Bayesian Space-Time Mapping of Childhood Malnutrition in Somalia

by

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DEDICATION

I dedicate this work to my parents, for establishing moral support, my education and more importantly their love that was my source of confidence and strength during my studies.

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SUBMISSION DECLARATION

I declare that the submitted material as a whole is not substantially the same as published or unpublished material that I have previously submitted, or am currently submitting, for a degree, diploma, or similar qualification at any university or similar institution. No parts of the works have been submitted previously for any aforementioned qualification.

ABSTRACT

Background: Malnutrition is a leading cause of childhood deaths in low- and middle-income countries and has permanent consequences for cognitive, physical and metabolic development. Globally, it is estimated that 26% and 8% children under-five years of age are stunted and wasted respectively. Approximately 90% of the world's malnourished children live in sub-Saharan Africa and Asia. Food insecurity, which is a major driver of malnutrition, has been shown to be linked to inter-annual variability in rainfall in most of the part of sub-Saharan Africa. In general, a seasonal rainfall higher than 500 mm in sub-Saharan Africa is required to sustain healthy agriculture, with frequent droughts and periods of flooding highlighting the tenuous nature of agro-pastoral livelihoods in many parts of Africa. Despite the high burden of malnutrition there is limited formal investigation of its spatial epidemiology globally, especially in the most affected countries. Most of the published research has focused on the demographic, socio-economic and individual factors associated with childhood malnutrition. Little is known, however, about its geographical and contextual determinants and how policies can be formulated using the subnational distribution of these factors.

Aim: The main aim of my work was to describe the space-time distribution of wasting and stunting in Somalia from 2007-2010 and determine their ecological comorbidity with Acute Respiratory Infection (ARI) and diarrhoea among children aged 6-59 months in Somalia.

Methods: Data from household nutritional surveys in Somalia from 2007 to 2010 form a total of 1,066 settlements covering 73,778 children were used for the analysis throughout this thesis. Advanced Bayesian geostatistical models using stochastic partial differential equation (SPDE) in integrated nested Laplace approximations (INLA) were used for the space-time analysis. This modelling technique permits for simultaneous modelling of related issues such as risk assessment, spatial dependence, predictions and quantification of uncertainty. In the first set of analysis, the marginal effects of predictors were computed to determine their inherent spatial variability across the country

(Study I). Using a novel approach, the seasonal and inter-annual variation of wasting was computed by first carrying out year-season prediction in the four main seasons in the country from 2007-2010. To then compute the effect size of each season, the survey year was used to define the temporal effect while the seasons were used separately to define the seasonality effects of wasting for the survey year (Study II). In both approaches, time-varying covariates were incorporated in the models to inform the temporal trends. The prevalence and spatial distribution of stunting between 2007 and 2010 was estimated and the role of environmental covariates in forecasting the risk of stunting was explored (Study III). Finally, a joint modelling was undertaken of wasting, stunting and underweight; and stunting, acute respiratory infection (ARI) and diarrhoea (Study IV); to concurrently determine their correlation and shared components (Study V).

Results: In the period 2007-2010, the prevalence of childhood malnutrition remained very high throughout Somalia with all administrative regions reporting above acceptable levels of wasting, as defined by the WHO as above 5% prevalence. The average prevalence of wasting, stunting and mid-upper arm circumference (MUAC) <125 mm in Somalia from 2007 to 2010 was 21%, 31% and 36%, respectively, values which meet the thresholds classified as ‘critical’ by the WHO. In addition, there was evidence of significant geographical and secular variations in the burden of malnutrition in Somalia, with South having higher levels as compared to the North in the country and clear seasonal variation was observed with a relative rise during the dry seasons and reduction during the rainy seasons. Environmental factors like rainfall and vegetation were major drivers of these variations. This study also demonstrated that wasting, stunting and underweight in children 6-59 months in Somalia shared common risk factors with evidence of correlation in space. Finally, the study showed clearly that the spatial shared component between ARI, diarrhoea and stunting was higher in the southern part of the country.

Conclusion: Understanding the seasonal and annual fluctuations of different forms of malnutrition and their drivers in different regions can be used to target interventions in communities at high risk during emergency humanitarian interventions. Integrated programming and interventions focused on the common risk factors of the three indicators and specifically in regions where the co-distribution is highly prevalent may be a more effective way of reducing the burden of malnutrition in Somalia.

LIST OF PUBLICATIONS

I. **Kinyoki D,** Berkley J, Moloney G, Kandala N-B, Noor A. Predictors of the risk of malnutrition among children under the age of five years in Somalia. *Public health nutrition*. 2015;2014(0011):4-5

II. **Kinyoki DK,** Berkley JA, Moloney GM, Odundo EO, Kandala NB, Noor AM. Space-time mapping of wasting among children under the age of five years in Somalia from 2007 to 2010. *Spatial and spatio-temporal epidemiology*. 2016;16:77-87.

III. **Kinyoki DK,** Berkley JA, Moloney GM, Odundo EO, Kandala NB, Noor AM. Environmental predictors of stunting among children under-five in Somalia: cross-sectional studies from 2007 to 2010. *BMC public health*. 2016;16:654.

IV. **Kinyoki DK**, Kandala NB, Manda SO, Krainski ET, Fuglstad GA, Moloney GM, Berkley JA, Noor AM. Assessing comorbidity and correlates of wasting and stunting among children in Somalia using cross-sectional household surveys: 2007 to 2010. *BMJ open*. 2016;6(3):009854.

V. **Kinyoki DK,** Manda SO, Moloney GM, Odundo EO, Berkley JA, Noor AM, Kandala NB. Modelling the ecological comorbidity of acute respiratory infection, diarrhoea and stunting among children under the age of five years in Somalia. *International Statistical Review*. 2017: 0(0), 1–13.

LIST OF ABBREVIATIONS

AR	Auto-regressive
ARI	Acute Respiratory Infection
BIC	Bayes Information Criterion
CPO	Conditional Predictive Ordinate
CrI	Credible Interval
DIC	Deviance Information Criteria
EVI	Enhanced Vegetation Index
FSNAU	Food Security and Nutrition Analysis Unit
GAM	Global Acute Malnutrition
GDP	Gross Domestic Product
GFs	Gaussian Fields
GMFR	Gaussian Markov Random Fields
GRFs	Gaussian Random Fields
GRUMP	Global Rural-Urban Mapping Project
IDP	Internally Displaced People
INLA	Integrated Nested Laplace Approximations
IQR	Interquartile Range
KEMRI	Kenya Medical Research Institute
LOD	Log-Odds
MAPE	Mean Absolute Prediction Error
MBG	Model Based Geostatistics
MCMC	Markov chain Monte Carlo
MDGs	Millennium Development Goals
MODIS	MODerate-resolution Imaging Spectroradiometer
MOH	Ministry of Health
MPE	Mean Prediction Error
MUAC	Mid-Upper Arm Circumference
NI	Numerical Integration
NTNU	Norwegian University of Science and Technology
OR	Odds Ratio
OTPs	Outpatient Therapeutic Feeding Programmes
PIT	Probability Integral Transform
QC	Quintile Correction

RMSE	Root Mean Square Error
SAM	Severe Acute Malnutrition
SCs	Stabilization Centers
SDGs	Sustainable Development Goals
SMART	Standardized Methodology for Survey in Relief and Transition
SPDE	Stochastic Partial Deferential Equation
TSFP	Targeted Supplementary Feeding Programmes
UN	United Nations
UNFAO	United Nations Food and Agriculture Organization
UNICEF	United Nations Children's Fund
WAIC	Watanabe-Akaike information criterion
WHO	World Health Organization

AN OVERVIEW OF THE STUDIES

Study	Short title	Data source	Study design	Outcome	Statistical method	Level of analysis
Study I	Predictors of malnutrition	FSNAU survey data 2007-2010	Cross-sectional	Childhood wasting, stunting, and Low-MUAC	Spatial-temporal Bernoulli regression model	Individual child
Study II	Space-time mapping of wasting	FSNAU survey data 2007-2010	Cross-sectional	Childhood wasting	Geostatistical model	Cluster / Village
Study III	Environmental predictors of stunting	FSNAU survey data 2007-2010	Cross-sectional	Childhood stunting	Geostatistical model	Cluster / Village
Study IV	Comorbidity and correlates of wasting and stunting	FSNAU survey data 2007-2010	Cross-sectional	Childhood wasting, stunting, underweight	Geostatistical shared component model	Individual child
Study V	Comorbidity of stunting, ARI and diarrhoea	FSNAU survey data 2007-2010	Cross-sectional	Childhood stunting, ARI and diarrhoea	Geostatistical shared component model	Individual child

FSNAU - Food Security and Nutrition Analysis Unit

THESIS STATEMENT

This thesis made two main contributions in the field of nutrition.

***Methodological contribution**: In this work, advanced Bayesian geostatistical models were used to model the risk and spatial distribution of different forms of malnutrition. This is the first study to use Bayesian space-time geostatistical models using stochastic partial differential equation (SPDE) in integrated nested Laplace approximations (INLA) to model the risk of malnutrition at very high spatial resolution in Somalia. This modelling approach was able to determine and extract the marginal effects of the predictors at subnational level. The use of two different approaches to fit the temporal trend, quantify and adjust for seasonal effects in modelling the risk of wasting was also novel. The first approach focused on the year-season prediction in the four main seasons in the country. This was where the year and the corresponding season of survey together were used to define the temporal effects. In the second approach, the year was used to define the temporal effect while the seasons were separately used to define the seasonality effects of wasting within a year. For these two approaches, time-varying covariates were incorporated in the models corresponding with month of survey. In addition, we jointly modelled wasting, stunting and underweight; stunting, ARI and diarrhoea, and concurrently determine the shared correlates in a shared component model.*

***Potential policy applications:** Within the sub-Saharan Africa region, this is the most detailed national study on the spatial and temporal distributions of undernutrition. This study shows that the prevalence of malnutrition in Somalia remains at critical levels across the whole country but with strong spatial and temporal heterogeneity and with the southern regions having higher levels as compared to the north. Within each region, specific areas of relatively high risks have been identified and this spatial information can be used for better subnational targeting of interventions. This study has also demonstrated that wasting, stunting and underweight in children 6-59 months in Somalia share common risk factors with evidence of correlation in space. The analysis also* *shows variable seasonal and annual fluctuations of stunting and wasting in different regions with common environmental and epidemiological risk factors. ARI and diarrhoea, which are also the other leading causes of morbidity and mortality in Somalia, have common risk factors. The combination of this information can be used to develop integrated interventions targeted to high risk areas and season and in synergy with other interventions targeted at alleviating the impact of common childhood illnesses.*

INTRODUCTION

Nutritional epidemiology

Nutrition status is both an outcome and impact measure considered as a key indicator to monitor when assessing progress towards achieving the Sustainable Development Goals (SDGs)[1]. Almost a billion people are undernourished globally with 98% of them in resource-poor settings[2,3]. Globally, malnutrition contributes to between 35% of childhood deaths and 21% to 50% in the resource-poor settings[4,5]. Previous studies show that 53% of all deaths in young children are attributable to under-nutrition[6-8]. Maternal and child undernutrition is an underlying cause of 3.5 million deaths, accounting for 35% of the disease burden in children younger than 5 years. The number of deaths in children less than 5 years old attributed to stunting and severe wasting constitute the largest percentage of risk factors in this age group[4]. Although the risk of dying is highest among the severely malnourished, the high prevalence of moderate malnutrition contributes a larger proportion to increased burden of death among children[7]. Chronic malnutrition that can persist at the moderate levels for a long period of time does not require hospital admissions, unless coupled with serious illnesses. A severely wasted child can also have severe stunting and may require inpatient management[9,10].

At individual level, malnutrition can be caused by inadequate food intake, infections, psychosocial deprivation, environmental triggered factors and to some extent genetic variability[11,12]. In children, malnutrition mainly affects the physical growth, physiologic functions and the immune system. Among the clinical manifestations of malnutrition is increased susceptibility to infections[11,13,14]. These depend on the duration and degree of malnutrition, the type of nutrients that are missing in the diet, age and concomitant infections[11,15,16].

Child growth is recognised internationally as the best global indicator of physical well-being in children because poor feeding both in quality and quantity and infections are major factors that affect physical growth and mental development[17]. The outcome of child's growth is related to the overall standard of living and access to basic needs, such as access to food, housing and health care[18]. Child-growth assessments thus not only serve as means for evaluating health and nutritional status of children but also provide a reliable measurement of the inequalities in health faced by populations. Various criteria have been used to classify a child as having experienced normal or subnormal growth. Several anthropometric indices have been used to measure malnutrition. Wasting is defined by low weight-for-height; stunting is low height-for-age and underweight is low-weight-for-age. Mid upper arm circumference (MUAC) is also commonly used to define malnutrition and measures the muscle mass at the upper arm[19,20]. These anthropometric measures are usually expressed statistically as Z score, percentiles, or percent of median[20].

For surveillance purposes, the World Health Organization (WHO) has classified the prevalence of different forms of malnutrition in order to assess the severity of child undernutrition as a basis for making public health decisions. These classifications have been used in summarizing population prevalence in order to establish intervention priorities. It is important to note that the “trigger levels” vary according to the different anthropometric indicators. The prevalence range shown in Table 1 are those currently recommended [21,22] to classify levels of stunting, underweight and wasting.

Table 1: Classification for assessing severity of growth deficits by prevalence ranges among children under 5 years of age [21,22].

	Severity of growth deficits by prevalence ranges (%)			
Indicator	Low	Medium	High	Very high
Stunting	<20	20-29	30-39	≥40
Underweight	<10	10-19	20-29	≥30
Wasting	<5	5-9	10-14	≥15

Nutrition programmes encourage the use of stunting and wasting in assessing the nutritional status of children, designing intervention programs, and assessing their impact[23-25]. Therefore, internationally set health goals have been assessed on the basis of improvements on the rates of linear growth retardation (stunting)[26]. Although underweight or low weight-for-age was selected as one of the indicators to track progress in addressing hunger in MDGs, it has been repeatedly criticised because of the emergent problem of childhood obesity in countries in transition thus overstating the progress in underweight and masking stunting[27]. Stunting and wasting have been seen to co-exist with obesity and therefore recommended as indicators of choice in regions where overweight is a common problem[27,28]. Some studies still insist that underweight can be used as a global indicator in regions where wasting is common[29] because underweight combines information about linear growth retardation and weight for length/height[19].

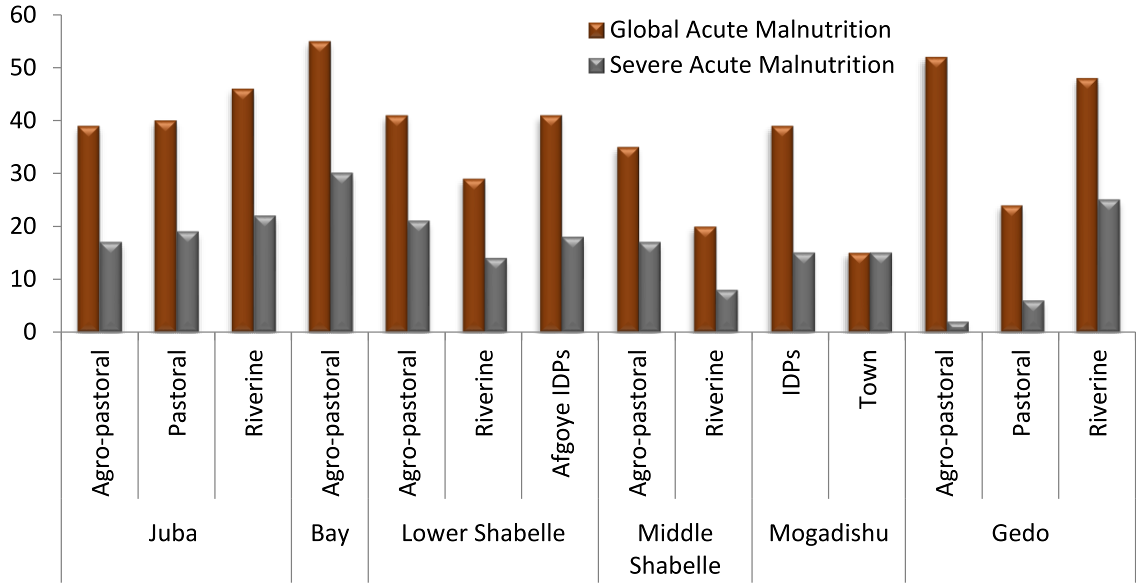
Studies in resource-poor settings have shown that wasting and stunting may be dependent on each other when compared to WHO standards[30,31]. If linear growth falters due to infection or poor diet, catch-up growth might be attained once the infection is eliminated or the diet improves. However in resource-poor settings, where dietary intake may be consistently inadequate or there is a high rate of infectious diseases, catch-up growth may be impossible, resulting in stunting[31 32]. In this context, wasting might precede linear growth retardation and therefore it is possible that wasting directly influences linear growth[33]. In addition, the relationship between infection, specifically diarrheal and respiratory diseases with nutritional status has been studied widely[34,35]. Studies show that height deficits are proportional to diarrheal prevalence in children[36]. Although with adequate nutrition and improved environmental conditions between diarrhoea episodes, children can demonstrate catch-up growth[37,38], persistent or frequent diarrheal diseases in children can lead to permanent growth retardation[39-41]. In addition, persistent diarrhoea in children is often associated with respiratory tract infections[42,43]. Children presenting with multiple forms of malnutrition have been reported to be at a higher risk of mortality when compared to children with one form of malnutrition[44].

Malnutrition in Somalia

The rate of acute malnutrition was declared by UN to be highest in the world in Somalia in 2011. This may be associated with the volatile political situations, civil unrest, drought and floods and possibly infection[45]. According to nutrition and mortality surveys conducted in 2011, the number of Somali people in a food security crisis was estimated to be 2.85 million or approximately 35% of the population including an estimated 241,000 children who are acutely malnourished in the southern region of Somalia alone, of whom 57,000 are in severe state, reflecting about 7% increase in the cases from 2010[45],[46]. In most of the regions of South Central zone in Somalia indicated that the rates of acute malnutrition remained near or above 30%, and depict a very critical nutrition phase[45](Figure 1).

The distribution of malnutrition varies across space and time, influenced by climatic conditions and other factors with definable spatial and temporal dependencies[47]. In Somalia, for example, conflict and drought lead to frequent displacement of vulnerable people leading to disruptions in livelihoods[48]. The common causes of morbidity and mortality in Somalia are diarrhoea, including cholera, respiratory infection, malaria and measles[49,50]. Due to high insecurity, Somalia has been a host of a large number of internally displaced people (IDP). IDPs are considered to be among the poorest and vulnerable to infections[46]. Limited access due to insecurity in South Central Somalia has inhibited health activities contributing to spread and sustained high levels of these diseases[48]. In addition, as a result of internal displacement and drought, food insecurity and health problems, the country continues to suffer persistent high malnutrition rates[48]. All these conditions co-occur at the same time predisposing the population to high levels of morbidity and mortality[50].

Figure 1: The rate of malnutrition in South-central Somalia[45].



Predictors of malnutrition

The causes of malnutrition are numerous. These causes are intertwined with each other and are hierarchically related. UNICEF conceptual framework of child health and survival recognizes and integrates the biomedical consequences, as well as the underlying socio-economic determinants and consequences of malnutrition[51,52]. The most immediate (or proximate) determinants of malnutrition are poor diet and illness[51]. Diarrheal diseases and lower respiratory infections have been implicated in this regard[53-56]. The biological mechanisms that underlie the impact of infectious diseases on growth are well documented and include decreased dietary intakes owing to catabolism, malabsorption and anorexia among others. Although that impact of infection on growth is clear at individual child level, there exists a controversy on the impact of infection on growth at the population level. It is not clear on average how much growth deficits in developing country children is as a result of infectious diseases vs poor diet[28].

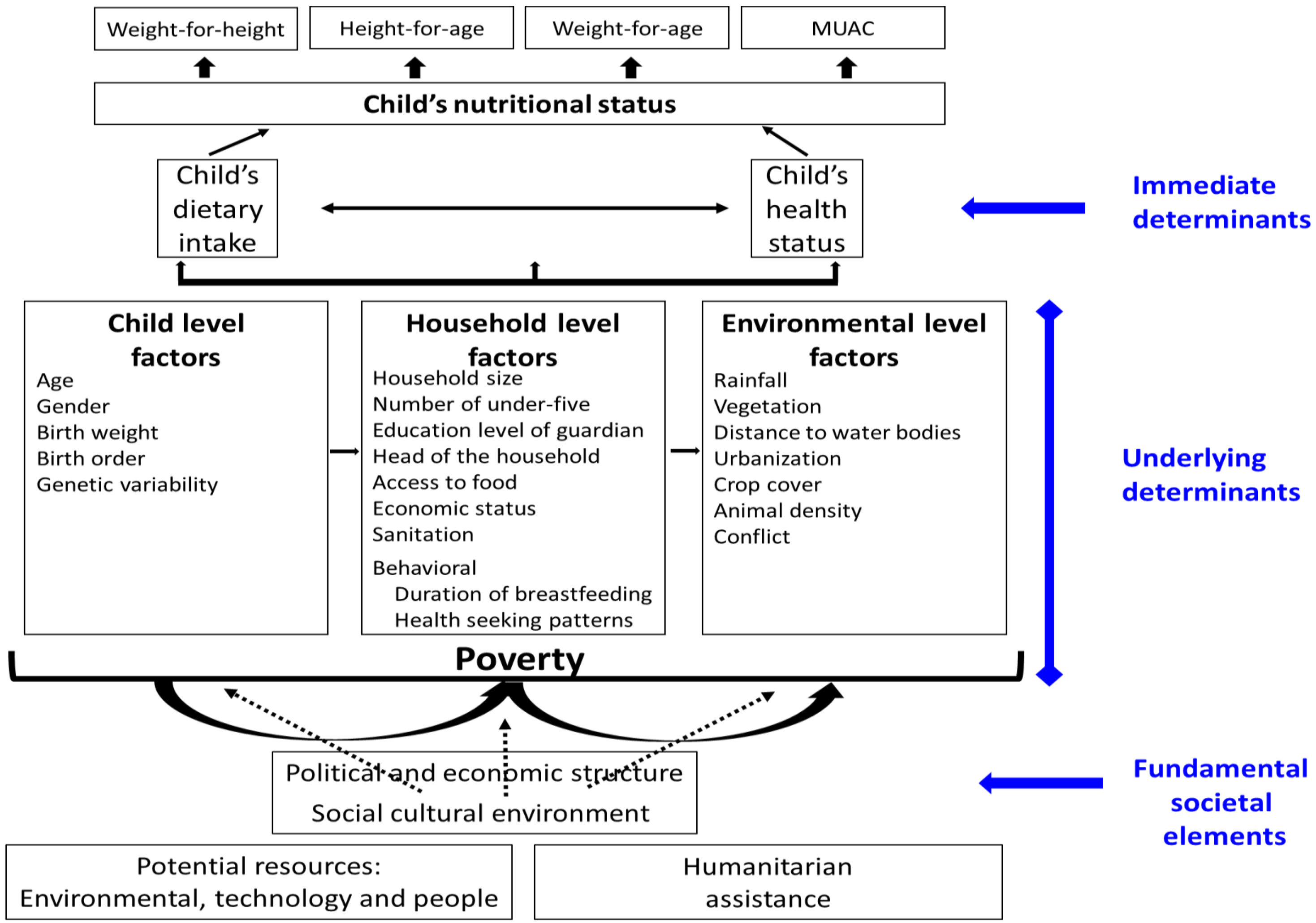
Poor diet and illness are themselves caused by a set of underlying factors that include family access to food and maternal care-taking practices. Finally, these underlying factors are influenced by the basic socioeconomic and political conditions within which poor families are attempting to raise well-nourished children. An accurate understanding of the relationships among these various causes of malnutrition and the relative contribution of each is essential for the design of efficient and effective programs to reduce malnutrition and its consequences. Because the resources directed at improving nutritional status are relatively scarce, it is critical that these resources are directed at interventions that will have the largest impact and will lead to lasting improvements[19,57].

Previous literature show that male gender[16], older children, short birth interval in the household[58], higher family size, low maternal education[59], poor feeding practices [60,61] are positively associated with under-nutrition in children. Studies conducted in developing countries have shown that younger children[15], low parental education[62,63], poverty[15,63], low maternal intelligence, food insecurity[64], rural residential area[16], sub-optimal infant feeding practices[62] and poor sanitary facilities in the household [16] have a negative effect on the nutritional status of a child. Infection is reported to directly cause malnutrition [14,60] and also as a contributing factor of malnutrition[6,65].

The volatile political situation and civil unrest in Somalia have led to a chronic and continuing humanitarian crisis that is at the root of the high prevalence of malnutrition. Somalia is also prone to drought and floods[66]. Many of the environmental and manmade shocks have been multiple and recurrent, over stretching families' coping mechanisms resulting in inadequate access to and availability of food at household level[67].

However, even in years of relative stability and improved food production, the malnutrition rates in some regions of Somalia have been consistently high, pointing to the important role of other underlying causes. These include sub optimal infant, young child and maternal feeding and care practices as documented by the National Micronutrient and Anthropometric Nutrition Survey 2009, Knowledge, attitude and practice survey (KAPS) 2007 and MICS 2006 results. Morbidity is high while access to and utilisation of quality health services is limited[68,69]. The water and sanitation situation is poor. Feeding, care and hygiene practices are inadequate not only due to lack of public services but also due to cultural practices and beliefs[66](Figure 2).

Figure 2: Theoretical conceptual framework of child health and survival in Somalia.



Spatial and temporal modelling of health outcomes

There are two broad categories of spatial (geographic) data models. These are the vector data model, which represents phenomena in terms of the spatial primitives, consisting of points, lines, areas, surfaces, and volumes; and the raster data model (sometimes referred to as the grid model), which represents phenomena as occupying the cells of a predefined, grid-shaped tessellation. The point data has been mostly applied in point pattern analysis to determine if objects or events in a study region are clustered together, or they present a regular pattern or are randomly distributed. A line is a sequence of ordered vertices, where the beginning of the line is a special vertex called the start node and the end a special vertex called an end node. This type of data has been applied in network analysis of the health issues. Data observed in polygon entities with defined boundaries are referred to as lattice or areal data. The polygon boundaries may be created by the researcher in some fields of study or may be administrative boundaries created for different purposes. This type of data is mainly applied in Small area estimation (SAE) is a statistical technique that provides reliable estimates of a target variable in a set of small geographical areas[70]. SAE is applied in survey data where it is impossible to have values of the target variable in all the small areas of interest. Finally, Raster data has been used in interpolation of occurrences either in conventional kriging or model based geostatistics.

Measures of outcome variables at locations or time close together are more likely to be alike than those further apart resulting to space and time dependence of observations[71]. This spatial and temporal dependence implies that many samples of geographical data do not satisfy the conventional statistical assumption of independence of observations and therefore they are termed to be spatially correlated[72]. Spatial dependency is the correlation among values of the same variable observed at close geographical location. This may also occur in time series data, referred to as temporal correlation and can be defined as correlation between time-shifted values of time series data. Spatial-temporal correlation is the correlation of values of a variable over space and time[73]. These both correlations introduces a deviation from the independent observations assumption of classical statistics. Prediction of risk-base on point-referenced data that is sparsely distributed should allow for spatial-temporal auto-correlation, failing which, the significance of risk factors is overstated[74,75].

Despite the fact that many surveys are carried out over geographically vast regions that differ significantly in vegetation, climatic, and social aspects, a lot of the analysis of these data is carried out ignoring the spatial difference that exist. Spatial statistics methods account for the spatial variation inherent in data collected over space and can be used for statistical inference. The spatial methods can be implemented in Bayesian framework via a Markov chain Monte Carlo (MCMC) techniques[72]. Traditionally, Markov models in spatial statistics have been largely confined to discrete spatial domains such as lattices and regional adjacency graphs[76]. Recently, a model-based geostatistical (MBG) approach has been applied to point-referenced data[77,78]. Geostatistics refers to a branch of spatial statistics in which the data consist of a finite sample of measured values relating to an underlying spatially continuous phenomenon[78]. Model-based geostatistics is a phrase that was coined to describe an approach to geostatistical problems based on the application of formal statistical methods under an explicitly assumed stochastic model[78]. This approach permits for simultaneous modelling of related issues such as risk assessment, spatial dependence, predictions and quantification of uncertainty[79].

The analysis and display of disease incidence and prevalence in maps is now established as a basic tool in the public health[80]. One of the earliest examples of disease mapping is the cholera mapping in relation to locations of water supply point as presented by Snow in 1854. Other early examples of spatial epidemiology include the study of rickets made by Palm (1890). Blum (1948) concluded sunlight as a causal factor for skin cancer based primarily on the geographical distribution of disease cases observed. The great motivation for application of spatial statistics in public health is the recognition of the maps as useful tools for illuminating potential causes of diseases[80].

Over time, this area of disease mapping has developed considerably to include point pattern analysis, lattice data analysis and geostatistical models[79]. The main areas of application can be broken down into disease mapping, disease clustering and ecological analysis[80]. This growth has led to a greater use of geographical or spatial statistical tools in the analysis. The major softwares that have been developed which allow modelling of spatially referenced data include MLwinN, WinBugs and BayesX. These are free applications that can fit models in a relatively easy manner using standard MCMC methods. Bayesian inference through MCMC although widely used can be of a challenge due to convergence problems and heavy computational loads[81]. The heavy computational load is as a result of linear algebra operation involving the big dense covariance matrices which occurs when handling large datasets[76]. Recently, Integrated Nested Laplace Approximations (INLA) has been developed as an alternative algorithm for Bayesian inferences[82]. The advantage of INLA-based approaches is mainly the computational speed and can be easily adapted through R project through R-INLA package[82].

Rationale for this study

Malnutrition is a leading cause of deaths in children in low- and middle-income countries and has permanent consequences for cognitive, physical and metabolic development. Almost a billion people are undernourished globally with 98% of them in resource-poor settings. Previous studies show that 53% of all deaths in young children are attributable to under-nutrition. The rates of acute malnutrition in Somalia have been cited among the highest in the world. The situation has been exacerbated by both prolonged drought and famine and persistent conflict in the country. Food insecurity, which is a major driver of malnutrition, has been shown to be linked to inter-annual variability in rainfall in most of the part of sub-Saharan Africa. In Somalia for example, the mean monthly rainfall per year for 2007 -2010 ranged from 2 to 104 mm. In general, a seasonal rainfall higher than 500 mm in sub-Saharan Africa is required to sustain healthy agriculture, highlighting the tenuous nature of agro-pastoral livelihoods in many parts of Somalia.

Despite the high burden of malnutrition there is limited formal investigation of the epidemiology of malnutrition in Somalia. Much research has focused on the demographic factors associated with childhood malnutrition. Less is known, however, about the geographical and contextual factors associated with childhood malnutrition. Drawing upon a more appropriate and recent spatial analysis perspectives, this research offered an alternative to more traditional ways of thinking about the factors associated to childhood malnutrition to fill this research and knowledge gap. The analysis of spatial variation in childhood malnutrition is important. Such a focus is consistent with the Somalia national health initiative, which aims to reduce and ultimately eliminate health inequalities among gender, racial/ethnic, socioeconomic, and geographic groups. In addition, a spatial analysis should help identify regions of the country that have a relatively high proportion of childhood malnutrition ‘hot-spot clusters’, which may in turn lead to the development and implementation of more effective geographically differentiated intervention programs.

AIM AND OBJECTIVES

Overall aim

The overarching aim of this PhD project was to map space-time distribution of wasting and stunting; and determine their comorbidity with ARI and diarrhoea among children under the age of five years in Somalia. To achieve this, this study, sought to first determine the predictors of different forms of malnutrition among children under the age of five years in Somalia. Secondly, map the distribution of stunting and wasting among the same age group at similar spatial and temporal resolutions over the period 2007-2010 and thirdly, determine the spatial comorbidity of different forms of malnutrition; and with diarrhoea and acute respiratory infection (ARI). It is anticipated that this will help inform a wholistic approach towards reducing the burden of malnutrition given the complex emergency nature of Somalia. The work relies on a unique geocoded data on malnutrition assembled in a period of 4 consecutive years and across different seasons in Somalia.

Specific objectives

1. To undertake an analysis of the predictors of wasting, stunting and low-(MUAC) among children under the age of five years in Somalia (**STUDY I**).
2. To determine the seasonal variability of wasting among children under the age of five from 2007 to 2010 (**STUDY II**).
3. To examine environmental predictors of stunting among children under-five in Somalia: cross-sectional studies from 2007 to 2010 (**STUDY III**).
4. To assess comorbidity and correlates of wasting, stunting and underweight among children under the age of five years in Somalia from 2007 to 2010 (**STUDY IV**).
5. To map the ecological comorbidity of stunting, acute respiratory infections and diarrhea among children under-five in Somalia: cross-sectional studies from 2007 to 2010 (**STUDY V**).

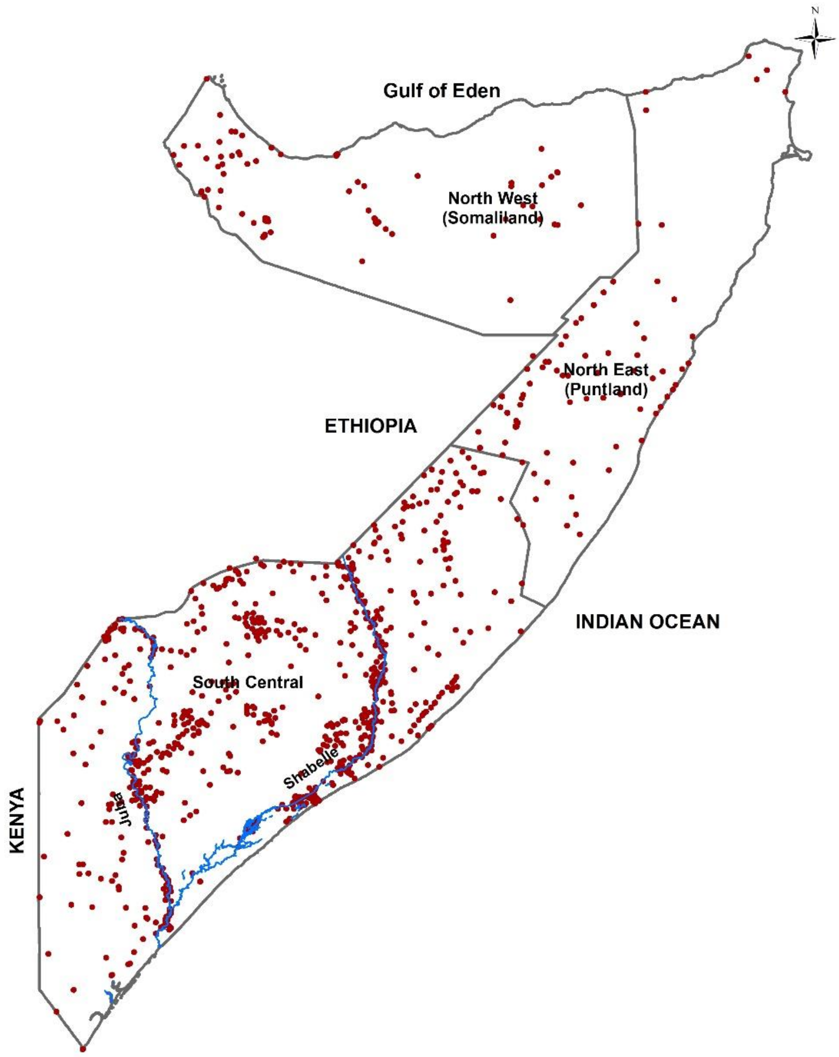
METHODS

Study design

The study uses the largest available nutrition dataset in Somalia obtained from Food Security and Nutrition Analysis Unit-Somalia (FSNAU) of the UN Food and Agriculture Organization (UNFAO). This study used data from the period 2007 to 2010. These data were assembled through bi-annual seasonal nutrition assessment surveys using Standardized Methodology for Survey in Relief and Transition (SMART) methods, indicators and tools for data collection. A stratified, multistage cluster sampling design was used where the sampling frame of a selected district was based on three livelihood definitions (pastoral, agro-pastoral and riverine), within which thirty rural communities and thirty households within each community were selected at random. A list of all villages and population within each of the assessed livelihoods was used to estimate the total population for the assessment area. Respective samples sizes (number of households and number of children) were calculated using the Epi Info/Ena 2008 software (Center for Disease Control (CDC) in USA) after considering the population size, estimated prevalence and desired precision. The selection of households within the village was done randomly from a list of eligible names or a map of households where possible. Where these were not available, the number of households in the village was estimated from the population figures (the total population divided by the mean household size)[46]. Probability proportional to size (PPS) sampling was implemented in all the surveys in this time period.

These data are unique in a number of ways: they are conducted across seasons and have been assembled consecutively over four years, the sample size is large and consists of over 70,000 children, all survey villages have been geocoded and therefore allow for micro-geographic analysis of the data, and the survey variable list is extensive and covers a large number of cluster, household and individual indicators (Figure 2). These data were augmented with high resolution environmental data on rainfall, temperature, vegetation and urbanization (Table 2).

Figure 3: Map showing the distribution of clusters sampled during the FSNAU nutrition surveys conducted between 2007 and 2010 in Somalia. The country is divided into three main zones: Northwest, Northeast and South-central.



Quality assurance

Prior to data collection, Food and Security and Nutrition Analysis Unit (FSNAU) conducted a short training of enumerators and supervisors. The training covered interview techniques, sampling procedure, inclusion and exclusion criteria, sources and reduction of errors, taking of accurate measurements (height, weight and MUAC), diagnosis of oedema and measles, verification of deaths within households, handling of equipment, and the general courtesy during the assessment. During the last day of the training, pre-testing of the questionnaire and equipment were carried out in non-selected clusters[83].

Quality of data was also ensured through supervision of field work by FSNAU coordination team. Filled questionnaires were cross checked on daily basis and observed and confirmed of measles cases, severe malnutrition and death cases were recorded by the supervisors. In addition, accuracy of equipment (weighing scales) was monitored by regularly measuring objects of known weights[83].

The data was entered into the computer using the data entry template. Before doing the definitive analysis, any errors in the data was identified and corrected. Quality assurance during data collection and entry was done by using automated plausibility checks function in Emergency Nutrition Assessment (ENA) for Standardized Monitoring and Assessment of Relief and Transitions (SMART) surveys which tests the following parameters: missing/flagged data, age distribution, overall sex ratio, digit Preference: weight, height and muac distribution, standard deviations of weight-for-height, Skewness of weight-for-height, Kurtosis of weight-for-height and Poisson distribution[83].

Variables

Anthropometric measures were used to compute wasting, stunting and underweight using WHO 2006 references. A child was defined as wasted, stunted or underweight when his/her Z-score for weight-for-height, height-for-age or weight-for-age respectively, was below −2. Additionally, children with MUAC below 125mm were classified as having 'low MUAC'. A child who reported to have ARI or diarrhea in the last 2 weeks before the survey was reported to have these health conditions.

The predictors for this study were selected using both the WHO conceptual framework on childhood stunting [84] and the UNICEF conceptual framework of child health and survival[85]. The underlying predictors were related to household, maternal and environmental factors. At the child-level, Vitamin A supplementation in the last six months, diarrhoea, acute respiratory infections

(ARI) and incidence of febrile illness in the last two weeks before the survey, polio and measles vaccination history, gender and age of the child were examined in this study. In addition information was collected on child age, weight, height, MUAC, gender, nutritional supplementation, access to staple foods, health status and vaccination history as well the mother's age and MUAC. For each household, information recorded included the household size and age structure, gender of the household head, and access to different types of foods in the last 24 hours.

The effect of a set of five distal environmental covariates associated with vector-borne diseases and food security[86] on the indices of malnutrition were examined. These were rainfall, enhanced vegetation index (EVI), mean temperature, distance to water, and urbanization. Rainfall and mean temperature were derived from the monthly average grid surfaces obtained from WorldClim database. The EVI values were derived from the MODerate-resolution Imaging Spectroradiometer (MODIS) sensor imagery[87] for period 2000-2010 while the urbanization information was obtained from Global Rural Urban Mapping Project (GRUMP) [88](Figure 4). All the environmental covariates were extracted from 1 x 1 km spatial resolution grids. Rainfall, temperature and EVI were summarized to compute seasonal averages using the four main seasons in Somalia: December to March, the 'Jilal' season, a harsh dry season; 'Gu' which is the main rainy season from April to June; from July to September is the second dry season, the 'Hagaa'; and the short rainy season known as 'Deyr' from October to November. Detailed description of the other variables used in this study can be found in Table 2.

Figure 4: Maps showing spatial distribution of the environmental covariates in Somalia.

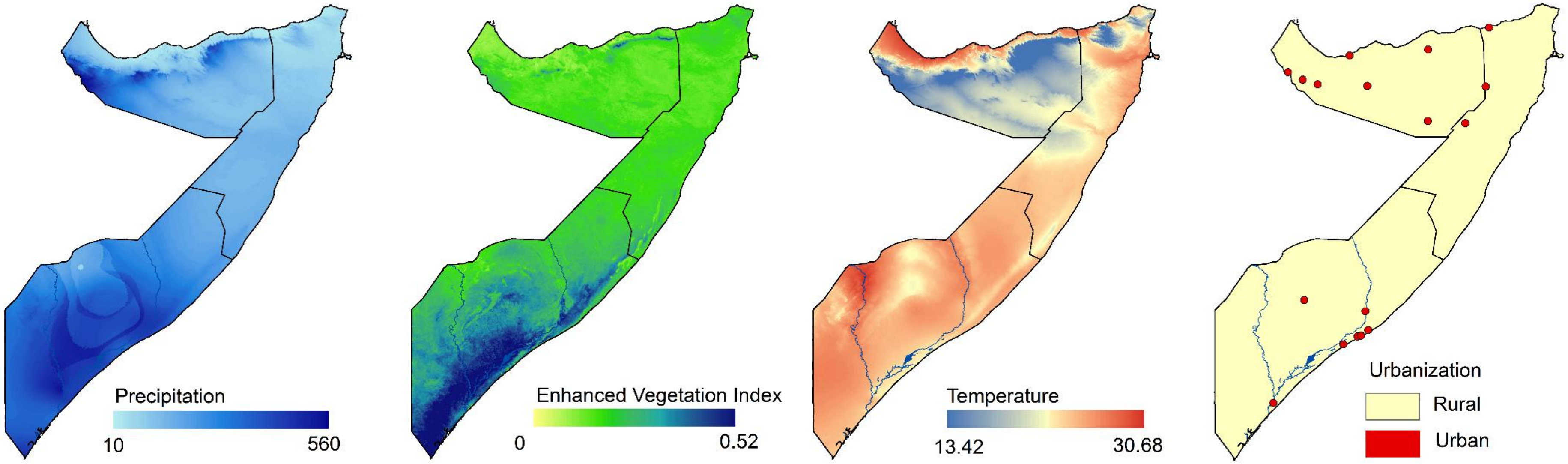


Table 2: Detailed description of the variables used in the study. The predictors were divided into three categories; child specific predictors, household level predictors which also included food and nutrition predictors, and climatic or environmental variables.

Variable	Type	Description
Response variables		
Wasting	Categorical	1 = Weight-for-height (cut-off point <-2 SD = malnutrition) 0 = otherwise (cut-off point <-2 SD = malnutrition)
Stunting	Categorical	1 = Height-for-age (cut-off point <-2 SD = malnutrition) 0 = otherwise
Underweight	Categorical	1 = Weight-for-age (cut-off point <-2 SD = malnutrition) 0 = otherwise (cut-off point <-2 SD = malnutrition)
(MUAC)	Categorical	1 = MUAC (cut-off point <-125mm = malnutrition) 0 = otherwise (cut-off point <-2 SD = malnutrition)
Diarrhoea	Categorical	1 = Diarrhoea (In the last 2 weeks) 0 = otherwise
Acute Respiratory Infection (ARI)	Categorical	1 = ARI positive (In the last 2 weeks) 0 = otherwise
Child specific predictors		
Vitamin supplements	Categorical	1 = yes (In the last 6 months) 0 = otherwise
Measles vaccinations	Categorical	1 = yes

		0 = otherwise
Polio vaccination	Categorical	1 = yes (Complete doses)
		0 = otherwise
Febrile Illness	Categorical	1 = fever positive (in the last 2 weeks)
		0 = otherwise
Suspected measles	Categorical	1 = yes (In last 1 month)
		0 = otherwise
Gender	Categorical	1 = Female
		0 = otherwise
Age of the child	Continuous	Age of children from 6 to 59 months (in months)
Household level predictors		
Household size	Continuous	Number of people in the household
Number of under fives	Continuous	Number of children under the age of five years in the household (0-59 months)
Household gender female	Categorical	1= Female
		0 = Male
Age of the mother	Continuous	Age of the mother in years
MUAC of the mother	Continuous	MUAC of the mother in cm
Food and nutrition predictors		
Carbohydrates	Categorical	1 = yes (Access to at least one type of carbohydrates in the last 24 hours)

		0 = otherwise
Protein	Categorical	1 = yes (Access to at least one type of protein in the last 24 hours)
		0 = otherwise
Fats	Categorical	1 = yes (Access to at least one type of Fat in the last 24 hours)
		0 = otherwise
Fruits and vegetables	Categorical	1 = yes (Access to at least one type of Fruits and vegetables in the last 24 hours)
		0 = otherwise
Climatic / Environmental data		
Distance to water	Continuous	In km, user derived using ArcGIS 10.1 (ESRI Inc. NY, USA)
Enhanced Vegetation Index (EVI)	Continuous	Ranges from 0-1 and derived from temporal Fourier analysed Advanced Very High Resolution Radiometer (AVHRR) data
Rainfall	Continuous	Seasonal mean rainfall in mm obtained from WorldClim dataset
Temperature	Continuous	Annual mean temperature in ˚C obtained from WorldClim dataset
Urbanization	Categorical	Global Rural Urban Mapping Project Modified (GRUMPMod), 1=Urban, 0=Rural
Season	Categorical	**Jilaal** =December to March, **Gu**=April to June, **Hagaa**=July to September, **Deyr**=October to November,

Overview of statistical analyses

In geo-statistics, Gaussian fields (GFs) forms an important building block in modern hierarchical models and a finite number of observations on GFs are considered as a realization of multivariate Gaussian distribution. This is because the Gaussian random field is assumed to be a continuous indexed field[78]. In order to evaluate the likelihood function, or the distribution of the random effect, a multivariate Gaussian density is computed on a log scale as shown below,

$$-\frac{1}{2}(\mathrm{nlog}(2\pi)+\log(|\Sigma|)+[\mathrm{x(s)}-\mu_x]^T\,\Sigma^{-1}[\mathrm{x(s)}-\mu_x])$$

where $\sum$ is a dense matrix of $n \times n$. During computation, the dense matrix is factorized with operation order of $O(\mathrm{n}^3)$ which make the computation very heavy because of the big $"n"$. Some of the solution to this problem is the use of empirical variogram to fit the parameters of the correlation function[78]. This method ignores the use of the likelihood from the data and the assumption of the multivariate Gaussian distribution[72]. This has been proved to be insufficient since the likelihood and the multivariate Gaussian distribution of the random effects are important in model based geo-statistical approach[78]. Recently, Lindgren *et al*., 2011 suggested that one can express a large class of random field models as a solution to continuous domain of stochastic partial differential equations (SPDEs), and develop explicit links between the parameters of each SPDE and the elements of precision matrices for the weights in a discrete basis function representation[76,89]. This SPDE is formulated as a link between Gaussian random fields (GRFs) and the Gaussian Markov Random Fields (GMRFs)[76].

In this model, GMRF is used as the fundamental building block in the models and as currently implemented in R-INLA package is a high-dimensional basis representation, with simple local basis functions[76]. The inference using GMRF is easier because the computation of for example two dimensional GMFR model will cost $O(\mathrm{n}^{3/2})$ with the corresponding precision matrix and hence easier to carry out analysis where the big "n" is concerned[76]. For spatial-temporal model, covariance function and the dense covariance matrix of the Gaussian field are replaced by a neighbourhood structure and a sparse precision matrix respectively that together define a GMRF[81]. This finite-dimensional GMRF that substitutes infinite-dimensional GRF can be expressed as shown in below,

$$x(u) = \sum_{i=1}^{n} \psi_i(u) w_i$$

here the $\{w_i\}$ represents the Gaussian distributed weights and Ψ_i are piece-wise linear basis functions defined on a triangulation of the domain with n nodes defined as mesh. With SPDE models, it is easier to introduce non-stationarity because the differential operators act locally with little control similar to local increments in Gibbs-specifications of Markov models[76].

The backbone of the analysis in this study was undertaken using spatial-temporal Bayesian methods that allowed for robust predictions and measurement of model uncertainties**.** This modelling procedure was used to determine predictors, prevalence, seasonal fluctuation, spatial distribution and co-distribution of different forms of malnutrition. These approach was also used to determine how malnutrition was co-distributed with diarrhea and ARI. The models used here accounted for the spatial variation inherent in data collected over space hence used for statistical inference.

In this work, these recently suggested methods, where one can express a large class of random field models as a solution to continuous domain stochastic partial differential equations (SPDEs), and develop explicit links between the parameters of each SPDE and the elements of precision matrices for the weights in a discrete basis function representation were used in Bayesian geostatistical framework[76,89]. .

Using this approach, different forms of malnutrition were modelled at 1 x 1 km spatial resolution using the data and selected covariates. The use of SPDE approach in INLA made the computations easier while dealing with large precision matrices[76]. For spatial-temporal model, covariance function and the dense covariance matrix of the Gaussian field were replaced by a neighborhood structure and a sparse precision matrix respectively that together defined a

GMRF[81]. This is the first study to use Bayesian space-time geostatistical models using SPDE in INLA to model the risk of malnutrition at very high spatial resolution. Previous efforts in predicting malnutrition have focused on ecological and areal data analysis[90,91]. These methods give mean estimates at regional or district level but do not capture the variability of risk that occurs within regions.

Model selection

To assess the predictive performance of the models, we generated a validation dataset by randomly selecting 10% holdout set of the data using a sampling algorithm which de-clusters over space and time. Four performance indices were chosen to evaluate predictive performance and model fit: root-mean-square error (RMSE), mean prediction error (MPE), mean absolute prediction error (MAPE), and the correlation coefficient between the predicted and the observed values. The RMSE is simply the square-root of the mean of the squared difference between the posterior predicted mean and observed value and it is used to measure the accuracy of the model. The MPE provides a measure of the bias of the predictor, the MAPE provides a measure of the mean accuracy of individual predictions, and the correlation coefficient provides a measure of association between the observed data and prediction sets[92]. The correlation between the observed and predicted data was visualized using scatter plots with a least-squares best fitting line and histograms (Studies I and II).

Further, the marginal excursion probabilities for each prevalence class based on the estimated posterior distribution were simultaneously calculated using numerical integration (NI) method as implemented by Bolin and Lindgren 2012[93]. Areas where the stochastic process exceeded a critical level according to the WHO, were then significantly determined using the positive excursion function in NI method and the parametric family of excursion sets[93] (Studies III, IV and V).

Finally, we compared the Deviance Information Criteria (DIC), Watanabe-Akaike information criterion (WAIC) and Conditional Predictive Ordinate (CPO)

(Gelman, Hwang, & Vehtari, 2014) for the shared component model and separate models as a measure of best fit. WAIC as implemented by Gelman and colleagues has been shown to be a consistent residual metric in model comparison.[94] This method estimates pointwise out-of-sample prediction accuracy from a fitted Bayesian model using the log-likelihood evaluated at the posterior simulations of the parameter values. WAIC is based on the series expansion of leave-one-out cross-validation (LOO)[94] (Study V).

Ethical Considerations

Data were collected as part of the routine biannual nutrition surveys designed and implemented by Food Security and Nutrition Unit (FSNAU) in Food and Agriculture Organization (FAO) of United Nations in collaboration with UNICEF Somalia office to evaluate nutrition status of children in Somalia. Therefore this was a secondary analysis of data. All data were anonymised by the FSNAU before presenting it for analysis. The ethical approval was provided through permission by the Ministry of Health Somalia, Transitional Federal Government of Somalia Republic, Ref: MOH/WC/XA/146./07, dated 02/02/07. Due to the high illiteracy rate of the population, informed consent was obtained verbally from all participating households and individuals. An additional 10% was added to the sample size to allow for drop out or refusal to participate.

SUMMARY OF THE STUDIES

STUDY I

Title: Predictors of the risk of malnutrition among children under the age of five years in Somalia

Objective: To determine the predictors of wasting, stunting and low-MUAC among children under the age of five years in Somalia

Methods: Special emphasis was given to understanding the relationships between the underlying household and environmental predictors with these forms of malnutrition controlling for child level predictors. Cross-sectional nutritional surveys undertaken from 2007 to 2010 were analysed using three separate Bayesian hierarchical spatial-temporal regression models to investigate the determinants of wasting, stunting and low-MUAC in Somalia. This was the first nationwide formal analysis of the predictors of malnutrition in Somalia.

Results: The analysis shows that the average prevalence of wasting, stunting and MUAC <125 mm in Somalia from 2007 to 2010 was 21 %, 31 % and 36 %, respectively, values which meet the thresholds classified as 'critical' by the WHO. Among the child-level variables, fever or diarrhoea in the two weeks before survey were significantly associated with wasting and stunting and low MUAC. Female children had a significantly lower likelihood of wasting and stunting, but a higher likelihood of low MUAC. Compared to children below the age of 12 months, older children had lower prevalence of wasting and low MUAC, but increased prevalence of stunting. Prior vitamin A supplementation in the previous six months before the survey was associated with less wasting and low MUAC, but had no significant effect on stunting. Access to staple sources of proteins within the 24 hours prior to survey was associated with less malnutrition as defined by all three indicators. Children who had consumed any of the staple sources of carbohydrates within the 24 hours prior to the survey had lower risk of wasting and stunting. Access to fruits and vegetables was associated with a small reduction in stunting. Larger household size and number of children under five years were associated with small increase in malnutrition. Higher MUAC of the mother was also associated with a small reduction in all three categories of malnutrition. Of the selected environmental covariates, the intensity of vegetation cover was the predictor that showed the greatest association with the three indicators of malnutrition. Change of season from Deyr (October to November short rains) to Gu (April to June short rains) was associated with lower risk of wasting and low-MUAC, but no association with stunting.

STUDY II

Title: Space-time mapping of wasting among children under the age of five years in Somalia from 2007 to 2010

Objective: To determine the sub-national seasonal and inter-annual prevalence and trends of wasting from 2007 to 2010 among children aged 6-59 months in Somalia.

Methods: To achieve this, two main models were used: the first model focused on the year-season prediction in four main seasons of the surveys: December to March, the 'Jilal' season, a harsh dry season; 'Gu' which is the main rainy season from April to June; from July to September is the second dry season, the 'Hagaa'; and the short rainy season known as 'Deyr' from October to November. This is where the year and the corresponding season of survey together were used to define the temporal effects. The main drive for the first model was to get the predicted prevalence of wasting in all the seasons in each year of survey from 2007 to 2010. In the second model, the year was used to define the temporal effect while the seasons were separately used to define the seasonality effects of wasting within a year. This model was used to determine the effect size of the four seasons in Somalia. The two models were implemented in stochastic partial differential equation (SPDE) approach in integrated nested Laplace approximations (INLA).

Results: Precipitation, Enhanced Vegetation Index (EVI) and temperature had a significant association with the risk of wasting. The results showed that there was no region in Somalia with acceptable levels of wasting, as defined by the WHO as less than 5% prevalence. The risk was highest in South Central zone followed by North West (Somaliland) and lowest in North East (Puntland). There was minimal variation of wasting across years, but a clear seasonal variation was observed with a relative rise during the dry seasons and reduction during the rainy seasons. Overall, there was no change in wasting from 2007 to 2009 but a slight decrease in 2010. The mean difference of the prevalence of wasting between the dry and wet seasons ranges from 0% - 5%, depending on location. The change in the prevalence varied from one region to the other while there were some region with minimal change.

STUDY III

Title: Environmental predictors of stunting among children under-five in Somalia: cross-sectional studies from 2007 to 2010

Objective: To estimate the prevalence and distribution of stunting among children under five years in Somalia between 2007 and 2010 and explore the role of environmental covariates in forecasting risk of stunting.
Methods: The prediction of the risk of stunting was done using two models. In the first model (model 1), the risk of stunting was forecast for a future year by using the environmental covariates for this year and the coefficients derived from a regression analysis of the relationship between stunting and the environmental covariates of the preceding years using a geostatistical model. Therefore the forecasting for 2008 was made using 2007 datasets and 2008 covariates; 2009 using 2007 and 2008 datasets and 2009 covariates; and finally 2010 using 2007-2009 datasets and 2010 covariates to determine how well environmental covariates can be used to forecast the rates of stunting in Somalia. In second model (model2), the whole dataset and the environmental covariates from all the years were used to fit the model parameters and predict the risk of stunting from 2007 to 2010 using a space-time geostatistical model. This model was considered as the gold-standard for our analysis as it used the whole data in simultaneous modelling of risk and the prediction of uncertainty and accounted fully for the complete spatial and temporal dependence to predict to each year from 2007-2010[79]. This model results were used to validate the predictive power of model 1.

Results: The two main environmental covariates used in study were rainfall and vegetation cover. The difference in the risk of stunting in the two models was less than 3% in all the regions in Somalia for all the years of study. The rate of stunting in Somalia varies by zones and regions. In general, the risk of stunting is consistently higher in the South Central region of Somalia than in North East and North West regions. This study showed that the use of the patterns of environmental shocks related to rainfall variability and vegetation cover to predict the rates of stunting can help identify populations that are likely to be affected by a high prevalence of stunting to guide interventions.

STUDY IV

Title: Assessing comorbidity and correlates of wasting and stunting among children in Somalia using cross-sectional household surveys: 2007 to 2010

Objective: To assess the spatial relationship between wasting, stunting and underweight and investigate the shared determinants among children under the age of five years in Somalia.

Methods: A Bayesian hierarchical shared component model was fitted to model the putative risk factors and the spatial component concurrently. Risk maps of the common and specific spatial components at 1 x 1 km resolution were derived.

Results: The correlation between regional means of relative risks was highest between stunting and underweight, followed by wasting and underweight, while the correlation between wasting and stunting was relatively low. There were several common underlying components of the three measures that influenced the spatial co-distribution of the three indicators of malnutrition in Somalia. Access to foods high in protein and vegetation cover, a proxy of rainfall or drought, were strong correlates of wasting and stunting. Age, gender, illness, access to carbohydrates and temperature were also common correlates of all three indicators. The relationships in spatial distribution were significant for the three pairs of indicators. The shared component displayed a strong spatial gradient in the South-North direction in all the shared components examined in this study. This confirms a high risk of all forms of malnutrition in the southern regions, especially around the two main rivers of Juba and Shebelle, compared to North regions of Somalia. The relationship in the spatial distribution was highest between stunting and underweight, followed by wasting and underweight and lowest between wasting and stunting with larger effects observed in the southern regions of Somalia.

STUDY V

Title: Modelling the ecological comorbidity of acute respiratory infection, diarrhoea and stunting among children under the age of five years in Somalia.

Objective: To determine the ecological comorbidity of acute respiratory infections (ARI), diarrhoea and stunting among children under the age of five years in Somalia and identify areas where the comorbidity is highly prevalent.
Methods: Shared-component model was used to fit common unobserved and unmeasured spatial risks to determine the areas that the indicators strongly co-exist[95-97]. This was done controlling for child, household and the following geographical covariates: rainfall, enhanced vegetation index (EVI), temperature and urbanization.
Results: The statistical framework used to determine the comorbidity in this study has an advantage in that its latent component have a direct interpretation in terms of the prevalence of the comorbidity of the health conditions and related risk factors which are either shared by several or specific to one of the health conditions. There was a significant co-occurrence of ARI, diarrhoea and stunting among children below the age of five years in Somalia. Although the mean posterior spatial effects were highest between the ARI and diarrhoea there were more hotspots for the co-incidence of diarrhoea and stunting as compared to ARI and diarrhoea. The posterior spatial residual effects between ARI and stunting were relatively low. Significant hotspots of the health conditions were highlighted in the south and central regions of the country.

DISCUSSION AND CONCLUSION

Interpretation of the main findings

Although fever, diarrhoea, gender and age of the child, household size and access to foods were significant predictors of malnutrition, the strongest association was observed between all three indicators of malnutrition and enhanced vegetation index (EVI) in Study I. A unit increase EVI was associated with 38%, 49% and 59% reductions in wasting, stunting and children with low MUAC respectively. EVI, a proxy predictor of vegetation cover, was found to have the largest association with the three indices of malnutrition analysed. EVI is a satellite imagery derived variable and characterizes the global range of vegetation state ranging from 0 (no vegetation cover) to 1 (high vegetation cover). Highly vegetated areas are a product of a combination of several variables including rainfall, seasonal and permanent water features and to some extent underground water. In Somalia, it is an important correlate of availability of water for agriculture and pasture for livestock and may impact on the household food security[98]. Given the large overall effect this index has on malnutrition and the susceptibility of Somalia to droughts it is likely that its real relationship with malnutrition over the study period when a major drought occurred is underestimated.

Somalia, like most East and Horn of Africa countries, is prone to frequent droughts that often progress into famine, characterised by extreme food insecurity and malnutrition[48]. The large and significant associations of the malnutrition indicators in Somalia with the climatic indices such as EVI observed in this study support this link. However, they also provide unique opportunities for using these climate indicators, which can be quantified at reasonable temporal and spatial resolutions[99], to forecast possible risks of malnutrition to support effective planning. This approach can then be validated through rapid and inexpensive household surveys and may provide a dynamic process to support readiness to respond to emerging nutritional threats in the country.

In study II, geospatial models was used by combining survey data with climatic and seasonal determinants. The study showed that rate of wasting is generally at critical levels throughout the country, with most of the areas remaining in the 'critical' and 'very critical' range. Minimal variation of wasting across years, but a clear seasonal variation was observed with a relative rise during the dry seasons and reduction during the rainy seasons. The rate of wasting was highest during the main dry season in the December to March period when compared to the short dry season. During rainy seasons, the risk was higher in the main rainy season in April – June when compared to the short rainy season in October – November. The regions that showed consistent high levels of wasting in the four years were Gedo and Bay. Over time, the largest reduction was observed in the central region when compared to other parts of the country.

Wasting in Somalia is linked to high seasonal and inter-annual variability in rainfall. Studies in Gambia report seasonal fluctuation of wasting between 4%-10% while in Niger the fluctuation was from 7% - 17% in chidren[100,101]. Food insecurity which is the main drive of malnutrition has been shown to be linked to inter-annual variability in rainfall in most of the part of sub-Saharan Africa[101]. The mean monthly rainfall per year for 2007 -2010 ranged from 2 to 104 mm in the country. In general, a seasonal rainfall higher than 500 mm in sub-Saharan Africa is required to sustain healthy agriculture, highlighting the tenuous nature of agro-pastoral livelihoods in many parts of Somalia[102].

The findings from study III revealed that the distribution of stunting in Somalia has substantial spatial heterogeneity with prevalence consistently higher in the regions of the South Central zones compared to those in the North. Data on environmental changes related to the variability of rainfall and vegetation cover provide unique opportunities to predict future rates of stunting and can help identify populations that are likely to be most affected to guide interventions. This is consistent with previous literature that spatial patterns of food insecurity in sub-Saharan Africa are correlated with the rainfall anomalies and vegetation cover[103]. Droughts that have been experienced in the Horn of Africa have directly resulted in food crises in 1984-1985, 2000-2001 and 2002-2003 and caused widespread famine in 25 African countries[103]. For example, the drought in Ethiopia in 2003 affected approximately 13 million people[104]. In 2011, some parts of southern Somalia were affected by famine in which approximately 4 million people, nearly half the country's population, faced a humanitarian crisis[105]. In West African countries, the intensity of poverty was shown to be inversely associated with the vegetation cover[106] .

We implemented a joint spatial analysis of malnutrition among children under the age of five years in Somalia to identify shared and separate determinants and spatial components of wasting, stunting and underweight in the Study IV. The correlation between regional means of relative risks was highest between stunting and underweight, followed by wasting and underweight, while the correlation between wasting and stunting was relatively low. There were several common underlying components of the three measures that influenced the spatial co-distribution of the three indicators of malnutrition in Somalia. Research and nutrition programmes have focused on wasting and stunting in accessing nutritional status, designing programs, and assessing impact[4,24,25,107]. Access to foods high in protein and vegetation cover, a proxy of rainfall or drought, were strong correlates of wasting and stunting. Age, gender, illness, access to carbohydrates and temperature were also common correlates of all three indicators.

Stunting increases throughout the first 2-3 years of life in many resource-poor settings, whereas wasting occurs during the first year of life after which it stabilizes, as expected[30]. Wasting was also noted to have a relatively shorter duration and greater seasonal variability when compared with stunting[30]. This may explain the observed low association between wasting and stunting. Thus, the use of cross sectional survey data to describe trends in wasting may have some limitations since the observed prevalence has short interval fluctuations and varying substantially between seasons[108]. As a result, a high incidence of wasting of short duration might be missed, misrepresenting the relationship of wasting with the other indicators. Longitudinal data which follow children's growth from birth looking at the wasting, stunting and the combination of the two can provide better understanding of the relationships[31].

Study V further investigates the ecological comorbidity of ARI, diarrhea and stunting using shared component model. This study demonstrated significant co-occurrence of ARI, diarrhoea and stunting among children below the age of five years in Somalia. Although the mean posterior spatial effects were highest between the ARI and diarrhoea there were more hotspots for the co-incidence of diarrhoea and stunting and between ARI and stunting.

These findings are consistent with previous studies that suggest that both the cumulative incidence and longitudinal prevalence of diarrhoea have a significant association with stunting prevalence[109]. In childhood, diarrhoea predisposed to malnutrition by impairing weight gain over a short period, while for significant impairment in height gain occur over a longer period[37]. It is also thought that a child needs to recover from weight loss before resuming linear growth, and this contributes to reduction in catch-up growth[32]. Recurrent weight faltering associated with multiple diarrhoea episodes may lead to linear growth faltering but catch-up growth is possible given adequate diet and time between infections[32]. However in resource-poor settings such as Somalia, where dietary intake is consistently inadequate and there are high rates of infectious diseases, the process of catch-up growth may never be possible resulting in a high level of stunting[31,32]. A biological link between diarrhoeal diseases and ARI is plausible where persistent diarrhoeal diseases may lead to acute malnutrition, which in turn increases the risk of ARI[43].

Implications for policy and recommendations

Somalia, like most East and Horn of Africa countries, is prone to frequent droughts that often progress into famine, characterized by extreme food insecurity and malnutrition[48]. The large and significant associations of the malnutrition indicators in Somalia with the climatic indices such as EVI observed herein support this link. However, they also provide unique opportunities for using these climate indicators, which can be quantified at reasonable temporal and spatial resolutions[99], to forecast possible risks of malnutrition to support effective planning. This approach can then be validated through rapid and inexpensive household surveys and may provide a dynamic process to support readiness to respond to emerging nutritional threats in the country. Somalia is regarded as a country with some of the worst indicators of health in the world and in the current study the prevalence of fever and diarrhoea was relatively high and strongly associated with malnutrition. Regardless of the causal relationships, the majority of the available evidence on population health status in Somalia is likely to be suggestive and probably inadequate given the instability in the country and generally limited health research.

The prevalence of wasting determined through nutrition surveys needs to be interpreted in relation to emergency levels and seasonal changes. This work has indicated that wasting varies widely according to spatial location, season and year-to-year conditions. Understanding the typical seasonal fluctuation is useful in assessing the severity of wasting at a particular location and time and this information can be used to predict the rates early enough in dry seasons for timely intervention. Timing of the peaks of wasting is relevant; for example the peaks of wasting in this study occurred during the dry seasons with the highest during the long dry season in December to March, which might have had an elevated effect on the prevalence in the long rainy season from April to June. This type of information can be used during emergency humanitarian interventions, which involve distribution of food aid, setting up community mobilization, stabilization centers (SCs), targeted supplementary feeding programmes (TSFP), outpatient therapeutic feeding programmes (OTPs) for the management of severe acute malnutrition in Somalia.

The rate of stunting in Somalia is spatially and temporally heterogeneous and rainfall and vegetation are major drivers of these variations. The use of environmental covariates as alternative to surveys for forecasting of stunting allows us to forecast the prevalence of stunting across the country at high spatial resolution. Nutrition responses in Somalia are primarily focused on responding to alarming rates of acute malnutrition. It has been estimated that if a package of nutrition-specific intervention that includes management of acute malnutrition and supplementation of multiple micronutrients is scaled up to 90% coverage, stunting would be reduced by 20% and this would reduce under-five mortality by 15%[25,110]. The finding from this work especially using the adjusted maps, may help programmes to target these interventions at the higher resolution to improve efficiency.

It is important to understand the prevalence of the co-occurrence of health conditions at community level in order to formulate prevention strategies common to the conditions[111]. Despite the cause of the conditions, ignoring comorbidity in this population where the prevalence is high could lead to an inappropriate prioritization of public health interventions for reducing the under-five mortality[42]. Our study not only estimates the prevalence of the shared components between the health conditions but also gives the spatial distribution of the components pointing out the priority regions with hotspots where interventions should be targeted. Our findings from the joint modelling of different forms of malnutrition suggest that if integrated programming and interventions focused on the common risk factors of the three indicators and specifically in regions where the co-distribution is highly prevalent may be a more effective way of reducing the burden of malnutrition in Somalia.

Currently, however, the funding for nutrition programme in Somalia is limited, unstable and often short term, preventing investment in longer term sustainable and resilience-building programmes[107]. As a result, for the large part humanitarian organizations are obliged to focus on high impact, 'life-saving' interventions to treat acute malnutrition without opportunities to invest in preventative programmes to reduce the overall caseloads and risk of undernutrition at scale[107]. Much of this is due to the focus of response in Somalia being emergency-driven. However the information provided by this study on the common drivers and the extent of geographical coexistence of wasting and stunting, can be used to develop more informed and planned interventions to achieve maximum impact within the short term and available funding.

Information generated from this study could also help in the development of an improved nutrition surveillance system with sensitive indicators of the different forms of undernutrition. This would include modifying data collection tools to reflect the main drivers of malnutrition and strategically position surveillance centers in regions that would provide the right information for intervention at the right time to inform the most appropriate response and maximize impact and investment[112].

Study limitations

There are some limitations to the present study. This study could not include all the variables likely to affect child malnutrition. Information on access to water and sanitation, which contributes to the prevalence of diarrhoea, was not collected in the FSNAU surveys used herein. Household income was collected only in the 2007 and 2008 surveys and thus excluded from the set of predictors. Household income was collected only in the 2007 and 2008 surveys and thus excluded from the set of predictors. The effect of the prolonged political conflict in Somalia was also not accounted for in the study. Exclusion of these key variables might have overstated the significance of other risk factors that were controlled for in the analysis. In addition, in hierarchical spatial models, the area variation not explained by the available covariates is split in two components, structured and unstructured for each region. Structured effects reflect the likely correlation between neighboring regions while unstructured effects are termed to be independent in each area. Therefore exclusion of these key variables might have also overstated the overall estimated prevalence of different forms of malnutrition in this work.

As shown in the results, the data come largely from rural areas and while urban areas were seen to have overall lower rates of undernutrition, there may be pockets of high levels of undernutrition not captured in the study. In addition, the location and timing of intervention programmes that may have affected the nutritional status of children and seasonal migration of the pastoral communities in search for pasture were not controlled for in our study.

There is some evidence that not all populations have the same body proportions. Somali babies have lower weight at birth, which may be thinness more than shortness[113]. In addition, the average Somali child is thinner and taller, by 12-24 months, with half the stunting prevalence (defined by height-for age) when compared to other children in the neighbouring East African countries[113]. It is also noted that pastoral children's growth patterns in pastoralist communities differ considerably from those of children in populations with agricultural livelihoods for example[100]. The technique may therefore underestimate stunting in some areas. There is also uncertainty of the different methods for determining age[22,114]. The age of the child was provided by their mothers during the surveys. Therefore the use of height-for-age to determine the prevalence of malnutrition among children in Somalia might have introduced a measurement error because of errors in the reported age of their children. Although the model performance varied slightly, our models identified extreme values as outliers and were unable to predict very low or high values but instead normalized them. However, while there might be some gaps in the way the data was distributed in space and time, the Geo-statistical model used in this study was proficient of making precise predictions using environmental covariates and controlling for both spatial and temporal autocorrelation concurrently[115-117].

The shared component modelling approach assumes that the latent risk factors have spatial structure. In addition, our methods assume that the components are independent hence no interaction between the effects of unknown covariates[118]. The prevalence of the comorbidity of diseases is highly depended on the population characteristics[42] and therefore the results from this study cannot be generalized to other populations. In addition, the data used in this study was from cross-sectional studies and therefore we are not able to account for the entire history of the disease exposure[109].

Perspectives for future research

Most available data are collected for programmatic purposes and are not necessarily hypothesis driven. Therefore, a stronger collaboration between nongovernmental organizations and the regional research community should be fostered to help utilize existing programmatic infrastructure to collect health data through carefully designed studies that meet both operational and scientific needs. This will allow for a better analysis of the burden of ill health and risk factors in Somalia within the context of the ongoing instability. In addition, further research should be undertaken using longitudinal studies to better understand the relationship between the health conditions and help define the role of control programmes in the prevention of these health conditions[109].

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