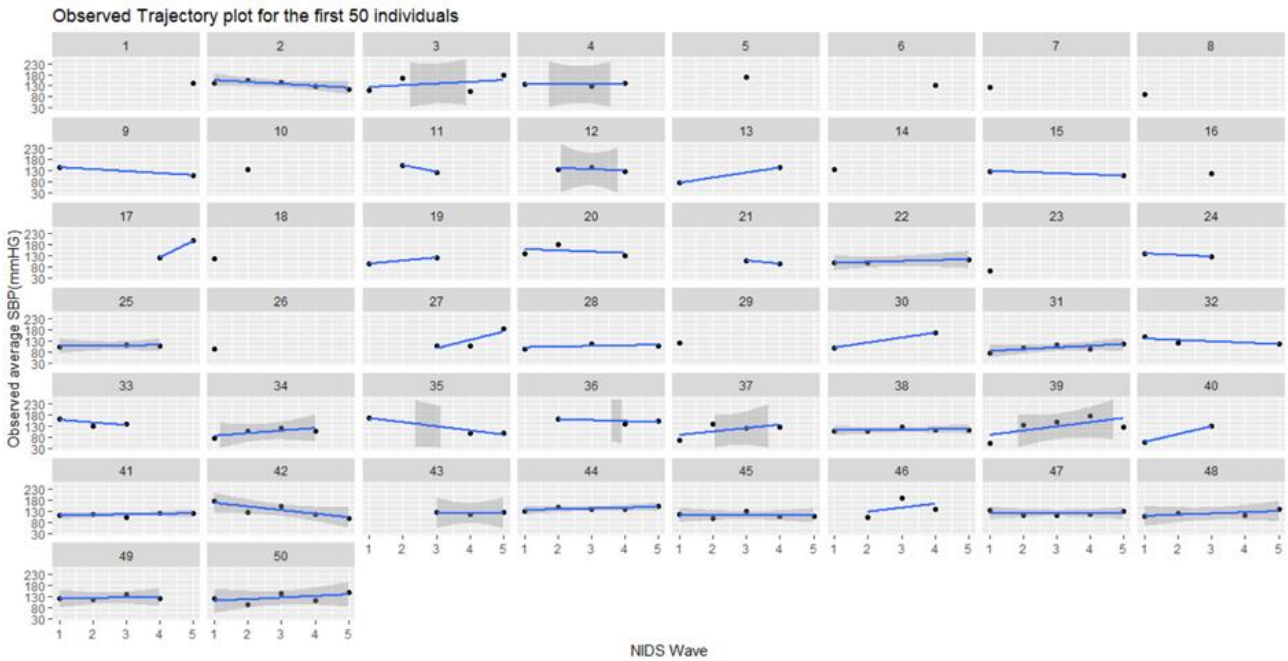


Figure 6.5. Observed Trajectory for the first 50 individuals in the sampled population.

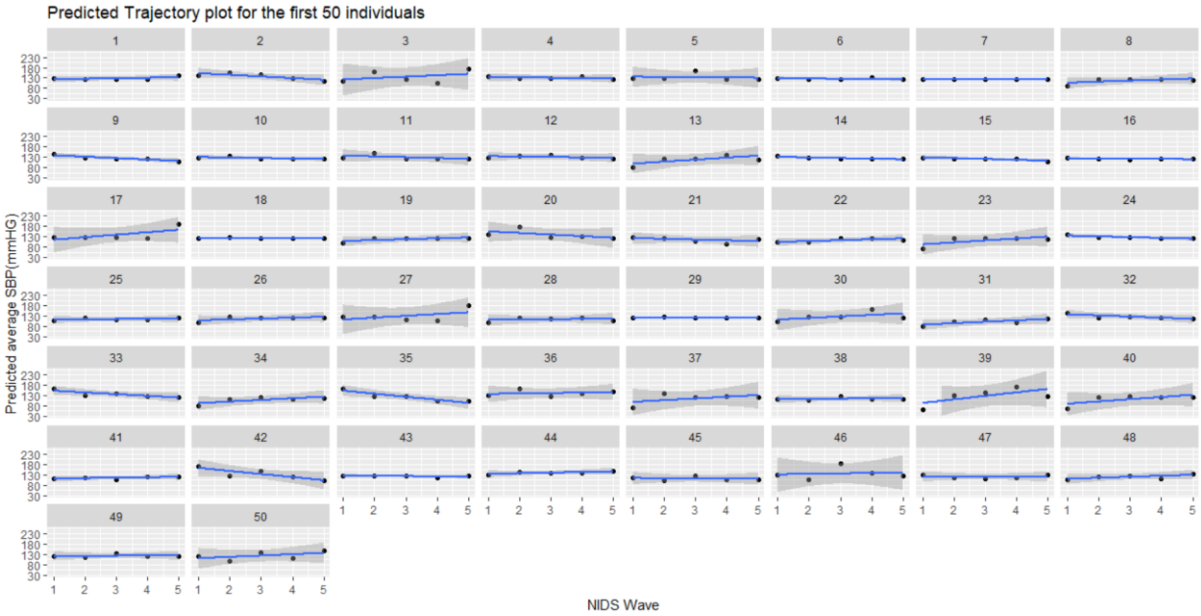


Figure 6.6. Predicted Trajectory for the first 50 individuals in the sampled population.

6.2.5. Prediction of Small Area Average Systolic Blood Pressure (SBP)

The next objective is to obtain prediction of small area mean for SBP at each time point from the estimated parameters of the random intercept repeated measurement HB linear mixed model. The SAE values were obtained by predicting the corresponding value for all non-sampled members of the total population within each small area. The small area mean μ_s in a given area, is defined as the conditional mean given the random area effects (Battese et al., 1988). That is $\mu_s = E[Y_s|u_s]$. Therefore, the goal is to predict the values of unobserved random variables (non-sampled individuals) based on some realized values (sample individuals) at separate time points. Estimating the small area means is equivalent to predicting small area means of non-sampled members of the target South African adult population, given the observed data and additional auxiliary information if available at area or unit level (Rao, 2003). Following (Battese et al., 1988; Datta & Ghosh, 1991; Ngaruye et al., 2017), the target vector in small area s at each time point was estimated as a combination of the mean SBP for observed individuals and the predicted mean SBP for non-sampled individuals a shown in equation 12 below.

$$\hat{\mu}_s = \frac{f_s}{n_s} Y_s^{(1)} + \frac{1 - f_s}{N_s - n_s} \hat{Y}_s^{(2)} \tag{6.8}$$

$$= \frac{1}{N_s} Y_s^{(1)} + \left(\frac{N_s - n_s}{N_s} \times \frac{1}{N_s - n_s} \right) \hat{Y}_s^{(2)}$$

$$= \frac{1}{N_s} \sum_e \sum_{b_0} \sum_s \left(Y_s^{(1)} + (\hat{\beta}_0^{(2)} + \hat{\beta}_1^{(2)}) \right)$$

Where $\sum_e$ and $\sum_{b_0}$ both denote the summation of the residual error and individual-specific random effects respectively; $Y_s^{(1)}$ denotes the observed sample individuals, $\hat{Y}_s^{(2)}$ represent the predicted values of non-sampled individuals, and f_s is the population fraction of sampled to non-sampled individuals for the small area ($f_s = \frac{n_s}{N_s}$).

We now describe the Bootstrap procedure to produce the small area estimates for the mean SBP among South African adults 18 years and older across the 52 Districts municipalities.

Step 1

Fit a random intercept and global slope hierarchical Bayes model.

Step 2

As a next step, obtain the Bayesian posterior mean and standard deviation for the following model parameters –

I) the population average baseline value (125.7mmHG) along with the standard deviation of the mean (0.15) and the variance of individual deviation from the population mean(3.63). From the extracted parameters, obtain a simulation of the baseline average for the non-sampled population using a normal distribution with mean 125.7mmHG and standard deviation of 3.78.

II) the population average change in SBP trajectory between 2008 and 2017(-1.27mmHG) along with the standard deviation (0.06). A global average change is then simulated from a normal distribution with mean -1.27mmHG and a standard deviation of 0.06.

III) the variance of the residual measurement error (20.30) combined with the empirical standard deviation of the difference between the two measurement pairs from the sampled population (9.60). We subsequently, obtained the simulation of

distribution of the error variance from a zero mean Gaussian distribution whose standard deviation is a sum of the estimated residual error standard deviation and the empirical standard deviation difference of the two measurement (29.90)

Step 3: Using the parametric Bootstrap Procedure, simulate the SBP measurement value for an unobserved individual i in each area s at time t (where t=1,…,T) using the model parameters from step 2.

Step 4: Predict the trajectory for this individual for the period T time points under study.

Step 5: Store the predicted trajectory and repeat steps 3-5 to obtain predicted trajectory for non-sampled individuals in each area ($N_s - n_s$).

Step 6: Combine the predicted values of non-sampled units ($\hat{Y}^{(2)}$) with sampled units ($Y^{(1)}$) to obtain the small area mean estimates for each district(n=52).

6.2.6. Computation of Predicted intervals using Bootstrap Simulation

Following the prediction of small area estimate for the average SBP value from the random intercept HB linear mixed model, we obtained a measure of precision of the estimates using Monte Carlo simulation technique. Obtaining the credible interval is a necessary step given that the SBP values of non-sampled individuals was generated from a single observed event. Estimating the confidence interval therefore enable us to assess how estimates would differ between samples from the same population. In other words, we want to know the variability of the average SBP estimates in the population. We quantified the variability by estimating the standard deviation and the 95% credible interval over 50 simulations.

6.3. Results

6.3.1. Results of hierarchical Bayesian Linear Mixed Model

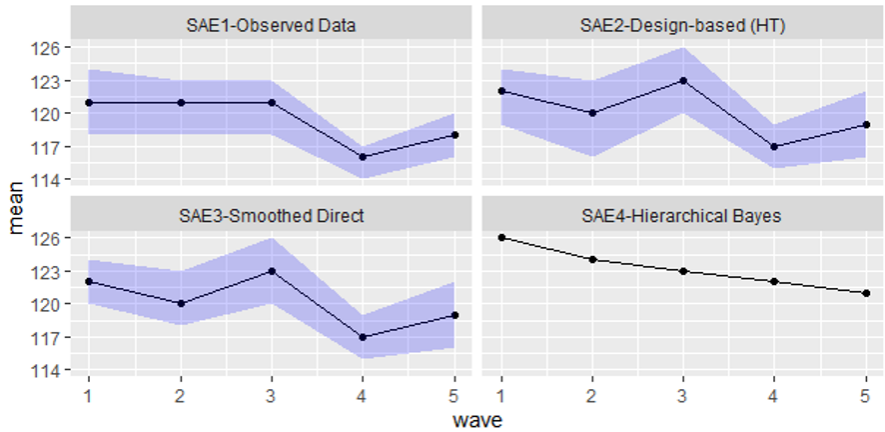
Results of the random intercept repeated measurement HB linear mixed model showed evidence of an overall significant reduction in systolic blood pressure among South African adults between 2008 and 2017. On average, a decrease of 1.37mm Hg (95%CI: -1.44 mm Hg,

-1.21mm Hg) was observed every two years. A population baseline average of 126.1 mm Hg (95%CI: 125.5 mm Hg, 126.7mm Hg) was also observed in 2008.

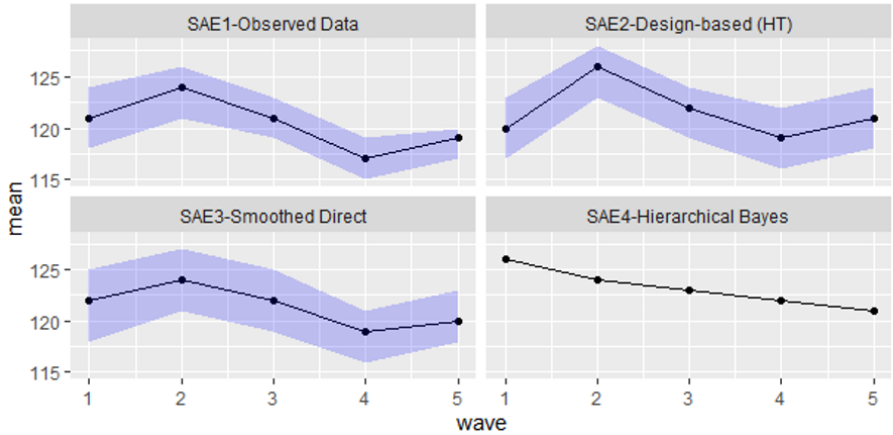
6.3.2. Comparison of SAE for Direct, Design-based, Smooth-Direct and RM-LMM

A complete result of the small area estimates obtained from the four methods along with variance estimation is presented in appendix A (Table A6.1-A6.4). The first three estimation approaches are based on cross-sectional analysis of the data. In other words, the assumption here is that each wave is nationally representative of the study population at the specific point. This assumption is in fact reasonable given that all waves were calibrated to the total population adjusted for age, sex and race structure within the population at the provincial level. The results from the Tables and the preliminary temporal trend plot (Figure 6.5) showed a pattern of similarity in estimates for the direct, design-based and spatially smoothed direct estimates. The model-base HB linear mixed effect model provides a linear estimation of similar trend across all districts (as shown in Figure 6.4). In other word, the model assumes that the mean change in SBP was the same across all the districts. This linear trend assumption, however, only provides a very preliminary basis to consider more complex and realistic HB linear mixed models that can better model the complexity in the data and account for trend across the districts. In addition, the linear mixed model in Figure 6.4, showed a very narrow 95% uncertainty interval (<1 in most cases). This further reflects the inadequacy of the random intercept linear mixed model to capture the uncertainty of the estimate and therefore requires the need to consider accounting for other important parameters including random slope, correlation between the random intercept and random slopes and the area level random effects and or spatial/temporal correlation.

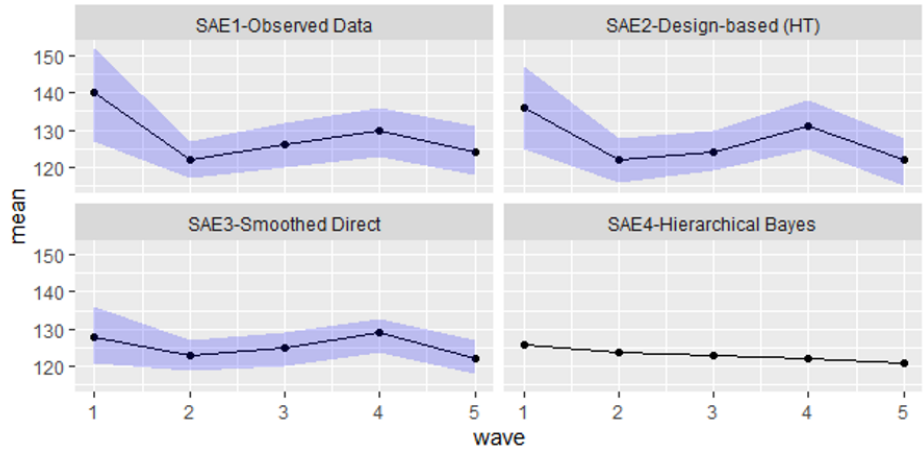
District 1 - Ekurhuleni



District 2 - City of Johannesburg



District 3 - Buffalo City



District 4 - Cacadu

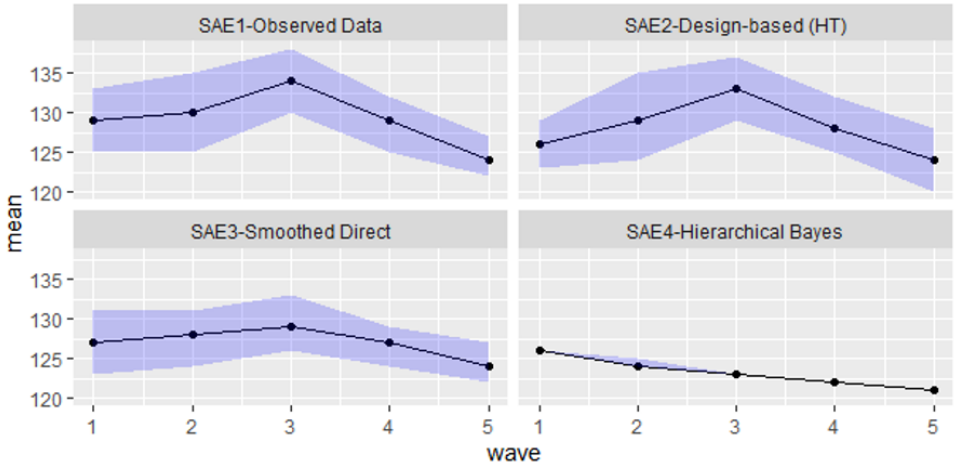


Figure 6.7. Local trend plots of average systolic blood pressure in South African Adults for the 52 districts from the observed, direct, smoothed direct and HB random intercept linear mixed double measurement model.

6.3.3. Comparison of Geographic pattern of small area Mean for Design-based and Spatially smoothed design-based Estimators

In this section, we compared the geographic distribution of small area estimates of average SBP derived from cross-sectional analysis of the NIDS surveys for two estimators. These are the designed-based estimates and spatially smoothed designed based estimates. Here, the objective was to evaluate geographic patterns and variation in the distribution of average SBP across the 52 district municipalities at each separate time point namely 2008, 2010,2012, 2014/15 and 2017. Both estimation methods revealed a general pattern that partitioned the entire study region into cluster of districts with elevated mean SBP in the southern part of the country and a cluster of districts that consistently showed low average SBP value across the 5 survey waves. Evidence of smoothing (observed as moderate reduction in estimated means) was found across the directs most especially in districts with elevate mean SBP (>30mmHG) as shown in Figures 6.5 to 6.9 below and Appendix 6A. Table A2 and A3.

Average SBP was generally lowest in 2017 across all districts. Between the study period (2008 to 2017), the most significant reduction (as assessed by non-overlapping 95% confidence interval in the spatially-smoothed estimates) was observed in Frances Baard, Pixley ka Seme, Uthukela, Umzinyathi, Nkangala, and Sedibeng (Table A6.3).

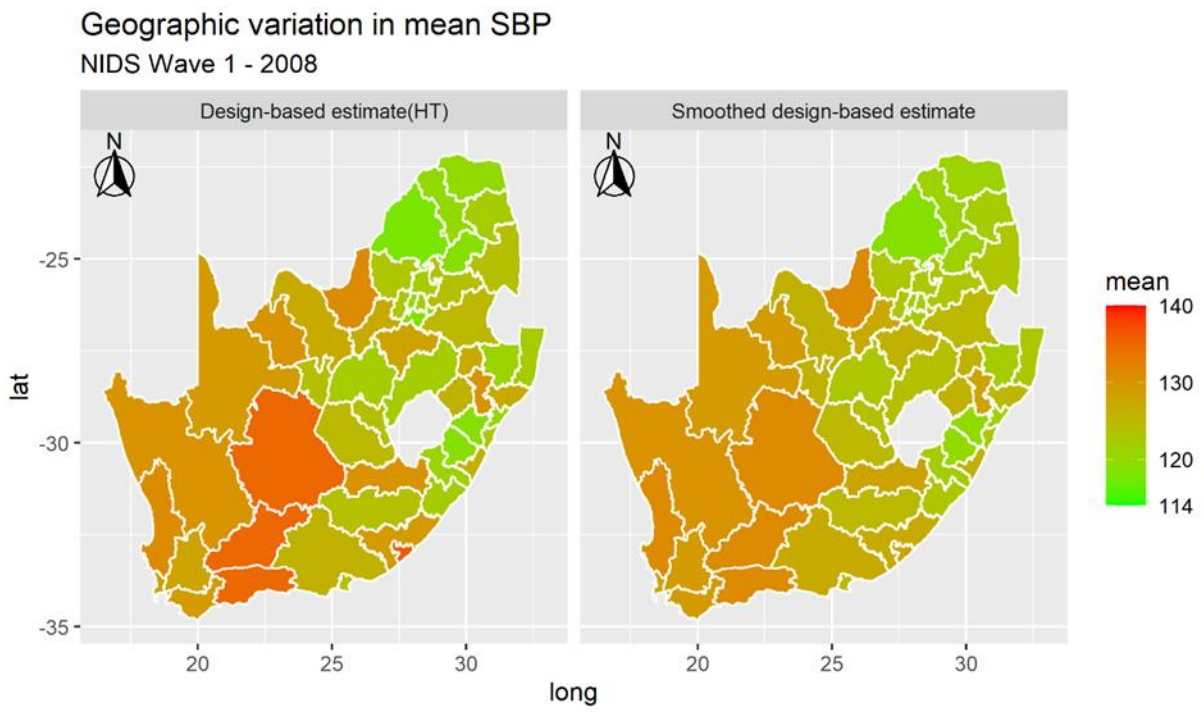


Figure 6.8. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially-smoothed direct estimates for the 2008 NIDS Wave.

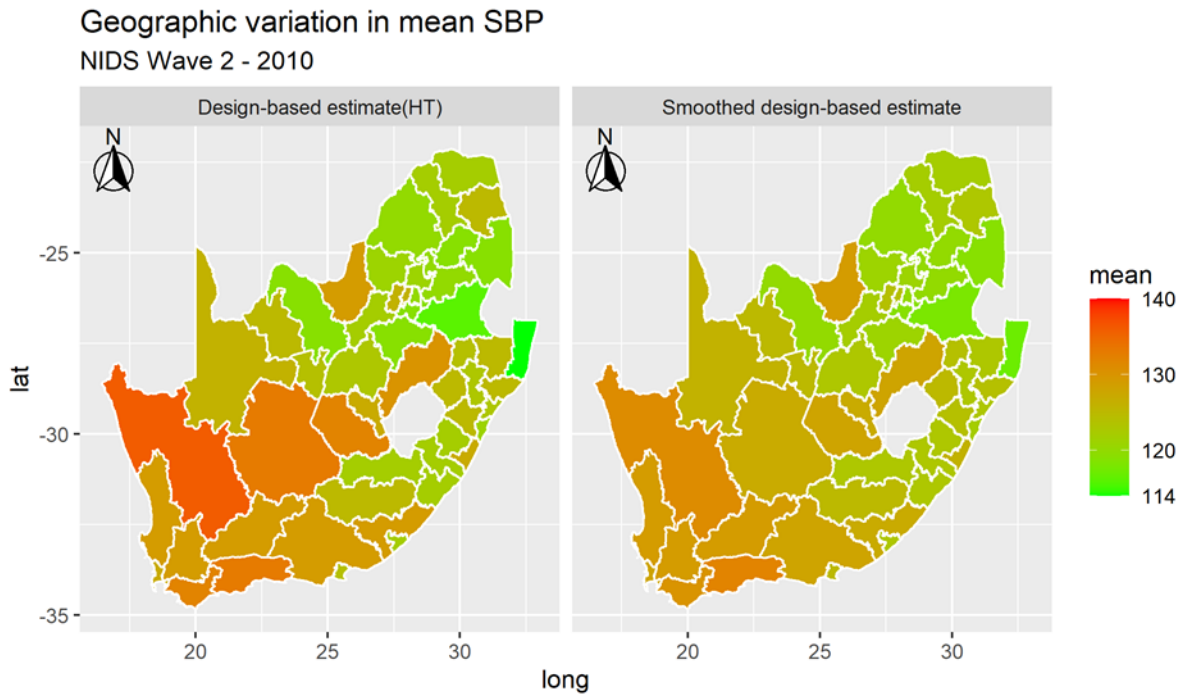


Figure 6.9. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially smoothed direct estimates for the 2010 NIDS Wave.

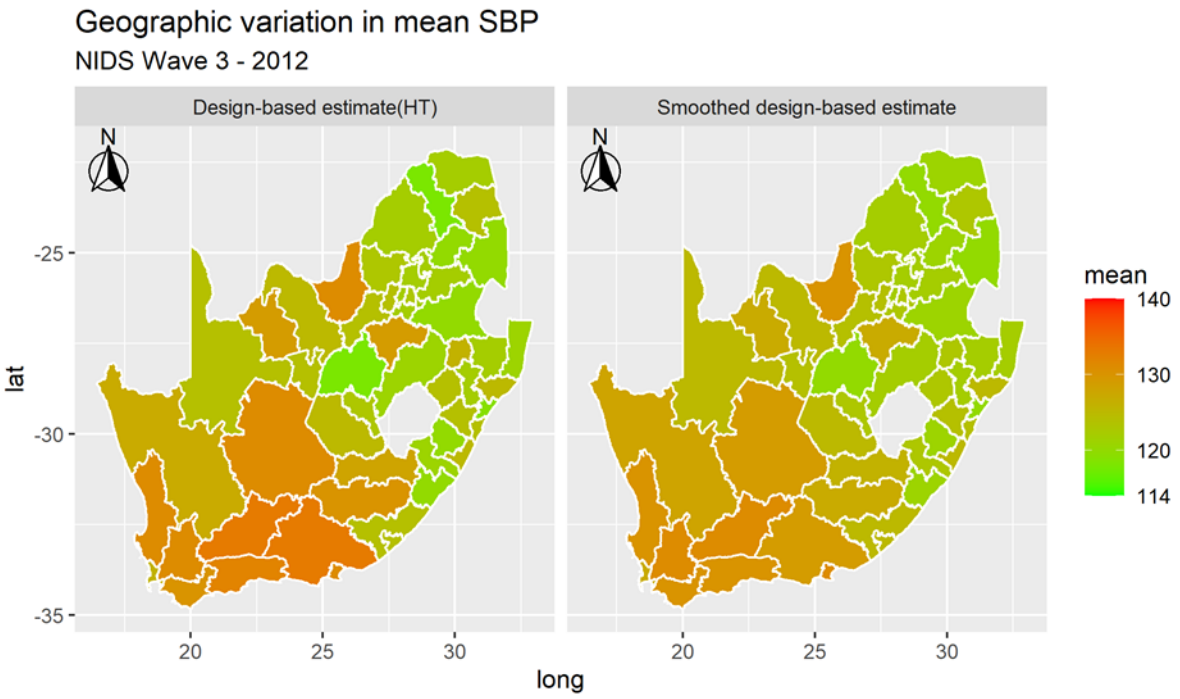


Figure 6.10. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially smoothed direct estimates for the 2012 NIDS Wave.

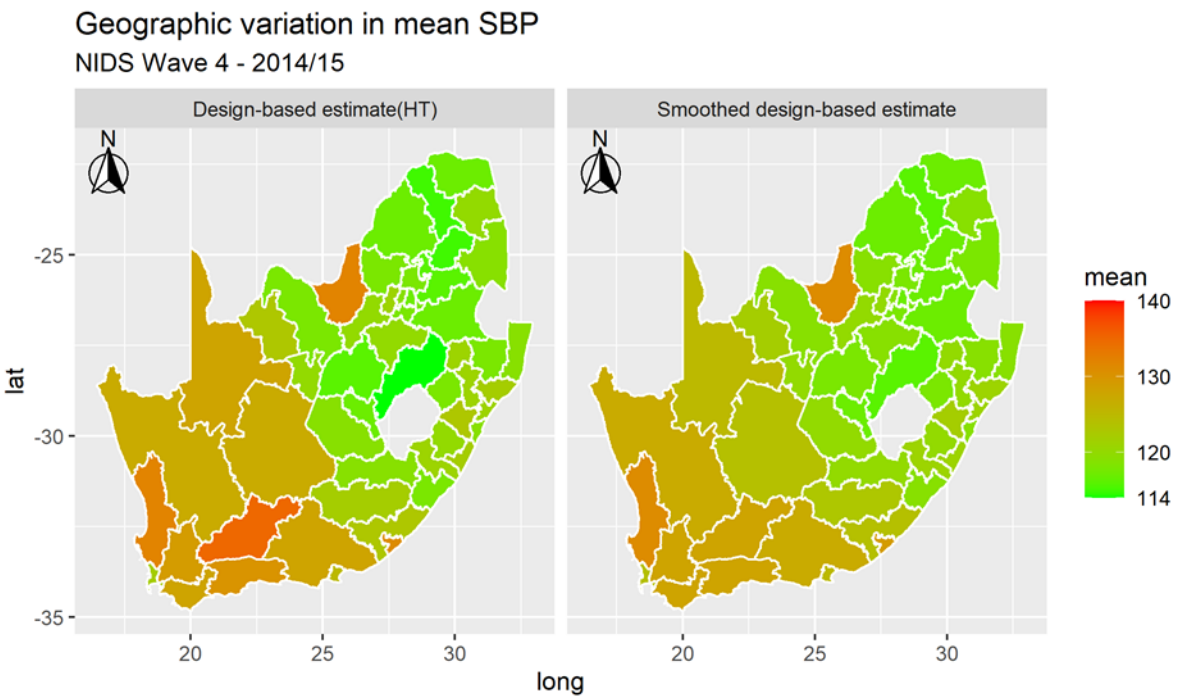


Figure 6.11. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially smoothed direct estimates for the 2014/15 NIDS Wave.

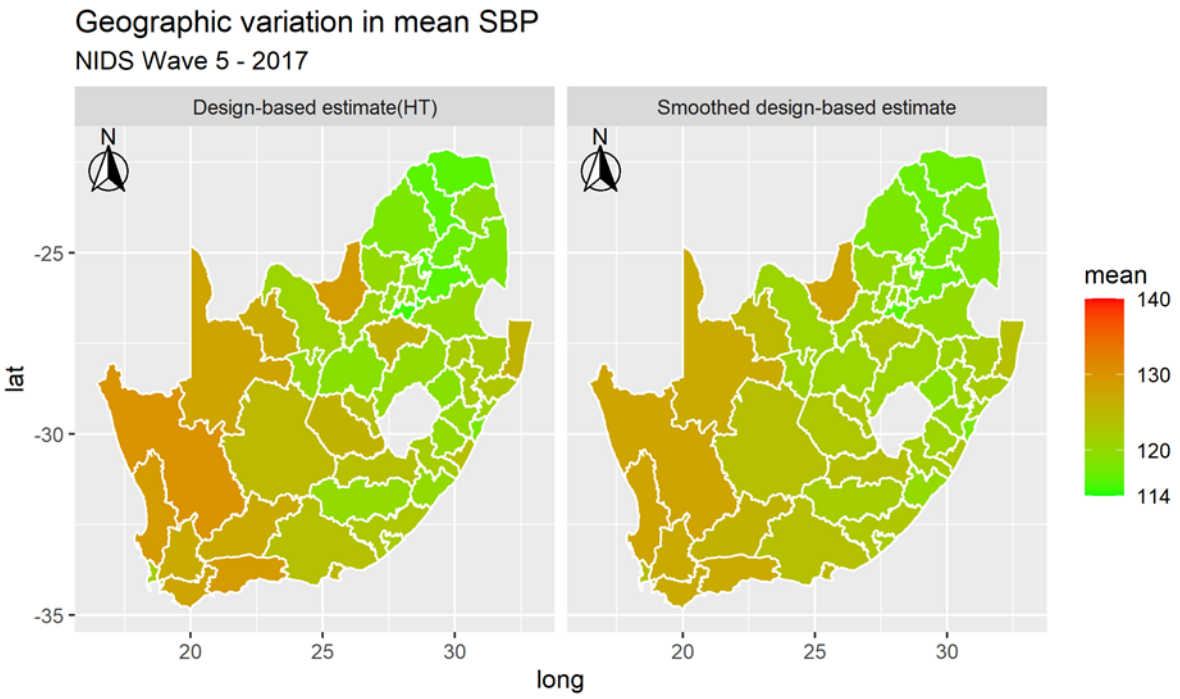


Figure 6.12. Geographic distribution of the mean systolic blood pressure from the Direct and Spatially smoothed direct estimates for the 2017 NIDS Wave.

6.4. Discussion

This study provides a starting point for future research to produce estimate of average systolic blood pressure in South African adults and to evaluate local trend at small area level using nationally representative complex cross-sectional and longitudinal surveys. However, findings of the Bayesian hierarchical linear mixed model revealed that on a global level, significant evidence of declining trend in the systolic blood pressure was observed among South Adults population between 2008 and 2017 (-1.18; 95%CI:1.25, -1.10).

In response to the growing burden of chronic diseases in South Africa, the government developed a strategic plan towards achieving significant reduction in the control and prevention by 2025. Two strategic documents have been developed, the first was to evaluate country progress between 2013 and 2017, and another strategic plan was released for the period 2020

to 2025 (DOH, South Africa, 2019). The two national strategic plans have three primary objectives: first, is the prevention of NCDs and promotion of health and wellness at population, community, and individual levels. Second is to improve control of NCDs through health systems strengthening and reform, and third is to monitor NCDs and their main risk factors and to conduct innovative research. Central to achieving all three objectives is the need to produce reliable small area estimates of blood pressure risk to understand geographic disparity in disease burden over time. This is a critical step to identify geographic hotspots of raised blood pressure, to monitor and evaluate performance trend and explore cost-effective options to deploy interventions at individual, household and community based on contextual profile.

In contrast to the pattern of declining trend observed in our study among South African adult, authors of recent studies of global and national trends in systolic blood pressure reported significant increase across countries in low and middle-income countries. For instance, a Lancet study by Danaei et al.(2011) assessed national, regional and global trend in systolic blood pressure from 1980 to 2008 for adults 25 years and older in 199 countries and territories. Findings showed a worldwide age-standardized mean SBP of 128.1mm Hg (95%CI:126.7-129.4) in men and 124.4mm Hg (123.0-125.9) in women. Both estimates are higher than observed in 2015 (mean: 119.7mmHg; 95%CI: 119.0mmHg -120.4mmHg) and 2017(mean: 120.4mmHg; 95%CI: 119.6mmHg -121.1mmHg) among South African adults.

A similar pattern of increasing trend was reported in a more recent study by Zhou et al.(2017). The study provided worldwide trends in blood pressure from 1975 to 2015 using a pooled data of 19.1 million individuals across 1479 population-based measurement studies. Their results showed consistent increase in raised blood pressure in sub-Saharan Africa between 1975 to 2015 raising concerns about the potential of most countries in the region attaining the target of reducing raised blood pressure prevalence by 25% by 2025. For instance, attainment of such reduction in South Africa implies an overall reduction of 30.1mmHg in average SBP (from estimated mean SBP in 2017 of 120.4mmHg) among South Africa adult population, which given the current trend (at -1.18mmHg) may appear to be an unattainable target. Both studies accounted for nonlinear trends in the Bayesian hierarchical formulation of the candidate model while our study only accounted for linear time trend.

In addition, results of the cross-sectional analysis of the NIDS data showed that the spatially smoothed direct estimates presented a geographic pattern of reduction in predicted mean SBP compared to the direct estimates, especially in districts with higher predicted mean SBP. This

approach to stabilizing area-specific and spatially structured variation in the outcome may therefore provide a robust alternative to effectively utilize nationally representative complex survey data from low and middle- income countries to produce more reliable small area statistics for official applications.

Findings from this study provide important evidence base to evaluate the South African national strategic plan and the performance of small areas (in this case the 52 district councils) in implementing the strategic plans of action.

CHAPTER SEVEN

CONCLUSION AND FUTURE WORK

7.1. Introduction

In this research work, we proposed novel statistical approaches to capture the complex sampling features inherent in nationally representative cross-sectional and longitudinal surveys within a Bayesian hierarchical generalized linear regression framework. More specifically, we described two statistical frameworks. First, we demonstrated the utility of the PDF/ST-STAR framework to modeling FGM/C likelihood among girls in three African countries using the Demographic and Health survey (DHS) sample data namely Kenya (for the period 2003 to 2014), Nigeria (for the period 2008 to 2018) and Senegal (for the period 2010 to 2017). Second, we proposed a repeated measurement hierarchical Bayes linear mixed effect model for producing small area estimation (SAE) of continuous population health outcomes such as systolic blood pressure (SBP) using nationally representative longitudinal survey data. We demonstrated the utility of the proposed SAE framework by producing small area estimates of average SBP for the South African adult population aged 18 years and older using the National Income Dynamics survey (NIDS) sample data for the waves 2008, 2010, 2012, 2014/2015, and 2017.

We demonstrated the utility of the PDF/ST-STAR approach to statistical modeling of FGM/C risk factor outcomes by testing three study Hypotheses. To evaluate the First hypothesis (Hypothesis 1), we identified influential risk factors (by effect size and significance of the 95% Bayesian credible interval) of FGM/C likelihood among girls operating at individual and community levels in space and time. For the second Hypothesis, we quantified the impact of modeling excess spatial-temporal variability in observed FGM/C prevalence on changes in the marginal influence of identified risk factors. The Third hypothesis provided an important and primary motivation for the study with the objective to evaluate whether observable changes can be detected in the influence of risk factor estimates operating at individual and community levels after accounting for the complex survey design features of the DHS sample data. To realize the objective of modeling the complexity of the DHS data, we modelled, explicitly, the two components of the survey sampling design – clustering and stratification. Both features, together, provide a natural nested structure of the survey samples similar to that observed in the general population: individuals within households exist in population groups, clustered in

small local communities, in turn nested within larger administrative geographical units (such as districts, states, region). In line with the recommendation of Skinner and Wakefield (2017), we evaluated the effect of regional stratification of the sampling design by modeling stratification as a fixed effect (with a fixed number of regional administrative units). In contrast, clustering was accounted for as an independently and identically distributed random effect. This acknowledged the random selection of DHS sample clusters from a cluster sampling frame (often unknown) and independently drawn at each survey time point.

To evaluate the fourth Hypothesis, we assessed the evidence for an overall change in the average SBP of South African adult population for the period 2008 to 2017 at the national level. The fifth Hypothesis evaluated evidence for geographic variation in the small area estimates of average SBP among South African adults separately for the year 2008, 2010, 2012 and 2014/2015 and 2017. We considered a spatially smoothed design-based SAE approach to cross-sectional analysis of the national income dynamics survey (NIDS) sample within a hierarchical Bayesian framework to evaluate hypothesis 5. This allowed us to account for the complex cross-sectional survey design features of the NIDS data and spatial dependence to ensure information borrowing across neighboring districts thereby improving the effective sample size in districts with small sample size

7.2. Conclusions and Policy implications of FGM/C study

Our study found significant support for the first three Hypotheses evaluated for reliable estimation of FGM/C risk factors using the PDF/STAR Framework for the relevant African countries of interest. In more specific terms, we identified existence of FGM/C risk factors that influenced the likelihood of the practice for each specific study period in Kenya, (2003 to 2014), Nigeria (2008 to 2018) and Senegal (2010 to 2017) respectively. We identified various set of risk factors operating both at individual and contextual (community) levels of influence across the three countries after accounting for excess spatial-temporal variability in the observed prevalence risk and the cluster design effect but not stratification design. For instance, among Kenyan girls aged 0-14 years, important individual level risk factors include: Social norms (daughters of cut women were more likely to be cut); Gender norms (household decision making by the father resulted in increased likelihood of cutting in a girl); Women's agency and extra-familiar opportunity (daughters born to women with low education were more likely to be cut) and demographic factors (girls born to mothers of Kisii, Masaai and Somali ethnicity

had higher likelihood of being cut while Muslims girls had significant increased likelihood of being cut compared to their Christian counterparts). Similarly, among Nigerian girls aged 0-14 years, important individual-level risk factors for the period 2008 to 2018 include: Social norms (girls were more likely to be cut when their mothers were cut, supported FGM/C continuation in her local community or believed FGM/C was a religious requirement); Gender norms(household decision making by mother and father increased likelihood of a girl being cut); Women's agency and extra-familiar opportunity (daughters of women with lower education attainment were more likely to be cut); Modernization (girls born to poorer households were more likely to be cut); Demographic factors (girls born to women in marital union were more likely to be cut; girls from Christian or other religious affiliation were less likely to be cut than Muslim girls; and girls from Igbo extraction were more likely to be cut than their Hausa counterparts).

Furthermore, important risk factors among Senegalese girls aged 0-9 years between the period 2010 and 2017 include: Social norms (girls were more likely to be cut when their mothers were cut, supported FGM/C continuation in her local community or believed FGM/C was a religious requirement); Gender norms (girls born to women who justified wife beating partner for sex refusal were more likely to be cut); Women agency(girls born to women with primary education were more likely to be cut compared to women with secondary or higher education); and extra-familiar opportunity(girls born to women with no or informal occupation were more likely to be cut than their counterparts born to economically empowered women); Modernization (girls in rural Senegal had increased likelihood of cutting than their urban counterparts). We note that after accounting for cluster design of the DHS and excess variability in space and time the study found no support for the influence of underlying demographic factors on the likelihood of FGM/C among Senegalese girls between the study period. Study also found significant positive influence of prevalence of FGM/C among women and their support for continuation of the practice in Nigeria and Senegal. Consequently, communities with higher prevalence of FGM/C related social norms had increased likelihood of cutting their girls.

In addition, accounting for the cluster design random effect in the model with space-time interaction provided significant improvement to model performance (as measured by logarithm of the conditional predictive ordinate at the individual level and the RMSE/R-Squared at area level) and notable changes in risk factor estimates. Subsequently, we observed notable changes to the influence of certain individual level risk factors on FGM/C likelihood among girls such

as social normative influences, particularly in Nigeria. Across the three countries, additional changes were observed in other risk factors including marital status, religion, education and wealth index. This was expected given that a substantial amount of variability between individuals in survey samples is largely attributed to clusters. In contrast, little variation exists between individuals within the same household level. These findings provide support for the third Hypothesis. We therefore conclude that accounting for the cluster design effect in statistical FGM/C risk factor modelling effort result in notable changes in the risk factor estimates.

In addition, by accounting for the clusters as a proxy measure of the local communities, the study was able to evaluate and quantify the role of context and separate its neighborhood influences from those that operate at higher administrative geography such as district or regional level. As a result, the study demonstrated for the first time, that a substantial amount of neighborhood effects observed at district, state or regional levels are largely explained by both known and unknown shared FGM/C risk factors operating across neighboring communities. These communities often have common socio-cultural norms and traditional belief systems that facilitate a geographical dependence that is rooted in and driven by a reference group (ethnic or religious) sense of identity.

Another important aspect of our finding is the need to consider partitioning the role of socio-normative influences into individual level and community level within a unified statistical framework. Such additional effort will benefit intervention and policy planers in deciding if the burden of practice is mostly driven by individual factors or group factors over a specific period. Therefore, these methodological considerations, together, provide important addition to the FGM/C statistical modeling literature and a major improvement on previous studies that considered similar hierarchical Bayesian approach to modelling FGM/C risk and determinants in sub-Saharan Africa(Kandala et al., 2019; Kandala & Shell-Duncan, 2019; Nnanatu et al., 2021).

In addition, findings demonstrated substantial improvement in model performance after accounting for excess variability due to spatial-temporal interaction effect of unobserved risk factors across the three countries. In our study, we identified Type I space-time interaction as proposed by Knorr-Held(2000) as the prior that best described the nature of spatial-temporal dynamics in the survey data across the three countries. This is not particularly surprising given that the temporal dimension of the data is low (three time point) and hence we expected to

detect less temporal dependence in the data. Also, the removal of spatial dependence at community level combined with small number of regions contributed to significant reduction in spatial dependence at regional level. Regional variation in FGM/C risk was observed across the three countries. In Nigeria, we found evidence for declining trend in FGM/C risk between 2008 and 2018 in the southern part of the country (including states such as Osun, Ekiti, Oyo, and Ondo), while an increasing trend was observed in the northern states especially in Kano, Kaduna, Jigawa and neighboring states. In Kenya, FGM/C risk was largely concentrated in the north-eastern region and Nyanza region of the country predominantly inhabited the Kisii, Somali and Masaai tribal communities. In Senegal, similar pattern of regional variation in FGM.C risk was found with highest risk observed in the southeastern and southern regions of Matam, Tabacounda, and Zinguichor. Risk was generally low in the western regions across the three survey time periods.

In relation to temporal changes in FGM/C risk, we found significant evidence of substantial decline in FGM/C likelihood among girls in Kenya between the period 2003 and 2014. In contrast however, evidence suggested a non-statistically significant upward trend in Nigeria for the period 2008 to 2018 and Senegal for the period 2010 to 2017.

Based on these findings, we therefore conclude that adjusting for the cluster design feature provide important considerations for statistical modeling of the demographic and health survey data in relation to FGM/C outcomes. Modelling efforts to quantify risk factor influence over specific period also need to give important statistical considerations to identifying and quantifying the impact of excess variability due to unobserved risk factors jointly interacting in space and time. Overall, findings showed substantial support for the three (3) study hypotheses evaluated. Consequently, we identified risk factors of FGM/C likelihood operating at individual and community level in space and time (Hypothesis 1) in Kenya, Nigeria and Senegal. Second, the study also showed that significant excess variability in FGM/C risk was due to unobserved risk factors operating simultaneously in space and time across the three countries (Hypothesis 2). Third, we noted a substantial changes and improvement in the spatial-temporal generalized model formulation (at global and covariate levels) after accounting for the cluster sampling design feature across the three countries (Hypothesis 3).

Study findings demonstrate that social normative influences operating at individual and community levels are the single most important drivers of persistence of FGM/C probability among girls in Nigeria between the period 2008 and 2018 and Senegal between the period 2010

and 2017. This conclusion was supported by the reduced impact of social norms in Kenya where a significant decline in the practice was observed prevalence over the years. In addition, our statistical approach showed significant evidence of change in risk factor estimates after accounting for cluster sampling design effect in the statistical model formulation but not the stratification design, notably in Nigeria. In addition to the social normative theory, additional support was found for the contribution of mother's Muslim religious affiliation, her formal education attainment, her ethnic group, and gendered normative influences as important predictors that a girl will be cut.

Therefore, intervention efforts towards FGM/C elimination and abandonment across the three countries should focus on greater understanding of socio normative influences operating within a specific context and reference group (locality or ethnic and religious group). Such understanding will provide invaluable insight to develop community-led strategies towards replacing harmful norms with healthy practices in a manner that shows empathy and respect. Effort should target high risk ethnic communities such as the Kisii and Somali in Kenya and Igbo and Hausa in Nigeria, given that FGM/C appears to be rooted cultural and traditional norms in both countries, as opposed to socially coordinated approach across many practicing communities in Senegal and neighboring countries. Additional effort for inclusion of Islamic religious leaders especially in high prevalent communities should be considered given the significant association of Muslim religious affiliation with the probability of girls getting cut across the three countries. Finally, study findings with respect to high prevalence regions may provide additional guidance for policy maker to evaluate effectiveness of FGM/C legislation framework in most affected communities within a specific region.

7.3. Conclusions and Policy implications of SBP study

Analyses of subnational small area trends in the average SBP among Adults in South Africa provided additional support for the fourth and fifth Hypotheses of the study. Findings provide significant evidence (as evaluated using the Bayesian credible interval) of an overall decline in mean SBP level of an average South African adult between 2008 and 2017 at national level and across majority of the district municipalities. However, observed trends varied significantly across districts. While a good number maintained a consistent decreasing trend over the ten-year period, a number of districts showed patterns of elevated increase in in 2017 after an initial reduction in 2015. Further investigation into the potential cause of this increase may be

warranted for effective prevention and control of raised blood pressure in most affected districts. Evidence from the study provides preliminary insight to evaluate country progress with respect to systolic blood pressure among South African adults, at district level in relation to the 25% reduction in blood pressure target by 2025.

For instance, we found evidence of overall significant reduction in the average systolic blood pressure of South African adults between the period 2008 and 2017. Findings from the spatially smoothed design-based estimator showed significant geographic variations in average SBP at district level for each consecutive cross-sectional time point of the NIDS samples. Results showed preponderance of areas with elevated SBP in the southern districts in 2008, 2010, 2012, 2014/2015 and 2017 (such as Overberg, Central Kaaro, West Cape) and cluster of areas with low mean SBP in the northern parts of the country. Findings showed overall reduction (-1.18; 95%CI:1.25, -1.10) across all districts from 2008 to 2017 with greatest reduction observed in Frances Baard and Pixley ka Seme in Northern Cape Province, Uthukela and Umzinyathi in Kwazulu-Natal Province, Nkangala in Mpumalanga Province, and Sedibeng in Gauteng Province.

However, cross-sectional analysis did not account for important features of the NIDS sample such as the repeated measurements of SBP during each wave, the longitudinal features of the NIDS waves and the problem of extremely small sample size at spatially disaggregated level. The proposed novel repeated measurement hierarchical Bayes linear mixed model aimed to address these limitations using as an alternative fully model-based SAE approach. However, findings of the repeated measurement model are only preliminary at best given the assumption of a common trajectory in SBP progression over time for all survey participants. This, in turn, produced small area estimates of SBP with a common slope across all the districts between 2008 and 2017 which is not likely to be a true representative of the actual local trend. More so, the model formulation was unable to account for important variability in space and time. Future work is needed to extend this simple model to evaluate more realistic and complex formulations. This is the first attempt to estimate systolic blood pressure burden among adult population at small area level in Africa using a nationally representative complex survey data.

In addition, results of the cross-sectional analysis of the NIDS survey data will provide additional insight into national progress and district level performance with respect to average systolic blood pressure among adult population in 2008, 2010, 2012, 2014/2015 and 2017.

7.4. Our contribution to the field of survey methodology

Our study made two significant contributions to the field of survey methodology. First, we proposed a novel approach to estimate individual level effect of risk factors of FGM/C outcomes using a spatiotemporal structured additive regression within a generalized linear additive modeling framework. While this family of semiparametric regression models is well known in the field of spatial and spatiotemporal statistics, our study provided additional extension to model simultaneously, national surveys with complex sampling designs and excess variation in risk due to specific space-time interaction structure within unified framework. Second, we proposed a novel small area estimation approach known as the repeated measurement linear mixed model for estimation of small area means and trends of continuous health outcomes within a Bayesian framework using individual level survey data. In addition, we proposed a Bootstrap procedure to obtain small area means and quantify associated uncertainties from the posterior estimates of Bayesian model parameters. The combination of Bayesian model-based inferential paradigm and Bootstrap for confidence interval estimation therefore provides a flexible means to model small area means of nationally representative longitudinal survey data.

7.5. Our contribution to the field of Public health

Furthermore, our study provided important framework to generate evidence using a theoretically driven ecologic approach to generate evidence to estimate risk at individual and geographic levels, estimate trends, identify important drivers of observed trend to better inform policy decisions and future research agenda in the field of FGM/C. The Proximate Determinants Framework (PDF) approach provides a standardized and theoretically driven analytical strategy to identify, quantify and compare important FGM/C risk factors and determinants across multiple countries in a manner that simultaneously quantifies the role of context at community level and the influence of space and time on the observed pattern of risk factor estimates at individual level.

Results of the FGM/C study will provide invaluable insight into country's FGM/C risk over the past few years to evaluate progress towards abandonment or elimination at subnational level by 2030. The FGM/C PDF therefore provides a standardized tool for comparison of experiences and evaluation of country progress in the light of the UN 2030 SDG elimination

goal (in space and time) across most affected countries in Sub-Saharan Africa. Identification of important risk factors will help provide deeper understanding of country-specific context, quantify influence of social normative factors, and most at-risk socio-demographic profiles to ensure better local targeting of appropriate interventions. More so, the availability of powerful computational algorithms in recent time ensures that the PDF can be evaluated within a coherent hierarchical Bayesian spatiotemporal structured generalized linear additive mixed regression framework.

7.6. Recommendations for statistical methodology for survey data

Evidence from our study has shown that modelling the excess variability between clusters (as independently and identically random effects in the case of Demographic and Health surveys) provided substantial improvement to the model fit (as measured by the DIC and WAIC) and predictive performance (as evaluated using the RMSE, R-squared at area level and logarithm of the conditional predictive ordinate at the individual level). Therefore, we recommend the need to account for the complexity of survey design feature, in particular the cluster design.

In addition, statistical survey modelers and global health practitioners should also consider the use of DHS clusters as a powerful source to evaluate and quantify the role of both measured and unmeasured factors operating within the community. The significance of such efforts ensure that neighborhood effects can be effectively decomposed to unobserved risk factors operating at ta community level and those operating at higher administrative level such as district, state, or regional level. Finally, given the increasing availability of nationally representative complex survey data at multiple time points, statistical spatial-temporal modelling effort should consider testing various prior assumptions regarding the spatial effect and the space-time interaction residual variability using the approach demonstrated in our study.

7.7. Future work for FGM/C study

Future research effort is needed to implement simulation studies to assess the significance of the observed changes in the risk factor estimates after accounting for the cluster design effects. Here, the objective is to assess the accuracy and robustness of the risk factor estimates in the

presence of cluster design effect using bias to evaluate the effects estimates and 95% coverage to evaluate variability in effect estimates from one sample to another. Future work also needs to be done to apply the proximate determinants framework (PDF) to identify FGM/C risk factor profile and map FGM/C prevalence trends across other countries in sub-Saharan Africa. For the FGM/C risk factor study, future work needs to conduct further simulation study to evaluate the bias and coverage of the proposed model formulation with cluster design effect.

7.8. Future work for Blood Pressure study

A key limitation of the present study is that the model-based HB approach only considered a simple random intercept model as a preliminary attempt to produce small area estimate from repeated measurements of continuous health outcome obtained from nationally representative longitudinal survey data. Future work is needed to extend this preliminary framework to more complex and flexible models that account for individual-specific slopes, spatial, temporal and spatiotemporal random effects. We also note that while the cross-sectional SAE approaches accounted for the hierarchical features of the survey design to acknowledge that individuals were nested within households, clusters, and districts respectively, the hierarchical Bayesian model with random intercept and global slope did not account for this nested structure of the sampling design. Future extension of the model is needed to evaluate additional benefits of accounting for the cross-sectional design features within a longitudinal framework to predicting small area estimate of blood pressure. However, a major challenge in implementing such a complex model formulation on a nationally representative survey sample within a Bayesian framework is largely computational. This we hope to overcome by exploring recently developed computational techniques such as INLA, STAN and NIMBLE.

In addition, future work is needed to incorporate auxiliary covariates (such as age, gender, and race stratification) or rather adjust for the survey weights calibrated for the age-sex-race population totals across the 52 districts to strengthen predicted small area estimates from the HB model-based approach. The benefits of other auxiliary covariates such as household index of deprivation will also be evaluated. Similarly, we aim to conduct a simulation study on small area estimates from the HB linear mixed models to examine the bias, variance and the mean squared error (MSE) compared to the direct and spatially smoothed methods. Similar simulation can be conducted to assess how much improvement does the spatially smoothed direct methods provide.

Similarly, future work on small area estimation of mean SBP is needed to conduct simulation study on the performance of the small area estimates from the repeated measurement HB linear mixed models to examine the bias and 95% coverage of the estimates. Extensions to the Hierarchal Bayesian formulation is needed to account for missing observations and assess informative dropout (Si et al., 2020). Extension is also needed to incorporate a weighting adjustment to the longitudinal model as recently proposed by (Si et al., 2020) to improve the design unbiasedness and consistency of the estimates. It has also been shown that the multivariate approach for model-based methods in small area estimation may achieve substantial improvement over the usual univariate approach (Datta & Ghosh, 1991). Subsequent extension therefore required to borrow information by jointly modelling systolic and diastolic blood pressure to obtain more reliable estimates and improve model efficiency by accounting for correlation between the two measurements.

Proposed model formulation needs to account for spatial and temporal trends by incorporating temporally varying spatial effects and a potential non-linear temporal correlation. Model extensions such as random slope with/without correlated random intercepts and slopes should also be considered given that previous formulations of such models have shown substantial improvement over the random intercept model presented in Chapter 5. Further, we seek to extend the model formulation to obtain small area estimates for average systolic and diastolic blood pressure within a joint modelling framework to borrow strength to improve small area estimates. A preliminary evaluation showed a substantial degree of correlation between the SBP and DBP among South African adult population of interest in our study. The predictive influence of incorporating auxiliary covariates such as index of deprivation will also be assessed. More realistic model formulation that explicitly account for the complex survey design of the NIDS sample will be considered. Such features include nested structure of individuals in each district within households and clusters. This is an important attempt to ensure that the nested structure of the NIDS sample is acknowledged within a longitudinal framework as we have demonstrated in the cross-sectional design-based SAE approach. Sixth, Future work will extend the general linear formulation of the repeated measurement model to a more generalized setting for small area estimation of binary (prevalence) and count(incidence) outcomes.

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APPENDICES

Appendix A3. Results Tables for Chapter 3

Table A3.1. Characteristics surrounding Female Genital Mutilation/Cutting among Kenyan Girls aged 0-14yrs from 1998 to 2014.

Variable	**1998 KDHS**		**2003 KDHS**		**2008 KDHS**		2014 KDHS	
	N=4,069, FGM=9.9		**N=4,048, FGM=9.4%**		**N=7,195, FGM=7.6%**		**N=12,434, FGM= 3%**	
	n (%)	P-value	n (%)	P-value	n (%)	P-value	n (%)	P-value
Age group(girls)		<0.001		<0.001		<0.001		<0.001
0-4	2,125(5.3)		2,287(7.0)		2,644(3.8)		4,453(0.3)	
5-9	1,221(13.8)		1,118(11.4)		2,478(7.2)		4,479(2.4)	
10-14	723(17.1)		643(14.8)		2,074(12.8)		3,506(7.3)	
Age group(mother)		<0.001		<0.001		<0.001		<0.001
15-19	144(0.0)		175(1.0)		137(0.0)		218(0.0)	
20-24	678(0.7)		694(2.0)		1,009(0.7)		1,354(0.5)	
25-29	972(5.2)		922(4.1)		1,561(5.0)		3,088(1.7)	
30-34	798(7.1)		863(7.9)		1,864(5.1)		3,143(3.5)	
35-39	795(17.9)		656(12.7)		1,304(11.3)		2,475(4.5)	
40-44	419(21.5)		491(24.6)		822(13.3)		1,396 (3.8)	
45-49	262(22.9)		248(22.8)		499(21.9)		762(5.1)	
Residence		<0.001		0.001		<0.001		<0.001
urban	773(4.4)		841(5.8)		1,245(2.6)		4,093(1.9)	
rural	3,296(11.2)		3,207(10.4)		5,950(8.6)		8,345(3.5)	
Region/Province		<0.001		<0.001		<0.001		<0.001
nairobi	280(2.7)		301(4.9)		360(0.3)		1,070(0.0)	
central	441(4.8)		542(2.9)		632(0.8)		1,311(0.2)	
coast	308(4.2)		336(7.3)		598(3.8)		1,109(2.0)	
eastern	701(9.6)		656(7.5)		1,230(6.7)		1,760(1.6)	
nyanza	885(23.0)		613(15.4)		1,155(15.7)		1,800(6.4)	
rift valley	971(9.2)		1,022(11.3)		2,212(5.8)		3,508(0.9)	
western	484(0.2)		473(0.7)		817(0.0)		1,474(0.2)	
northeastern	-		105(61.0)		191(65.5)		407(42.0)	

Mother's Education		<0.001		<0.001		<0.001		<0.001
no education	601(22.1)		664(26.7)		999(23.2)		1,433(15.1)	
primary	2,383(9.0)		2,411(7.1)		4,480(5.4)		7,427(1.5)	
secondary	997(5.5)		782(4.1)		1,401(4.9)		2,822(1.5)	
higher	87(2.3)		191(1.1)		316(1.7)		755(0.8)	
Father's Education		<0.001		<0.001		<0.001		<0.001
no education	335(24.5)		473(30.3)		722(27.9)		1,111(15.8)	
primary	1,855(10.9)		1,837(8.3)		3,526(5.9)		5,979(2.0)	
secondary	1,393(7.3)		1,095(5.9)		2,030(5.7)		3,470(1.6)	
higher	158(8.8)		323(4.2)		551(1.7)		1,163(1.2)	
Religion		0.019		<0.001		<0.001		<0.001
muslim	214(4.7)		328(29.2)		594(29.8)		978(21.0)	
roman catholic	1,132(12.5)		1,013(9.1)		1,470(6.6)		2,428(2.2)	
protestant/other chris	2,615(9.1)		2,592(7.2)		4,879(5.5)		8,868(1.3)	
no religion	86(13.2)		101(8.2)		253(2.5)		164(0.3)	
Ethnicity		<0.001		<0.001		<0.001		
luo	579(0.6)		476(1.2)		910(0.0)		1,308(0.0)	<0.001
kalenjin	574(8.5)		468(7.3)		1,174(5.6)		1,743(0.5)	
kamba	486(7.2)		476(5.3)		826(3.9)		1,388(0.4)	
kisii	422(49.6)		224(43.2)		441(43.1)		760(15.6)	
kikuya	695(4.5)		812(3.5)		1,142(1.0)		2,151(0.0)	
luhya	599(0.0)		641(0.6)		1,119(0.0)		1,953(0.3)	
maasai	73(29.5)		134(36.6)		110(24.4)		383(3.1)	
embu	295(13.1)		38(13.8)		72(8.4)		80(1.3)	
meru			202(5.5)		356(3.6)		609(0.7)	
mijikenda/swahili	208(1.1)		220(1.9)		427(0.4)		612(0.0)	
somali	7(7.9)		169(54.8)		255(57.2)		475(37.2)	
taita/taveta	35(22.1)		43(28.2)		68(11.8)		109(1.3)	
turkana	-		81(8.0)		-		218(0.0)	
samburu	-		-		-		82(4.0)	
other	93(5.0)		63(11.8)		292(14.9)		561(6.2)	
Wealth Quintile				<0.001		<0.001		<0.001
lowest	-		835(13.9)		1,644(14.9)		2,708(7.2)	
second	-		831(12.0)		1,426(9.4)		2,591(2.5)	

middle	-		762(10.2)		1,422(5.9)		2,532(2.6)	
higher	-		770(6.7)		1,414(4.1)		2,384(1.5)	
highest	-		850(4.3)		1,288(2.0)		2,223(0.7)	
Marital Status		<0.001		<0.001		0.105		<0.001
never in union	271(1.0)		247(1.7)		364(3.3)		570(0.4)	
currently married	3,384(10.2)		3,315(9.6)		5,920(8.2)		10,352(3.3)	
formerly married	414(13.6)		486(12.1)		912(5.4)		1,516(2.1)	
Mother from mixed ethnicity household		0.383		0.302		0.343		0.053
no	937 (10.8)		907 (7.4)		1,553(7.3)		5,597(3.0)	
yes	80(6.9)		71(11.8)		162(4.0)		667(1.4)	
Age at circum(mother)						<0.001		<0.001
daughter fgm negative			-		1,777(12.3±4)		4,152(11.8±4)	
daughter fgm positive			-		816(9.0±3)		704(8.4±3)	
Age at circum(girl)								
daughter fgm positive			-		782(7.5±2.2)		-	
Mother currently working		0.002		0.071		0.038		<0.001
no	1,548(7.5)		1,351(10.8)		2,489(9.3)		3,536(5.5)	
yes	2,517(11.4)		2,695(8.7)		4,678(6.6)		8,885(2.0)	
Occupation(moth)		<0.001		0.008		0.020		<0.001
formal	290(5.8)		207(4.0)		1,460(4.8)		1,084(1.5)	
informal	2,316(12.1)		2,625(9.0)		1,848(7.1)		8,325(2.0)	
not working	1,457(7.2)		1,212(11.3)		2,412(10.1)		2,968(6.3)	
Occupation(fath)		0.004		0.035		0.433		0.424
formal	642(7.0)		443(7.2)		2,023(6.1)		1,896(2.6)	
informal	2,599(11.8)		2,835(10.8)		3,304(7.3)		9,756(3.2)	
not working	111(13.6)		-		15(8.3)		156(2.5)	
Mother worked for cash in the last 12 months		0.002		0.033		0.006		<0.001
no	1,455(7.3)		1,211(11.3)		2,331(10.1)		2,971(6.3)	
yes	2,612(11.4)		2,835(8.6)		4,863(6.4)		9,234(2.0)	
Type of earning(moth)				0.146		<0.001		<0.001
other	-		713(10.3)		1,248(13.5)		2,032(3.4)	
cash	-		2,007(8.1)		3,287(3.7)		6,665(1.5)	

Expenditure of wife's earning decided by wife or jointly		0.189		0.068		0.003		0.220
father	12(0.0)		195(12.6)		265(10.8)		455(1.4)	
mother alone	981(7.9)		1,264(7.4)		1,143(3.9)		2,602(2.0)	
father and mother	362(11.5)		549(8.1)		1,296(2.6)		1,996(1.2)	
Expenditure of father's earning decided by wife or jointly						0.041		0.250
father	-		-		2,410(8.5)		4,508(3.6)	
mother alone	-		-		360(13.5)		847(2.8)	
father and mother	-		-		2,912(6.7)		4,782(2.9)	
Mother makes more money than father						0.221		0.152
no	-		-		1,731(3.1)		3,599(1.4)	
yes	-		-		790(4.7)		1,261(2.2)	
Mother's employment all year or seasonal		0.007		0.858		0.224		0.140
all year	1,858(12.7)		1,734(8.7)		2,767(7.0)		5551(2.2)	
Seasonal/ occasional	616(7.5)		984(8.5)		1,765(5.4)		3,138(1.5)	
Mother's health care decision				0.192		<0.001		<0.001
father	-		1,430(11.2)		1,677(12.5)		2,342(4.7)	
mother	-		1,837(8.9)		1,699(7.9)		3,942(2.4)	
father and mother	-		489(8.8)		2,659(5.7)		4,135(3.3)	
Final say on making large household purchase				0.012		0.003		0.047
father	-		2,052(9.2)		2,136(10.8)		3,060(4.1)	
mother	-		779(13.2)		849(9.5)		0(0.0)	
father and mother	-		811(9.6)		3,029(5.8)		2,162(2.8)	
Final say on making household purchases for daily needs				0.431		<0.001		
father	-		1,262(9.5)		2,858(36.6)			
mother	-		1,743(11.0)		1,806(32.5)			
father and mother	-		655(9.7)		1,082(50.2)			
Father beat mother						0.277		0.163
no	-		-		3,099(6.6)		2,889(3.7)	

yes	-		-		2,092(8.1)		123(2.4)	
Polygnous union		0.375		0.376		0.384		0.0785
no	3,503(10.7)		3,517(9.8)		6,434(7.9)		11,035(3.0)	
yes	262(8.8)		284(11.8)		433(6.2)		887(4.3)	
Marriage arranged				<0.001		<0.001		<0.001
no	-		3,133(7.2)		5,887(5.7)		10,244(2.3)	
yes	-		654(23.4)		984(20.7)		1,578(8.7)	
Mother experienced any emotional violence				0.090		0.898		<0.001
no	-		2,172(8.6)		3,822(8.0)		3,368(4.2)	
yes	-		758(11.0)		1,685(7.9)		1,787(1.6)	
Mother experienced any less severe violence				<0.001		0.994		0.002
no	-		1,700(7.2)		3,377(8.0)		3,142(4.1)	
yes	-		1,229(11.9)		2,127(8.0)		2,010(2.1)	
Mother experienced any severe violence				0.002		0.575		0.015
no	-		2,672(8.6)		4,517(7.8)		4,167(3.6)	
yes	-		255(15.1)		987(8.7)		974(1.9)	
Mother experienced any sexual violence				0.910		0.289		0.015
no	-		2,438(9.2)		4,639(8.3)		4,492(3.5)	
yes	-		490(9.0)		867(6.4)		661(1.7)	
Beating justified if mother goes out without telling father				<0.001		0.007		0.342
no	-		2,276(7.5)		4,520(6.0)		9,066(2.9)	
yes	-		1,706(12.2)		2,543(9.3)		3,264(3.3)	
Beating justified if mother neglects the children				<0.001		0.002		0.017
no	-		1,637(7.3)		3,767(5.5)		7,576(2.6)	
yes	-		2,364(11.1)		3,302(9.1)		4,770(3.6)	
Beating justified if mother argues with father				<0.001		0.002		0.301
no	-		1,988(6.4)		4,520(5.9)		9,184(2.9)	
yes	-		1,989(12.6)		2,503(9.6)		3,120(3.4)	

Beating justified if mother refuses sex with father				<0.001		<0.001		<0.001
no	-		2,551(6.8)		5,052(5.3)		9,858(2.6)	
yes	-		1,361(14.2)		1,943(12.4)		2,402(4.7)	
Beating justified if mother burns food				0.035		0.568		0.338
no	-		3,247(8.8)		5,996(7.1)		11,232(3.1)	
yes	-		717(11.5)		1,059(7.9)		1,052(2.5)	
FGM prevalence(mother)		<0.001		<0.001		<0.001		<0.001
no	2,267(0.3)		2,471(0.4)		4,370(0.1)		8,812(0.2)	
yes	1,802(22.0)		1,577(23.5)		2,471(21.5)		3,622(9.9)	
Person who performed circumcision(mother)						0.205		0.003
medical personnel	-		-		377(10.0)		432(4.4)	
traditional attendant	-		-		2,264(90.0)		4,374(95.6)	
Person who performed circumcision(daughter)								
medical personnel	-		-		299(34.7)		-	
traditional attendant	-		-		565(65.3)		-	
FGM required by religion						<0.001		<0.001
no	-		-		6,107(4.5)		11,663(1.4)	
yes	-		-		551(46.7)		771(27.8)	
Mother support continuation of fgm		<0.001				<0.001		<0.001
no	2,959(5.1)		-		5,733(4.0)		11,184(1.1)	
yes	836(29.2)		-		700(41.8)		1,027(23.1	
Mother believes FGM is required by community		<0.001		<0.001				<0.001
no	2,236(1.1)		2,565(1.3)*		-		11,171(1.0)	
yes	1,833(20.7)		1,483(23.6)*		-		1,243(21.1)	
Mother owns house alone or jointly								0.006
no	-		-		-		4,775(2.2)	
yes	-		-		-		7,653(3.5)	
Mother owns land alone or jointly								0.820

no	-		-		-		5,507(3.1)	
yes	-		-		-		6,905(3.0)	
Mother lived in city, town, countryside or outside of kenya								<0.001
nairobi/mombasa/kisumu	-		-		-		659(0.0)	
other town	-		-		-		1,112(5.4)	
countryside	-		-		-		10,564(2.9)	
outside kenya	-		-		-		91(1.2)	
Mother lived in city, town or countryside before moved here								0.011
nairobi/mombasa/kisumu	-		-		-		882(0.7)	
other town	-		-		-		1,374(2.0)	
countryside	-		-		-		6,384(2.6)	
outside kenya	-		-		-		64(1.6)	
Years lived continuously in location(yrs)								<0.001
0	-		-		-		647(1.8)	
1-10	-		-		-		5,138(1.9)	
11-20	-		-		-		3,045(2.9)	
21 or more	-		-		-		3,439(5.0)	
Number of trips in the last 12 months								<0.001
0	-		-		-		6,825(4.1)	
1-25	-		-		-		5,501(1.6)	
26-50	-		-		-		60(2.1)	
51 or more	-		-		-		46(2.7)	
Frequency of reading newspaper or magazine				<0.001		<0.001		<0.001
not at all	-		2,679(12.5)		4,793(10.0)		8,959(3.9)	
less than once a week	-		712(3.7)		1,226(2.6)		2,098(0.5)	
at least once a week	-		652(3.2)		1,166(3.0)		1,372(0.8)	
Reads newspaper once a week		<0.001		<0.001		<0.001		<0.001
no	2,789(12.8)		2,679(12.5)		4,793(10.0)		8,959(3.9)	
yes	1,271(3.6)		1,364(3.4)		2,393(2.8)		3,472(0.6)	

Frequency of listening to radio				<0.001		<0.001		<0.001
not at all	-		760(20.5)		1,264(17.0)		2,570(7.6)	
less than once a week	-		373(11.2)		689(10.3)		1,665(3.9)	
at least once a week	-		2,914(6.3)		5,238(5.0)		8,199(1.4)	
Listens to radio everyday		<0.001		<0.001		<0.001		<0.001
no	1,661(13.1)		760(20.5)		1,264(17.0)		2,570(7.6)	
yes	2,388(7.8)		3,287(6.9)		5,927(5.6)		9,864(1.8)	
Frequency of watching television				<0.001		0.002		<0.001
not at all	-		2,806(11.0)		4,571(9.3)		7,222(4.4)	
less than once a week	-		339(7.8)		821(6.1)		1,617(1.8)	
at least once a week	-		900(5.2)		1,800(3.8)		3,589(0.6)	
Watches TV every week		<0.001		<0.001		<0.001		<0.001
no	3,145(11.1)		2,806(11.0)		4,571(9.3)		7,222(4.4)	
yes	880(5.7)		1,239(5.9)		2,622(4.5)		5,207(1.0)	
Total	**4,069(9.9%)**		**4,048(9.4%)**		**7,195(7.6%)**		**12,434(3.0%)**	

*In 2003 women were asked if FGM was practiced in the community.

Table A3.2. Unadjusted and adjusted posterior odds ratios (POR) and associated 95% credible regions of circumcision of Girls ages 0-14 across selected covariates (Kenya, DHS 2014) from Bayesian Geo-additive Models.

Predictor	**Level**	**Model A OR (95% CI)**	**Model B OR (95% CI)**	**Model C OR (95% CI)**
DEMOGRAPHIC				
Place of residence	Rural *(ref)*			1.00
	Urban			1.31 (0.87, 1.99)
Religion				
	Christian (*ref*)			1.00
	Muslim			5.50 (2.65, 10.60)
	No religion			1.10 (0.25, 3.71)
Wealth index				
	Middle (*ref*)			1.00

	lower			1.21 (0.76, 1.99)
	lowest			0.94 (0.58, 1.59)
	Higher			0.86 (0.43, 1.66)
	Highest			0.45 (0.18, 1.00)
Ethnicity				
	Embu*(ref)*			1.00
	Kalenjin			--
	Kamba			0.42 (0.1, 1.69)
	Kikuya			--
	Kisii			11.73 (3.69,37.38)
	Luhya			1.39 (0.28, 6.86)
	Luo			--
	Maasai			0.77 (0.25, 3.04)
	Meru			--
	Mijikenda/Swahili			--
	Other			0.74 (0.26, 2.45)
	Samburu			--
	Somali			1.63 (0.46, 6.66)
	Taita-taveta			0.23 (0.01, 2.53)
	Turkana			-
SOCIAL NORMS				
Mother cut				
	No (*ref*)	1.00	1.00	1.00
	Yes	3.94 (2.05, 7.63)	4.30 (2.12, 7.99)	1.97 (0.69, 6.01)
Proportion of cut women	***See graph***			***See graph***
Support continuation				
	Be stopped (*ref*)			1.00
	Continued			3.08 (1.76, 5.55)
	Depends			1.37 (0.49, 3.26)
Proportion of women who support continuation	***See graph***			***See graph***
BELIEFS				

FGM/C is required by religion				
	No *(ref)*			1.00
	Yes			1.5 (0.93, 2.45)
Proportion of women who believed FGM/C is required by religion	***See graph***			***See graph***
WOMEN'S AGENCY				
Mother's education				
	Higher (*ref*)			1.00
	No education			1.25 (0.35, 3.87)
	Primary			0.71 (0.19, 2.27)
	Secondary			0.76 (0.23, 2.46)
WOMEN'S OPPORTUNITIES				
Father beats mother				
	No (*ref*)			1.00
	Yes			1.21 (0.77, 1.82)
	Missing (Not available)			1.01 (0.72, 1.44)
Mother's occupation				
	Formal (*ref*)			1.00
	Informal			1.08 (0.61, 1.9)
	Not working			0.62 (0.3, 1.28)
Mother is in a polygamous union				
	No (*ref*)			1.00
	Yes			1.23 (0.86, 1.69)
Marriage by arrangement	No (*ref*)			1.00
	Yes			0.89 (0.65, 1.2)
Woman owns house	No (*ref*)			1.00
	Yes			1.75 (1.14, 2.86)
Woman owns land	No (*ref*)			1.00
	Yes			0.75 (0.48, 1.16)
Who decides?				

Wife's expenditure	Alone *(ref)*			1.00
	Husband/partner			0.52 (0.2, 1.32)
	With hus/partner			0.68 (0.39, 1.18)
	Missing (Not Available)			0.9 (0.53, 1.48)
GENDER NORMS				
Female positive attitude to wife beating:				
Wife beating for going out				
	No *(ref)*			1.00
	Yes			1 (0.68, 1.45)
Wife beating for neglecting the children				
	No *(ref)*			1.00
	Yes			1.51 (1.06, 2.2)
Wife beating for arguing with the husband				
	No *(ref)*			1.00
	Yes			1.03 (0.67, 1.56)
Wife beating for denying husband sex				
	No *(ref)*			1.00
	Yes			0.79 (0.53, 1.19)
Wife beating for denying husband food				
	No *(ref)*			1.00
	Yes			0.82 (0.48, 1.36)
Who makes large household purchases	Alone *(ref)*			1.00
	Husband/partner			1.4 (0.85, 2.13)
	With husband/par			0.91 (0.57, 1.41)

Who makes decision on mother's health	*Alone(ref)*			1.00
	Husband/partner			1.17 (0.77, 1.86)
	With husband/par			0.92 (0.62, 1.41)
Age difference				
	Wife is older *(ref)*			1.00
	10 years younger			0.82 (0.44, 1.77)
	1-4 yrs younger			0.79 (0.37, 1.63)
	5-9 yrs younger			0.47 (0.23, 1.00)
	Same age			0.34 (0.12, 1.00)
MEDIA INFORMATION				
Read Newspaper				
	No (*ref*)			1.00
	Yes			0.7 (0.38, 1.3)
Listen to Radio				
	No (*ref*)			1.00
	Yes			1.66 (1.15, 2.37)
Watch Television				
	No (*ref*)			1.00
	Yes			0.69 (0.42, 1.14)

Model A: Unadjusted Bayesian Multivariate Regression model. Model B: Adjusted for unobserved total spatial effects. Model C: Fully Adjusted Model. POR = Posterior Odds Ratio; CI= Credible Interval.

Table A3.3. Unadjusted and adjusted posterior odds ratios (POR) and associated 95% credible region (CR) of circumcision of Girls ages 0-14 across selected covariates (Kenya, DHS 2003-2014 combined) from Bayesian Geo-additive Models.

Predictor	**Level**	**Model I** **OR (95% CI)**	**Model II OR (95% CI)**	**Model III** **OR (95% CI)**

DEMOGRAPHIC				
Place of residence				
	Rural *(ref)*			1.00
	Urban			1.17 (0.92, 1.51)
Religion				
	Christian (*ref*)			1.00
	Muslim			2.48 (1.77, 3.35)
	Others			0.53 (0.29, 0.87)
Wealth index				
	Middle (*ref*)			1.00
	lower			0.93 (0.76, 1.06)
	lowest			1.03 (0.82, 1.21)
	Higher			0.86 (0.66, 1.07)
	Highest			0.55 (0.42, 0.72)
Married				
	Currently (*ref*)			1.00
	Formerly			0.92 (0.79, 1.16)
	Never			0.94 (0.59, 1.59)
Ethnicity				
	Embu*(ref)*			1.00
	Kalenjin			1.09 (0.55, 2.48)
	Kamba			0.71 (0.35, 1.52)
	Kikuya			0.64 (0.25, 1.6)
	Kisii			12.07 (5.79, 27.4)
	Luhya			1.59 (0.49, 5.03)
	Luo			0.89 (0.28, 2.87)
	Maasai			4.17 (1.83, 9.45)
	Meru			0.27 (0.12, 0.61)
	Mijikenda/Swahili			--
	Other			2.17 (1.07, 4.76)
	Samburu			--
	Somali			4.39 (2.12, 9.79)
	Taita-taveta			3.59 (1.72, 8.91)

	Turkana			-
SOCIAL NORMS				
Mother cut				
	No (*ref*)	1.00	1.00	1.00
	Yes	24.22 (16.62, 37.35)	25.40 (17.00, 33.57)	27.29 (24.62, 30.38)
WOMEN'S AGENCY				
Mother's education				
	Higher (*ref*)			1.00
	No education			5.78 (3.27, 10.71)
	Primary			3.3 (1.85, 5.83)
	Secondary			2.06 (1.08, 3.85)
Mother's occupation				
	Formal (*ref*)			1.00
	Informal			1.00 (0.84, 1.17)
	Not working			1.03 (0.88, 1.28)

Model I: Unadjusted Model. Model II: Adjusted for unobserved geospatial effects and demographic covariates. Model III: Fully Adjusted Model. POR = Posterior Odds Ratio; CI= Credible Interval

Appendix A4. Results Tables for Chapter 4

Table A4.1. Comparison of the queen and rook first order contiguity matrix for modeling spatial dependence using the proper Besag model.

Country	Rook adjacency matrix (WAIC)	Queen adjacency matrix (WAIC)
Kenya	6391	6391
Nigeria	9255	9255
Senegal	8010	8010

Appendix A5. Results Tables for Chapter 5

Table A5.1. Model hyperparameters for Kenya study: posterior median and 95% credible intervals for the estimated marginals of the precisions of the prior variances of age of mother - τ_m, age of girl - τ_g, proportion of mothers cut within community - τ_{p1}, non-unstructured spatial effects - τ_v, structured spatial effects - τ_u, nonlinear temporal effects - τ_t, and space-time interaction effect -τ_{st}, and cluster design effect -τ_c.

Parameter	Model 1 Median(95CI)	Model 2 Median(95CI)	Model 3 Median(95CI)	Model 4 Median(95CI)	Model 5 Median(95CI)
$\boldsymbol{\tau_m}$	209(58,598)	222(70,599)	202(56,562)	203(58,567)	283(170,611)
$\boldsymbol{\tau_g}$	76(22,232)	86(27,297)	57(16,181)	57(16,180)	72(35,202)
$\boldsymbol{\tau_{p1}}$		85(18,323)	87(15,416)	93(15,510)	54(9,179)
$\boldsymbol{\tau_v}$			10.4(1.8,49.3)	9(1.5,49.6)	8.6(2.1,28.6)
$\boldsymbol{\tau_u}$					
$\boldsymbol{\tau_t}$			2.97(1.26,6.60)		
$\boldsymbol{\tau_{st}}$				2.8(1.1,7.1)	2.4(1.1,4.4)
$\boldsymbol{\tau_c}$					1.14(0.89,1.54)

Table A5.2. Model hyperparameters for Nigeria study: posterior median and 95% credible intervals for the estimated marginals of the precisions of the prior variances of age of mother - τ_m, age of girl - τ_g, proportion of mothers cut within community - τ_{p1}, proportion of mothers that supported FGM continuation within community - τ_{p2}, proportion of mothers that cut for religious reasons within community - τ_{p3}, non-unstructured spatial effects - τ_v, structured spatial effects - τ_u, nonlinear temporal effects - τ_t, space-time interaction effect - τ_{st}, and cluster design effect -τ_c.

Parameter	Model 1 Median(95CI)	Model 2 Median(95CI)	Model 3 Median(95CI)	Model 4 Median(95CI)	Model 5 Median(95CI)
$\boldsymbol{\tau_m}$	60(11,318)	71(13,407)	45(29,56)	48(16,156)	81(15,378)
$\boldsymbol{\tau_g}$	147(39,458)	140(36,451)	126(61,286)	109(30,397)	97(23,416)
$\boldsymbol{\tau_{p1}}$		0.19(0.03,1.03)	90(15,421)	89(35,223)	80(10,420)
$\boldsymbol{\tau_{p2}}$		0.04(0.01,0.18)	84(37,221)	81(30,207)	83(12,429)
$\boldsymbol{\tau_{p3}}$		76(9,375)	83(32,168)	92(29,267)	63(7,304)

τ_v			0.99(0.56,1.80)	6.2(4.0,9.8)	0.6(0.3,1.3)
τ_u					
τ_t			13.6(6.8,33.1)	11.6(3.7,32.9)	13.3(2.3,55.3)
τ_{st}			0.8(0.7,1.0)	0.9(0.5,1.8)	1.0(0.5,1.7)
τ_c					0.45(0.38,0.55)

Table A5.3. Model hyperparameters for Senegal study: posterior median and 95% credible intervals for the estimated marginals of the precisions of the prior variances of age of mother - τ_m, age of girl - τ_g, proportion of mothers cut within community - τ_{p1}, proportion of mothers that supported FGM continuation within community - τ_{p1}, proportion of mothers that cut for religious reasons within community - τ_{p3}, non-unstructured spatial effects - τ_v, structured spatial effects - τ_u, nonlinear temporal effects - τ_t, space-time interaction effect - τ_{st}, and cluster design effect -τ_c.

Parameter	**Model 1 Median(95CI)**	**Model 2 Median(95CI)**	**Model 3 Median(95CI)**	**Model 4 Median(95CI)**	**Model 5 Median(95CI)**
τ_m	237(71,697)	230(65,643)	231(64,642)	235(70,654)	253(82,791)
τ_g	22(6,74)	18(4,74)	16(4,61)	17(5,64)	18(5,69)
τ_{p1}		48(3,313)	77(12,327)	94(20,388)	83(12,449)
τ_{p2}		78(10,471)	92(17,468)	87(19,349)	92(14,512)
τ_{p3}		82(11,461)	80(13,338)	98(16,559)	86(14,417)
τ_v			6.4(1.8,21.7)	10.6(2.5,49.0)	7.7(2.0,31.0)
τ_u					
τ_t					
τ_{st}			5.4(2.5,11.5)	5.1(2.3,11.0)	6.2(2.2,17.6)
τ_c					1.4(1.1,1.7)

Table A5.4. Observed versus predicted for Kenya and Measures of fit.

	2003		**2008**		**2014**	
ID	Observed	Predicted(95%CI)	Observed	Predicted(95%CI)	Observed	Predicted(95%CI)
1	0.029	0.032(0.006,0.082)	0.011	0.011(0.001,0.039)	0.001	0.002(0.000,0.009)
2	0.066	0.067(0.032,0.122)	0.044	0.042(0.020,0.080)	0.040	0.041(0.017,0.077)
3	0.071	0.072(0.027,0.145)	0.164	0.162(0.103,0.239)	0.050	0.051(0.021,0.095)
4	0.046	0.043(0.016,0.095)	0.007	0.011(0.003,0.028)	0.000	0.002(0.000,0.008)
5	0.603	0.609(0.428,0.776)	0.670	0.665(0.539,0.782)	0.419	0.418(0.251,0.594)
6	0.175	0.176(0.107,0.256)	0.140	0.139(0.094,0.192)	0.076	0.078(0.031,0.141)
7	0.124	0.124(0.056,0.221)	0.079	0.080(0.037,0.144)	0.009	0.010(0.002,0.032)
8	0.008	0.011(0.002,0.034)	0.000	0.002(0.000,0.009)	0.003	0.001(0.000,0.007)
RMSE	**0.0026**		**0.0026**		**0.0012**	
AR^2	**1.000**		**1.000**		**1.000**	

Table A5.5. Observed versus predicted for Nigeria and Measures of fit.

	2008		**2013**		**2018**	
ID	Observed	Predicted(95%CI)	Observed	Predicted(95%CI)	Observed	Predicted(95%CI)
1	0.23	0.23(0.12,0.39)	0.17	0.17(0.07,0.32)	0.16	0.16(0.09,0.30)
2	0.02	0.01(0.00,0.06)	0.02	0.03(0.00,0.09)	0.00	0.00(0.00,0.03)
3	0.02	0.03(0.00,0.08)	0.02	0.02(0.00,0.07)	0.09	0.08(0.03,0.16)
4	0.10	0.10(0.04,0.21)	0.16	0.16(0.08,0.28)	0.10	0.11(0.04,0.24)
5	0.04	0.05(0.01,0.15)	0.26	0.26(0.12,0.46)	0.48	0.48(0.30,0.68)
6	0.03	0.03(0.01,0.08)	0.01	0.01(0.00,0.04)	0.00	0.01(0.00,0.04)
7	0.00	0.00(0.00,0.01)	0.00	0.01(0.00,0.04)	0.00	0.00(0.00,0.02)
8	0.08	0.08(0.05,0.12)	0.04	0.04(0.01,0.11)	0.01	0.02(0.00,0.05)
9	0.01	0.02(0.00,0.07)	0.04	0.03(0.00,0.12)	0.02	0.02(0.00,0.09)
10	0.14	0.15(0.06,0.28)	0.03	0.04(0.00,0.13)	0.07	0.08(0.02,0.20)
11	0.11	0.12(0.03,0.27)	0.20	0.20(0.09,0.35)	0.03	0.05(0.01,0.13)
12	0.34	0.34(0.19,0.50)	0.11	0.12(0.03,0.24)	0.12	0.14(0.04,0.29)
13	0.39	0.39(0.20,0.61)	0.43	0.43(0.23,0.63)	0.38	0.39(0.16,0.66)
14	0.29	0.28(0.12,0.50)	0.23	0.24(0.11,0.42)	0.02	0.04(0.01,0.14)
15	0.11	0.11(0.04,0.23)	0.01	0.01(0.00,0.07)	0.02	0.03(0.00,0.11)
16	0.00	0.00(0.00,0.02)	0.02	0.03(0.00,0.09)	0.01	0.02(0.00,0.08)
17	0.45	0.45(0.26,0.65)	0.38	0.39(0.23,0.56)	0.64	0.63(0.42,0.81)
18	0.00	0.03(0.00,0.15)	0.63	0.63(0.49,0.75)	0.71	0.71(0.55,0.85)
19	0.07	0.07(0.02,0.19)	0.57	0.57(0.44,0.70)	0.81	0.81(0.67,0.91)

20	0.84	0.84(0.70,0.92)	0.48	0.48(0.37,0.60)	0.50	0.50(0.34,0.69)
21	0.00	0.00(0.00,0.03)	0.00	0.00(0.00,0.02)	0.32	0.26(0.10,0.49)
22	0.00	0.00(0.00,0.02)	0.07	0.09(0.01,0.23)	0.13	0.13(0.03,0.29)
23	0.04	0.04(0.01,0.10)	0.00	0.01(0.00,0.04)	0.00	0.01(0.00,0.04)
24	0.65	0.65(0.46,0.79)	0.37	0.37(0.23,0.52)	0.19	0.19(0.08,0.36)
25	0.14	0.14(0.05,0.28)	0.07	0.07(0.01,0.18)	0.08	0.09(0.02,0.24)
26	0.06	0.06(0.01,0.14)	0.06	0.07(0.02,0.13)	0.24	0.21(0.06,0.45)
27	0.04	0.05(0.00,0.15)	0.16	0.15(0.10,0.24)	0.42	0.42(0.22,0.63)
28	0.07	0.07(0.02,0.15)	0.00	0.01(0.00,0.05)	0.00	0.01(0.00,0.08)
29	0.34	0.33(0.16,0.53)	0.36	0.36(0.19,0.55)	0.29	0.30(0.11,0.53)
30	0.47	0.47(0.28,0.66)	0.26	0.27(0.11,0.47)	0.15	0.16(0.04,0.37)
31	0.56	0.56(0.37,0.73)	0.39	0.39(0.22,0.55)	0.14	0.14(0.02,0.38)
32	0.03	0.02(0.00,0.07)	0.00	0.09(0.01,0.24)	0.12	0.12(0.03,0.28)
33	0.12	0.12(0.04,0.24)	0.07	0.08(0.03,0.16)	0.03	0.04(0.01,0.10)
34	0.04	0.04(0.01,0.14)	0.25	0.25(0.13,0.39)	0.26	0.28(0.09,0.53)
35	0.03	0.04(0.01,0.14)	0.17	0.17(0.09,0.30)	0.26	0.26(0.14,0.42)
36	0.00	0.01(0.00,0.05)	0.06	0.07(0.01,0.17)	0.62	0.61(0.42,0.78)
37	0.05	0.06(0.01,0.13)	0.34	0.34(0.22,0.48)	0.28	0.29(0.12,0.49)
RMSE	**0.008**		**0.015**		**0.014**	
AR^2	**0.999**		**0.994**		**0.996**	

Table A5.6. Observed versus predicted for Senegal and Measures of fit.

	2010		**2015**		**2017**	
ID	Observed	Predicted(95%CI)	Observed	Predicted(95%CI)	Observed	Predicted(95%CI)
1	0.07	0.06(0.03,0.11)	0.01	0.02(0.00,0.05)	0.03	0.03(0.01,0.06)
2	0.00	0.00(0.00,0.01)	0.00	0.00(0.00,0.01)	0.00	0.00(0.00,0.01)
3	0.00	0.00(0.00,0.01)	0.02	0.02(0.00,0.03)	0.00	0.01(0.00,0.02)
4	0.13	0.15(0.06,0.28)	0.28	0.29(0.17,0.42)	0.38	0.38(0.26,0.52)
5	0.03	0.02(0.01,0.05)	0.01	0.02(0.00,0.04)	0.02	0.02(0.01,0.05)
6	0.00	0.01(0.00,0.02)	0.05	0.05(0.03,0.09)	0.01	0.01(0.00,0.04)
7	0.39	0.39(0.27,0.52)	0.45	0.45(0.32,0.57)	0.30	0.30(0.20,0.40)
8	0.05	0.05(0.03,0.07)	0.00	0.00(0.00,0.01)	0.01	0.01(0.00,0.03)
9	0.43	0.43(0.29,0.57)	0.56	0.55(0.41,0.67)	0.56	0.56(0.44,0.67)
10	0.50	0.49(0.35,0.63)	0.44	0.44(0.31,0.56)	0.38	0.38(0.26,0.50)
11	0.23	0.23(0.15,0.32)	0.31	0.30(0.21,0.39)	0.26	0.26(0.19,0.32)
12	0.40	0.40(0.27,0.53)	0.39	0.39(0.28,0.51)	0.41	0.40(0.30,0.51)
13	0.01	0.01(0.00,0.02)	0.00	0.00(0.00,0.01)	0.01	0.01(0.00,0.03)
14	0.19	0.19(0.10,0.32)	0.41	0.40(0.27,0.54)	0.26	0.27(0.16,0.39)
RMSE	**0.005**		**0.007**		**0.003**	
AR^2	**0.999**		**0.999**		**0.999**	

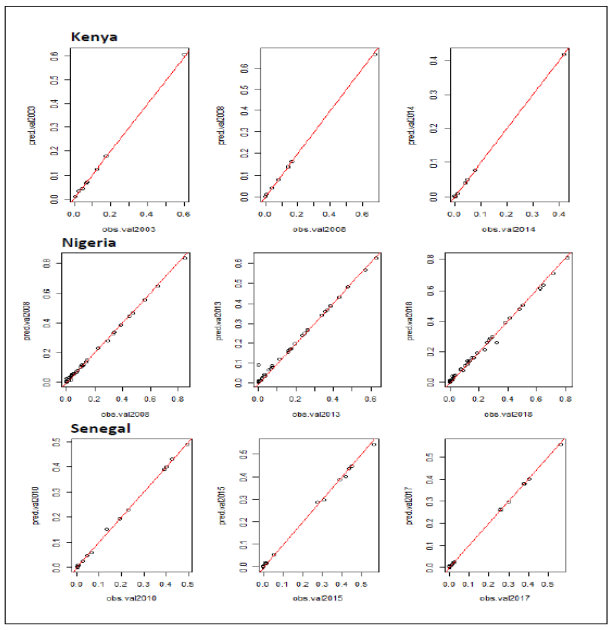

Figure A5.1. A plot of Observed versus Predicted prevalence risk for the best Bayesian model by country.

Appendix A6. Results Tables for Chapter 6

Table A6.1. Small area estimates of systolic blood pressure (SBP) in South African adults from the observed data (unadjusted for weights).

Area ID	**SURVEY YEAR**				
	2008	2010	2012	2014/15	2017
	Mean(95%CI) *(var; se; cv%)*	Mean(95%CI) *(var; se; cv%)*	Mean(95%CI) *(var; se; cv%)*	Mean(95%CI) *(var; se; cv%)*	Mean(95%CI) *(var; se; cv%)*
1	121(118-124) *(1.99;1.41;1.16)*	121(118-123) *(2.24;1.50;1.24)*	121(118-123) *(1.31;1.14;0.95)*	116(114-117) *(0.82;0.90,0.78)*	118(116-120) *(0.95;0.97;0.82)*
2	121(118-124) *1.76;1.33;1.10*	124(121-126) *(1.61;1.27;1.03)*	121(119-123) *(1.03;1.01;0.84)*	117(115-119) *(0.68;0.83;0.71)*	119(117-120) *(0.69;0.83;0.70)*
3	140(127-152) *(40.28;6.35;4.54)*	122(117-127) *(6.23;2.50;2.04)*	126(120-132) *(8.90;2.98;2.37)*	130(123-136) *(11.14;3.34;2.58)*	124(118-131) *(10.09;3.18;2.56)*
4	129(125-133) *(3.55;1.88;1.46)*	130(125-135) *(6.59;2.57;1.98)*	134(130-138) *(3.81;1.95;1.46)*	129(125-132) *(3.22;1.80;1.39)*	124(122-127) *(2.10;1.45;1.17)*
5	130(123-136) *(10.75;3.28;2.53)*	129(124-134) *(6.94;2.63;2.05)*	127(122-131) *(5.29;2.30;1.82)*	124(119-128) *(5.45;2.33;1.89)*	125(121-129) *(4.81;2.19;1.75)*
6	126(124-129) *(1.73;1.31;1.04)*	127(125-130) *(1.56;1.25;0.98)*	129(126-132) *(2.75;1.66;1.29)*	124(121-127) *(2.02;1.42;1.15)*	122(120-125) *(1.77;1.33;1.09)*
7	132(129-135) *(2.09;1.45;1.09)*	125(122-127) *(2.24;1.50;1.20)*	128(125-132) *(3.18;1.78;1.39)*	118(116-121) *(1.57;1.25;1.06)*	125(122-127) *(1.85;1.36;1.09)*
8	122(120-124) *(1.15;1.07;0.88)*	123(120-125) *(2.19;1.48;1.21)*	121(119-124) *(1.44;1.20,0.99)*	119(116-121) *(1.27;1.13;0.95)*	120(118-122) *(1.18;1.09;0.90)*
9	123(120-126) *(2.23;1.49;1.22)*	125(121-129) *(3.62;1.90;1.52)*	122(119-125) *(2.33;1.53;1.25)*	122(119-126) *(2.53;1.59;1.30)*	123(121-126) *(1.83;1.35;1.10)*
10	125(123-128) *(1.70;1.30;1.03)*	124(121-128) *(2.77;1.66;1.34)*	131(128-133) *(1.60;1.27;0.97)*	125(122-127) *(1.84;1.36;1.09)*	125(123-128) *(1.59;1.26;1.01)*
11	126(122-130)	131(127-135)	126(123-129)	118(115-121)	124(121-127)

	(4.16;2.04;1.62)	*(5.02;2.24;1.71)*	*(2.72;1.65;1.31)*	*(2.15;1.47;1.24)*	*(2.66;1.63;1.31)*
12	124(121-127) *(1.88;1.37;1.11)*	125(122-129) *3.08;1.76;1.40)*	120(118-123) *(1.98;1.41;1.17)*	117(114-120) *(1.77;1.33;1.14)*	120(117-122) *(1.67;1.29;1.08)*
13	123(119-126) *(3.54;1.88;1.54)*	132(127-136) *(5.97;2.44;1.86)*	122(118-125) *(2.74;1.66;1.36)*	115(112-117) *(1.85;1.36;1.18)*	120(117-123) *(2.50;1.58;1.31)*
14	129(126-133) *(3.63;1.90;1.47)*	122(118-126) *(4.01;2.00;1.64)*	128(124-131) *(2.89;1.70;1.33)*	120(117-124) *(2.96;1.72;1.43)*	126(122-131) *(4.76;2.18;1.73)*
15	125(121-130) *(4.75;2.18;1.74)*	129(125-133) *(4.18;2.04;1.58)*	125(121-129) *(3.82;1.95;1.56)*	117(114-120) *(2.30;1.52;1.29)*	124(120-127) *(2.63;1.62;1.31)*
16	123(120-126) *(1.69;1.30;1.06)*	122(119-125) *(2.35;1.53;1.26)*	124(121-126) *(1.58;1.26;1.02)*	116(113-118) *(1.60;1.26;1.09)*	117(115-119) *(1.21;1.10;0.94)*
17	122(119-125) *(2.03;1.42;1.17)*	123(120-126) *(2.45;1.57;1.28)*	124(121-126) *(1.71;1.31;1.06)*	121(117-124) *(2.66;1.63;1.35)*	120(117-123) *(2.47;1.57;1.31)*
18	124(122-126) *(1.19;1.09;0.88)*	121(119-123) *(1.05;1.03;0.85)*	123(121-125) *(1.06;1.03;0.84)*	117(115-118) *(0.72;0.85;0.72)*	117(115-119) *(0.82;0.90;0.77)*
19	126(124-128) *(1.31;1.14;0.91)*	127(125-129) *(1.00;1.00;0.79)*	125(123-127) *(1.04;1.02;0.82)*	121(119-123) *(0.94;0.97;0.80)*	124(122-126) *(0.98;0.99;0.80)*
20	120(117-124) *(3.18;1.78;1.49)*	127(123-130) *(2.93;1.71;1.35)*	123(120-125) *(1.56;1.25;1.02)*	123(120-125) *(1.40;1.18;0.96)*	119(117-121) *(1.17;1.08;0.91)*
21	127(125-129) *(1.38;1.17;0.92)*	125(122-127) *(1.57;1.25;1.00)*	*123(121-125)* *(0.95;0.97;0.79)*	118(117-120) *(0.98;0.99;0.84)*	119(118-121) *(0.75;0.87;0.72)*
22	131(128-133) *(2.08;1.44;1.11)*	125(122-127) *(1.58;1.26;1.01)*	125(123-127) *(1.10;1.05;0.84)*	122(119-124) *(1.58;1.26;1.03)*	122(120-125) *(1.53;1.24;1.01)*
23	128(125-131) *(1.98;1.41;1.10)*	124(122-127) *(1.47;1.21;0.98)*	123(120-125) *(1.36;1.17;0.95)*	123(120-125) *(1.29;1.14;0.93)*	121(119-123) *(1.10;1.05;0.87)*
24	123(120-125) *(1.54;1.24;1.01)*	126(124-128) *(1.30;1.14;0.91)*	124(121-126) *(1.69;1.30;1.05)*	119(116-121) *(1.60;1.26;1.06)*	122(119-124) *(1.51;1.23;1.01)*
25	124(121-127) *(2.75;1.66;1.34)*	115(113-118) *(2.11;1.45;1.26)*	121(118-124) *(2.51;1.58;1.31)*	118(115-121) *(2.48;1.58;1.33)*	124(121-127) *(2.18;1.48;1.19)*
26	127(124-130) *(1.92;1.39;1.09)*	125(122-127) *(1.88;1.37;1.10)*	126(123-128) *(1.52;1.23;0.98)*	120(118-123) *(1.21;1.10;0.91)*	121(119-124) *(1.36;1.17;0.96)*
27	121(119-124) *(1.51;1.23;1.01)*	122(119-125) *(2.39;1.54;1.26)*	120(117-123) *(2.00;1.42;1.18)*	120(117-122) *(1.25;1.12;0.94)*	121(119-124) *(1.50;1.22;1.01)*
28	119(116-122) *(3.12;1.77;1.49)*	124(122-127) *(1.52;1.23;0.99)*	119(117-121) *(0.97;0.98;0.83)*	123(120-125) *(1.43;1.20;0.98)*	120(117-122) *(1.21;1.10;0.92)*
29	122(120-124) *(1.11;1.05;0.86)*	123(121-125) *(1.22;1.11;0.90)*	123(121-125) *(1.02;1.01;0.82)*	118(116-119) *(0.53;0.72;0.62)*	116(115-118) *(0.48;0.69;0.59)*
30	124(121-126) *(1.67;1.29;1.05)*	126(123-129) *(2.55;1.60;1.27)*	124(121-127) *(2.45;1.56;1.26)*	120(117-123) *(2.41;1.55;1.29)*	120(117-124) *(2.77;1.66;1.38)*
31	122(119-125) *(2.15;1.47;1.20)*	121(118-124) *(2.71;1.65;1.36)*	123(120-125) *(2.14;1.46;1.20)*	117(114-120) *(1.65;1.29;1.10)*	117(114-120) *(2.02;1.42;1.22)*
32	121(118-124) (2.05;1.43;1.19)	123(120-126) *(2.53;1.59;1.29)*	119(116-122) *(2.31;1.52;1.28)*	115(112-118) *(1.77;1.33;1.16)*	116(113-118) *(1.53;1.24;1.07)*
33	118(115-120) (1.53;1.24;1.05)	120(117-123) *(1.79;1.34;1.12)*	121(119-123) *(1.38;1.18;0.97)*	116(114-118) *(1.06;1.03;0.88)*	117(115-119) *(1.01;1.01;0.86)*
34	119(116-122) *(1.81;1.35;1.13)*	120(117-122) *(1.24;1.11,0.93)*	120(118-123) *(1.59;1.26;1.05)*	118(115-120) *(1.65;1.28;1.09)*	117(115-120) *(1.39;1.18;1.00)*
35	124(122-127) *(1.22;1.10;0.89)*	117(115-119) *(1.06;1.03;0.88)*	119(118-121) *(0.97;0.98;0.82)*	117(115-119) *(1.07;1.03;0.88)*	120(118-121) *(0.78;0.88;0.74)*
36	124(121-127) *(2.31;1.52;1.22)*	119(116-123) *(3.52;1.87;1.57)*	122(119-126) *(2.74;1.65;1.35)*	116(113-118) *(1.52;1.23;1.06)*	116(114-119) *(1.31;1.15;0.99)*
37	125(123-127) *(1.11;1.05;0.84)*	120(118-121) *(0.59;0.77;0.64)*	120(118-122) *(0.96;0.98;0.82)*	119(117-121) *(0.90;0.95;0.80)*	119(117-121) *(0.86;0.93;0.78)*
38	132(129-136) *(3.66;(1.91;1.45)*	125(121-129) *(3.99;2.00;1.59)*	127(123-131) *(3.97;1.99;1.57)*	121(119-124) *(1.88;1.37;1.13)*	126(122-129) *(2.96;1.72;1.37)*
39	128(125-131) *(2.37;1.54;1.20)*	137(133-140) *(2.81;1.68,1.23)*	126(123-129) *(2.14;1.46;1.16)*	128(125-131) *(1.87;1.37;1.07)*	129(126-131) *(1.48;1.22;0.95)*
40	136(132-141) *(6.04;2.46;1.80)*	132(128-136) *(4.54;2.13;1.62)*	129(124-134) *(5.37;2.32;1.80)*	125(121-129) *(3.92;1.98;1.59)*	123(119-127) *(3.50;1.87;1.52)*

41	128(125-131) *(2.91;1.71;1.33)*	126(123-129) *(1.92;1.38;1.10)*	123(120-126) *(2.52;1.59;1.29)*	124(121-126) *(1.76;1.33;1.07)*	126(123-129) *(2.45;1.57;1.25)*
42	125(121-128) *(3.23;1.80;1.44)*	124(121-128) *(3.67;1.91;1.54)*	124(120-127) *(2.85;1.69;1.37)*	120(117-122) *(2.10;1.45;1.21)*	120(117-122) *(1.62;1.27;1.07)*
43	123(120-126) *(2.65;1.63;1.33)*	121(118-125) *(3.05;1.75;1.44)*	122(119-125) *(2.88;1.70;1.39)*	116(114-119) *(1.89;1.37;1.18)*	117(115-120) *(1.69;1.30;1.11)*
44	130(127-132) *(1.74;1.32;1.02)*	120(118-123) *(1.52;1.23;1.02)*	126(123-128) *(1.51;1.23;0.98)*	119(116-121) *(1.49;1.22;1.03)*	118(116-121) *(1.87;1.37;1.16)*
45	128(125-131) *(2.10;1.45;1.13)*	120(117-122) *(1.40;1.18;0.99)*	126(123-129) *(2.59;1.61;1.28)*	117(115-120) *(1.85;1.36;1.16)*	118(116-121) *(1.48;1.22;1.03)*
46	130(125-136) *(8.90;2.98;2.29)*	121(117-126) *(5.50;2.34;1.94)*	124(119-130) *(7.91;2.81;2.27)*	119(114-123) *(4.91;2.22;1.87)*	121(116-126) *(5.98;2.45;2.03)*
47	128(126-131) *(2.24;1.50;1.16)*	125(122-128) *(2.57;1.60;1.28)*	124(122-126) *(1.22;1.11;0.89)*	120(118-122) *(0.83;0.91;0.76)*	120(118-122) *(0.86;0.93;0.77)*
48	132(128-135) *(3.94;1.98;1.51)*	131(127-136) *(4.63;2.15;1.64)*	132(129-135) *(2.54;1.59;1.21)*	134(131-137) *(2.41;1.55;1.16)*	126(123-128) *(1.72;1.31;1.04)*
49	129(126-132) *(2.31;1.52;1.18)*	129(126-132) *(2.31;1.52;1.17)*	131(129-134) *(1.80;1.34;1.02)*	129(127-132) *(1.33;1.15;0.89)*	127(125-129) *(1.27;1.13;0.89)*
50	136(133-139) *(2.08;1.44;1.06)*	132(128-135) *(3.13;1.77;1.34)*	134(131-137) *(2.31;1.52;1.13)*	132(130-135) *(1.76;1.33;1.00)*	130(127-132) *(2.07;1.44;1.11)*
51	131(127-134) *(3.36;1.83;1.40)*	133(128-138) *(6.48;2.55;1.91)*	131(128-134) *(2.56;1.60;1.22)*	132(129-135) *(2.62;1.62;1.23)*	129(126-132) *(2.58;1.61;1.24)*
52	135(131-138) *(2.93;1.71;1.27)*	131(128-135) *(3.65;1.91;1.46)*	132(129-135) *(2.43;1.56;1.18)*	127(124-130) *(2.37;1.54;1.21)*	126(124-128) *(1.47;1.21;0.96)*

Table A6.2. Design-based estimates of systolic blood pressure (SBP) in South African adults.

Area ID	**SURVEY YEAR**				
	2008	2010	2012	2015	2017
	Mean(95%CI) *(var; se; cv%)*	Mean(95%CI) *(var; se; cv%)*	Mean(95%CI) *(var; se; cv%)*	Mean(95%CI) *(var; se; cv%)*	Mean(95%CI) *(var; se; cv%)*
1	122(119-124) *(1.90;1.38;1.13)*	120(116-123) *(2.56;1.60;1.34)*	123(120-126) *(2.46;1.57;1.27)*	117(115-119) *(1.06;1.03;0.88)*	119(116-122) *(2.44;1.56;1.31)*
2	120(117-123) *(2.45;1.57;1.31)*	126(123-128) *(2.06;1.44;1.14)*	122(119-124) *(1.60;1.27;1.04)*	119(116-122) *(2.26;1.50;1.26)*	121(118-124) *(2.14;1.46;1.21)*
3	136(125-147) *(29.83;5.46;4.01)*	122(116-128) *(9.33;3.05;2.51)*	124(119-130) *(8.19;2.86;2.30)*	131(125-138) *(10.86;3.30;2.51)*	122(115-128) *(10.62;3.26;2.68)*
4	126(123-129) *(2.87;1.69;1.34)*	129(124-135) *(7.42;2.72;2.11)*	133(129-137) *(14.33;2.08;1.57)*	128(125-132) *(2.78;1.67;1.30)*	124(120-128) *(3.51;1.87;1.51)*
5	129(122-136) *(13.15;3.63;2.82)*	129(123-136) *(11.81;3.44;2.66)*	124(119-129) *(5.52;2.35;1.89)*	123(118-128) *(6.65;2.58;2.10)*	123(118-128) *(6.97;2.64;2.15)*
6	124(121-127) *(2.23;1.49;1.20)*	125(122-129) *(2.96;1.72;1.37)*	130(120-140) *(25.02;5.00;3.84)*	122(118-126) *(4.88;2.21;1.81)*	120(117-123) *(2.22;1.49;1.24)*
7	130(127-133) *(2.67;1.63;1.26)*	122(119-125) *(2.66;1.63;1.34)*	128(125-132) *(3.74;1.93;1.51)*	119(116-123) *(3.31;1.82;1.53)*	124(122-127) *(1.97;1.40;1.13)*
8	122(120-124) *(1.04;1.02;0.84)*	122(119-126) *(2.61;1.62;1.32)*	120(118-123) *(1.78;1.33;1.11)*	118(115-120) *(1.77;1.33;1.13)*	120(118-123) *(1.54;1.24;1.03)*
9	121(118-124) *(2.09;1.45;1.19)*	122(118-125) *(2.77;1.66;1.37)*	121(117-125) *(3.72;1.93;1.59)*	121(118-124) *(2.28;1.51;1.24)*	122(119-125) *(2.06;1.43;1.18)*
10	124(121-127) *(1.87;1.37;1.55)*	124(121-128) *(2.89;1.70;1.37)*	131(128-134) *(2.07;1.44;1.10)*	125(121-128) *(2.61;1.62;1.30)*	125(122-128) *(1.89;1.38;1.10)*
11	125(121-129) *(3.76;1.94;1.55)*	132(126-137) *(8.61;2.93;2.23)*	125(121-128) *(2.51;1.58;1.27)*	119(115-124) *(4.73;2.17;1.82)*	126(119-133) *(13.10;3.62;2.87)*
12	122(120-125) *(1.85;1.36;1.11)*	123(120-126) *(2.63;1.62;1.32)*	118(116-121) *(1.98;1.41;1.19)*	116(114-119) *(2.23;1.49;1.28)*	119(117-122) *(2.09;1.45;1.21)*
13	122(118-126) *(3.92;1.98;1.63)*	130(126-135) *(5.66;2.38;1.83)*	121(117-124) *(3.68;1.92;1.59)*	114(112-117) *(1.64;1.28;1.12)*	120(117-124) *(3.07;1.75;1.46)*

14	128(123-133) *(5.94;2.44;1.90)*	119(113-124) *(8.01;2.83;2.38)*	129(126-132) *(2.98;1.73;1.34)*	120(115-124) *(4.86;2.21;1.84)*	126(121-130) *(5.51;2.35;1.87)*
15	124(120-128) *(4.62;2.15;1.73)*	127(124-130) *(2.92;1.71;1.35)*	123(119-127) *(3.93;1.98;1.61)*	117(113-120) *(2.81;1.67;1.44)*	124(120-127) *(3.56;1.89;1.53)*
16	119(115-124) *(4.58;2.14;1.79)*	119(115-123) *(3.39;1.84;1.55)*	122(120-125) *(1.48;1.22;0.99)*	118(115-122) *(2.89;1.70;1.44)*	115(112-117) (2.12;1.46;1.27)
17	123(119-127) *(3.79;1.95;1.58)*	126(121-132) *(7.64;2.76;2.19)*	124(121-127) *(2.54;1.60;1.29)*	121(118-124) *(2.30;1.52;1.26)*	120(117-124) (2.78;1.67;1.39)
18	122(120-125) *(1.31;1.15;0.94)*	121(118-123) *(1.29;1.13;0.94)*	122(119-125) *(1.83;1.35;1.11)*	118(115-120) *(1.39;1.18;1.00)*	119(116-121) (1.14;1.07;0.90)
19	126(124-129) *(1.64;1.28;1.01)*	127(125-129) *(1.11,1.05;0.83)*	125(123-128) *(1.42;1.19;0.95)*	122(119-124) *(1.66;1.29;1.06)*	124(122-126) (1.28;1.13;0.91)
20	119(114-123) *(3.04.46;2.11;1.78)*	125(119-130) *(7.16;2.68;2.15)*	124(121-128) *(3.25;1.80;1.45)*	123(120-125) *(1.67;1.29;1.06)*	120(117-122) (1.84;1.36;1.13)
21	126(124-129) *(1.44;1.20;0.95)*	125(122-127) *(1.90;1.38;1.11)*	124(122-126) *(1.09;1.04;0.84)*	118(116-120) *(1.07;1.03;0.88)*	119(117-121) (0.98;0.99;0.83)
22	130(126-134) *(3.26;1.81;1.39)*	123(120-126) *(2.21;1.49;1.21)*	122(119-125) *(2.14;1.46;1.20)*	121(118-124) *(2.46;1.57;1.30)*	122(119-125) (2.63;1.62;1.33)
23	127(124-130) *(2.56;1.60;1.26)*	124(121-127) *(2.93;1.71;1.38)*	126(118-133) *(14.17;3.76;2.99)*	121(119-124) *(1.69;1.30;1.07)*	122(119-124) (1.70;1.30;1.07)
24	121(119-124) *(1.54;1.24;1.02)*	125(122-127) *(1.32;1.15;0.92)*	122(120-125) *(1.51;1.23;1.01)*	118(115-120) *(1.72;1.31;1.11)*	122(119-125) (1.86;1.36;1.12)
25	122(119-125) *(2.66;1.63;1.33)*	114(111-117) *(2.30;1.52;1.33)*	121(117-124) *(3.45;1.86;1.54)*	119(115-123) *(3.73;1.93;1.63)*	126(122-129) (2.97;1.72;1.37)
26	127(124-129) *(1.86;1.36;1.08)*	125(122-128) *(1.95;1.40;1.12)*	125(123-128) *(1.97;1.40;1.12)*	122(120-125) *(1.80;1.34;1.10)*	123(120-126) (2.11;1.45;1.18)
27	120(118-122) *(1.45;1.21;1.00)*	123(119-126) *(3.32;1.82;1.49)*	119(115-122) *(3.38;1.84;1.55)*	121(117-124) *(2.85;1.69;1.40)*	121(119-124) (1.94;1.39;1.15)
28	119(116-122) *(2.38;1.54;1.29)*	122(120-125) *(2.12;1.46;1.19)*	120(116-123) *(3.08;1.75;1.46)*	120(116-123) *(3.68;1.92;1.61)*	120(116-125) (5.20;2.28;1.90)
29	123(120-125) *(1.47;1.21;0.99)*	121(119-124) *(1.18;1.09;0.90)*	124(121-126) *(1.53;1.24;1.00)*	119(117-120) *(0.88;0.94;0.79)*	118(116-119) (0.88;0.94;0.80)
30	122(120-125) *(1.82;1.35;1.11)*	125(121-128) *(3.02;1.74;1.39)*	124(121-127) *(2.26;1.50;1.21)*	120(117-123) *(2.84;1.69;1.40)*	119(116-122) (2.71;1.65;1.38)
31	120(117-123) *(2.59;1.61;1.34)*	122(119-125) *(2.73;1.65;1.36)*	122(118-125) *(3.60;1.90;1.56)*	117(114-120) *(2.48;1.58;1.35)*	116(113-120) (2.70;1.64;1.41)
32	120(117-123) *(2.31;1.52;1.26)*	122(119-125) *(2.59;1.61;1.32)*	118(115-121) *(2.35;1.53;1.30)*	115(112-118) *(2.14;1.46;1.27)*	116(113-119) (2.20;1.48;1.28)
33	118(115-120) *(1.61;1.27;1.08)*	120(117-123) *(2.14;1.46;1.21)*	122(119-125) *(2.17;1.47;1.20)*	117(115-120) *(2.13;1.46;1.24)*	118(116-121) (1.65;1.28;1.08)
34	119(114-124) *(6.51;2.55;2.14)*	119(117-121) *(1.23;1.11;0.93)*	120(117-123) *(2.07;1.44;1.20)*	115(110-120) *(6.45;2.54;2.21)*	117(114-121) (3.66;1.91;1.63)
35	125(122-128) *(2.54;1.59;1.27)*	116(113-118) *(1.52;1.23;1.07)*	120(118-123) *(1.18;1.09;0.90)*	117(115-119) *(1.30;1.14;0.98)*	120(117-123) (2.15;1.47;1.22)
36	124(120-127) *(3.44;1.85;1.50)*	120(116-124) *(4.23;2.06;1.71)*	122(118-126) *(3.76;1.94;1.59)*	116(113-119) *(2.28;1.51;1.30)*	116(113-119) (1.94;1.39;1.20)
37	124(122-126) *(1.18;1.09;0.88)*	119(116-121) *(1.82;1.35;1.14)*	120(117-122) *(1.46;1.21;1.01)*	119(116-121) *(1.45;1.20;1.01)*	118(116-121) (1.41;1.19;1.01)
38	130(127-133) *(2.63;1.62;1.25)*	125(121-129) *(4.55;2.13;1.71)*	129(124-134) *(6.34;2.52;1.96)*	123(120-126 *(2.17;1.47;1.20)*	127(123-131) (4.23;2.06;1.62)
39	130(126-134) *(3.69;1.92;1.48)*	136(131-140) *(5.23;2.29;1.69)*	127(124-131) *(3.26;1.81;1.42)*	127(124-131) *(3.08;1.75;1.38)*	130(127-132) (1.65;1.29;0.99)
40	135(130-140) *(6.49;2.55;1.89)*	133(119-147) *(52.88;7.27;5.46)*	131(127-135) *(4.01;2.00;1.53)*	127(120-134) *(12.65;3.56;2.80)*	125(119-130) (6.86;2.62;2.10)
41	129(125-133) *(3.83;1.96;1.52)*	126(123-130) *(3.29;1.81;1.43)*	124(121-127) *(2.78;1.67;1.34)*	128(123-132) *(5.67;2.38;1.87)*	128(124-131) (2.98;1.73;1.35)
42	124(121-128) *(3.31;1.82;1.46)*	124(121-128) *(3.12;1.77;1.42)*	124(120-127) *(3.64;1.91;1.54)*	120(117-123) *(2.11;1.45;1.21)*	120(117-122) (1.65;1.29;1.07)
43	123(120-126)	121(117-125)	123(120-127)	118(115-122)	120(115-126)

	(2.62;1.62;1.32)	*(3.96;1.99;1.64)*	*(3.83;1.96;1.58)*	*(4.09;2.02;1.71)*	(7.85;2.80;2.33)
44	129(126-132) *(1.72;1.31;1.02)*	120(118-123) *(1.84;1.36;1.13)*	126(124-129) *(1.65;1.28;1.02)*	119(116-121) *(1.69;1.30;1.09)*	120(116-124) (4.49;2.12;1.77)
45	127(124-129) *(1.83;1.35;1.07)*	119(117-121) *(1.14;1.07;0.90)*	125(122-128) *(2.36;1.54;1.23)*	118(115-122) (3.22;1.79;1.52)	121(117-124) (3.47;1.86;1.54)
46	133(126-140) *(13.24;3.64;2.74)*	124(118-130) *(9.30;3.05;2.46)*	134(122-146) *(36.83;6.07;4.54)*	125(118-133) *(14.55;3.82;3.05)*	122(118-126) (4.85;2.20;1.80)
47	128(125-131) *(1.99;1.41;1.10)*	127(123-130) *(2.74;1.66;1.31)*	126(123-129) *(2.26;1.50;1.20)*	122(120-124) *(1.16;1.08;0.89)*	122(119-124) (1.53;1.24;1.02)
48	131(126-137) *(7.60;2.76;2.10)*	129(123-135) *(9.24;3.04;2.35)*	131(126-135) *(5.86;2.42;1.85)*	132(127-137) *(6.44;2.54;1.92)*	129(126-133) (3.32;1.82;1.41)
49	128(125-132) *(2.83;1.68;1.31)*	129(126-132) *(2.59;1.61;1.25)*	131(128-135) *(2.44;1.56;1.19)*	129(127-132) *(2.08;1.44;1.11)*	127(125-130) (1.65;1.29;1.01)
50	135(129-141) *(8.88;2.98;2.20)*	133(129-137) *(4.24;2.06;1.55)*	132(127-137) *(5.84;2.42;1.83)*	130(126-135) *(5.94;2.44;1.87)*	129(122-135) (10.24;3.20;2.49)
51	129(126-132) *(2.77;1.66;1.29)*	132(127-137) *(6.44;2.54;1.97)*	130(126-134) *(3.48;1.86;1.44)*	128(121-134) *(10.95;3.31;2.59)*	128(124-131) (3.42;1.85;1.45)
52	135(131-139) *(3.83;1.96;1.45)*	129(124-134) *(6.54;2.56;1.97)*	133(130-136) *(2.72;1.65;1.24)*	135(127-144) *(17.52;4.19;3.09)*	127(124-129) (1.78;1.34;1.05)

Table A6.3. Spatially-Smoothed Direct estimates of systolic blood pressure (SBP) in South African adults.

Area ID	**SURVEY YEAR**				
	2008	2010	2012	2014/15	2017
	Mean(95%CI) (var)	Mean(95%CI) (var)	Mean(95%CI) (var)	Mean(95%CI) (var)	Mean(95%CI) (var)
1	122(120-124) (1.26)	120(118-123) (1.58)	123(120-126) (1.79)	117(115-119) (0.89)	119(116-122) (1.79)
2	122(118-125) (3.84)	124(121-127) (2.62)	122(119-125) (2.40)	119(116-121) (1.96)	120(118-123) (1.71)
3	128(121-136) (14.27)	123(119-127) (4.43)	125(120-129) (5.03)	129(124-133) (5.30)	122(118-127) (5.69)
4	127(123-131) (3.91)	128(124-131) (3.42)	129(126-133) (3.52)	127(124-129) (1.92)	124(122-127) (1.66)
5	127(122-132) (6.53)	127(123-131) (4.00)	125(122-127) (1.72)	124(120-128) (4.16)	123(119-126) (3.26)
6	125(122-128) (2.44)	125(123-128) (2.03)	127(123-131) (4.01)	123(119-126) (2.84)	122(119-124) (1.86)
7	128(125-132) (2.80)	123(120-126) (2.09)	126(122-130) (3.53)	120(117-123) (2.35)	124(122-126) (1.04)
8	123(120-126) (2.16)	123(120-127) (2.58)	121(119-122) (0.57)	119(117-121) (1.15)	120(120-121) (0.15)
9	122(119-126) (2.70)	123(119-127) (4.00)	123(119-127) (3.77)	121(117-124) (3.36)	122(119-125) (2.54)
10	125(122-127) (1.62)	125(122-127) (1.63)	131(129-133) (1.26)	125(122-128) (2.36)	125(122-127) (1.66)
11	125(123-127) (0.67)	128(125-132) (3.22)	125(122-127) (1.95)	120(117-123) (2.20)	123(120-127) (3.17)
12	123(121-126) (1.80)	123(120-126) (2.30)	120(118-123) (1.64)	118(115-121) (1.91)	121(118-123) (1.81)
13	124(120-127) (3.65)	128(125-131) (1.97)	122(119-126) (3.21)	116(114-118) (1.05)	121(118-124) (2.28)
14	126(122-130) (3.71)	121(117-125) (3.88)	127(124-129) (1.87)	119(116-122) (2.21)	123(121-126) (1.76)
15	124(122-127)	127(126-128)	123(121-125)	117(115-119)	123(121-125)

	(2.04)	(0.29)	(1.33)	(1.37)	(0.93)
16	122(118-126) (3.64)	119(118-121 (0.72)	123(121-124) (0.76)	118(116-120) (1.25)	116(114-117) (0.71)
17	123(121-125) (1.29)	124(120-127) (3.49)	124(121-126) (1.31)	120(117-122) (1.65)	120(117-123) (2.11)
18	123(120-125) (2.20)	121(119-123) (1.40)	122(120-124) (1.10)	118(116-120) (1.14)	119(117-121) (1.02)
19	126(124-127) (0.54)	126(124-129) (1.20)	125(123-127) (1.00)	121(119-123) (1.34)	123(121-125) (1.26)
20	120(117-123) (2.12)	124(121-127) (2.73)	124(121-126) (1.82)	122(120-124) (1.03)	120(118-123) (1.65)
21	126(123-129) (2.33)	125(123-126) (0.90)	123(121-125) (0.98)	118(116-120) (1.31)	119(118-121) (0.81)
22	128(125-131) (2.20)	123(120-126) (3.11)	122(119-126) (2.53)	120(118-123) (1.80)	121(118-124) (2.24)
23	126(124-129) (1.64)	124(121-127) (2.00)	123(120-127) (3.84)	120(118-123) (1.11)	121(120-123) (0.94)
24	122(120-124) (1.13)	123(120-127) (2.51)	122(121-124) (0.90)	119(116-121) (1.83)	122(120-124) (1.38)
25	123(119-127) (3.59)	117(113-121) (4.05)	122(118-125) (2.88)	119(116-123) (3.33)	124(121-127) (2.88)
26	125(122-129) (3.13)	124(121-127) (2.11)	125(122-127) (1.42)	121(119-124) (1.35)	122(120-125 (2.00)
27	121(118-123) (1.22)	123(120-125) (1.9)	120(118-123) (1.84)	121(118-123) (1.89)	121(119-123) (1.19)
28	120(117-123) (2.36)	123(120-125) (1.55)	121(118-124) (1.96)	120(117-123) (2.38)	121(118-124) (2.94)
29	123(120-126) (1.96)	122(119-125) (1.88)	124(121-126) (1.19)	119(117-121) (1.10)	118(116-120) (1.13)
30	122(118-126) (3.42)	123(120-127) (2.55)	123(120-126) (2.47)	119(116-122) (2.36)	118(115-121) (2.42)
31	121(117-124) (4.09)	122(119-125) (2.86)	121(117-126) (4.28)	117(115-119) (1.28)	117(114-120) (2.36)
32	121(118-124) (2.89)	122(119-125) (2.09)	120(116-123) (2.86)	116(114-118) (1.48)	117(115-119) (1.22)
33	119(117-122) (1.59)	120(119-122) (0.90)	122(119-125) (2.50)	117(115-120) (1.81)	118(116-121) (1.16)
34	121(117-124) (3.19)	120(117-123) (2.00)	121(118-123) (1.78)	117(113-120) (2.61)	118(116-120) (1.00)
35	125(121-128) (2.61)	118(115-121) (2.08)	121(119-123) (1.11)	117(116-119) (0.90)	120(118-122) (1.16)
36	123(121-126) (2.04)	120(118-123) (1.97)	122(119-125) (2.33)	117(114-119) (1.38)	117(115-119) (0.98)
37	123(121-126) (1.86)	119(117-121 (1.38)	120(119-121) (0.47)	118(117-120) (0.90)	118(117-120) (0.81)
38	129(127-131) (1.01)	125(121-128) (3.83)	127(123-130) (3.19)	122(120-125) (1.87)	125(123-128) (2.18)
39	130(126-133) (2.48)	131(127-135) (4.09)	128(125-131) (2.80)	127(124-130) (2.13)	128(126-131) (1.38)
40	131(128-135) (3.18)	127(122-131) (4.96)	129(127-132) (1.51)	124(121-127) (2.64)	124(121-127) (2.19)
41	129(125-132) (2.65)	126(123-130) (2.69)	125(122-127) (1.74)	125(121-128) (3.41)	127(124-129) (1.34)
42	126(122-129) (3.35)	125(122-127) (1.17)	124(122-126) (1.47)	120(119-122) (0.75)	121(119-123) (1.26)
43	123(120-126) (2.19)	121(119-124) (1.99)	123(120-127) (2.82)	119(116-121) (1.24)	120(116-123) (2.98)
44	128(120-126) (1.70)	120(118-123) (1.07)	125(123-128) (1.72)	119(116-121) (1.69)	120(117-123) (2.48)

45	126(124-129) (1.78)	120(118-121) (0.77)	125(123-127) (0.89)	119(116-122) (1.82)	121(118-124) (1.94)
46	127(123-131) (4.49)	122(118-126) (4.21)	124(121-129) (4.04)	120(116-123) (2.80)	121(118-124) (2.34)
47	128(126-130) (1.27)	128(124-132) (3.38)	127(124-129) (1.43)	124(121-126) (1.77)	124(121-127) (2.23)
48	131(129-133) (0.79)	129(126-132) (2.69)	130(127-133) (2.54)	131(129-133) (1.03)	128(124-131) (2.76)
49	129(126-132) (2.34)	129(126-132) (2.05)	131(128-133) (1.37)	128(126-131) (1.97)	127(125-129) (0.94)
50	131(126-136) (5.78)	132(129-135) (1.93)	130(126-134) (3.78)	128(126-131) (3.37)	127(123-131) (3.84)
51	129(126-132) (2.87)	130(126-134) (4.52)	130(127-133) (2.24)	128(124-131) (3.84)	127(125-130) (1.67)
52	131(128-135) (3.65)	129(125-133) (4.00)	131(128-134) (2.43)	128(124-132) (4.00)	126(124-129) (1.17)

Table A6.4. Small Area Mean estimates of systolic blood pressure (SBP) in South African adults from the double measurements hierarchical Bayes linear mixed model with random intercept.

Area ID	**SURVEY YEAR**				
	2008	2010	2012	2014/15	2017
	Mean(95%CI) (se)	Mean(95%CI) (se)	Mean(95%CI) (se)	Mean(95%CI) (se)	Mean(95%CI) (se)
1	126(126,126) (0.02)	124(124,124) (0.02)	123(123,123) (0.02)	122(122,122) (0.02)	121(121,121) (0.02)
2	126(126,126) (0.01)	124(124,124) (0.02)	123(123,123) (0.02)	122(122,122) (0.01)	121(121,121) (0.01)
3	126(126,126) (0.04)	124(124,124) (0.04)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)
4	126(126,126) (0.06)	124(124,125) (0.05)	123(123,123) (0.06)	122(122,122) (0.05)	121(121,121) (0.05)
5	126(126,126) (0.05)	124(124,124) (0.03)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)
6	126(126,126) (0.05)	124(124,124) (0.04)	123(123,123) (0.05)	122(122,122) (0.04)	121(121,121) (0.04)
7	126(126,126) (0.07)	124(124,124) (0.06)	123(123,123) (0.05)	122(122,122) (0.07)	121(121,121) (0.06)
8	126(126,126) (0.03)	124(124,124) (0.03)	123(123,123) (0.04)	122(122,122) (0.03)	121(121,121) (0.03)
9	126(126,126) (0.05)	124(124,125) (0.04)	123(123,123) (0.05)	122(122,122) (0.04)	121(121,121) (0.04)
10	126(126,126) (0.03)	124(124,124) (0.03)	123(123,123) (0.04)	122(122,122) (0.03)	121(121,121) (0.03)
11	126(126,126) (0.10)	124(124,125) (0.09)	123(123,123) (0.09)	122(122,122) (0.10)	121(120,121) (0.08)
12	126(126,126) (0.05)	124(124,124) (0.03)	123(123,123) (0.05)	122(122,122) (0.04)	121(121,121) (0.04)
13	126(126,126) (0.05)	124(124,125) (0.04)	123(123,123) (0.04)	122(122,122) (0.05)	121(121,121) (0.04)
14	126(126,126) (0.06)	125(124,125) (0.05)	123(123,123) (0.06)	122(122,122) (0.05)	121(121,121) (0.05)
15	126(126,126)	124(124,125)	123(123,123)	122(122,122)	121(121,121)

	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
16	126(126,126) (0.04)	124(124,125) (0.03)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)
17	126(126,126) (0.04)	124(124,125) (0.04)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)
18	126(126,126) (0.02)	124(124,124) (0.02)	123(123,123) (0.02)	122(122,122) (0.02)	121(121,121) (0.02)
19	126(126,126) (0.05)	124(124,124) (0.04)	123(123,123) (0.05)	122(122,122) (0.05)	121(121,121) (0.04)
20	126(126,126) (0.04)	124(124,124) (0.03)	123(123,123) (0.03)	122(122,122) (0.03)	121(121,121) (0.03)
21	126(126,126) (0.05)	124(124,125) (0.05)	123(123,123) (0.05)	122(122,122) (0.04)	121(121,121) (0.04)
22	126(126,126) (0.06)	124(124,125) (0.05)	123(123,123) (0.06)	122(122,122) (0.05)	121(121,121) (0.04)
23	126(126,126) (0.07)	124(124,125) (0.04)	123(123,123) (0.05)	122(122,122) (0.05)	121(121,121) (0.05)
24	126(126,126) (0.05)	124(124,125) (0.04)	123(123,123) (0.05)	122(122,122) (0.04)	121(121,121) (0.04)
25	126(126,126) (0.05)	124(124,125) (0.04)	123(123,123) (0.05)	122(122,122) (0.05)	121(121,121) (0.05)
26	126(126,126) (0.04)	125(124,125) (0.04)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)
27	126(126,126) (0.05)	124(124,125) (0.05)	123(123,123) (0.05)	122(122,122) (0.04)	121(121,121) (0.04)
28	126(126,126) (0.06)	124(124,125) (0.06)	123(123,123) (0.05)	122(122,122) (0.05)	121(121,121) (0.05)
29	126(126,126) (0.02)	124(124,124) (0.02)	123(123,123) (0.02)	122(122,122) (0.02)	121(121,121) (0.02)
30	126(126,126) (0.04)	125(124,125) (0.03)	123(123,123) (0.04)	122(122,122) (0.03)	121(121,121) (0.03)
31	126(126,126) (0.03)	124(124,124) (0.03)	123(123,123) (0.03)	122(122,122) (0.03)	121(121,121) (0.03)
32	126(126,126) (0.04)	124(124,124) (0.03)	123(123,123) (0.03)	122(122,122) (0.04)	121(121,121) (0.03)
33	126(126,126) (0.04)	124(124,124) (0.04)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)
34	126(126,126) (0.03)	124(124,124) (0.03)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)
35	126(126,126) (0.03)	124(124,124) (0.03)	123(123,123) (0.04)	122(122,122) (0.03)	121(121,121) (0.03)
36	126(126,126) (0.03)	124(124,124) (0.03)	123(123,123) (0.03)	122(122,122) (0.03)	121(121,121) (0.03)
37	126(126,126) (0.03)	124(124,124) (0.03)	123(123,123) (0.03)	122(122,122) (0.03)	121(121,121) (0.03)
38	126(126,126) (0.09)	125(124,125) (0.07)	123(123,123) (0.07)	122(122,122) (0.07)	121(121,121) (0.06)
39	126(126,126) (0.13)	124(124,125) (0.12)	123(123,123) (0.11)	122(122,122) (0.10)	121(120,121) (0.09)
40	126(126,126) (0.09)	125(124,125) (0.09)	123(123,123) (0.09)	122(122,122) (0.08)	121(120,121) (0.07)
41	126(126,126) (0.07)	125(124,125) (0.07)	123(123,123) (0.07)	122(122,122) (0.07)	121(121,121) (0.06)
42	126(126,126) (0.06)	124(124,125) (0.05)	123(123,123) (0.06)	122(122,122) (0.05)	121(121,121) (0.06)
43	126(126,126) (0.03)	124(124,124) (0.02)	123(123,123) (0.03)	122(122,122) (0.03)	121(121,121) (0.03)
44	126(126,126) (0.05)	124(124,125) (0.04)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)

45	126(126,126) (0.06)	124(124,125) (0.06)	123(123,123) (0.07)	122(122,122) (0.06)	121(121,121) (0.06)
46	126(126,126) (0.05)	124(124,125) (0.04)	123(123,123) (0.05)	122(122,122) (0.04)	121(121,121) (0.04)
47	126(126,126) (0.02)	124(124,125) (0.02)	123(123,123) (0.02)	122(122,122) (0.02)	121(121,121) (0.01)
48	126(126,126) (0.06)	124(124,125) (0.06)	123(123,123) (0.07)	122(122,122) (0.05)	121(121,121) (0.06)
49	126(126,126) (0.04)	124(124,125) (0.04)	123(123,123) (0.04)	122(122,122) (0.04)	121(121,121) (0.04)
50	126(126,126) (0.08)	124(124,125) (0.06)	123(123,123) (0.07)	122(122,122) (0.07)	121(121,121) (0.06)
51	126(126,126) (0.05)	124(124,125) (0.05)	123(123,123) (0.05)	122(122,122) (0.04)	121(121,121) (0.05)
52	126(125,126) (0.13)	124(124,125) (0.14)	123(123,123) (0.13)	122(122,122) (0.14)	121(120,121) (0.10)