Examining the impact of protracted conflicts on mortality in humanitarian emergencies

Using small-scale surveys and conflict data from Yemen

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To my parents David and Martha Ogbu.

To Ike, Agnes, Chinagorom, Emeka, Ify, Nduka Ogbu and An-Sofie Vandermeulen.

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To all the children whose circumstances have driven into childhood adultification.

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AAH Action Against Hunger

ACLED Armed Conflict Location and Event Data Project

BCDR Baseline Crude Death Rate

BBC British Broadcasting Corporation

CNN Cable News Network

CAR Central African Republic

CRED Center for Research on the Epidemiology of Disasters

CRVS Civil Registration and Vital Statistics System

CE-DAT Complex Emergency Database

CI Confidence Interval

CARE Cooperative for Assistance and Relief Everywhere

COVID-19 Coronavirus disease 2019

CDR Crude Death Rate

DRC Democratic Republic of Congo

DHS Demographic and Health Surveys

DI Development Initiative

DD Direct violent Deaths

ENA Emergency Nutrition Assessment

EPI Expanded Program on Immunization method

FAO Food and Agriculture Organization

GRT Gelma and Rubin Test

GT Geweke Diagnostic Test

GBD Global Burden of Disease

GDP Gross Domestic Product

HPD Highest Posterior Density

IDP Internally Displaced People

IOM International Organization for Migration

LSMS Living Standard Measurement Surveys

MICS Multiple Indicator Cluster Surveys

MENA Middle East and North Africa

MCMC Markov Chain Monte Carlo

MSF Medecins Sans Frontieres

Mpop median population

MCQ Methodological Quality Criteria

MoH Ministry of Health

MoPHP Ministry of Public Heath Population

NGO Non-Government Organization

NATO North Atlantic Treaty Organization

OHCHR The Office of the United Nations High Commissioner for Human Rights

PCDR Posterior Crude Death Rate

PPC Posterior predictive check

PPS Probability Proportion to Population

SMART Standardized Monitoring and Assessment of Relief and Transitions

U5DR Under-five Death Rate

U5MR Under-five Mortality Rate

UN United Nations

UNICEF United Nations Children's Fund

UNDP United Nations Development Program

UNHCR United Nations High Commissioner for Refugees

UNOCHA United Nations Office for the Coordination of Humanitarian Affairs

UNRWA United Nations Relief and Works Agency

USD United States Dollars

WFP World Food Program

WHO World Health Organization

YDP Yemen Data Project

Summary

Many protracted crises are largely in resource poor settings affecting billions of people around the world. Efforts are being made globally to mitigate the impact of protracted crises on affected populations. However, these places typically lack the required health information systems for the collection of birth and death records needed to conduct a comprehensive assessment of the public health status and needs of the population. In particular, Yemen has been experiencing drawn out conflict, exposing children and adults to untold hardship and diseases as well as the risk of losing their lives increases as the crisis continues.

A comprehensive nationwide analysis of the impact of the protracted crisis in Yemen on mortality is lacking. However, over the course of the crisis in Yemen, series of small-scale surveys have been conducted on regional/zonal levels for planning purposes by humanitarian organizations operating on ground. Because of the costs and the impracticability of conducting an in-depth, nation-wide assessment, we have attempted to conduct an effective and robust investigation for a better understanding of the impact of the conflict on mortality by combining the sparse, publicly available data.

We started by assessing the methods used for the collection and presentation of mortality data obtained from the small-scale survey. We found no strict adherence to standardized methodology guidelines, and reporting of mortality and sample size data. Adherence to methodological guidelines and complete reporting of surveys in humanitarian settings will vastly improve the estimation of mortality rate and also uptake of key data on health indicators of the affected population. We also assessed the change in number of deaths as a result of the conflict using a Bayesian mixture model approach. Despite an increase in the estimated number of deaths attributed to the conflict, we observed uncertainty surrounding the point estimates, which calls for caution while interpreting the result from our data. The difference observed could range from fewer deaths, or more deaths during the conflict when compared to period before the conflict. In addition, we developed a simple and parsimonious classification of insecurity level using publicly available data.

We examined the relationship between patterns in under-five mortality and level of insecurity using a Bayesian finite mixture model, and we found that high number of under-five deaths are clustered around regions/zones experiencing high levels of insecurity.

Chapter 1: Introduction

1.1 Protracted crises

Protracted crises refer to emergency situations —commonly linked to natural disasters and conflicts and result from the interaction of different complex events — where a large part of the local population is exposed to higher risk of deaths, diseases and the disruption of their livelihoods over an extended period of time [1]. However, there is no broad agreement on the criteria for identifying countries in protracted crisis. The United Nations Food and Agriculture Organization (FAO) considers a country to be in protracted crisis if it (i) experiences crisis that require external assistance in at least 8 of the past 10 years, (ii) receives 10% or more of official development assistance as humanitarian aid for the past 10 years and (iii) is a low-income country facing food insecurity [2]. The Development Initiatives (DI) identifies countries in protracted crisis as countries that at least for five consecutive years have been under the United Nations-coordinated humanitarian or refugee response plans[3].

Often the term has been applied to environments where population are susceptible to the negative consequences of conflict and political instability such as Afghanistan, Yemen, Sudan, Somalia, Nigeria or the Democratic Republic of the Congo (DRC). Places experiencing protracted crises have specific contexts and situations, but they frequently have several common features, such as dysfunctional governance, insecurity and conflict, breakdown of infrastructures and essential services, food insecurity, and a significant reliance on aid [1, 2]. Prolonged crises destroy the capacity to provide security; physical, human and economic capital; and the healthcare of the affected population. Consequently, there is unusually elevated level of mortality from direct and indirect causes in such environments [1, 4, 5].

Protracted crises are becoming more prevalent, and the impacts are not restricted to the immediate loss of lives and essential infrastructures but also hinder the prospect of the affected population to recover and create a sustainable future. Eleven countries out of the 34 countries indicated to be in protracted crisis at the end of 2020 account for more than 1 billion of the world population and more than 390 million children between the age of 0 – 14 years old [6-8]. The majority of these countries are low-income countries, and they house the world's most vulnerable population.

1.2 Characteristics of environment in protracted crises

Although, there is no commonly accepted definition of protracted crises yet, the events and contexts in which they occur are as diverse as the crises themselves, but they share similar characteristics.

1.2.1 Dysfunctional government

Ineffective governance is one of the common characteristics of places in protracted crisis, and it has a direct impact on the wellbeing of the population. Governance in such environments is often highly polarized with declining political power to address systemic risks such as terrorist attacks, communal clashes, electoral fraud and endemic corruption. Accountability, transparency and effective legal/judicial systems are lacking in these settings thereby creating environments where public and political elites can misuse scarce resources earmarked for the developmental of education, healthcare, roads, electricity and water infrastructure without any recourse for the needs of the public [9]. For instance, in Nigeria, as a result of weak judiciary and legislative arm of government, corrupt officials are known to be acquitted by the comprised legal system [10, 11]. In DRC the same pattern is observed; few officials own and control almost every sector of the economy and wield substantial political power in the national legislature, effectively providing them with immunity against prosecution [12, 13]. Data from Worldwide Governance Indicators showed that countries in protracted crisis rank very low in effective governance score [14]. Consequently, the failure of the system to ensure that funds earmarked for important infrastructure development are used as intended perpetuates the cycle of inefficient governance.

1.2.2 Conflict and insecurity

Lack of investment in essential infrastructures and weak governance create dissatisfaction and promote the proliferation of homegrown, armed opposition. Armed insurrections against legitimate governments plague the political landscapes of countries like Yemen, Afghanistan, Nigeria, Sudan, Democratic Republic of Congo and Syria [15-17]. Continual and prolonged insurrections weaken the ability of the government to function properly and erode any progress made in the past. Usually, armed conflicts promote the destruction and deterioration of the existing government security apparatus, exposing the population to insecurity and negatively impacting their health. For example, besides creating a state of insecurity, the on-going conflicts in Yemen, Syria and Northeast Nigeria have contributed to the deaths of more than 1 million people and the displacement of many more between 2001 and 2022 [18-22]. Conflict and insecurity are common characteristics of places in protracted crisis but may not be the primary factor in the prevailing political situation. While insecurity may be widespread – as observed in countries like Ethiopia, the Democratic Republic of Congo, Nigeria, and Uganda – most violent conflicts are limited to certain regions/states [19, 23, 24].

1.2.3 Breakdown of infrastructure

Infrastructures refer to the physical and organizational structures that are essential for the proper functioning of a society, such as the creation and establishment of industries, buildings, health services, electricity supply, telecommunications, roads and railroads [25]. Inadequate and outdated infrastructures are common characteristics of environments experiencing prolonged crisis. The quality and accessibility of infrastructures in these environments lag well behind that of countries that have had long periods of stability. Road networks, electricity generation, access to sanitation and health infrastructures, predominantly controlled by state run agencies, are mostly in poor conditions and lack proper maintenance. The breakdown of infrastructures in these environments could be due to lack of investment, destruction of facilities during conflicts and increased performance pressure on outdated, existing facilities. For example, in East Ghouta, Syria, it was reported in 2019 that only 55% of the Assad forces occupied neighborhoods had access to electricity and drinking water (generally obtained from expensive and unreliable water tanker trucks), an estimated 90% of the sewage system was inoperable or destroyed, and hospitals and schools were in a state of extensive disrepair [26]. A 2019 news article reported that 80% of primary healthcare facilities in Nigeria were not functional [27]. In spite of the increased demand for electricity, only 22.6% of rural Nigerian populations have access to source of electricity [28]. To mention but a few, the states of infrastructure in Yemen, Afghanistan, DRC, Sudan and Ethiopia exhibit similar patterns [29-31]. The lack of investment in critical infrastructures and the poor states of the existing ones systematically obstruct access to such vital services — increasing risk of mortality.

1.2.4 Food insecurity

In 2020, it was estimated that over 700 million people are facing hunger globally with more than 40% of those individuals being from low-income countries [32]. The proportion of undernourished persons in low-income countries experiencing long-term crises is 2.5 to 3 times higher than in other low-income nations. According to the same research, more than 170 million people in countries experiencing long-term crises were undernourished in 2013, accounting for around 20% of the world's undernourished population [33]. The 10 hungriest countries in 2021 were all facing protracted crises [34].

The agricultural sector provides food and income to the majority of the 500 million people in over 20 countries that are afflicted by protracted crisis [33]. In addition to inadequate agricultural facilities, the magnitude of destruction of arable land by a combination of conflicts and natural hazards is responsible for the elimination of main sources of food production, resulting in the worsening of food insecurity in these environments. In conflict situations the destruction of farmlands and disruption of supply channels create artificial scarcity and increase in the prices of food items – resulting in increase in cases of malnutrition in the affected population. For example, in South Sudan, malnutrition was prevalent among school aged children and adolescents. The failure of crops, destruction of farm lands, loss of livestock, destruction of transport and supply infrastructures, and the influx of returnees put pressure on the price of available food [35] hence, exacerbating of food insecurity. In the Democratic Republic of Congo, a study of regional pattern of malnutrition among children suggests that, malnutrition is higher in conflict-affected provinces that are prone to lack of public infrastructures and low farming activities due to conflict and reliance on food aid [36].

1.2.5 Reliance on aid

The proportion of humanitarian assistance received by countries in protracted crisis as a share of total assistance is usually high (10 percent or more of their official development assistance) [2]. These countries rely heavily on development assistance as well as humanitarian aid to carry out development programs and respond to emergencies. The dependency on foreign assistance may be the result, in part, of poor governance and lack of investment in essential infrastructures due to prevailing crisis. For instance, according to data from World Bank database, Syria, Ethiopia, Afghanistan, Nigeria, and Yemen are among the six countries with the highest total amount of net official development assistance received in past five years (i.e., 2015 to 2019, at this moment no data on 2020). These countries are amongst the top ten receivers of development assistance and official aid in the last 10 years [37].

1.2.6 Duration of crises

There is no consensus on how long a crisis should be to qualify as protracted. For more than a decade, Nigeria, the Central African Republic (CAR), Sudan, Afghanistan, Somalia, Yemen, and Syria have been engulfed in crises of various forms and scales [16, 18, 19, 38, 39]. For prolonged (armed) conflict the duration can be classified as either one main conflict that has persisted over a long period or a series of different conflicts that occur over an extended period [40]. For instance, the conflicts in Syria, Nigeria, Yemen, Afghanistan, and the CAR are a mix of major and minor conflicts that have lasted for more than a decade. These conflicts have produced fragile environments that persistently expose a large number of individuals to increase risk of humanitarian crisis [3, 41].

Often, extended violence is aggravated by wide variety of other problems, such as food insecurity, drought, and displacement. Weak governance, conflicts and insecurity, dependence on aid, extended periods of conflict and breakdown of infrastructure are common characteristics of environments in protracted crisis that collectively contribute to the duration of the crisis. These features are frequently present in these contexts in varying degrees, fueling one another and creating a cycle of unending crises.

1.3 Concept of protracted crises, protracted conflicts and humanitarian emergencies

In the previous section, we described protracted crises as events that exposed a large number of the population to high risk of deaths, hunger, diseases and destruction of their means of livelihood. In addition, protracted crises may be manmade (armed conflict) or caused by natural hazards, or a combination of both.

Humanitarian emergencies can be caused by natural disasters, famine, outbreak of diseases or armed conflicts, and these event(s) pose a threat to the health, security and safety of a large group of people [42]. Humanitarian crises can be broadly classified into natural disasters, man-made emergencies (i.e., armed conflicts, industrial accidents, road and air accidents, fires) and complex emergencies. Complex emergencies refer to a major humanitarian crisis caused by a combination of natural and man-made variables that considerably undermine the livelihoods of the affected population/areas/regions [43]. Factors such as food insecurity, armed conflicts and displacement can lead to humanitarian crisis.

In general, armed conflicts are responsible for the top 10 humanitarian crises in the world and are a major cause of humanitarian emergencies in low-income countries around the world [44, 45]. The deterioration of economic, social, health and government structure, leading to increased deaths, food insecurity, forced migration and displacement, are among the major impacts of these crises. Typically, prolonged armed conflict leads to protracted crises, which result in humanitarian emergencies. In this thesis the terms humanitarian crisis, humanitarian emergencies, protracted conflict and protracted crisis are used interchangeably.

1.4 Global overview of protracted crises

Over the last 15 years the number of countries experiencing protracted crisis has increased from 15 in 2015 to 31 in 2019 where over a billion people are exposed to increased risk of death, food insecurity and displacement [3]. In 2020 more than 160 million people were assessed to be in need of humanitarian assistance and protection [41], and protracted conflicts created one of the world's worst humanitarian crises in Yemen [46]. In the face of the steadily degenerating food insecurity, restricted access to basic medical services and clean water, the spread of preventable and communicable diseases become rife and mortality status of the affected population deteriorate.

In protracted conflicts, women and children constitute a significant number of affected and deaths, mostly from preventable diseases [47, 48]. In Syria in 2015, there was resurgence of cases of water borne diseases due to breakdown of health facilities and the destruction of water plants by the fighting forces, which necessitated Syrians using untreated water from the rivers [49]. In war-ravaged provinces in Afghanistan, similar patterns were observed, contributing to cholera epidemics killing more than 100 people in three provinces [50]. In South Sudan between 2014 and 2017, 28,676 cases of cholera and 644 deaths were reported [51].

The extent to which conflicts affect mortality depends largely on the intensity, duration and proximity to battle zones. As the wars intensify and drag out, the level of insecurity worsens and further destructions of moribund infrastructures continue, the availability and accessibility of essential services becomes severely limited. Suppliers may find it extremely difficult to transport goods to such zones and existing businesses are prone to attack and looting. As experienced in DRC, the cost of medicine and food were higher in war zones due to looting and violence [4]. A 2019 study on women and children living in areas of armed conflict in Africa suggested that women of childbearing age are at an increased risk of death from nearby high-intensity armed conflicts. This is attributable to increased hazard of childbirth due to destruction of health facilities and limited access to and dysfunction of medical services due to protracted conflict [52].

Due to the complexity of protracted armed crises and prevailing social inequalities in such settings, the impact of crises on the health status of the affected population are disproportionate. To address the adverse effects of protracted crises, humanitarian and operational agencies depend largely on results of nutrition and mortality assessments of the affected population.

1.4.1 Assessing the level of needs in humanitarian crisis

The systematic collection of reliable and empirical evidence is essential in understanding and tackling public health issues faced by vulnerable population. In humanitarian settings, collecting comprehensive epidemiological data is extremely difficult because of lack of functional health information systems and insecurity. Usually, national surveys like Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS) and Living Standard Measurement Surveys (LSMS) are sources of reliable data for public health indicators. The DHS and LSMS are programs that assist developing countries in the collection of nationwide data which are used in the monitoring and evaluation of developmental programs [53, 54]. However, these surveys are expensive [55], take time to conduct and frequently exclude conflict regions due to insecurity [56]. The health status of populations in protracted crises change rapidly, which makes the use of the large-scale surveys with long term intervals inappropriate for decision making by humanitarian agencies despite the robust methodology of these surveys [57]. To address the need for data in emergency settings, the small-scale Standardized Monitoring and Assessment of Relief and Transitions (SMART) methodology was designed to effectively collect quality data on nutrition and mortality indicators by targeting the exposed population in emergency settings, usually using a multi-stage cluster sampling method [58, 59].

In the first stage, the population (known or estimated) is divided into distinct clusters, areas, or villages. The clusters are randomly selected based on the probability proportional to population size (PPS) — this gives each household equal chance of being selected. In the second stage, households are selected from the clusters using either simple random sampling, systematic sampling or the modified Expanded Program on Immunization method (EPI). All members of selected households are included for the assessment of Crude Death Rate (CDR); children less than five years are included in the assessment of Under-five Death Rate (U5DR). Children between the age of 6 – 59 months are assessed for anthropometric measurements. These surveys are conducted at lower geographical levels. Because of the sample size requirements for small-scale survey, the results of individual surveys are limited and difficult to extrapolate [57, 60-62]. Nevertheless, the aggregation of survey estimates from different areas (usually within a given geographical region) can provide an important insight on regional and national levels.

In humanitarian settings, mortality indicators like CDR and U5DR are mostly collected through small-scale surveys. CDR expresses the total number of all-cause deaths that occurred in the total population within a certain period. U5DR is the age-specific mortality rate that indicates the number of deaths amongst children less than five years old within a defined period. Mortality rates are one of the main indicators for measuring health status of the affected populations because death is a final common outcome that identifies and highlights underlying health and nutrition problems [63, 64]. The elevation of the CDR and U5DR above the standard emergency threshold baseline indicates a worsening of the health profile of the affected population [65]. However, obtaining reliable estimate of mortality in a crisis is fraught with outdated lists of sampling and population units, under reporting of deaths (sometimes for fear of losing assistance), age misclassification and the exclusion of highly insecure zones during survey [56, 66].

The problem of accurate assessment of mortality profiles in conflict settings is more pronounced in displaced populations. The population may be scattered, making it difficult to estimate population denominators. Conversely, the most affected may find themselves in a safer zone hence, leading to over-estimation of the mortality profile [67]. In normal situations, populations of interest are easy to define, and frequently and systematically collected information are readily available [68]. During conflicts, deaths are very difficult to measure due to lack of functioning civil registration and vital statistics system (CRVS). In addition, the number of deaths is mostly reported by the media or controlling forces and is thus subject to controversy.

Conflict related mortality is broadly classified into direct and indirect conflict deaths. The Office of the United Nations High Commissioner for Human Rights (OHCHR) defines **direct conflict deaths** as deaths that are caused directly by violent acts within the conflict. Violent acts include the use of weapons, torture, gender-based violence, intentional killing using starvation, and denying prisoners access to essential goods and services and healthcare [69]. **Indirect deaths** are deaths from loss of access to adequate food, water and proper sanitation, healthcare services and safe working condition, which are caused or aggravated by the conflict [69]. Data on direct and indirect deaths are sparse, which negatively affects the estimation of deaths due to conflicts. In low-resource environments, this issue is magnified when attempting to establish a link between individual-level factors and conflict related mortality. The estimation of number of deaths in conflict settings is very complex, and these complexities are especially notable for deaths from indirect causes, which, in most cases, form a significant number of conflict-related deaths [70].

1.4.2 Concept of baseline and excess mortality estimates

The excess mortality attributed to conflict is the difference between the conflict period estimate and the pre-conflict mortality estimate (baseline mortality rate). The idea of the pre-conflict mortality value (baseline mortality) in humanitarian emergencies is such that the baseline mortality values are unrelated to the emergency situation under consideration [71]. Mortality baseline is the term used to describe the pre-crisis mortality level in the affected population or another population not involved in the emergencies but which shares a similar pre-emergency demographic profile [72]. The baseline mortality level signifies a stable period in the population and a return to the baseline rate is an indication that the situation has improved [73]. In crisis settings, however, it is difficult to obtain an accurate measure of pre-crisis mortality because updated and existing health statistics are lacking. The estimation of the baseline value in unstable settings is a difficult exercise and it is more complicated when considering victims of forced migration. In displaced population for instance, it is challenging to measure the baseline mortality rate due to difficulties in the proper identification and definition of the population [73]. Secondly the displaced population may have a more elevated mortality level than normal and the timeline for assessment of the baseline mortality may extend into a period when the mortality rate is likely to have been affected by the crisis [73]. Despite these challenges, the comparison of the baseline mortality rate and conflict mortality estimate is fundamental in assessing the severity of the crisis.

The choice of baseline value is very important in the estimation of the change in mortality profile in humanitarian emergencies because the lower the baseline value, the higher the mortality attributed to the crisis. For example, a study conducted in DRC indicated a difference of 900,000 excess deaths depending on whether the Sphere threshold or the United Nations Children's Fund (UNICEF) reported baseline value was used [48]. In a bid to circumvent the controversy surrounding the choice of baseline and to ensure a robust estimate; later studies conducted in Iraq took a different approach by estimating baseline mortality rate using pre-conflict mortality data collected together with conflict-period mortality information from a nationwide retrospective cluster sampling survey [74-76]. In the absence of existing baseline data, the Humanitarian Charter and Minimum Standard in Humanitarian Response (Humanitarian Charter) suggested a context specific threshold as baseline values. Nonetheless, the use of this baseline rate has been contentious [77] and is treated as an on-going concern.

There are different sources for choosing or estimating mortality baseline in humanitarian settings. The commonly used sources are (i) recommended threshold value reported by the Humanitarian Charter [65], (ii) estimates from surveys conducted prior to the crisis, (iii) estimates from retrospective nutrition and mortality surveys.

The use of recommended Sphere threshold by the Humanitarian Charter (i) or retrospective estimated baselines (ii and iii) is not without limitations. The recommended thresholds are based mostly on regional (which are incredibly heterogenous) averages, which are not frequently updated and not a true reflection of the recent situations. The use of estimates from retrospective surveys that were conducted long after or during the crisis are plagued with recall bias. Households might not remember events that happened in the distant past and might report traumatic deaths as recent events, which can lead to incorrect estimation of the mortality rate [5].

DHS and MICS provide comprehensive estimates in secure situations, and these estimates could serve as the pre-conflict baseline. However, given the protracted nature of most conflicts, the DHS estimate might not be readily available given the frequencies in which they are conducted. They are also prone to exclude insecure areas and may underestimate true mortality estimates. In addition, these surveys largely lean on monitoring situation of women and children, and, in some cases, do not provide estimates on overall all-cause mortality [78, 79].

An emerging option for mortality estimation is data from burial site surveillance. Such data can serve as sources of information for estimation of mortality level and cause of death at population level. This method is most feasible and least costly in poor countries where cremation is not practiced and burials are conducted at dedicated sites [80]. This approach has the advantage of tapping into the existing sociocultural structures in resource-poor settings. [81]. In spite of the advantages of this method, due to insecurity, cultural and religious reasons, physical access to the locations or records may not be feasible when required [80].

The use of Earth Observatory technology is becoming more accessible to the public, and is increasingly used in humanitarian emergencies [82, 83]. The use of high-resolution satellite imagery of cemeteries in estimating mortality rates is gaining ground, especially in fragile settings. Using remote-sense methodologies and tools eliminates the barriers posed by the need for physical visits to the sites or collection of physical records of the burial site activities.

Recent studies have used the combination of geospatial data on burial sites and statistical methods to assess excess mortality during the COVID-19 pandemic [84, 85]. This technique can serve as method for estimation of mortality rate during conflicts and for estimation of baseline mortality rates.

1.4.3 Mortality and gender differences in protracted conflicts

The pathway through which conflicts affect different segments of the population (i.e., women or men) is better understood by examining objective evidence of the different parts of conflict related deaths. This is important for the benefits of integrating gender equality in humanitarian emergencies [86] and also for effective implementation of post-conflict developmental programs. Conflicts increase overall mortality in the population and are likely to affect civilian women disproportionate to men due to differences in their socio-economic status and the interaction of sociocultural and biological factors [87].

Arguably, men may experience higher mortality in terms of direct, combat-related deaths since they form the majority of the combat forces and are more likely to be participants in war either directly or indirectly. For instance, a study published in 2008 indicated that deaths from injuries among men between the age of 15 and 59 increased substantially from 31.2% before the invasion to 63.5% after United States invasion in Iraq [88]. Retrospective surveys conducted in DRC indicated that deaths due to violence are common in men, and mortality rates were higher for both men and male children under 5 years old than for females counterparts [48]. A cross sectional study conducted in Iraq in 2006 showed that more than 90% of the recorded violent deaths were among men, mostly within fighting age range of 15 to 44 [74]. A study conducted in 2008 on violent war deaths in 13 countries from 1955 to 2002 reported that 81% of the estimated war deaths are amongst males [89].

Amongst children less than five years old, studies have yielded contrary results in terms of gendered mortality differences. In spite of the mixed results of the effect of gender on under-five mortality [90, 91], studies have indicated that in normal conditions females have lower mortality odds than male children [92-97].

Considering weapon type, women are the second most likely to die from explosive weapon after children [98]. According to the World Health Organization (WHO), in 2016, 60% of maternal deaths and 53% of under-five death occurred in crisis settings [99]. Despite that, the overall immediate deaths from conflicts being higher for men than women [100, 101], studies have indicated elevated mortality in women during and immediately after conflict [102, 103].While indirect deaths form the bulk of conflict related deaths, civilian deaths accounted for 70.6% of violent deaths recorded in the Syrian war between March 2011 and December 2016, and deaths amongst civilian women increased during this period [104].

When considering the cycle of war, the overall decrease in the gap between men and women's life expectancy in conflict-affected areas implies that women are disproportionately the victims of conflicts [87]. Women bear the greater burden of indirect effects of conflict such as dealing with the death or maiming of loved ones, poor obstetrical care, increased maternal mortality and further deterioration of already poor economic status [105]. The elevated excess mortality amongst women maybe further exacerbated because of complications from food insecurity. Further, women and children bear a great proportion of the long-term impact of conflicts from the destruction and deterioration of the health and social infrastructures [71, 102].

1.4.4 Displacement in humanitarian crises

Globally, with the growing number of countries in protracted crises, several millions of people are forced to leave their homes and cut ties with their social and support systems either temporarily or permanently. Displacement covers a range of people forced to leave their homes. Displaced persons can be IDPs who, while forced from their homes into camps or into homes of other families or relatives, do not cross international borders. Refugees are displaced persons that are forced to seek safety across international borders. The United Nations High Commissioner for Refugees (UNHCR) reported that at the end of 2019, of the more than 75 million that were displaced because of conflicts, persecution and human rights violation, about 38% were refugees and about 62% were displaced persons [106].

Another UNHCR report found that worldwide, at the end of 2020, more than 82 million people were forcibly displaced. The report further stated that about 26.4 million are refugees under the UNHCR and the United Nations Relief and Works Agency for Palestine Refugees (UNRWA) mandates. Forty-eight million are internally displaced person (IDPs), and the remaining 8 million are both asylum seekers and Venezuelans displaced abroad. The same report indicated that four sovereign states in protracted conflict (Syria, Afghanistan, South Sudan and Palestine) accounted for more than 65% of the total number of reported refugees. Further, more than 80% of IDPs are within countries experiencing protracted armed conflict and violence [107].

The burden of displacement is worst in conflict settings, where the assessment and implementation of humanitarian aid to the displaced are hindered by actions of hostile groups and complicated by difficulties in locating the victims. Further, armed conflicts cause the destruction of hospitals, schools, social infrastructures, and the loss of jobs and other means of livelihood, forcing families to leave in search of means of sustenance and security elsewhere. These pose a threat to the health and safety of the most vulnerable, placing them in situations where access to essential health services are lacking and highly restricted [108].

Forced displacement in humanitarian settings exposes the affected population to elevated risks of poor health outcomes. In humanitarian emergencies, excess mortality is higher in IDPs because they are less likely to be identified and cared for, unlike refugee populations that are traceable and under the protection and care of UNHCR [60, 67]. A retrospective nutrition and mortality survey conducted among conflict-displaced peoples in Iraq indicated elevated crude and under-five mortality that was more than double the Sphere Emergency standard for the Middle East region. Preventable diseases accounted for 30% of the recorded deaths among the IDPs [109]. Similar surveys observed the same trend amongst internally displaced camps in Eastern Chad and North-Eastern Nigeria [110, 111].

The main causes of mortality in displaced populations during humanitarian emergencies are cholera, diarrhea, measles and acute respiratory diseases [100, 112]. The unavailability of potable water, unhygienic, crowded living arrangements and improper sewage systems expose populations affected by protracted crises to increased risks of communicable diseases. For instance, UNICEF reported that in Yemen, between April of 2017 and December of 2018, almost 1.4 million suspected cases of cholera were recorded and over 28 percent of those affected were children less than five years old [113]. A study of a cholera outbreak in Nigeria in 2018 indicated cases were elevated in areas affected by the ongoing insurgency [114]. A 2021 report from Borno State showed that 75% of the reported cases of cholera and 68% of the cholera related deaths occurred in the areas most affected by the ongoing conflict, particularly in camps with weak health facilities, shortages of clean water and poor hygiene [115]. Similar patterns were observed in an outbreak of measles in Nigeria, where the highest number of suspected cases and associated deaths were recorded in local governments and districts with a high number of internally displaced persons [116]. Likewise, mortality estimates in 16 countries experiencing crisis-related displacement revealed the number of deaths due to diarrheal disease to be higher than conflict-related deaths in children less than five years old [117].

Mortality patterns among refugee populations are often dissimilar to that of IDPs. The main causes of mortality among refugees are violence and usually occur shortly before fleeing, while in transit, or immediately after arrival [118]. The higher mortality risk during transit or upon arrival in a camp may be the consequences of shortage of food and medical health care prior to or during the journey to the camps [67]. Similarly, preventable diseases such as acute respiratory diseases, diarrhea and measles are also leading cause of deaths amongst refugees with children being most affected [112, 119]. Generally, the mortality level in refugees decreases to levels similar to the general host population upon their continual stay in the camps. This is likely because of effective targeted humanitarian response and the protective status accorded refugees [120]. Refugee populations have been shown to exhibit better mortality profile than IDPs and affected resident populations [60].

In general, there is paucity of data on gender disaggregation of mortality among displaced populations in humanitarian settings. However, a retrospective survey conducted in camps for IDPs in Darfur indicated that adult males have higher mortality risk [5]. Findings from a similar study conducted in four districts amongst internally displaced persons in Uganda shows that the ratio of male to female deaths is higher than 1 and the percentage of violent deaths in males was also elevated [121]. The majority of violent deaths occur outside of camps, which might be the consequence of the crowded living situations within camps forcing males to engage in dangerous activities outside the camps. Nevertheless, women and children still form a greater share of the victims of forced displacement [122, 123].

1.5 Rationale of the study

Since the escalation of the conflict in early 2015, millions of Yemenis have been subjected to adverse conditions. The protracted conflict resulted in humanitarian crises, which contributed to the level of overall mortality in the country. However, comprehensive analysis of the impact of the ongoing conflicts on mortality is limited. Hence, there is need for evidence that contributes to the comprehensive assessment of mortality in Yemen in order to inform humanitarian decisions subsequently reduce the level of mortality.

The lack of national level evidence may be because of lack of updated nationwide representative data or the capacity to conduct a comprehensive assessment due to insecurity, and the difficulties in generalizing results obtained from surveys conducted at zonal/regional level. Hence, policy decisions are based on media report and small-scale surveys conducted by humanitarian organizations. Given the resources committed to gathering data from humanitarian settings and the advancement of open-access conflict data, there is continual need to investigate effective and robust methods of combining these data to evaluate the impact of humanitarian emergencies on public health on national scale.

The major objectives of this thesis are:

1 To identify changes in the implementation of mortality survey methodology and how it affects mortality estimates in humanitarian emergencies. We assessed how the duration of conflict impacts the implementation of the surveys. This objective was addressed in Chapter 3. To this purpose, we analyzed 77 surveys conducted in Yemen between 2011 and 2019. We used descriptive analyses to assess survey qualities such as sampling methodology, completeness of reporting of under-five death rate and mortality sample of children less than five years old. We gave a number of suggestions that could improve the estimation of mortality rates and increase uptake of results in the research community.

2 To investigate the impact of protracted conflict on overall mortality in affected population. We realized this objective in Chapter 4, we used Bayesian Poisson-Gamma model to estimate the change in pre- and conflict-period crude mortality using 91 surveys conducted in Yemen between 2012 and 2019. We attributed the difference between the mortality estimates to the ongoing conflict.

3 To assess the relationship between conflict insecurity and pattern of under-five deaths in affected population. In chapter 5, using 54 surveys conducted in Yemen between 2015 and 2019, we assessed the relationship between patterns of death in children less than five years and armed insecurity using Bayesian Poisson finite mixture model. With this approach, we were able to identify unobserved subpopulations in the population and assess how the relationship between protracted insecurity changes across the subpopulations.

Chapter 2: Context and methodology

2.1 Study setting

2.1.1 Geography, climate and the people of Yemen

The name Yemen comes from the Arabic language meaning "South Arabia." Moreover, some authors have described it to mean "happy" and "blessed" [124, 125]. For a very long time, Yemen was the center of civilization in the Arabic peninsula with a rich culture, flourishing economy and unique histories. The present-day port of Aden and the city of Sana'a once served as an important hubs for textiles, spices, frankincense and myrrh, and other luxury products trade routes, which brought prosperity to Yemen and attracted travelers from all tribes and beliefs [126].

The present-day Republic of Yemen was formed on May 22, 1990, after the unification of the People's Democratic Republic of Yemen (South Yemen) and the Yemen Arab Republic (North Yemen) [127]. The Republic of Yemen is located on the western part of the Asian continent and shares a border with Oman to the Northeast and Saudi Arabia to the North. To the south, the country is bounded by the Gulf of Aden and Arabian Sea and to the west by the Red Sea. The country comprises of 22 administrative units called governorates with its capital in the City of Sana'a. The 22 governorates are further divided into 333 districts [128].

Figure 2-1: map of Yemen governorates [116].

The country covers an area of over 520,000 square kilometers including the islands of Socotra and Perim (administered by the Aden governorate). The topographic features of the country range from mountainous in the interior (highest elevation of more than 12,000 feet above sea level) to coastal plains to the west, south and east, and desert to the north [127]. Rainfall in Yemen is not evenly distributed; the western highlands receive more rainfall followed by the mountainous areas in the south, while the northern and eastern part are arid and rarely receive rainfall. The climate conditions vary from 0°C in dry winter and more than 40°C in summer with very low rainfall. In spring and autumn, the temperatures range between daytime maximum of 35°C to a nighttime minimum of 15°C [127]. The country has an estimated population of 29.8 million people of which a sizeable 39.1% are under the age of fifteen.

Less than 40% of the population are urban dwellers with an annual urban growth of 3.7% [129]. The major urban cities are Sana'a and Aden with an estimated population of 3.1 million and 1 million people, respectively [130]. Yemenis are predominantly Arab and a very small minority of south Asians, Afro-Arab and Europeans. The official language of Yemen is Arabic, and the national religion is Islam; 99.1% of the population are Muslims and the remaining 0.9% are Jewish, Christians, Baha and Hindus [130].

2.1.2 Political context

The modern political activities of Yemen can be traced back to the withdrawal of the Ottoman Empire. Northern Yemen gained independence from the Ottoman Empire in 1918 and became a republic in 1962 [130]. Shortly after assuming power in 1962, revolutionary forces deposed the Crown Prince Muhammad al-Badr with the support of Egypt and created the Yemen Arab Republic in the North. This threw the country into a civil war between the revolutionary forces and forces loyal to the deposed leader and supported by Saudi Arabia and Jordan [131]. The conflict between the two factions continued until the withdrawal of Egyptian troops, tanks and heavy artillery and the cessation of aid by Saudi to the royalists in 1967 [131]. Finally, in 1968, the opposing leaders reached an agreement and by 1970, Saudi Arabia recognized the Yemen Arab Republic [127].

While in the south, in 1839 the British seized Aden for strategic reasons — control to the entrance of the Red Sea, and it became a Crown colony in 1937 [132]. The British were forced to leave the province in 1963 after several years of upheaval spurred by Arab nationalism and anti-colonialism [133]. The British decision to withdraw started a two-year era of harsh political conflict in Aden and the protectorates, as various factions battled for control of the fate of South Yemen [132]. In 1970, three years after the withdrawal of the British, the Southern Yemen adopted a communist government system.

Between 1970 and the unification of North and South Yemen, a series of conflicts broke out between the sides mostly due to border disputes. In 1972, North Yemen initiated a war with South Yemen. The war lasted for 23 days and an agreement (Cairo Agreement of October 1972) based on a plan to unify the country into a democratic state was reached [134]. Apart from internal conflicts within both sides, fighting again erupted between the South and the North in 1979. In May 1990 the North and South united as the Republic of Yemen with Ali Abdallah Saleh as the president [131].

Four years later, following the declaration of secession of the South, the president declared a state of emergency and dismissed the vice-president Ali Salem al-Beid and Southern officials loyal to him. This led to a brief civil war (70 day war) between the armies of the North (government forces) and the separatist Southern army, and the war ended with the defeat of the Southern army [135].

From 2000 through 2014, clashes and insurrections from Al-Qaeda and Houthi groups took center stage in the crises in Yemen. Following series of clashes with the Houthis, the presidential panel approved a draft of the constitution that would accommodate the Houthi's demands [136]. The Houthis rejected the deal and seized control of Sana'a.

Table 2-1: Highlights of events of the on-going conflict in Yemen 2014 – 2021

2014 - 2016	2016 - 2017	2018 - 2019	2020 - 2021
The on-going civil war in Yemen started in 2014 when the Iranian backed Houthi rebels took control of Sana'a and demanded for a change of government. March 2015: the Houthi rebels seized the International Airport in Aden and appointed a presidential council to replace President Hadi, thereby forcing him to flee. Three days later, Saudi Arabia, the United Arab Emirates formed a coalition with the	A UN effort to broker peace between the warring parties in April of 2016 failed [139]. August 2016: the coalition forces closed the airport in Sana'a to commercial flight. Airstrike on a funeral in Sana'a killed more than 100 people and injured 500 in October [140]. May 2017: the Houthi rebels claimed to have fired missile at the Saudi Arabian capital of Riyadh.	August 2018: more than 50 civilians were killed and 170 wounded in a series of attacks in the port city of Al Hodeidah. Coalition airstrikes hits a bus in a busy market in Saada, killing over 45 people including children and wounding more than 70 [142]. In 2019, the Houthi rebel attacked oil pipelines and facilities in Saudi Arabia using drones. One person was killed and 7 wounded by a drone attack on Abha International Airport in Saudi Arabia. In same	The major event of the conflict in 2020 was the killing of an Al-Qaeda leader in Marib in early 2020 [143]. February 2020: a coalition warplane was shot down by Houthi rebels. Retaliatory coalition airstrikes killed more than 32 people, including 26 children and 6 women in al-Jawf. July 2020: Hajjah governorate, an airstrike killed seven children and a woman [144].

internationally recognized Yemeni government and declared war on the Houthi rebels [137]. The Saudi-led, US-supported coalition began air strikes and a naval blockade. The UN Security Council imposed arms embargo on the Houthis. The military campaign spread to other governorates — Sana'a to Abyan, Marib, Dhale, Aden, Lahij, Taiz, Sahwah and Saada resulting in more than 2,000 deaths [138].	November 2017: total blockade of Yemen was imposed in response to missiles fired at a Saudi airport by Houthi rebel. A few days later the blockade was partially lifted. In December 2017, Houthi rebels announced the killing of former president Saleh in Sana'a [141].	year, more than 20 persons were killed in attempts to take over Aden from the rebels. More than 100 troops were killed by Houthi missiles and over 68 were wounded in a military camp in Marib.	October 2020, both sides to the conflict completed a major UN brokered prisoner swap [145] . February 2021, Houthi rebels attempted to take control of Marib. March 2021, the rebels conducted missile airstrikes in Saudi Arabia targeting oil tankers and facilities.

Air and drone attacks have dominated the conflict in Yemen. Between 2015 and the end of 2021 more than 23,000 air/drone strikes were carried out across Yemen with attacks heavily concentrated in cities with high population density such as Amanat al Ashima, Sannaa, Sadaah, Marib and Taizz [146].

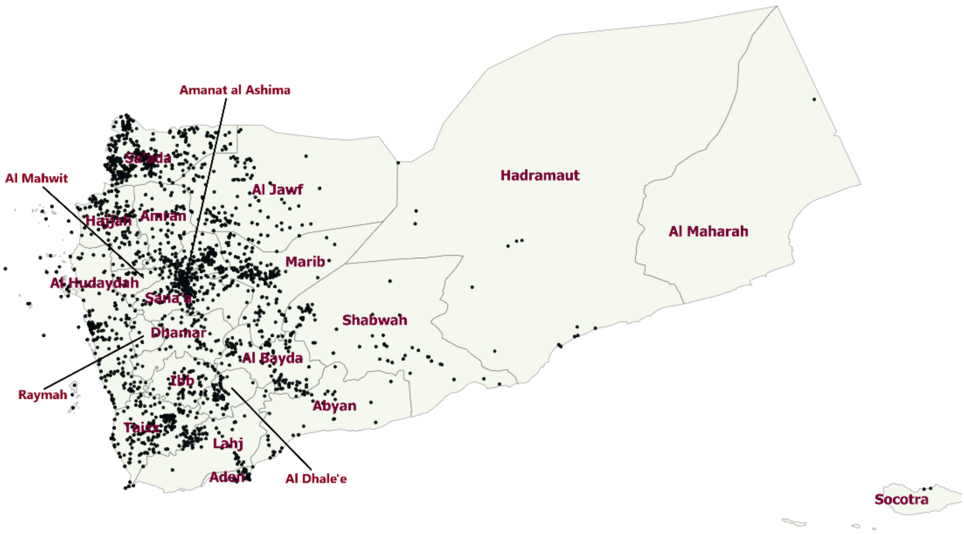

Figure 2-2: Map of air/drone strikes in Yemen between 2015 and 2021. The data was obtained from ACLED [146].

2.1.3 Socio-economic environment

Presently, Yemen is experiencing one of the worst humanitarian crisis in the world, with estimated 80% of the population in dire need of humanitarian assistance [147]. In Yemen, the economy is largely cash-based, and the financial and banking system are both very unstable and dominated by the state. Oil constitutes 75% of government revenue, and agriculture, the second largest sector, accounts for 20% of gross domestic product (GDP) and employs more than 50 percent of the labor in the country [148, 149]. However, due to the conflict, the loss of revenue from oil and agriculture sectors created severe shortage of human capital and foreign exchange earnings, leading to huge decreases in government spending. The future depends on political stability, improvement in security and the generosity of international donors [150]. For instance, while the GDP of Yemen has dropped from 42 billion USD in 2014 to about 22.5 billion USD in 2019, the humanitarian aid increased from 430 million USD to 4 billion USD within the same time frame [151, 152] (see figure 2.3). Despite the intervention of international communities through donations and humanitarian aid towards curbing the devastating effects of the years of destructions, the situation in Yemen is still grim and needs continued, adequate attention [46].

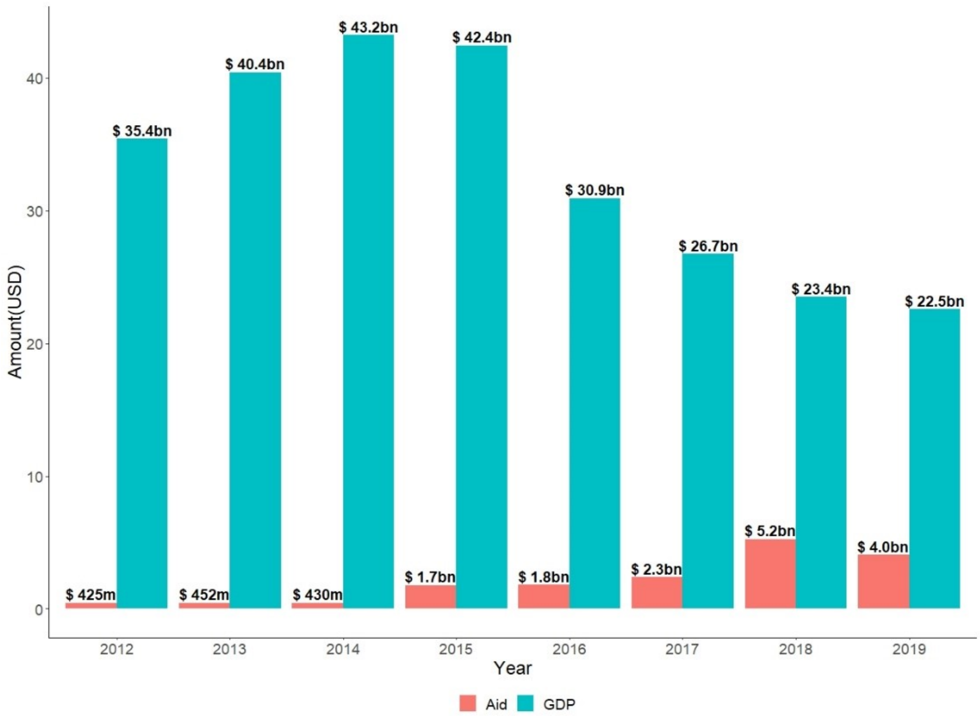

Figure 2-3: Trends in foreign aid and GDP from 2012 - 2019 in Yemen. Source: UNOCHA Financial Tracking Service, [153]

2.1.4 Health sector

The principle function of the health system in Yemen is to provide services that improve, maintain, prevent and control the spread of diseases, and restore the health of individuals and the communities [154]. However, the health system in Yemen is grossly underdeveloped, under-funded and lacking in all its core functions [155]. The ongoing armed conflicts put the fragile health system under enormous strain and in a state of near collapse. The destruction of hospitals and medical infrastructures and the targeting of medical personnel [156], have reduced physical access to health care and services. More than 19 million people lack access to basic health services due to insecurity and 50 percent of the health facilities are not functioning. Functioning facilities are facing severe shortages of medicine, equipment and personnel [157]. The gaps in health services negatively impact the most vulnerable civilians. In addition, due to the dysfunctional and degraded health system, children are now prone to vaccine preventable diseases like cholera, measles and diphtheria.

Assessing the current health status of the population is very difficult, given the lack of updated and reliable statistics. The last national health survey was conducted in 2013, and current information on maternal and child health on national level is lacking. The last DHS report, conducted in 2013, indicated a decrease in U5DR from 150 deaths per 1000 live births in 1985 to 53 deaths per 1000 live births in 2011 [78]. Apart from improvement in U5DR prior to the on-going conflict, maternal mortality fell from estimated 365 to 148 deaths per 100,000 births in 10 years (2003 to 2013). Despite the improvement in maternal and child health care indicators (figure 2.4), the on-going conflict has considerably rolled back the progress made in improving the health sector in the last years.

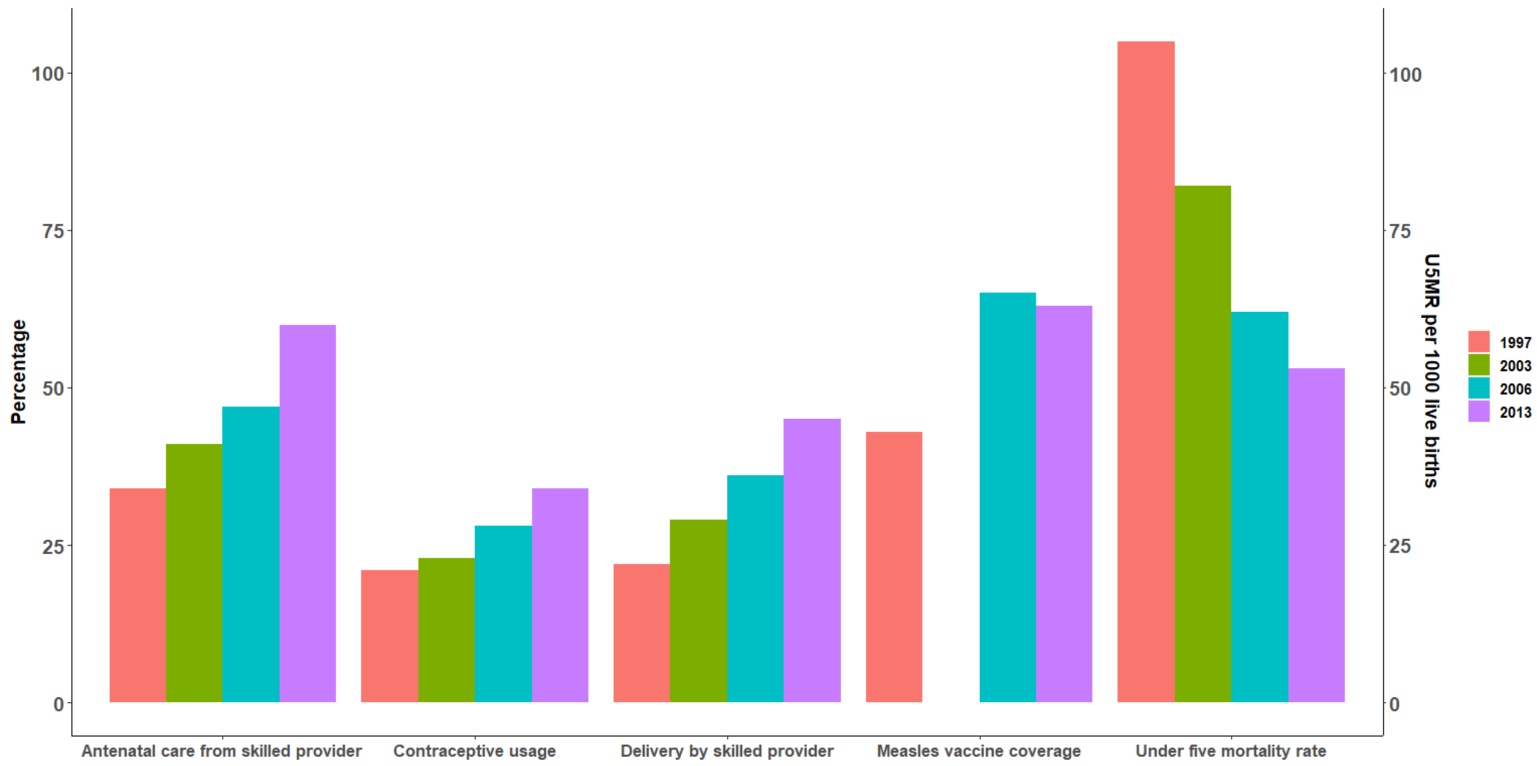

Figure 2-4: Trends of maternal and child health care indicators in Yemen, 1997 – 2013. Data source: The YDHS 2013 [78].

According to the Yemen DHS-2013, there is remarkable disparity in access to health services between the urban and rural populations, and this might explain why childhood mortality and other indicators are worse in rural areas than in urban areas. With the current state of insecurity and decaying health system, coupled with forced displacement throughout the country, the UN Sustainable Development Goals (SDG3) aimed at providing equal access to health care, to safe and affordable medicines, and vaccines by 2030 seems unattainable [158].

2.1.5 Yemen current outlook

Due to more than three decades of political instability, the destruction of critical infrastructures, the lack of investment in economic and social infrastructures, and a long-running armed conflict, Yemen is considered one of the poorest countries in Middle East and North Africa (MENA) and has the worst socio-economic and demographic profile [159, 160]. According to the United Nations Development Program (UNDP) the percentage of the population living in poverty is projected to jump from 47% in 2014 to 79% if the conflict continues through 2022 [147]. The last census was conducted in 2004, and the reported crude death rate of 7.5/1000 was about 42% higher than the UN regional average [161]. The 2013 DHS estimated a U5DR of 53 per 1000 live births, more than twice the UN reported value of 25.1 per 1000 live births for the MENA region [78, 162, 163].

More than 2.5 million suspected cases of cholera and over 3,900 deaths associated with cholera were reported between October and December 2016. More than 26% of children were five or under. Additionally, the most affected areas were those with restricted access to drinking water and proper sanitation [164, 165]. Nearly 1,300 suspected cases of diphtheria were reported in 2017 with a case fatality of 5.6%, and 46% of the reported cases were from individuals unvaccinated against diphtheria [166]. As the conflict rages on and the health system is further destroyed, routine immunization programmes and early warning surveillance are continually disrupted, increasing the risk of the spread of diseases in the community. Apart from suspected cases of cholera and diphtheria, in 2019, almost 60,000 suspected cases of dengue fever with over 200 deaths were reported in Yemen, doubling the reported cases from 2018 [167]. The total reported cases of measles in Yemen in the five years of the conflict is 6267 cases higher than the total cases in the five year prior to the conflict [168].

Continual insecurity, combined with the on-going COVID-19 pandemic, has placed hundreds of thousands of internally displaced Yemenis at greater risk of food insecurity. About 37% of displaced families are facing food shortages and about 40% have no access to income [169].

2.2 Overview of the study data

Quality data and appropriate statistical techniques are important in understanding the effect of protracted conflict on mortality in settings where data is scarce. We collected publicly available data from multiple sources. The use of publicly available data from multiple sources increases the richness of the data, provides broader insight and reiterates the pressing need to improve access to secondary data for scientific research [170].

Small-scale SMART surveys are reliable source of quality epidemiological data from crisis settings. Important mortality information such as the number of deaths (adults and children under five years old), number of adults and children under-five years that left/joined the household and number of births that occurred during the recall period are collected by the surveyors. Important information on morbidity and nutrition indicators such as vaccination status, cases of diarrhea, prevalence of cough and fever, weight and height and presence/absence of oedema are also collected from children living in the household at the time of the interview [58].

2.2.1 Mortality

The key mortality indicators used in the humanitarian emergencies are CDR and U5DR. These indicators can be further transformed into excess deaths. CDR measures all causes of death in all age groups, while the U5DR is a measure of all causes of death in children less than five years of age. The Complex Emergency Database (CE-DAT) provides the main source of mortality data used in this study [https://cedat.be/]. CE-DAT is a repository of mortality and nutrition surveys from communities affected by complex emergencies. The database was created in 2003 and was managed by the Center for Research on the Epidemiology of Disasters (CRED) at UCLouvain. The main objective of CE-DAT is to collate and make nutrition and mortality rates from surveys conducted in complex emergencies available to the public. In addition to nutrition and mortality rates, the database captures the period the surveys were conducted, funding sources, sample size, targeted population, recall period, and morbidity rates. This provides an excellent collection of mortality, nutrition and morbidity data for operational agencies, researchers and policy makers. The reported death rates are estimated based on information (recall period, number of deaths, number births and number of people living or joining the household within a given period) collected through retrospective surveys.

As at the time of this writing, the CE-DAT database contained 3,432 surveys from 58 countries and territories [57]. Ideally, the CE-DAT team collates data contributed by agencies such as the UN, non-governmental organisations (NGOs), and ministries of health. These agencies were not obliged to contribute but freely provided these data to the CEDAT team. In addition, the team also collated data from survey reports that were freely available online. The team received/gathered the survey reports, reviewed the reports and ensured the reports met the criteria laid out in the CE-DAT methodology before uploading to the database. The CE-DAT no longer upload/update the database due to funding constraints.

2.2.2 Conflict events

Gathering quality and timely data in conflict settings is very difficult mainly due to political considerations and affiliations and the absence of existing functioning CRVS system. These issues justify the creation of non-profit agencies that collect timely and quality disaggregated conflict data that are not within the sphere of influence of the warring parties. We sourced conflict event data from two public databases, the Yemen Data Project (YDP) and the Armed Conflict Location & Event Data Project (ACLED).

The Yemen Data Project (https://yemendataproject.org/) is a data collection project designed to collect and disseminate data on the on-going conflict in

Yemen. The YDP is a non-profit project set up in 2016 to provide independent and neutral records of the war in the absence of official records. This helps to improve transparency and provide a rich source of data to the international and humanitarian communities.

YDP gathers information from sources such as international and local news reports, social media and reports from non-governmental organization. The data collection team is well trained in data collection and research many of whom are Yemenis with a good knowledge of the local context. The team verifies and cross-references the data to minimize bias. The YDP classifies air campaign data into two categories: air raids and air strikes. Air raids refers to air strikes in a particular area within one hour; due to difficulties in verifying each strike on a target a minimum estimate is reported.

The Armed Conflict Location & Event Data Project (ACLED) is a non-profit organization registered in the United States with the main objective of colleting, analyzing and mapping disaggregated conflict data. The database captures the dates, agents, fatalities type and location of political violence and protest across the globe. ACLED data are classified into six event types; battles, explosions/remote violence, violence against civilians, riots, protests and strategic developments, which are further divided into twenty-five sub-event types.

The main sources of ACLED data are international and non-governmental institutions, local conflict observatories and media outlets including both traditional and social mediums. According to ACLED, a targeted approach is used in collecting data from social media like Twitter and WhatsApp by relying on established, verifiable sources. Given the unique context of conflict, the use of data from multiple sources minimizes reporting biases but does not necessarily improve reliability. ACLED adopts methods that are specific to each context using tailor-made sourcing strategies from individual regions/ countries to improve the reliability of the data [171]. After the gathering of the data, ACLED researchers process the data through two review stages to ensure consistency. At the end of the review, the data are cleaned and formatted before uploading for public usage.

See ACLED methodology and coding review for detailed explanation: https://acleddata.com/resources/methodology/

Modeling sub-event data in humanitarian settings

Bayesian analysis is a statistical technique that allows the incorporation of prior information into the data analysis process. This prior information could be from previous studies or based on expert knowledge. The modeling framework allows the incorporation of all available evidence in modeling the bias inherent in the presence of different data sources. The use of Bayesian modeling techniques provides additional flexibility and new insights into exploring data from multiple sources. Further, it gives more intuitive and meaningful interpretation, and in the presence of small samples, it produces narrower confidence intervals [172, 173].

The use of hierarchical modeling approach accounts for variations from different data sources. The Bayesian hierarchical mixture model has been used to estimate crude mortality and in assessing the relationship between mortality and nutrition indicators in humanitarian settings [61, 62, 174]. In this approach, estimates from different surveys are used to calculate pooled effects while borrowing strength across the individual surveys. The merit of this method is that the pooled effect size or between survey heterogeneity can be calculated even when the number of surveys is small. In general, retrospective cluster surveys are conducted to obtain mortality status in conflict periods, and the data are analyzed using either a classical regression approach or estimates comparing against pre-crises period to ascertain the impact of crises on the population [48, 74, 75, 175]. This approach necessitates conducting post conflict surveys that capture mortality that happens in the distant past. These types of surveys are more prone to recall bias than do mortality surveys conducted during the crisis period. It also requires a substantial amount of human and economic investment. The use of various small-scale surveys conducted during the crisis period to make decisions on a national level provides an alternative to conducting a retrospective nationwide survey [57, 61, 62, 71, 175, 176].

2.3 Overview of statistical analysis

2.3.1 Bayesian analysis

The Bayesian technique is one of two main types of inferential modeling (Frequentist & Bayesian techniques). Unlike the Frequentist framework, the Bayesian technique considers the unknown parameters of interest as random and therefore are assigned a probability distribution. Given that all unknown parameters are considered random variables in Bayesian statistics, prior distribution(s) must be defined from the onset [177]. The definition of probability in the Bayesian context reflects our prior belief. The Bayesian approach provides the tools to update our prior understanding within the context of new data. It also provides robust estimates even when the sample size is small via the use of informative priors [178]. The Bayesian technique is easy to use when dealing with missing data, provides exact inference rather than asymptotic inference and provides more accurate estimation of parameter uncertainty. However, the Bayesian approach is not without limitations. The choice of priors may be subjective and time consuming, and the implementation of complex methodologies can be computationally demanding [177, 179, 180].

The underlying principle of the Bayesian technique is the incorporation of prior beliefs in the data analysis process given available evidence in order to produce posterior estimates. A graphical representation of the Bayesian modeling techniques is represented in figure 2-5.

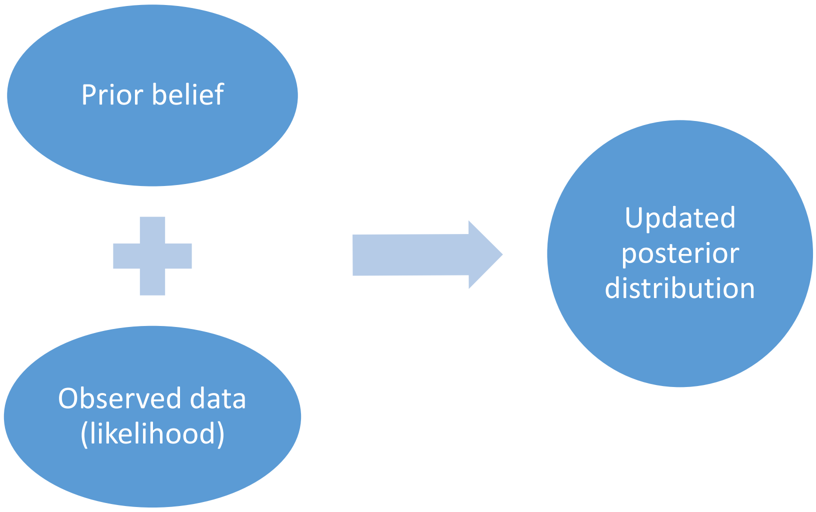

Figure 2-5: Bayesian framework

Prior and Posterior Distribution

One of the major controversies surrounding Bayesian analysis is the choice of prior distribution. The prior is a reflection of the information available before data are included in the statistical analysis [177]. Accordingly, we let $P(\theta)$ represent the prior distribution that expresses our uncertainty about the parameter θ without considering the available data y_i. The three broad interpretations and sources of prior distributions in a Bayesian framework are i) a Frequentist distribution based on past data, (ii) an objective representation of rationale beliefs of a parameter and , (iii) a subjective measure of what the researcher believes about the parameter [181]. Prior information about the parameter of interest should be incorporated into the prior density if available — informative prior. If not, a prior with very little contribution to the posterior should be used — non-informative prior [182].

Non-informative priors – generally referred to as vague or diffuse priors or reference priors – are priors that do not influence the posterior. They are priors whose contribution to the posterior is dominated by the data. They are used where scientific objectivity is of paramount concern or when no prior information is available. Informative priors are used in the presence of relevant prior information on the parameter of interests and are especially useful when the available data are small compared to the parameter space [180]. These priors are obtained from expert knowledge or from previous studies, and the main task with these priors is the conversion of qualitative knowledge from the expert to a probabilistic value [179]. The other sets of priors are the conjugate priors — priors with the same distribution family as the posterior distribution.

The posterior probability is derived by updating the prior probability using the Bayes theorem. To calculate the posterior estimate, let us assume that the observed random variable $y = (y_1, y_2, \dots, y_n)$ is independent and θ is a vector of unknown parameters. The probability distribution of y for known value of θ is expressed as:

$$P(y|\theta) = \prod_{i=1}^{n} \big(p(y_i|\theta)\big) \qquad 2\text{-}1$$

Our interest lies in obtaining the posterior distribution which is a combination of prior distribution $P(\theta)$ and the likelihood $P(y|\theta)$. Mathematically, this is expressed using the Bayes' theorem:

$$P(\theta\,|y) = \frac{P(y|\theta) * P(\theta)}{P(y)} \propto P(\theta)P(y|\theta) \qquad 2\text{-}2$$

Hence, the posterior distribution is proportional to the prior distribution and the likelihood function, where

$$P(y) = \int P(y|\theta)P(\theta)\, d\theta \qquad 2\text{-}3$$

To calculate the posterior probability if the posterior and prior distribution are of the same distributional form (conjugate prior), Bayes' theorem can be easily solved analytically. In most applications, the posterior and prior distribution are of different distributions. Even in cases where a conjugate prior does exist, the posterior distribution can only be expressed in a complex form that requires solving high dimension integrations [180]. This issue can be resolved using a numerical approximation method such as the Markov Chain Monte Carlo simulation (MCMC). The MCMC methods are iterative sampling techniques that sample from the posterior distribution, and inferences are based on the results of large samples drawn by the MCMC algorithms. Gibb's sampling is one of the common techniques of the MCMC algorithm used in simulating a Markov Chain. This technique partitions the random variables of interest and samples from each partition at a time conditioned on the recent value of the sample obtained [183]. The development of MCMC methods and the advancement of fast and powerful computers are responsible for the wide application of Bayesian approach [179, 180].

Convergence and model fit

One of the major steps after model specification and fitting is to ensure convergence. Bayesian model convergence can be ascertained either through graphical or statistical measures. Graphical methods are usually the first step in checking model convergence because they are quick and easy to interpret. Trace plots are the most commonly graphical convergence diagnostic tools. This involves inspecting the MCMC chains by ensuring proper mixing between the chains. The density plot is another important diagnostic plot. Geweke diagnostic (GT) and Gelma and Rubin (GRT) tests are common statistical measures used for convergence checks. The GT procedure divides the Markov Chain into two halves and compares the posterior mean of both halves based on the null hypothesis that the means of the two halves are equal [184]. The GRT statistics (R hat) measures the ratio of the pooled between chains and within chains variance of a parameter [185]. R hat values greater than 1 are an indication of non-convergence, and the further away from 1, the more severe the non-convergence.

Another important step in Bayesian analysis is the assessment of model fit. One of the main model checking procedures is the posterior predictive check (PPC). PPCs are based on the idea that data simulated from the fitted model should be similar to the data from which the model is fitted. Divergence between the simulated data and observed data is an indication of the violation of model assumptions [186]. The PPC can be assessed graphically or by the computation of Bayesian p-values. If the model is true the p-value is more likely to near 0.5 than closer to 0 or 1 (less than 0.05 or large than 0.95, suggest serious lack of model fit) [186]. The posterior predictive check approach is not without criticism — double use of the data for both model fitting and checking — it is acceptable to use PPC for the measure of model adequacy and not for model comparison [187-190].

The mathematical formulation of the PPC is shown in equation 2-4 below; y is the observed data with vector of parameter θ, y_{rep} represents replicated data that would be obtained from data model and $p(y|\theta)$ is the posterior predictive distribution for y_{rep}.

$$\mathrm{p}(\mathrm{y_{rep}}|\mathrm{y}) = \int \mathrm{p}(\mathrm{y_{rep}}|\theta)\mathrm{p}(\theta|\mathrm{y})\mathrm{d}\theta \qquad \text{2-4}$$

The expression $\mathrm{p}(\theta|\mathrm{y})$ is approximated as $\mathrm{p}(\mathrm{y}|\theta)\mathrm{p}(\theta)$.

The discrepancy between the observed data and posterior predictive distribution is quantified using the test statistic's Bayesian p-value, expressed as $\Pr(T(y_{rep}, \theta) \geq T(y, \theta)|y)$. This is the proportion of the simulated values for which the test statistic has a value equal or greater than the observed values [190].

2.3.2 Bayesian credibility intervals and mortality estimates

Mortality estimates play a central role in decision making in humanitarian emergencies. As such, researchers compute mortality point estimates with the lower and upper limits to indicate the level of certainty surrounding the estimates. In classical statistical frameworks, the confidence interval (CI) can be described as a range of values for a variable of interest constructed so that this range has a specified probability of including the true value of the variable [191]. For instance, for a confidence limit set at 95%, if the experiment is repeated 100 times, 95% percent of the time the true value of interest will fall within the interval. The approach for the calculation of CIs in the classical statistical approach is based on the assumption of sampling distribution and the Central Limit Theorem [179]. The width of the confidence interval is an indication of how trustworthy the estimate is; the narrower the confidence interval, the more trustworthy the estimate.

The credibility interval is a central idea in Bayesian inference, and its main goal is to summarize the uncertainty around an estimate. The credible interval is the range of values where the probability of covering the parameter of interest is equal to 1- α [192]. This is the interval with more plausible values of the parameter under consideration. For a given α level and parameter of interest θ, the (1- α)% credibility interval can be defined as the interval where the integration or sum of the posterior probability distribution equals (1- α) [193] which can be expressed as:

$$\int_c P(\theta|y)d\theta = 1 - \alpha, 0 \leq \alpha \leq 1$$

where c is the subset of a parameter space. The credible interval depends on prior distribution, and unlike traditional confidence intervals, the boundaries of the credibility intervals are assumed to be fixed and the estimated parameter is considered to be a random variable.

There are two main types of Bayesian credibility intervals: the equal tail interval and highest posterior density interval (HPD). The equal tail credibility interval is an interval in which the posterior estimate of interest lies between lower quantile representing 2.5% percentile of the posterior distribution and an upper limit representing 97.5% percentile of the posterior distribution [194]. The equal tail probability is easy to compute but might produce values with lower probability inside the interval than outside the interval when the posterior distribution is asymmetric [179]. To circumvent this, the HPD is used. The HPD is based on the assumption that all the values within the interval have a higher probability of representing the posterior estimate of interest than values outside the interval [194]. The Bayesian estimation of intervals has a probabilistic interpretation, which is more meaningful and estimated from the population distribution rather from hypothetical sampling distribution [179].

In humanitarian settings, the primary objective of the SMART surveys is the assessment of nutrition indicators and not mortality estimation. Consequently, sample sizes are usually insufficient for mortality estimation [195], which produces estimates with wider confidence interval. Besides, the exclusion of certain areas or the inability to access all selected household/clusters due to reasons associated with the humanitarian emergencies [196, 197] might produce estimates with great uncertainty. If the evidence from the data is weak due to poor sample size, the inclusion of prior believe under the Bayesian approach will help to strengthen the estimates, hence, the narrower of the level of uncertainty surrounding the estimates [173]. However, this is not a fix for poor sample size but rather an attempt to mitigate the impact of poor sample on the estimates.

2.3.3 Bayesian Hierarchical Model

A Bayesian hierarchical model consists of parameters such that the values of some of the parameters depend on the values of other parameters [180]. In hierarchal models, the prior distributions in the model are also assigned prior distributions. Given model parameter θ, prior parameter α and data y with the distributional form $P(\theta|\alpha)$, the posterior distribution can be expressed as:

$$P(\theta|y) \propto P(y|\theta)P(\theta;\alpha)P(\alpha;\beta) \propto P(y|\theta)P(\theta|\alpha)P(\alpha|\beta)$$

$P(\theta|\alpha)$ is the first level prior distribution which is assigned to the second level prior distribution, $P(\alpha|\beta)$. The second level parameter is the hyper-prior, and its parameter is the hyper-parameter. The dependence across parameters in hierarchical modelling allows parameters to borrow strength from the corresponding parameters of other groups. It is efficient in modeling data with complex data structure. For instance, in modeling count data, the inclusion of a gamma random term can capture the over-dispersed structure of the data. Also, in modeling cluster level data, a hierarchical model allows the capturing of both within- and between- cluster variability. For example, mortality data from the same region or country may be assumed to be similar compared to mortality data from a different region/country. Furthermore, hierarchical models reduce subjectivity and are easy to interpret because posterior estimates are averaged across different priors and are conditional distributions of simplified form [198].

2.3.4 Bayesian Finite Mixture model

Finite mixture models are utilized in situations where each observation is assumed to come from different unidentified subpopulations and each subpopulation belongs to a distribution density. The probability density of each of the subgroups is called a component of the model. The subpopulations are not constrained to come from the same distribution family. Finite mixture models can also be used to model data in which the number of suspected subpopulations is unknown and not fixed. Mixture modeling offers the advantage of modeling data that are not properly modeled by standard parametric distributions and provides an alternative to non-parametric methods [199].

For instance, the distribution of fatality from air raids may be explained by the gender differences or by rural-urban divide. However, in situations where information on group compositions is not available or impossible to observe, a finite mixture model can be used to identify the underlying unobserved subpopulations within the larger population. Further, in humanitarian emergencies, the unknown mechanisms (not related to gender/age or other demographic or clinical factors) responsible for the disproportionate effect of crisis on the health indicators of affected populations can be effectively modeled using finite mixture modeling approach.

The implementation of the finite mixture model using the Bayesian technique provides an easy way of combining results from different models and selecting the model that fits the data well. The Bayesian finite mixture technique is computationally intensive and also subject to label switching (non-identifiability). The use of MCMC algorithm for parameter sampling addresses these computational challenges. The placement of a constraint on the parameters of interests is one of the techniques used to resolve the issue of label switching [200]. Label switching occurs when the posterior distribution does not contain information required to distinguish say component 1 from component 2 in a mixture model making it difficult to summarize the posterior distribution and estimate the posterior mean [200, 201].

The Bayesian finite mixture model is expressed as follows:
Let $y_1, y_2, y_3, \dots y_n$ be independent observations from subpopulations k.

$$p(y|\eta, \beta) = \sum_{i=1}^{k} (\eta_i f(y: \beta)) \qquad 2\text{-}5$$

Where η_i is the mixing proportion, which are constrained to be positive, and $\sum_1^k \eta_i = 1$. $\beta = (\beta_1, \dots, \beta_k)$ is the vector of parameters for a specific component. The probability density function is represented as $f(y: \beta)$, and there is no restriction requiring that the probability density function in each component have the same distribution.

The formulation of the mixture model leads itself easily to the hierarchical model. The mixture parameter is the hyper-parameters of the latent variable φ_{ik}which takes value of 1 if an observation belongs to any of the kth components and takes a value of zero otherwise. For each $y = (y_1, y_2, y_3, \dots y_n)$ we assume $\varphi = (\varphi_1, \dots, \varphi_n)$ is missing and is indicative of the component label for each observation. Usually, the mixing parameter is considered a discrete prior and is assumed to follow a Dirichlet distribution of the form: $p(\eta_1, \ldots, \eta_k) \propto \prod_{i=1}^{k} \eta_i^{\delta-1}$. The common choice of prior is a uniform prior imposed on the mixing weights $(\delta_1, \ldots, \delta_k) = (1, \ldots, 1)$.

2.3.5 Bayesian Poisson-gamma mixture model

In chapter 4, we assess the change in mortality profile in Yemen using data from small-scale SMART surveys conducted between 2012 and 2019. Previous studies have used retrospective surveys in assessing change in mortality profile in conflict settings [48, 60, 74, 75, 175, 202, 203]. We divided the period into two units: pre-conflict period (2012 – 2014) and the conflict period (2015 – 2019). We estimated the pooled crude death rates for both periods, and assessed the difference to estimate the excess mortality attributed to the protracted crisis. The merits of our approach are i) it allows us to account for over-dispersion in count data by assigning a prior to individual-level estimates, ii) it provides more accurate estimates by borrowing strength from each observation, iii) it provides a Bayesian highest density interval for the baseline value, unlike the recommended Sphere values.

The model formulation is as follows: the number of deaths in *survey i* from *governorate n* follows a Poisson distribution expressed as

$$Y_{in} \sim Poisson(\lambda_i)$$

$$\lambda_i = \theta_i * \rho_i \qquad 2\text{-}6$$

where a first level gamma prior is assigned to θ, yielding $\theta_i \sim gamma(\alpha, \beta)$ and α *and* β are the shape and scale parameters, respectively.
In the next level we assigned non-informative gamma priors to the parameters of the gamma distribution, α and β. To circumvent the problem of convergence, an alternative parameterization was used in which a gamma prior was assigned to β and the parameter of interest μ (pooled mean estimate). The value of α was derived analytically from the mean of a gamma distribution as follows: $\alpha = \mu * \beta$. The value of the posterior mean μ is the pooled mortality estimates for the period under consideration. In the presence

of model coefficients, the usual normal prior can be assigned to the coefficients.

2.3.6 Bayesian Finite Poisson Mixture Model

We adopted the Bayesian finite mixture modeling technique in chapter 5. We modeled the effect of armed conflict on the mortality profile of children less than five years old by considering unobserved heterogeneity and the underlying latent group using a two-component Bayesian Poisson finite mixture model. In our work, we assumed that the number of deaths in children less than five years follows a Poisson distribution $\boldsymbol{y} \sim poi(\gamma)\ and\ \gamma = \lambda * offsets$ with a finite mixture formulation of the form:

$$f\left(\mathrm{y}\middle|\beta_1, \beta_2, \ldots, \beta_j\right) = \sum_{\mathrm{i=1}}^{2} \eta_i \mathrm{Poi}(\lambda_j) \qquad 2\text{-}7$$

$$\log(\lambda_{\mathrm{j}}) = \beta_{i,0} + \sum_{\mathrm{j=1}}^{\mathrm{n}} \beta_{i,j} \mathrm{x_j} + \log(\mathrm{offset_{i,j}}) \qquad 2\text{-}8$$

We used the mixing proportion $(\eta_1, \eta_2) \sim$ Dirichlet (c (δ_1, δ_2)), $s_j > 0$, and $\sum_i n_i = 1$. In this study, we assumed that both components (k=2) belong to a Poisson distribution. $\beta_{i,0}$ is the regression intercept for component *i*, and $\beta_{i,j}$ is the regression coefficient for variables x_j in component *i*. $\mathrm{Offset}_{i,j}$ accounts for differences in sample size (in our case is person days; see chapter 5 for explanation) for event *j* in component *i*. The model parameters were assigned normal prior $\beta_{i,j} \sim Normal(\mu, \sigma^2)$, where μ is the unknown mean and σ^2 is the variance. Furthermore, we imposed a constraint on the priors to circumvent the problem of label switching and to ensure identifiability.

We performed the data analyses for chapter 4 and 5 using the MCMC algorithm to simulate draws from the posterior distribution of the models. We used three MCMC chains with different starting values and checked for convergence by using the trace plots or Gelman-Rubin diagnostic plot [204]. We used posterior predictive checks to ascertain the model's goodness of fit. The statistical analyses for chapter 4, 5 and 6 were performed using RStudio version 4.0.2 and the R packages R2jags version 0.6.1 [205], HDInterval version 0.2.2 [206], ggplot2 version 3.3.2 [207] for graphics and QGIS for maps.

Chapter 3: Are the available assessment tools sufficient?

This chapter is adapted from:

Thomas Jideofor Ogbu, Debarati Guha-Sapir. "*Strengthening data quality and reporting from small-scale surveys in humanitarian settings: a case study from Yemen, 2011-2019*". Confl Health. 2021;15(1):33. Doi: 10.1186/s13031-021-00369-2

Abstract

Background

Under-five death rate is one of the major indicators used in assessing the level of needs and severity of humanitarian crisis. Over the years, a number of small-scale surveys based on Standardized Monitoring and Assessment of Relief and Transitions methodology has been conducted in Yemen, these serve as a guide for policy maker and the humanitarian community. The aim of this study is to identify critical methodological and reporting weaknesses that are easy to correct and would improve substantively the quality of the results.

Methods

We obtained seventy-seven surveys conducted across 22 governorates in Yemen between 2011 and 2019 and divided the analysis period into pre-crisis (2011 – 2014) and crisis period (2015 –2019) for comparison. We analysed survey qualities such as sampling methodology, completeness of reporting of Under-five death rate and mortality sample size for children less than five (children < 5) years old.

Results

Seventy-seven (71.9%) out of 107 surveys met the eligibility criteria to be included in the study. The methodological quality and reporting are as varied as the surveys. 23.4% (n=18) met the criteria for quality of sampling methodology, while 77.9 %(n=60) presented required information for the estimation of required mortality sample size and 40.3 %(n=31) met the quality check for reporting of Under-five death rate.

Conclusions

Our assessment indicated that there is no strict adherence to the sampling methodology set out in Standardized Monitoring and Assessment of Relief

and Transitions guidelines, and reporting of mortality and sample size data. Adherence to methodological guidelines and complete reporting of surveys in humanitarian settings will vastly improve both the quality and uptake of key data on health and nutrition of the affected population.

3.1 Background

Since the beginning of the ongoing conflict in 2015, the humanitarian crisis in Yemen has continued to deteriorate, negatively affecting all aspects of life in the country. Lack of food, decreasing access to safe water and sanitation services, and a dysfunctional health system continue to be the harsh and deadly realities of daily life [208]. In 2013, child deaths occurred at a rate of 53/1,000 live births, but by 2016 had increased by 7.2% [209]. At the end of 2019, more than three million were internally displaced persons (IDPs) and over 24 million were in need of humanitarian assistance [210]. While the expected deaths from direct and indirect causes at the end of 2019 is 233,000 deaths and children under the age of five accounted for 60% of these deaths [211].

Further complicating the situation, disease runs rampant, as health facilities are inaccessible or plagued with shortages of medicine, vaccines, electricity and health care workers [208, 212]. As a result, severe outbreaks of vaccine preventable and other diseases — measles, diphtheria and cholera outbreaks — occur regularly [166, 212, 213]. The severity of such outbreaks is difficult to assess as many deaths occur at home and remain unreported. Humanitarian organizations use small-scale surveys to fill such gaps and estimate mortality rates in affected communities, with the aggregation of this data creating a more accurate picture of a crisis.

In Yemen, available national level data are often inadequate and outdated — the last census is from 2004 while the most recent Demographic and Health Survey (DHS) is from 2013. Humanitarian aid programmes increased substantially since 2015, and are now in their fifth year of operations. They often lack useful evidence and credible field data essential for assessing the severity of the situation and equally importantly required for targeted and impactful interventions. Typically, mortality rates and other indicators, such as prevalence of common childhood diseases or vaccination coverage, are key inputs for decision-making and increasingly are collected through small-scale surveys.

In severe humanitarian crises, U5DR is a common indicator for setting priorities and assessing needs. These rates, measured against baseline estimates, provide insights into the effect of interventions aimed at containing mortality [214]. As data gets increasingly rare from these settings, the use of estimates from small-scale surveys allows for the evaluation of trends and impacts of key nutritional and health indicators [60-62]. Most are cross-sectional surveys using cluster samplings and are based on the now widely used 'Standardized Monitoring and Assessment for Relief and Transitions' (SMART) methodology [58, 65]. Statistically stable sampling methods and adequate sample sizes are essential to obtain representative and accurate results [215]. In addition, a key aspect for the findings to be credible and validated is a scientific and complete presentation of survey methods and results. There are on-going efforts to strengthen the quality of these surveys, which are an invaluable data source and serves the humanitarian community. More importantly, the results of these surveys and their reliability underwrite critical decisions on where and when to provide lifesaving aid. Operational researchers increasingly use this source of secondary data for identifying patterns and measuring trends [57, 60-62, 216, 217]. Any inherent methodological weaknesses related to application in the field can detract from the quality of their results and compromise decisions. Finally, these surveys and their management represent a fair proportion of humanitarian aid resources with a push towards efficiency and credibility.

Recognizing fully that the realities in humanitarian settings pose severe challenges to conduct field surveys, our focus of this paper is to identify critical methodological and reporting weaknesses that are easy to correct and would improve substantively the quality of the results. It is not an exhaustive critical sweep of all drawbacks in this approach.

3.2 Methods

Search strategy and exclusion criteria

We conducted a search of surveys in Yemen from two major sources – the Complex Emergency Database (CE-DAT) and the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) database. We also searched other online repositories maintained by humanitarian agencies, such as United Nations High Commission for Refugees (UNHCR), United Nations Children's Fund (UNICEF), World Food Program (WFP), World Health Organization (WHO), Médecins Sans Frontieres (MSF) International, Action Against Hunger (AAH), Cooperative for Assistance and Relief Everywhere (CARE) International and ReliefWeb. Additionally, we conducted a Google search and contacted experts at UNICEF Sanaa for possible nutrition and mortality surveys conducted in Yemen during the period under consideration.

We only included reports designed to assess the nutritional status and mortality of children <5 years old in Yemen. We excluded surveys from the following sources; (i) those conducted in refugee camps, whose populations are non-nationals and receive UNHCR aid; (ii) large-scale surveys, such as DHS (USAID), that do not qualify as being rapid or as frequent as small-scale surveys; and (iii) Emergency Food Security and Nutrition Assessment Surveys, which focus principally on food security. We also excluded surveys that were set up to assess only nutritional indicators, or those in Arabic which did not present a sufficient level of detail or transparent language when translated.

Data Extraction

We extracted the following data from survey reports: recall period, number of under five deaths within the recall period, under five sample size, number of births within the recall period, number of children <5 years old that joined/left the household within the recall period, and the reported U5DR. We also extracted confidence intervals, if reported, and if estimation of U5DR was stated as one of the main objectives of the survey. Additional data on sampling technique and survey methodology such as number of clusters selected, method of clusters and household selection and if data were collected from every household sampled, were extracted from reports and summaries.

Assessment of the methodological quality

We evaluated the reports using three main, straightforward but essential parameters:

a) The sampling methodology

b) Presentation of sample size calculation

c) Statistical reporting of U5DR

Given the lack of updated information on population size from various administrative levels in Yemen, we considered a sampling methodology to be sufficient if it is based on the guidelines presented in table 3-1. In cases where one of the survey objectives was to measure U5DR, nutrition survey guidelines recommend an additional sample size calculation for mortality that is representative of the targeted population [58, 218]. The calculation of sample size depends on recall period, design effect, precision, average household size, household non-response rate and expected mortality rate. The objective of the survey determines choices related to precision, recall period and design effect that influences sample size calculations. The choice of recall period will vary based on whether we expect to capture the effect of a famine or general variations in nutrition. For a report and its data to be considered of good quality, they should be methodologically transparent; the results should clearly state all parameters used for calculating and reporting U5DR, and to do so using the recommended standard units that allow for inter-survey, baseline comparisons and for comparisons with surveys from other conflict affected countries. The calculation of U5DR, as outlined in the SMART manual, requires information on the number of sampled under-five children, the recall period, the number of in/out-immigration of under-five children, and the number of births. If the estimated population of children <5 years old at the middle of the time interval under consideration is used as the denominator in calculating the U5DR, the mid-population should be reported. We appraise our three defined parameters based on the criteria presented in Table 3-1.

Table 3-1: Criteria for the assessment of methodological quality

Assessment	Methodological Quality Criteria (MQC)
Sampling methodology	For cluster surveys, the number of clusters chosen should be ≥ 30 [58, 219, 220] Clusters are selected using probability proportional-to-population-size sampling (PPS) [58, 221] In the second stage of sampling, households are selected using systematic or simple random sampling methods (not Expanded Program on Immunization methods (EPI)) [222] Mortality data are collected from all selected households, irrespective of presence/absence of children < 5 years old
Presentation of sample size calculation	Separate sample calculations and mortality estimates [59] Parameters required for sample size calculation are transparent/reproducible
Statistical reporting of U5DR	Information required for the estimation of U5DR are reported U5DR is expressed as number of deaths per 10,000/day [65] Confidence limits for U5DR are reported

3.3 Results

Study Characteristics

We extracted 107 survey reports conducted in Yemen between 2009 and 2019 from CE-DAT and the OCHA database. The surveys were in report format or detailed PowerPoint presentations. Of the 107 surveys, 77 were included in this study, covering the period 2011 to 2019. About 28.0% (n=30) of the surveys were excluded for reasons ranging from 'being conducted in camps' to those 'only assessing nutritional indicators' [223-227]. For the purpose of this study, we divided surveys into 'pre-conflict' (2011 – 2014) or 'conflict' periods (2015 – 2019). Thirty-one surveys (40.3 %) were from the pre-conflict period, and 46 (59.7 %) were from the conflict period.

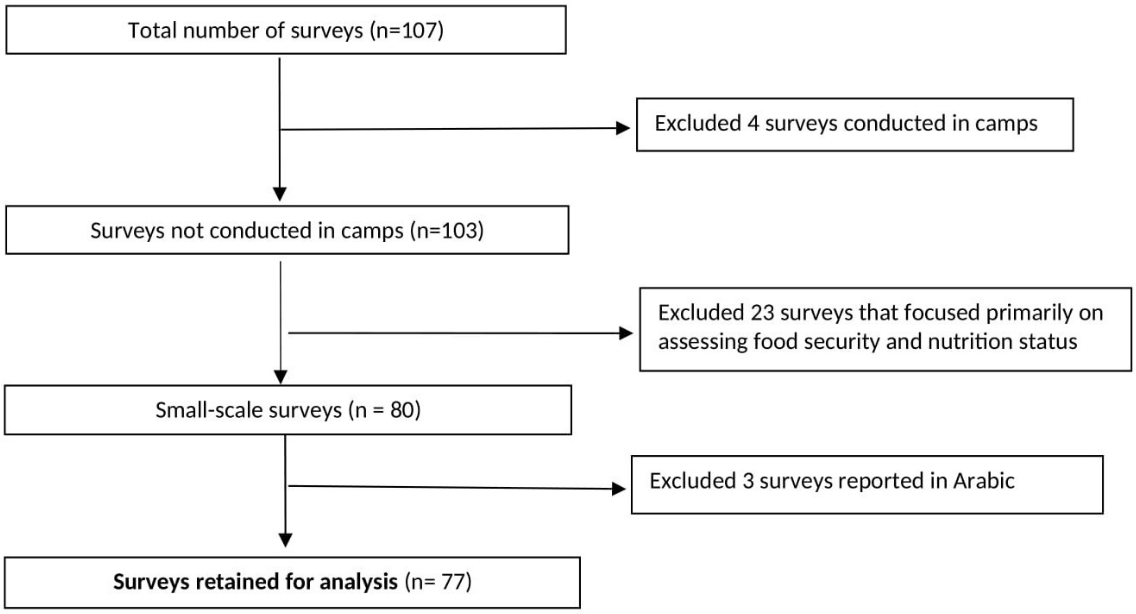

Figure 3-1:Survey selection process

Sampling Methodology

From the results in Table 3-2, all surveys (n=77) reported either using a 'Probability Proportionate to Population Size' (PPS) sampling methodology or reported using the SMART guidelines which recommend the use of PPS for cluster selection. All surveys (100%) reported using at least 30 clusters and the PPS method for cluster selection during the sampling process. In our dataset, nearly all surveys in the pre-conflict period (96.8%, n=30) and less than half of surveys in the conflict period (41.3%, n=19) used the EPI method of 'spin-the-pencil' assisted random start for household selection at the second stage of sampling. Furthermore, most surveys from both periods indicated that all selected households were surveyed for mortality, whether there were children <5 years old present or not. SMART Guidelines strongly recommend simple or systematic random sampling for household selection as a more statistically sound approach to reduce bias and increase representativeness than that of the modified EPI methods [58, 59]. Most of the surveys implemented in the field still used modified EPI methods (63.6%) to a varying degree.

Based on the MQC in Table 3.1, only 23.4% of surveys met all the criteria for sampling methodology: selecting at least 30 clusters, using PPS in the selection of clusters, using random or systematic methods for household selection, and surveying all selected households, irrespective of whether children <5 years old were present or not.

Table 3-2: Quality of sampling methodology for 77 surveys conducted in Yemen from 2011 - 2019

	Pre-conflict n(%) 31(100)	Conflict n(%) 46(100)	Total N(%) 77(100)
Sampling methodology			
PPS for selection of cluster	31(100)	46(100)	77(100)
Number of clusters ≥ 30	31(100)	46(100)	77(100)
Non-use of mod.EPI for selecting HH*	1(3.2)	27(58.7)	28(36.4)
All HH surveyed for U5DR**	31(100)	36(78.3)	67(87.0)
Sampling methodology criteria met	**1(3.2)**	**17(37.0)**	**18(23.4)**

* Non-use of modified EPI for selecting Household. For surveys that used modified EPI for selection household (pre-conflict n=30(96.8%), conflict, n= 19(41.3%); overall, n= 49(63.6%)) ** Of the 67 surveys 34 (50.7%) — pre-conflict n= 14 and conflict n=14 — reported appointment for revisit in the absence of members of the family or children.

Moreover, 40 surveys allowed for the calculation of standard error (SE) for both CDR and U5DR. We observed that the SE for CDR is consistently smaller than that of the corresponding U5DR, with the exception of one survey (Hajjah) which produced a larger SE for the CDR than for the U5DR. As large SEs effectively, limits their use for both advocacy and planning purposes. We note that the SMART methodology guidelines specifically recommend a separate calculation of sample size for the estimation of U5DR. However, with the exception of one, the SMART recommendation was not followed in any of the other surveys we have analyzed.

Presentation of sample size calculation

Among surveys in the pre-conflict and conflict periods, 77.4% and 78.3%, respectively, provided adequate information for the calculation of mortality sample size. Out of the 77 surveys included in this study, 60 (77.9%) surveys met the criteria for sufficient reporting of key parameters to recalculate mortality sample size namely: recall period, design effect, desired precision, expected death rate, non-response rate and average household size.

Statistical reporting of U5DR

Overall, of the 77 surveys in this study, 40.3% (n=31) met the criteria for the sufficient reporting of U5DR. Out of the 67 surveys that reported U5DR and its confidence intervals, expressed U5DR in widely used units of 10,000/day, 31 reported the parameter for the estimation of U5DR — number of deaths among children <5 years old, number of births, and the number of children <5 years old that joined or left the household within the recall period. A little more than 48.4% (n=15) of surveys conducted in the pre-conflict period (n=31) and approximately 34.8% (n=16) from the conflict period (n=46) met the criteria for sufficient reporting of U5DR.

Table 3-3: Quality of reporting of 77 surveys conducted in Yemen from 2011 – 2019

	Pre-Conflict n(%) 31(100)	Conflict n(%) 46(100)	Total N(%) 77(100)
Reported U5DR	27(87.1)	40(87.0)	67(87.0)
Parameters for U5DR est.	15(48.4)	16(34.8)	31(40.3)
U5DR expressed in 10,000/day	28(90.3)	40(87.0)	68(88.3)
Reported CIs for U5DR[a]	27(87.1)	40(87.0)	67(87.0)
U5DR reporting criteria met	**15(48.4)**	**16(34.8)**	**31(40.3)**
Calculated mortality sample size[b]	24(77.4)	36(78.3)	60(77.9)
Recall period	31(100)	46(100)	77(100)
Design effect	24(77.4)	36(78.3)	60(77.9)
Desired precision	24(77.4)	36(78.3)	60(77.9)
Expected death rate	24(77.4)	36(78.3)	60(77.9)
Non-response rate	24(77.4)	36(78.3)	60(77.9)
Average household size	24(77.4)	36(78.3)	60(77.9)
Sample size reporting criteria met	**24(77.4)**	**36(78.3)**	**60(77.9)**

[a] surveys that reported estimated 0/10000/day U5DR were considered to have reported Cis. [b] reported parameters for sample size calculation.

3.4 Discussion

The application of EPI and overall methodological quality

Overall, the majority of surveys within this study fall short of the aforementioned sampling methodology criteria, thus affecting the precision and robustness of results. The SMART sampling method, a two-stage cluster design developed independently of EPI, but informed by its approach. It borrowed the EPI 'spin-the pencil' assisted random start method for household selection at the second stage of sampling. The SMART team, clearly aware of the significant biases [58, 59] inherent in this approach, offered a second option to its field users. This option is consistent with the classical and sound methods of using full enumeration of the households in the cluster from which a simple random systematic sample was drawn.

For the first stage, both techniques use a two-stage cluster approach, based on PPS cluster selection methods. However, the second stage of household selection is where we begin to see discrepancies. In general, cluster sampling is widely used in humanitarian settings due to the lack of acceptable sampling frames, dispersed populations and security constraints [228-230]. Though efficient in humanitarian settings, this method cannot estimate mortality at lower administrative levels (i.e. divisions or districts) unless a sample of at least 30 high-resolution clusters are selected [71], which is difficult to do in such settings. Due to differences in cluster sizes, the chances of selecting individuals from the clusters are not equal. This produces selection bias and lowers the precision compared to simple random or systematic sampling techniques of the same size.

To circumvent these problems, surveyors use PPS in selecting clusters to ensure that larger clusters have a higher selection probability, compared to clusters of smaller sizes [58]. Sampling at least 30 clusters increases the number of households included for the mortality estimate, hence, improving precision [58, 71]. To ensure representativeness while minimizing bias, SMART recommends the use of simple random or systematic sampling methods over EPI methods for selecting households from the chosen clusters. Our analysis of 77 surveys revealed that the majority of assessments used modified EPI methods in the second stage for household selection, despite its disadvantages [222, 229]. For these reasons, the SMART guidelines are quite clear and methodologically sound; the challenge is to ensure adherence to these guidelines, especially with household selection, to produce valid and precise estimates [215] for use in policy decisions and scientific studies.

Reporting sample size calculation and U5DR statistics

The accurate and complete presentation of the survey methods, parameters used in sample size calculation and mortality estimation is foundational to establishing reliable and comparable mortality and nutritional estimates. Moreover, data reliability from small-scale surveys depends on the design, precision of estimates, consistency of reported results, and the availability of sufficient information required to validate mortality estimates and sample size. Among the surveys analysed, overall reporting was consistent, but at times, there was insufficient information on why certain choices were made in choosing values for sample size calculations.

Overall, the majority of surveys failed to provide sufficient information for recalculating U5DR. Reproducibility is important for researchers and NGOs to confirm independently the accuracy and precision of the U5DR. Indeed, the accurate estimation of U5DR cannot be overemphasized; improper validation can potentially bias the results significantly and those of subsequent studies that depend on these estimates. Most importantly, the results of these estimates influence policy decisions and drive the allocation of hundreds of millions of dollars in food aid and related resources to the Yemeni government, as observed from 2011 to 2019 [231-234].

Differences in survey quality between pre- and conflict periods

We may observe an improvement in the methodological quality and reporting over time due to accumulated experience and skills. If we compare methodologies used by the surveys in this study, we find that those conducted during a conflict period (2015 – 2019) show a qualitative improvement compared to those reported before the escalation of violence. For example, a governorate-level survey from the pre-conflict period (2013) selected at least 30 clusters using the PPS method and surveyed all chosen households using the EPI method, irrespective of the presence of children under-five [235]. In contrast, a conflict period (2018) survey in the same governorate employed simple random sampling methods to select households from an exhaustive list instead of using the EPI method [236]. While sample selection methodology undoubtedly improved between the first and second survey, unfortunately, the reporting quality still needed attention.

Analysis of the report narratives suggest that improvements in methodology, especially using random sampling for selecting households, require more time and effort. Thus, using experienced NGO SMART survey teams could allow for the rapid application of SMART guidelines in the field, including enumeration of households and random sampling. Indeed, two strengths of the commonly used EPI methods is its ease of use and established protocol – key attributes in a state of insecurity. However, standardized protocols, developed by the SMART team, have encouraged field surveyors to abide by SMART guidelines for second stage household's selection in the cluster sampling. This facility provided by the SMART secretariat has overridden the use of modified EPI methods (e.g. spin the pencil) in the household selection stage.

The reporting of sample size calculations and U5DR statistics were noticeably more complete in surveys from the pre-conflict period. Concerning the reporting where we notice little to no improvement over time, this may be due to priority placed on implementing the surveys, and subsequently followed by little interest in the actual 'writing up' of the results once the fieldwork is over. Finally, we summarize our findings and recommendations in table 3-4 below.

Table 3-4: Summary of findings and recommendation for improvements

Findings	Recommendations
Use of modified expanded program on immunization (EPI)	The SMART manual does not recommend the use of modified EPI, however, in humanitarian settings we recognize this method may be the most feasible, but should only be used when other options are not possible.
Insufficient reporting of parameters for estimating U5DR	Includes information on all parameters (number of deaths under-five, number of births, number of out/in – migration of children under-five and recall periods) for the estimation of U5DR
Incomplete reporting of mortality sample size estimates	Includes information on parameters used for sample size estimation in the survey; Clearly indicates and presents parameters used for nutrition and mortality sample size calculations separately. For surveys in different zones, sample size calculation should be clearly presented for each zone or indicated in the report that the same parameters were used for zones.
Use of CDR for the estimation of mortality sample size calculation	SMART manual recommends separate calculation of sample size for U5DR. We suggested that should this not be the case, enumerator should be able to indicator the reason for not calculating separate U5DR sample size.

Limitations

Our analysis is limited by the possibility that we may have inadvertently excluded surveys not found through the search strategy. However, we contacted field officers, from NGOs and the UN, but did not obtain any additional survey reports. We were also unable to address satisfactorily selection bias within surveys that may have otherwise been eliminated using simple random sampling or segmentation and sampling grid methods [222]. Future research, perhaps by the SMART team who are best placed to do so, should undertake comparative studies of at least the three aforementioned approaches to evaluate their performances and feasibility in conflict settings.

3.5 Conclusion

Overall, small-scale surveys remain essential, and often, the only source of secondary data for the humanitarian community. Thus, it is imperative to continually improve the design, methodology and reporting of such surveys. Our recommendations are not overwhelmingly difficult to implement but could have a substantial impact on the quality and usability of these surveys. However, we recognize that user needs of survey results vary according to their objectives and that the current level of detail may be sufficient in some circumstances. Adherence to methodological guidelines and complete reporting of surveys in humanitarian settings will vastly improve both the quality and uptake of key data on health and nutrition of the affected population. Moreover, even if the small-scale surveys address the issues raised in this study, there is a larger issue of the ability of such small samples to capture mortality in the first place. This requires a wider discussion by sampling experts along with the consideration of humanitarian realities in the field. Legitimate resource constraints in humanitarian setting for survey cost maybe an important driver to maintain small samples. Implementing such changes will require structural cooperation between academic and operational agencies within a constructive framework.

Chapter 4: How much of the deaths are avoidable?

This chapter is adapted from results submitted for publication as:

Debarati Guha-Sapir**, Thomas Jideofor Ogbu**, Sarah Elizabeth Scales, Maria Moitinho de Almeida, Anne-Francoise Donneau, Anh Diep, Robyn Bernstein, Akram al-Masnai, Jose Manuel Rodriguez-Llanes, Gilbert Burnham. Civil war and death in Yemen: Analysis of SMART survey data, 2012 – 2019. **PLOS Global Public Health**, Accepted.

Abstract

Background

Conflict in Yemen has displaced millions and destroyed health infrastructure, resulting in the world's largest humanitarian disaster. The objective of this paper is to examine mortality in Yemen to determine whether it has increased significantly since the conflict began in 2015 compared to the preceding period.

Methods

We analysed 91 household surveys using the Standardized Monitoring and Assessment of Relief and Transitions methodology, covering 2,864 clusters undertaken from 2012 – 2019, and deaths from Armed Conflict Location & Event Data Project database covering the conflict period 2015 - 2019. We used a Poisson-Gamma model to estimate the posterior means for the pre-conflict (μp, baseline value) and the conflict period (μc) to estimate nation-wide excess deaths and its association with security levels by governorate.

Results

The national estimated crude death rate/10,000 in the conflict period was 0.23 which is higher than the estimated baseline rate of 0.19. We estimated 168,212[19,913, 294,338] excess deaths that occurred between 2015 and 2019. A large share (67.2%) of the excess deaths were due to combat related violence. At the governorate level, PCDR varied across the country, ranging from 0.03 to 0.63 per 10,000 per day. Hajjah, Ibb, and Al Jawf presented the highest total excess deaths. Insecurity level was not statistically associated with excess deaths.

Conclusions

The health situation in Yemen was poor before the crisis in 2015. During the conflict, intentional violence from air and ground strikes were responsible for more deaths than indirect or non-violent causes. The provision of humanitarian aid by foreign agencies may have helped contain increases in indirect deaths from the conflict.

4.1 Background

The 2019 United Nations Office for Coordination of Humanitarian Affairs' (UNOCHA) Humanitarian Needs Overview on Yemen gives a shocking picture of the plight of a country in conflict forgotten by the rest of the world. More than 24 million Yemenis, or 80% of the population, require some type of humanitarian assistance, and 19.7 million lack adequate health care, including emergency services, routine vaccination, and maternity care [237]. The war has pushed nearly 10 million people to the brink of starvation, 2 million of them children with acute malnourishment. Further, 222 out of the 333 districts in the country are already one step away from famine [238, 239]. Within two years of the declaration of the conflict, 50% of children under five years of age were stunted due to severe and sudden food insecurity [240]. By the end of 2017, deaths from health facilities reached 8,757 with 50,610 injured due to the conflict [241]. Facility based deaths and patients who actually present at health service provider are known to be only the tip of the iceberg for these two indicators.

News coverage of this devastation was largely ignored until Yemen was knee-deep in the largest cholera outbreak in modern history. Major newspapers, (e.g., Washington Post, BBC, CNN) began reporting the outbreak at the end of August 2017, although suspected cases had already started to accelerate in April, 5 months earlier. The cumulative total from October 2016 to November 2019 is over 2 million suspected cholera cases 82 and 3,886 associated deaths, a case fatality rate of 0.17% [242]. Only beginning in May 2018, more than 18 months after the beginning of the outbreak, did the first cholera vaccine campaign start in Yemen. However, this devastation is not new. In 2016, the Global Burden of Disease Study (GBD) reported the second cause of death in Yemen to be "conflict and terror," with the same category as the leading cause of premature death [243]. Perhaps most frustrating for humanitarian workers in Yemen is that there is little they can do to address the underlying problem. Escalating in March 2015, the conflict is primarily between the Iran-backed Houthis, a Zaydi Shia movement, which drove out the elected Yemeni government, resulting in a Saudi-led counteroffensive in support of the ousted government. Feeding off the chaos, Al-Qaeda and the Islamic State of Iraq and the Levant (ISIL) thrived, expanding their reach in the country from their bases in Mukalla.

Since 2015, Yemen has been subjected to nearly 20,000 air/drone strikes – an average of 4,000 per year – severely damaging the already fragile and dysfunctional health facilities and destroying supply chains for food and medicine [146]. Economically, Yemen has largely collapsed; foreign exchange reserves have been depleted and foreign remittances diminished [244]. The Government is unable to pay for imports of food and commodities and cannot meet public sector salaries. Utilization of health care and preventive services such as immunisation or maternal services have declined [245, 246]. Child health indicators, such as on-schedule immunisation, anthropometric status, diarrhoeal disease incidence, and anaemia worsened nationally since 2016 [247]. El Becheraroui et al., observed that some governorates with high levels of violence displayed worse health indicators [209]. Despite over five years of war, there have been few attempts to estimate excess mortality, and these rare efforts were made difficult by the dysfunctional health information reporting or civil registration systems [248]. However, accurate mortality rates are central to inform policy and action priorities starting from, humanitarian response, credible advocacy, and short-term resource programming. It is equally important for social justice and reconciliation once peace is established [249]. In this paper, we examine overall mortality in Yemen, exploring whether it has increased significantly in the period of the current conflict (2015 - 2019) compared to the immediate pre-conflict period using Bayesian modeling techniques. We also examine the role of armed violent incidents, including air strikes, on mortality.

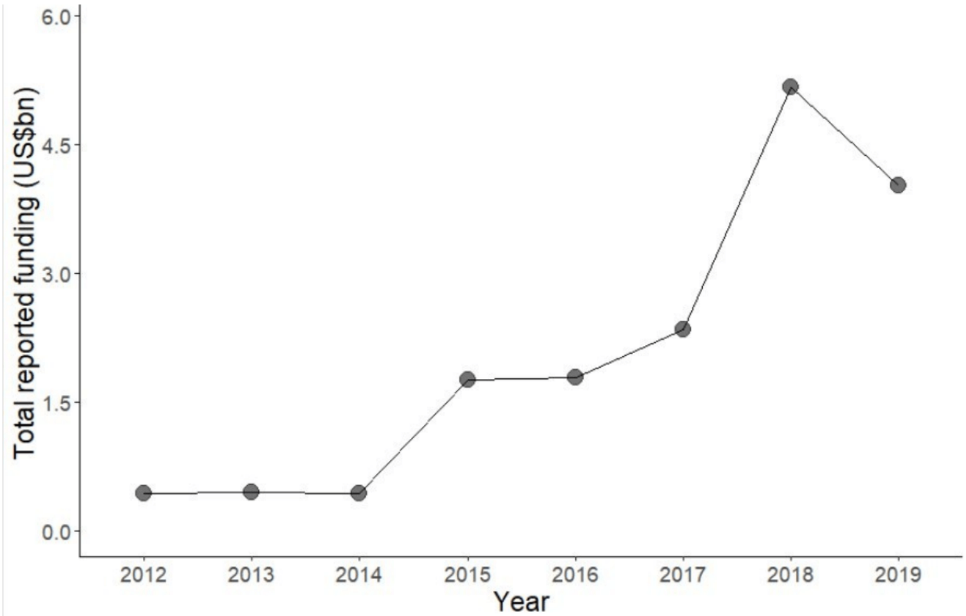

Figure 4-1: Humanitarian aid assistance to Yemen 2012-2019. *Data source: United Nations Office for the Coordination of Humanitarian Aid (UN-OCHA) [153]*

4.2 Methods

Data sources

We draw on surveys from the Complex Emergency Database (CE-DAT), a repository of small-scale surveys undertaken by humanitarian agencies and the United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA) [57]. The UN data include surveys undertaken by the World Food Programme (WFP), the Food and Agriculture Organisation of the United Nations (FAO), the Yemeni Ministry of Health (MoH), and the surveys done for the UN Emergency Food Security and Nutrition Assessment process (Appendix B-1). These surveys were chosen for the analysis because they provide the most recent mortality data with the highest resolution. All surveys used a standard two-stage random cluster sampling method. Furthermore, they all used the Standardized Monitoring and Assessment of Relief and Transitions (SMART) methodology and provided at least one estimate per governorate from 2012 to 2019 [58]. Our mortality data covered deaths from secured areas where household surveys were conducted and completed with death count from areas with active hostilities from the Armed Conflict Location and Event Data Project (ACLED) and the Yemen Data Project (YDP). For governorates without population values, we calculated denominators using population growth data from 2015 to 2019 and adjusted for displacement with data from UNICEF and the International Organization for Migration (IOM) [250] (Table 4-1).

Table 4-1: Summary characteristics of data sources for the period 2012 – 2019.

Variable	Source	Indicator	Description
Number of deaths	CE-DAT & UNOCHA	Mortality	Total no. of deaths within the recall period of the survey. We used the number as reported in each survey or estimated based on mortality information presented in the reports
Sample size	CE-DAT & UNOCHA	Mortality	Mortality sample size used in calculating crude death rate. We used the number as reported or estimated based on available information in the report.
Recall period	CE-DAT & UNOCHA	Mortality	Mortality recall period as used in the survey, in days or months.
Population estimate	MoH, UNICEF, World Bank, WorldPop & WorldOmeter	Population	Governorate population from 2015 - 2019 projected based on 2012 - 2014 average pop. Growth values in MoH and UNICEF reports. Country level population for 2015 - 2019 from World Bank and WorldOmeter. Population values were adjusted

			using IOM displacement data for each governorate.
Direct deaths	ACLED & Yemen Data project	Violence	No. of deaths due to violent events related to conflict such as battles, explosions, remote violence, protests.
Air/drone strike	ACLED & Yemen Data project	Violence	No. of air/drone strikes reported by ACLED

The earliest time point for which there were surveys which provided all the necessary data and used the Smart methodology was 2012. In total, we retained 91 surveys (28 from 2012 – 2014, and 63 from 2015 – 2019). The selection process is described in Figure 4-2.

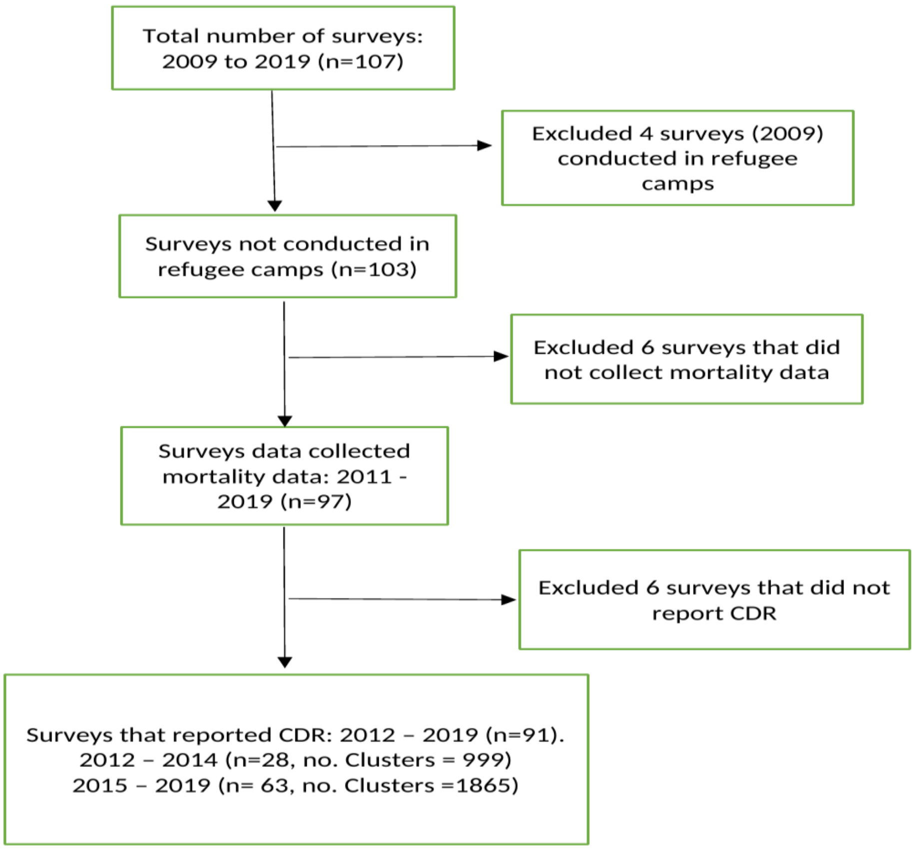

Figure 4-2: Survey selection flowchart

Mortality model

We used a standard approach to estimate excess mortality thus we established the national baseline crude death rate (BCDR) using surveys conducted in the three years preceding the 2015 crisis declaration, and then the posterior crude death rate (PCDR) from surveys conducted between 2015–2019. The difference is defined as the "total excess mortality." We applied a Poisson-Gamma model to estimate the posterior means for the pre- conflict BCDR (μp, baseline value) and the conflict period PCDR (μc) using the estimated number of deaths calculated for the whole population based on sample crude death rates (CDRs) and the recall period in person-days. Person-day calculation requires information on births and changes in household composition within a specified recall period of that survey (e.g., 3 or 12 months). However, since complete demographic profiles were not available for surveys, we approximated person-day values using the estimated population and mortality recall period [58].

To obtain the BCDR of the CDR (μp) and the PCDR of the CDR (μc), we used a hierarchical mixture of the Poisson-gamma model (Eq. (1)) for modelling the crude number of deaths obtained in the surveys (i = 1,2,3 ..., m), where m = 28 (number of surveys in pre-conflict period) or 63 (number of surveys in the crisis period). We modelled the crude number of deaths in each survey using a Poisson distribution (λ_i):

$$\lambda_i = pois\ (\theta_i * pt_i) \qquad 4\text{-}1$$

where, i is the number of surveys, pt_i is the person-days for survey i, θ_i is the crude death rate in survey i, and λ_i is the observed number of deaths. We assumed that the parameter of interest, θ, follows a gamma distribution (α, β). The choice of priors for μ and β are a non-informative gamma prior of the form dgamma(0 · 001, 0 · 001), where α is derived as the product of the mean and β. We ran 100,000 iterations with a burn-in of 50,000 to sample from the distribution via the Markov Chain Monte Carlo simulation. We checked convergence and assessed stationarity using Geweke diagnostics [184].

We estimated total excess deaths (TED) for the whole country for the period 2015-2019 using the formula below:

$$TED = \{(\ \mu_c - \mu_p\ ) * m * n * mpop\} +\ tot. direct\ deaths \qquad 4\text{-}2$$

μ_c = posterior mean CDR for conflict period /10000/day — (PCDR)
μ_p =posterior mean CDR for pre-conflict period /10000/day — (BCDR)
$m = \left(\frac{365}{10000}\right)$
n = number of years (2015 – 2019)

$mpop$ = median of the adjusted total population
$tot. direct\ deaths$ = total direct ACLED deaths from 2015 – 2019
$(\mu_c) * \left(\frac{365}{10000}\right) * n * mpop$ is the observed number of deaths
$(\mu_p) * \left(\frac{365}{10000}\right) * n * mpop$ is the expected number of deaths
$Total\ cumulative\ deaths = \ (\mu_c) * m * n * mpop + tot. direct\ deaths$

For governorate-level estimates, we estimated the PCDR. For each governorate with a single reported CDR between 2015 – 2019, we used this as the reported PCDR. These were calculated using the formula below:

$$\sum_{j=1}^{22}\{[(\alpha c_j - \mu_p) * m * (n * mpop_j)] + DD_j\} \qquad 4\text{-}3$$

$$\alpha c_j \begin{cases} \mu_c \text{ posterior CDR (PCDR) at governorate level} \\ \omega c_j \text{ reported conflict period CDR when only one value is available} \end{cases}$$

$mpop_j$ = median population by governorate

DD_j = direct violent deaths by governorate

The model building process is summarised in Appendix B-4.

Insecurity classification index method

Since 2015, in addition to ground warfare with gunshots and explosives, Yemen absorbed a minimum of 18,481 air/drone strikes, although not all strikes were reported [146]. The most targeted governorates were Sa'dah (4,932), Sana'a (2,013), Taizz (1,978), Hajjah (1,945), and Al Hudaydah (1,755) (Appendix B-2).

Globally, human security indices are commonly generated by combining multi-dimensional indicators such as jailed populations, the number of homicides, ease of access to small arms, and political instability rankings [251, 252]. In Yemen, such data are, in most part, missing. We therefore used publicly available data on violent deaths due to air/drone strikes and armed events (e.g., battles, explosions/remote violence, protests, and riots) to create a proxy index that broadly reflects the level of insecurity using the using the method described in Ogbu et al [253].

We assessed associations between the PCDR in governorates and their insecurity index using a one-way ANOVA test. All p values were two-tailed with one degree of freedom and α=0·05.

4.3 Results

The death rate in the conflict period (PCDR) was slightly higher than the baseline rates (BCDR) and had tighter confidence interval. The overall nation-wide excess death rate was 0.03/10,000 population. Often when baselines are not available in conflict settings, regional average mortality rates proposed by SPHERE Guidelines are used [65]. In this case, the 2011 SPHERE baseline was the average death rate in the North Africa and Middle East region i.e., 0.16 — a rate that is relatively low as most of the countries are in middle or upper-middle income economic categories. In this study, we used the survey-based baseline (BCDR) as those that provided the best available estimates that reflected the specific realities of Yemen. The excess death rate – the difference between PCDR and BCDR – is presented below (Table 4-2).

Table 4-2: Excess death rate estimates using baselines and conflict period CE-DAT surveys

	Rate estimates (10000/day) [LCL, UCL][a]
Total Crude Death Rate (2015 -2019)	0.23 [0.19, 0.27]
Posterior Crude Death Rate (PCDR)	0.20 [0.17, 0.24]
Baseline Crude Death Rate (BCDR)	0.19 [0.17, 0.22]
Indirect excess Crude Death Rate	0.01[-0.02, 0.05]*
Direct (Violent) Death Rate	0.02[b]
Total Excess Death Rate (TED)	0.03 [0.00, 0.06]

[a] LCL: lower credible level; UCL: upper credible level. * Non-significant
[b] No confidence interval provided by data source.

Applying the conflict period rates (PCDR) to the Yemen population, we estimate 1,115,024 deaths would have occurred in the 5-year crisis period, whereas we would have expected 946,812[820686, 1095111] deaths had the estimated baseline rate (BCDR) prevailed — a 17.8% increase in deaths. Excess deaths due to direct and indirect causes linked to the crisis led to 168,212[19,913, 294,338] more deaths. The estimated number of deaths in the conflict period could be less than the values obtained in the pre-conflict period or more. However, the excess deaths are subject to high uncertainty and it is not clear whether the estimated numbers is greater than 0 given the non-significant level of the excess indirect deaths.

Of these, 67.2% were due to direct combat related violence and the remainder were due to indirect causes. At the governorate level, PCDR varied across the country ranging from 0.11 to 0.35 per 10,000 per day. The excess deaths for each governorate are calculated from the governorate-wise excess death rates based on their population. Hajjah, Ibb, Aden, Saada, and Al Jawf present the highest total excess deaths. Hadramaut and Al Maharah, both sparsely populated, had some of the lowest rates along with Al Hudaydah, Dhamar and Lahj (Figure 4-3).

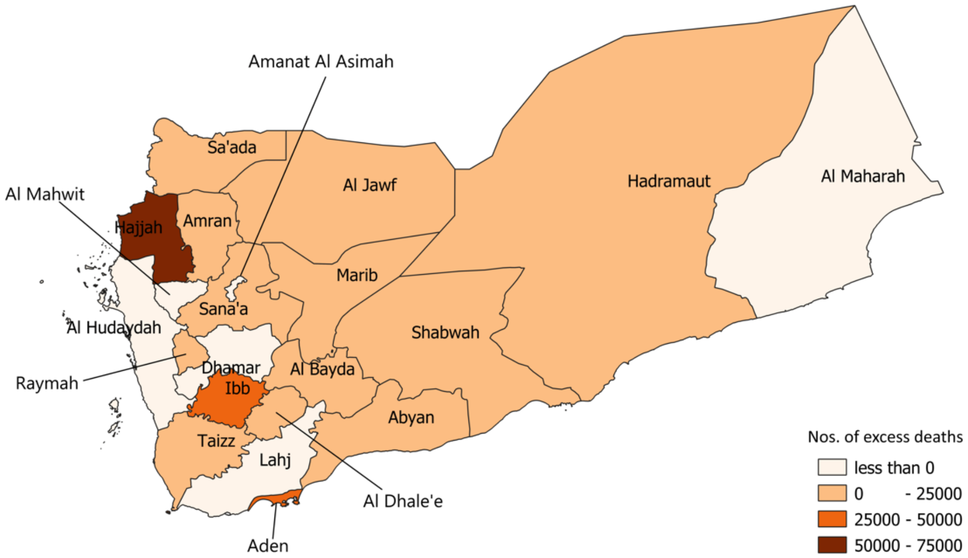

Figure 4-3: Geographical distribution of total excess deaths based on excess death rates by governorate. Source: Shape files extracted from Global Administrative Areas (2012). GADM database of Global Administrative Areas, version 2.0. URL: www.gadm.org. Created using QGIS version 3.10.3

The insecurity index was highest for the three governorates (Hajjah, Al Hudayda, Taizz) along the coastline (Figure 4-4) and those controlled by the Houthi faction (Appendix B-5). Sana'a was especially targeted, experiencing 4,932 attacks — about 1,000 attacks per year, on average. Sa'adah, Al Bayda, Aden and Al Dali were also exposed to high levels of violence and air strikes. All governorates in the mainland experienced air/drone strikes (Appendix B-2).

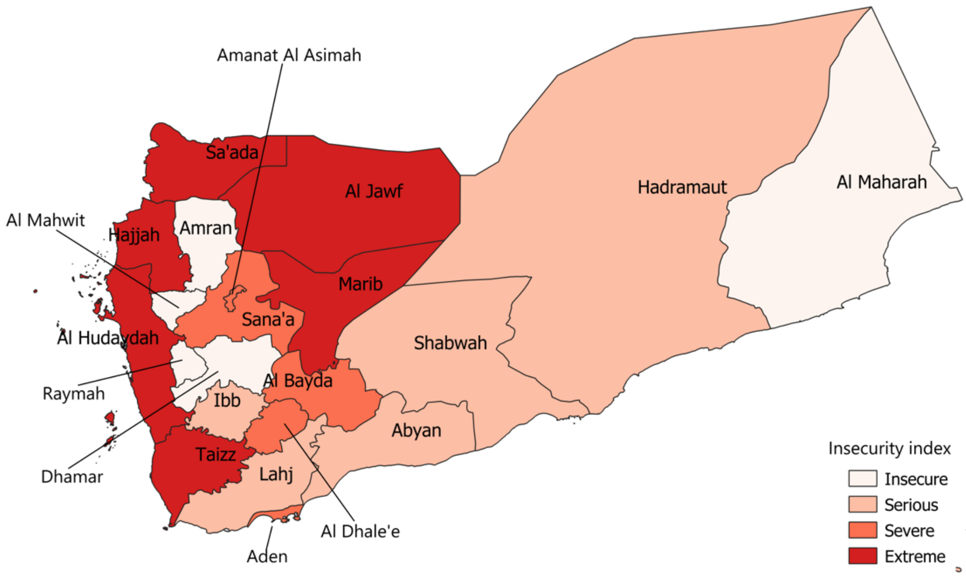

Figure 4-4: Geographic distribution of insecurity index levels, 2015-2019.

We found no evidence for differences in death rates between governorates that were extremely insecure compared to those with lower levels of insecurity (Figure 4-5).

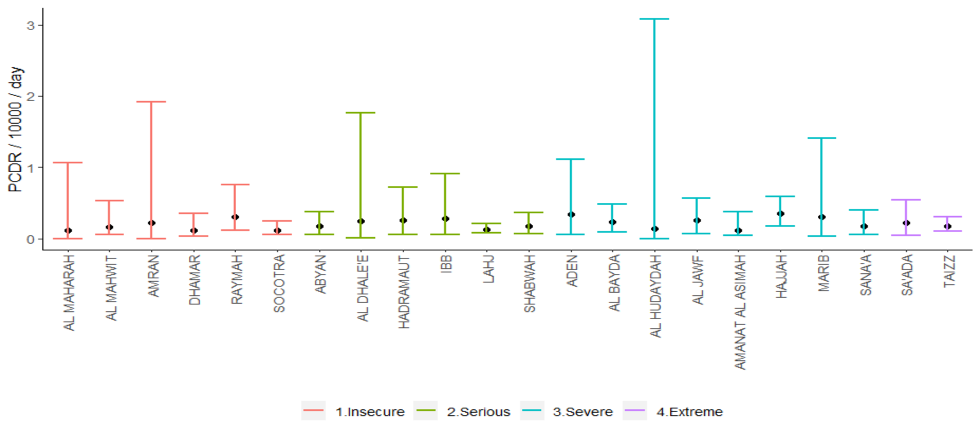

Figure 4-5: PCDR by governorate and insecurity level.

4.4 Discussion

Since the beginning of the civil war in 2015, humanitarian organizations and the press have reported high death tolls in Yemen [254-257] but reported qualitatively as "thousands" or "tens of thousands" of deaths. Undoubtedly many have died, but little statistical evidence has been presented to support increased death rates, reflecting the challenges the country faces in mortality surveillance [257].

Our results suggest a mixed outcome; the death tolls since 2015 could be greater than would be expected or similar to the estimated pre-war value. However, the conflict period death rate was not strikingly higher than the levels experienced by the country in the years preceding the current crisis. Second, a large share of excess deaths was due to armed violence, as recorded in ACLED and the YDP – another noticeable departure from scenarios seen in other civil conflicts where indirect deaths were by far the largest proportion of deaths [70, 258, 259]. Third, our index of human insecurity was not correlated with the estimated conflict period deaths, which were similar in all governorates regardless of their level of insecurity. The mere threat of air strikes and violence may have been enough to halt essential health care and other critical life-sustaining activities across the country, not just in governorates specifically targeted with intense air strikes and fighting.

We found the total number of deaths that occurred in Yemen in the five years of crisis was 17.8% higher than expected (ranging from 2.42% to about 26.87% more) – nearly 34,000 (3982 to 58867) each year of conflict on average. Other conflicts, such as those in Iraq, Darfur, Syria, and the Democratic Republic of Congo have reported higher conflict-related deaths, but, the circumstances of these conflicts are as diverse as the number of affected population [48, 76, 104, 176]. Prior to the beginning of the 2015 conflict, the Yemeni health system had already started a downward slide where health system broke down progressively and health status deteriorated unlike the concentrated violence and massacre in DRC [216, 260, 261]. Despite appeals from the humanitarian community, no intervention was mounted, and overseas aid remained low (Figure 4-1). As early as 2004, the census reported a crude death rate of 7.5/1,000 population, substantially higher than the UN regional average of 5.3/

1,000 population [161]. A decade later, data from the Demographic and Health Survey (DHS) reported child mortality of 53/1,000 live births, nearly twice that of the regional average [78, 163]. During this period, the population was essentially left to fend for themselves until 2015 when increasing militarisation garnered more international attention, surging international humanitarian aid to about four times of what it was in 2014 [244]. As widespread and intense fighting and air strikes continued in the country in parallel to huge increases in humanitarian funding, practical assistance to populations was unevenly distributed as insecurity reduced the reach of aid organisations [262].

Arguably, the level of excess mortality we find in our study could reflect the longstanding deterioration of health situation and non-existence of functional CRVS and health surveillance systems. Hence, when the conflict was declared in 2015, the mortality rate in the year preceding the crisis was not much different from those observed moving forward. Another explanation could also be due to limited access of insecure areas, which may have biased the survey results towards a better picture than in reality. While we included all violent deaths by governorate, these metrics may not be reflective of the true count. Such data from conflict countries face a universal bias as regions of high insecurity are often inaccessible to humanitarian actors and surveyors, including for DHS and other UN surveys [88]. More than 50% of the surveys used in this study specifically reported excluding areas due to inaccessibility or insecurity. Across many conflict affected countries, sample units from insecure areas are underrepresented or excluded due to accessibility concern for the safety of personnel [263]. Predictably, this is reflected in surveys undertaken in Yemen. This lack of access to zones with high violence may bias mortality rates in our, and most other, conflict-event surveys. However, on occasion, survey teams have accessed the population when armed incidents have abated due to the sporadic nature of violence in these areas. In Yemen, our study results admittedly cannot be considered definitive because of limited data on which we based our calculations but are sufficiently indicative of the reality on the ground.

Human insecurity in mainland governorates did not correlate positively with higher death rates, despite higher numbers of air strikes and armed attacks in some governorates. Armed violence, such as multiple target devices (e.g., bombs, grenades, or air strikes) or single target (snipers, killings) is a powerful force — not only on direct mortality but also on the pervasive disruption to civilian life. These incidents, even when there are no direct hits, profoundly disrupt access to food, markets, healthcare, and other critical conditions for survival by seeding fear of movements. In Yemen, severe and widespread personal and community insecurity, both real and perceived, has become part of daily life and hence, a consequence to survival.

In most conflicts, the greatest share of deaths is due to indirect causes such as health service breakdowns and food shortages. Direct causes do not usually contribute substantially to overall death rates [70, 258, 259]. In our study, Yemen is a rare example where almost two-thirds of excess deaths were due to violent causes and the remaining deaths due to indirect causes. Almost all governorates experienced sustained air strikes, with some receiving well over a thousand during the conflict (Appendix B-2). Exceptions include four sparsely populated governorates and the Socotra Archipelago, about 340 km off the Yemen mainland [264]. Our analysis suggests that lower levels of indirect excess mortality may have been due to reduced deaths from active humanitarian aid, and a high baseline due to prolonged past conflict.

Our findings should be considered within the context of fear and insecurity that these incidents generate in populations. This context results in the breakdown of essential services as salaries remain unpaid and staff are reluctant to expose themselves to risks of violence. These are aspects that are difficult to capture by quantitative models using secondary data, however sophisticated. Overall, these findings undoubtedly provide insight, but future mortality assessments will require detailed and complete surveys or registration systems to procure more robust datasets.

In summary, massive humanitarian aid to Yemen may have plausibly blunted the humanitarian health crisis in the civil population. The barrage of air strikes and continued ground violence, on the other hand, arguably had the opposite effect on violent causes of death.

When calculating a credible excess mortality estimate, the choice of baseline is an important challenge. For example, two well-known studies from Iraq used different baselines, leading to almost 100,000 deaths (5.5/1,000) in one and 405,000 (2.9/1,000 person-years) in the other [74, 76]. Similarly, excess mortality in Darfur was calculated based on World Bank reports (0.3/10,000/day), producing widely differing results from estimates by Reeves [65, 176, 265-267]. We chose to construct a baseline from locally implemented mortality surveys from the pre-crises period which give a timely, measures with better precision, and a local representation of mortality in Yemen.

We acknowledge that the number of surveys from the pre-conflict period limits the robustness of our baseline calculations. Poor data in conflict-affected countries such as Somalia, Afghanistan and several others is a persistent problem [268]. The inclusion of ACLED fatalities in our analysis present the possibility of double counting. However, rather than discounting information collected under difficult circumstances, these data issues underscore two urgent challenges. First, we need to develop innovative methodologies to collect data in high insecurity conditions, such as using remote sensing techniques. Besson et al (2020) provides a good example of how this technique can be used to calculate excess mortality in Yemen [84]. Second, innovative approaches that build on existing structures should be explored. Such as re-purposing traditional surveillance into sentinel systems in order to bridge the existing gap in data from high insecurity areas.

4.5 Conclusion

Recent moves by the USA, in ending US offensive military support, have limited the supply of weapons to the conflict. This opens the potential for reducing regional and national armed activities. Nonetheless, the underlying issues of the conflict are not likely to be resolved soon. Should access to vulnerable populations improve, one priority would be a national health and mortality survey to understand the full consequences of conflict on Yemen's population.

Chapter 5: Where are the most affected children in Yemen?

This chapter is adapted from a submitted manuscript:

Thomas Jideofor Ogbu, Jose Manuel Rodrigues-Llanes, Maria Moitinho de Almeida, Niko Speybroeck, Debarati Guha-Sapir. Human insecurity and child deaths in conflict: evidence for improved response in Yemen. **International Journal of Epidemiology**. Doi: *10.1093/ije/dyac038*

Abstract

Background

Since the beginning of the ongoing conflict in Yemen, more than 23,000 air strikes and over 100,000 fatalities have been recorded, with over 1,300 child fatalities and more than 900 child injuries linked to air raids. However, there are little literature on effect of the protracted armed conflict on pattern of child mortality using data from small-scale surveys. We aimed to identify the pattern of under-five death rate and its relationship with human insecurity in Yemen.

Methods

We created a human insecurity index (severely insecure vs insecure) for the 22 governorates in Yemen from 2015 to 2019, using data from the Armed Conflict Location and Event Database (ACLED). We matched this insecurity index with the corresponding under-five mortality data from the Complex Emergency Database (CE-DAT). We analysed the relationship between Under-five death rate and the insecurity level using a Bayesian finite mixture model which considers unobserved heterogeneity in clustered finite subsets of a population.

Results

We extracted 72 surveys, and 77.8% (n=56) were included in this study. We identified two subpopulations: subpopulation I— high average number of child deaths and a subpopulation II — low average number of child deaths. The log posterior mean of the under-five death rate is 1.10 (95% credible intervals: 0.36, 1.82) in the severely insecure group in subpopulation I, is threefold the estimate in subpopulation II. However, in subpopulation II, we found no association between the insecurity level and under-five death rate.

Conclusions

The pattern of child deaths is crucial in understanding the relationship between human insecurity and under-five death rate.

5.1 Background

Yemen has been an unstable country due to political conflict since at least 2004 [240, 269]. For many years, the region was divided between North Yemen and South Yemen, with capitals in Sana'a and the former British port city of Aden respectively [134]. The recrudescence of violence in 2015 was due to the attempt of the Houthi faction from the North to seize control of Yemen's capital Sana'a, ousting President Hadi. The conflict escalated when Saudi Arabia and the Gulf states supported the Sunni forces, with logistics and intelligence support from the USA, UK and France, while the Zaydi Houthi forces were backed by Iran [240, 270]. Starting in 2015, Yemen has been impacted by over 23,000 air strikes severely damaging already-fragile and dysfunctional health facilities and destroying supply chains for food and medicine [271], resulting to over recorded 110,000 deaths [146].

The Yemen Data Project (YDP) linked over 1,300 child fatalities and more than 900 child injuries to air raids [271]. The bombardment of essential facilities [30, 271] and high levels of insecurity across the country have hindered the flow of life-saving humanitarian aid and medical services to affected populations [272, 273]. Limited access to health services, difficulties in vaccine distribution, and poor sanitation has contributed to a surge in communicable disease outbreaks [274-276]. Food insecurity is also of great concern; out of 20 million Yemenis needing humanitarian assistance, two million are children under the age of five suffering from acute malnutrition, with an estimated 360,000 children facing severe acute malnutrition [208, 277]. However, because of ongoing violence and poor health information systems in the country, it is difficult to ascertain the true effect of the protracted armed conflict and general insecurity on child mortality. Despite extensive news coverage and advocacy on the effects of armed conflicts on child mortality in Yemen [274-276, 278, 279], a persistent gap in evidence remains.

Mostly, the needs of crisis-affected populations are assessed for operational purpose using data from small-scale surveys, designed for effective collection of information on the nutrition status, morbidity, and mortality indicators of the population. Typically, these surveys are based on the established Standardized Monitoring and Assessment of Relief and Transition (SMART) methodology [280]. Due to the simple and cost-effective nature of small-scale surveys, they can be conducted more often, and allow targeting specific populations at risk, unlike periodical large-scale national surveys, which fulfil different purposes [57]. For instance, the cost of a small-scale survey in Ethiopia was around 18,940 United States dollars (USD), while the overall median cost of small-scale surveys in East Africa ranged between 10,500 USD and 19,750 USD [281]. These are cheaper than the estimated 9.5 million USD and 530,000 USD required for the large-scale 2018 Demographic and Health Survey in Nigeria and 2012 Socioeconomic Survey in Ethiopia respectively [55, 282]. With prevailing high level of insecurity and political instability in conflict settings, conducting new national surveys is not only expensive, but also unfeasible. To circumvent the difficulties in collecting mortality data on a large-scale, existing historical data from retrospective small-scale surveys present a valuable opportunity.

The precise direct and indirect effects of armed conflict on children are difficult to ascertain, and the complexity of the relationship between child mortality and conflict are well recognized in conflict settings; including spatial and temporal variation [259, 283, 284] and dose-response effects with increasing levels of violence [285]. We aimed at identifying geographical areas where under-five mortality was higher based on the levels of insecurity. We used a Bayesian finite mixture model, which is efficient in measuring the model parameters as compared to frequentist alternatives. The foreseen goal is to develop a statistical application to spot areas requiring urgent intervention in humanitarian settings.

5.2 Methods

Data

We extracted under-5 mortality (U5M) data from small-scale SMART [280] survey reports, compiled from both the Humanitarian Response website of the UN Office for the Coordination of Humanitarian Affairs (OCHA) [286], and in the Complex Emergency Database (CE-DAT) managed by the Centre for

Research on the Epidemiology of Disasters (CRED) [287]. We included reports of mortality surveys conducted in Yemen between 2015 and 2019 that contained data on under-five mortality (U5M). We excluded surveys that did not provide at least three of the following: sample size, recall period, under-five death rate (U5DR), and number of under-five deaths. We also used data from the Armed Conflict Location and Event Data (ACLED)/Yemen Data Project (YDP) [271] for information regarding insecurity levels [146]. The survey was the unit of analysis and an observation refers to a data point extracted from any of the used variables at the survey level. Table 5-1 summarizes the different data sources and types.

Table 5-1: Data sources and variables.

Data source	Information extracted	Type of variable	Units / possible categories
OCHA [286]/CE-DAT [287]	U5 sample size	Discrete	number of children
	Mortality recall period		number of days
	U5 death counts		number of child deaths
	U5 death rate		deaths / 10000 / day
YDP [271]/ACLED [146]	Event type	Categorical	remote violence
			violence against civilians
			strategic development
			suicide
			battle- government regains territory/no change of territory
	Fatality	Discrete	number of fatalities

ACLED, Armed Conflict Location and Event Data; CEDAT, Complex Emergency Database. OCHA, United Nations Office for the Coordination of Humanitarian Affairs; YDP: Yemen Data Project.

Measures

Dependent variable

The outcome variable was the number of children under five years (U5D) of age who died within the recall period. In the absence of data on U5Ds, we used the equation below as an estimator:

$$(U5DR \times sample\ size \times recall\ period) / (10000) \approx \text{U5D} \qquad 5\text{-}1$$

Where the sample size is the number of children less than five years old included in survey, the recall period is a specific number of days in the past in which the number of persons at risk were assessed. In other words, the survey respondents should precisely place a death within the household in time relative to the beginning of the recall period. The end of the recall period is set to the date of the interview. In the study sample, the most common recall period was 90 days.

Independent variable

The calculation of a yearly human insecurity index for a given Yemen governorate is complicated by data scarcity and quantification challenges [252]. For example, using the non-hierarchical divisive cluster analysis in calculating global human security may require up to 29 indicators such as the number of internal security officers and police, homicides, jailed population, armed service personnel and heavy weapons per 100,000 people, likelihood of violent demonstration and ease of access to small arms and light weapons [251]. In the absence of the aforementioned data, we developed a simple approach as a proxy to human security index, based on publicly available conflict data from ACLED/YDP.

The independent variable was the insecurity level (i.e. our proxy for human security) of each governorate, derived from records in ACLED/YDP databases. We used the number of fatalities as well as the frequencies of events as a way to better approximate human security measurement. We weighted the yearly fatalities with number of events (Battles, Explosions/Remote Violence, Protests, Riots, Strategic Development and Violence against civilians as classified by ACLED), and we categorize the sum into quantiles:

$$\mathrm{WF_{pr}} = \sum_{q=1}^{6} \left[\frac{\mathrm{e_{pqr}} * \mathrm{F_{pqr}}}{\mathrm{E_{qr}}} \right] \qquad 5\text{-}2$$

Where e_{pqr} = number of events q in governorate p for year r

$\mathrm{E_{qr}}$ = sum total of events q in all governorates in year r

$\mathrm{F_{pqr}}$ = total fatalities from events q in governorate p for year r

$\mathrm{WF_{pr}}$ = sum of weighted fatalities in governorate p for year r.

$$\mathrm{Q_x(g)} = \inf\{x \in \mathrm{R} : g \leq \mathrm{F(x)}\} \qquad 5\text{-}3$$

For 5-quantile g = 0.2, 0.4, 0.6, 0.8, where $x = \mathrm{WF_{pr}}$. The indicator variable 'Insecurity Level' (ISL) is defined as:

$$\mathrm{ISL} = \begin{cases} 0, & \text{insecure for } g < 0.5 \\ 1, & \text{severe insecurity for } g > 0.5 \end{cases} \qquad 5\text{-}4$$

Statistical analysis

Given that our outcome variable (U5D) was count data and its generation naturally implies an underlying Poisson process, hence, we assume that our data follows such a distribution. We assessed the association between U5DR and insecurity level using a Bayesian finite Poisson mixture model. The advantage of this model over the single Poisson component model is that it accounts for variations and unobserved heterogeneity across and within a finite set of components and the effect of independent variables varies across the components [288, 289]. The Bayesian framework allows us to effectively account for sources of variability, incorporate priors, and generate an easily interpretable posterior probabilistic value [172, 290].

While methods to estimate and select the number of components in finite mixture modelling exist [199, 291, 292]. Following our hypothesis, we started fitting a two components model increasing at each iteration the number of components up to six. The number of empty components increased when the number was set to three or more. Hence, we settled for a two-component model.

We fitted two models: a two-component fixed-effect model and a two-component mixed-effect model with insecurity level as a fixed effect in both models. In the latter, we used a simple random effect term to account for possible correlations within measurements from the same units of analysis. We included an offset term (person_days = sample size x recall period in days) in the models to account for differences in recall period and sample size. The finite mixture model can be written as:

$$\mathrm{f}\left(\mathrm{y} \middle| \beta_1, \beta_2, \ldots, \beta_j\right) = \sum_{\mathrm{j=k}}^{\mathrm{n}} n_j \mathrm{Poi}(\lambda_j) \tag{5-5}$$

Where;

j=1,..,k is number of components, the mixing proportion $n_j \sim$ Dirichlet(c (s_1,...,s_k)), $s_j > 0$, and $\sum_j n_j = 1$. In a finite mixture model, there is no restriction for the components to be of the same parametric family. In this study, we assume that both components (k=2) belong to a Poisson distribution. The fixed and mixed effect models are expressed as:

$$\log\left(\lambda_{\mathrm{ij}}\right) = \beta_{j,0} + \sum_{\mathrm{i=1}}^{\mathrm{m}} \beta_{j,i} \mathrm{x_i} + \log(\mathrm{person\_days_{ij}}) \tag{5-6}$$

$$\log\left(\lambda_{\mathrm{ij}}\right) = \beta_{j,0} + \sum_{\mathrm{i=1}}^{\mathrm{m}} \beta_{j,i} \mathrm{x_i} + \log\left(\mathrm{person\_days_{ij}}\right) + \mathrm{U_i} \tag{5-7}$$

$\beta_{j,0}$ is the regression intercept for component j, $\beta_{j,i}$ is the regression coefficient for variable x_i in component j, $\mathrm{person.days_{ij}}$ is the person-days for individual i in component j, U_i is the random effect term, m is the number of independent variables and $U_i \sim N(0, \sigma_u^2)$.

We used the Gibbs sampler to simulate draws from the posterior distribution of the Poisson finite mixture model. We used three Markov Chain Monte Carlo (MCMC) chains with different starting values of 100,000 iterations and a burn-in of 50,000 draws. We checked for convergence by using Gelman-Rubin diagnostic and trace plots [204]. We used posterior predictive checks to ascertain the model's goodness of fit (Appendix C).

In the absence of any specific priors to be incorporated in the modelling process, we assigned a non-informative normal prior to the models' parameters, given as $\beta_{ij} \sim N(0{,}1.0e-6)$. Label switching is a common challenge experienced in finite mixture modelling. We imposed a constraint on the priors of the parameter estimates to ensure identifiability [200]. For mixing weights (η), we assigned a Dirichlet prior of the form η ~ Dirichlet (c (0.5, 0.5)) [293]. For the mixed effect model, we assigned a non-informative prior $\sigma^2 \sim N(0, \tau^2)$ to the random term, with a non-informative gamma prior on tau, $\tau^2 \sim IG(0.001, 0.001)$. For those units of analysis with less than two observations, the error term was set to zero.

To classify observations into subpopulations based on the model, we obtained the probability of each observation to belong to a specific component. Using the posterior means of the allocation probabilities, we grouped all observations with higher probability of belonging to component 1 into subpopulation I and observations with higher probability of belonging to component 2 into subpopulation II. We computed the posterior means for the subpopulations and for the whole sample, to account for over-dispersion we use Poisson-Gamma model, using non-informative normal and inverse gamma priors (Appendix C).

5.3 Results

We extracted 72 surveys conducted in Yemen from 2015 to 2019; of these surveys, 77.8% (n=56) were included in the study (Figure 5-1).

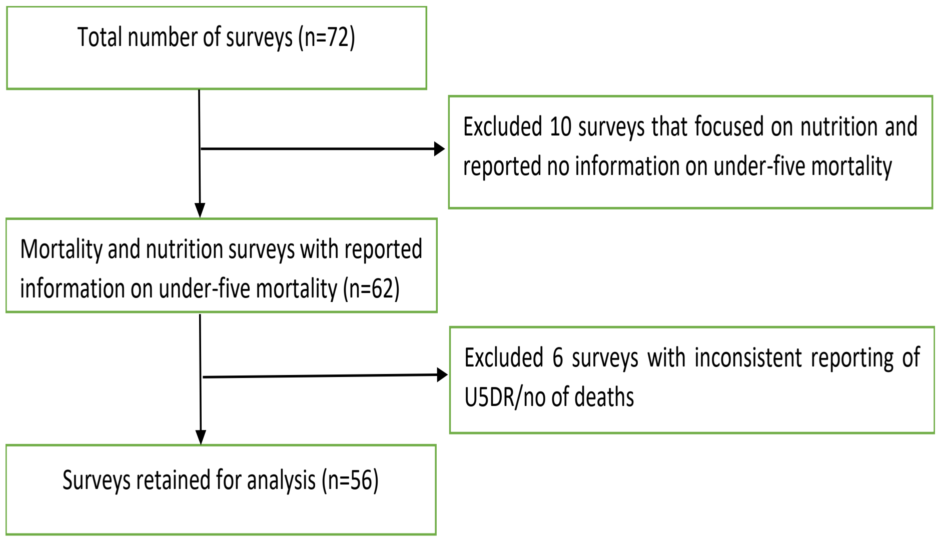

Figure 5-1: Flow diagram showing survey selection process

The data covered 22 governorates with a total sample of 32,240 children under-five years of age. The number of deaths in children less than five years in the sample was 125 with a mean (SD) U5DR of 0.22/10000/day (0.28). The mean (SD) recall period was 106 days (93). A more detailed description of the analysed data is shown in Appendix C.

The results (table 5-2) show that the probability of belonging to component 1 is lower than the probability of belonging to component 2. The log posterior mean of U5DR in component 1 is approximately twice the U5DR in component 2. This result indicates an association between U5DR and 'severely insecure' settings. In contrast, we find no association between number of under-five deaths and insecurity level in component 2.

Table 5-2: The association between pattern of U5D and insecurity level

Parameters	Parameter estimates (HDI) Component 1	Component 2
Intercept	-1.52 (-2.23, -0.81)	-3.10 (-4.08, -2.07)
Severe insecurity	1.10 (0.36,1.82)	0.35 (-0.58,1.38)
eta *	0.40 (0.21,0.60)	0.60 (0.41,0.79)

*eta is the probability of belonging to a component. HDI: Highest Density Interval, this is an interval in which all points within the interval have higher probability density than points outside the interval. The parameter estimates are log form.

Furthermore, we identify group membership, by assigning observations with higher probability of belonging to component 1 to sub-group 1 (subpopulation I) or to sub-group 2 for those with higher probability of belonging to component 2 into sub-group 2 (subpopulation II). The results indicate that the majority of observations in sub-group 1 have high number of U5D (HU5D), while most observations in sub-group 2 have low number of U5D (LU5D). More than a third (35.7%, n=20) of observations were classified into the HU5D group with an average of 5 deaths (SD +/- 5.3). In contrast, the average number of U5Ds in the LU5D group was 0.5 (SD+/- 0.97).

We illustrate the use of the classification method to monitor the likelihood of child mortality at governorate level in Yemen (Figure 5-2)

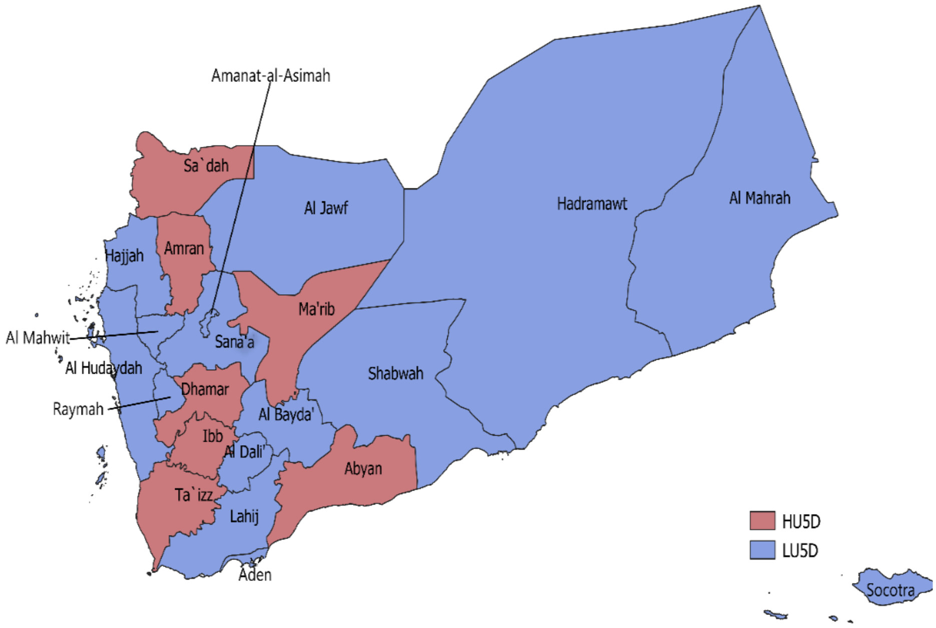

Figure 5-2: Geographical classification of subpopulations.

HU5D refers to the High Under Five Deaths group and LU5D is the Low Under Five Deaths resulting from the modelling. As the classifications of child death likelihoods depend on changing variables measuring violence and child mortality, these groupings also vary over time. The map illustrates the use of the statistical method developed to identify priority areas for intervention. We showed the classification results based on first available by year.

The pooled subpopulation posterior U5DRs with 95% credible intervals were 0.58 (0.46, 0.72) per 10,000 per day in the HU5D group and 0.06 (0.04, 0.15) per 10,000 per day in the LU5D. The pooled U5DR in the HU5D group is more than two-fold the overall estimate and five-fold the U5DR in the LU5D. Figure 5-3 shows the variation in the U5DR and overall U5DR.

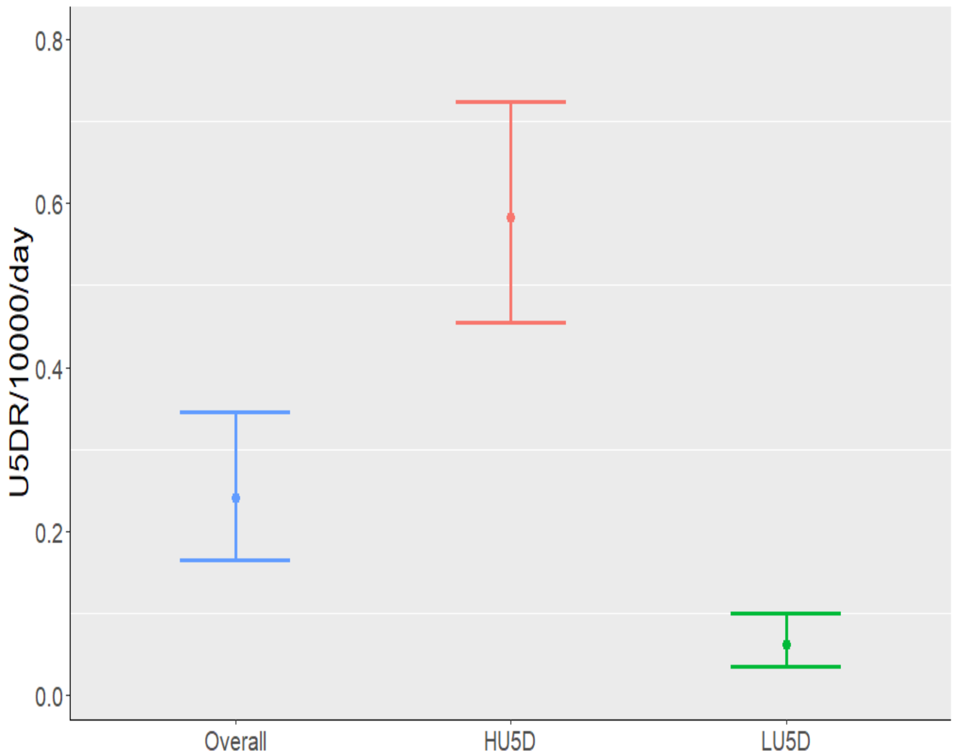

Figure 5-3:Overall and subgroup Bayesian mean estimates of U5DR

Overall category (blue) indicates the under-five death rate for the full dataset. HU5D (red) stands for the High Under Five Deaths group whereas LU5D refers to the Low Under Five Deaths grouping resulting from the modelling. All data is shown with 95% credible intervals.

The inclusion of a random effect term generated unstable (unrealistic) estimates and convergence issues at times. To circumvent the latter, we ran the model with different starting values, increasing the number of iterations; being these strategies unsuccessful we retained the estimates of the fixed effect model.

5.4 Discussion

In this study, we found differences in the association between conflict-related insecurity and under-five mortality in the two subpopulations. The main findings of this study, a clear and robust association of insecurity with child mortality, points to the fact that using such a straightforward index, we could increase efficiency in targeting of child populations at higher risk for mortality. To our knowledge, this is the first attempt at understanding where child deaths are likely to be significantly higher based on a simplified broad insecurity classification using publicly accessible data in humanitarian settings; often, data in such settings are hard to source.

Identification of two latent subpopulations

We investigated the association between under-five deaths and insecurity level using the Bayesian finite Poisson mixture model, which can detect hidden relationships due to unobserved heterogeneity. The results of our analyses suggest that patterns in number of under-five deaths is important for examining the relationship between U5DRs and insecurity levels in protracted crises.

Previous studies have shown that armed conflict has devastating consequences on child mortality rates [209, 259]. Children born in armed conflict zones are more likely to have a poor mortality profile when compared to children born in non-conflict zones – mostly due to indirect deaths from lack of access to health care services, food, and lifesaving humanitarian aid due to insecurity [259, 294]. Other studies have shown that U5DRs were higher in battleground zones [4], and in regions with an already higher *pre-conflict* mortality rate [295]. It is possible that, in addition to not being in battleground zones, the LU5D subpopulation would have had a better pre-conflict mortality status. However, the advantage of having a better health status before the insecurity began may erode as the conflict drags out.

Differences in the effect of armed conflicts on mortality

Our data demonstrate the relationship between an increase in the U5DR and insecurity levels. Within the HU5D subpopulation, we observe that the U5DR at the ‘severely insecure’ level is about three-fold that of the ‘insecure’ level, and this association is significant [48, 259]. The destruction of health facilities, transportation routes and supply facilities hinder access to health care and prevents prompt and complete immunization programmes. This low level of immunization was probably responsible for the outbreak of diphtheria and suspected cases of cholera [166, 296] in Yemen. In addition, the high prevalence of malnutrition increases the risk of death in children less than five years old [297]. Malnutrition is partly explained by increasing food costs due to obstacles in food importation [298] and blockages of humanitarian assistance [299], coupled with the destruction of agricultural and market/distribution infrastructures.

In the LU5D subpopulation, there is no association between insecurity level and child mortality; however, the U5DR in ‘severely insecure’ setting is about one and half fold as much as that in less ‘insecure’ settings. This result partially conforms to what we observe in the HU5D subpopulation. This might be indicative of pre-existing patterns of disease, the level of food insecurity, and the underlying general health status of the subpopulation. It is possible that the low number of U5Ds reflects a better prior health status, which may improve the subpopulation’s coping capacity and lower their vulnerability in times of crises [295]. In addition, the type and intensity of armed conflict can influence mortality profiles in the affected areas [300]. For instance, high-intensity armed conflict increases mortality in affected population, and even more so in children [258]. Thus, the subpopulation with a low U5DR may be associated with an area experiencing low-intensity armed conflict.

The premise that child mortality during armed conflict is more pronounced in highly insecure areas is consistent with mortality rates observed at the various insecurity levels. Moreover, the intensity of conflict and location of the affected population are possible reflections of the observed differences among subpopulations. In view of this, these results add to the existing literature that establishes the effect of armed violence on child mortality, proposing that insecurity levels can be a predictor of child mortality, albeit we only established this in areas with high death counts. We show that refining mortality distributions by underlying subpopulations and levels of insecurity provides insights on how the impacts of armed conflict vary across affected populations and where these impacts are likely to concentrate.

Crucially, these results have implications for aid targeting and stabilisation priorities in highly volatile humanitarian settings, exemplified here in the Yemeni context. While our findings are intuitive, they show how advanced statistical methods can automatically generate a threshold to prioritize intervention areas, optimising the use of aid to save lives.

The modelling of deaths in conflict have been problematic in the past, due to the over dispersed nature of count data, excess zeros, and difficulties to model validation as more advanced models of the zero-inflated family are proposed. This first analysis shows a very efficient way to model this data for operational purposes. The strong association found suggest that areas with such high levels of insecurity should be prioritized. More research is warranted, for example looking into important programmatic outcomes such as malnutrition levels to reinforce these findings here, and include other conflicts.

Limitations

This study carries some limitations. Survey reports, while containing valuable information, lack the details required for precise mapping of event data to the surveyed area. Some surveys excluded insecure areas from the sampling process, and we are unaware of the level of bias this may introduce in our analysis. Thirdly, we may not have included all available small-scale surveys conducted within this period due to limitations in our search strategy. We may also have omitted variable(s) that might be of interest, such as morbidity indicators, nutrition indicators and availability of health care. The use of a dynamic insecurity score and the inclusion of a spatio-temporal element in the modelling process may provide improved further insights. Finally, at this moment, we are not aware of a method for validating the insecurity index. Nevertheless, our results, based on estimates from small-scale surveys in Yemen, reaffirm the strong association between U5DR and insecurity in conflict settings, as measured in the present study.

5.5 Conclusions

This study, with small-scale survey data from the armed conflict in Yemen, contributes to our understanding of under-five mortality and levels of insecurity in conflict and protracted crises. In concordance with previous studies, our findings indicate that high levels of insecurity in conflict are associated with increased number of U5DR. Furthermore, our results show that the association between conflict-related insecurity and under-five mortality varies according to the trends in number of U5Ds. This trend is important in studying the relationship between U5DRs and insecurity levels and helps to identify subpopulations with specific characteristics that better describe the group mortality profile. Investigation of mortality, morbidity, and nutrition trends and disparities in protracted crises should further improve our understanding of the global burden of armed conflict on children. In the future, targeted aid based on such evidence could mitigate the long-term and indirect consequences of conflict on children.

Chapter 6: General discussion, conclusion and future perspectives

6.1 General discussion

The aim of this thesis is to understand the impact of protracted crisis on mortality using conflict data and estimates from small-scale surveys. In this chapter, I summarise the findings of the study by first discussing the importance of mortality assessment tools used in humanitarian emergency and the potential of uptake by the research community. Secondly, I highlight the effect of protracted crisis on the mortality status of the population. Third, I describe the impact of insecurity on the pattern of child death. Fourth, I discuss the limitations of the study and possible steps for future improvement.

Improving the quality of assessment tools and the uptake of SMART surveys

The unavailability of reliable and updated epidemiological data in places experiencing protracted crisis limits the planning capacity of operational agencies and policy makers in providing accurate assessments of the needs of the affected population. In stable and resource-rich settings, data from death registration, continual surveillance and/or population-based surveys are the major source for gathering evidence on the public health status of the population. Conversely, in resource-constrained settings and humanitarian emergencies, epidemiological information is usually gathered through small-scale retrospective surveys. The value of human and economic resources earmarked each year to tackle humanitarian emergencies in protracted crises are often based on evidence from these retrospective surveys. Accordingly, it is vital to consistently improve the tools that provide evidence and form the basis of funding operations.

Despite the coordination and cooperation between different agencies to strengthen civil registration and vital statistics systems in the region [301] (including the government in the MENA Region, the United Nations Economic and Social Commission for Western Asia (ESCWA), the United Nations Economic Commission for Africa (ECA) and the United Nations

Economic and Social Commission for Asia and the Pacific (ESCAP)), the birth and death registration systems in Yemen has much room for improvement [302]. A 2019 report by ESCWA indicated that the completeness of birth registration in Yemen showed some improvement from 39% of births recorded in 2003 [301] to 53% of births in the period 2015 – 2018 [303]. This estimate (53%) places Yemen ahead of only two countries – Somalia (7%) and Pakistan (40%) – out of the 26 MENA countries in the WHO Eastern Mediterranean Region included in the report. Furthermore, the completeness of the death registration in Yemen is still very low, and might have declined from 13% in 2003 to around 10% in the period 2015 – 2018, to reach a level only slightly higher than Somalia's completeness of death registration.

Prior to the ongoing conflict in Yemen, the major sources of public health data were through population health surveys and census data. However, data collection of such scales and magnitude are interrupted during armed conflicts due to concerns related to the safety of the enumerators, difficulties in assessing displaced populations, and lack of resources due in part to diversion of resources by local and international actors towards military expenditures. For example, between 2010 and 2019, there was an upward increase in military spending because of the war against Boko Haram terrorists in northeast Nigeria [304]. In Yemen there is no official data on military spending since the beginning of the on-going conflict. However, Saudi Arabia, one of the parties in the on-going conflict, has one of the highest military expenditures in the region [305]. Despite the 37% decrease in total military expenditure (potentially due to low oil prices) during the conflict period compared to four years before its military involvement in Yemen in 2015, Saudi Arabia continues to import arms to execute its military activities in Yemen [306].

Since the beginning of the conflict, more than 100 small-scale surveys based on SMART methodology have been conducted to evaluate the health status of the different regions/zones in Yemen by collecting mortality, morbidity and nutrition data. These surveys are ideal in conflict settings such as Yemen because of their financial and logistic advantages over large-scale surveys. Operational agencies, international organizations, ministries of health and foreign governments rely on the results of these surveys for planning and implementation of relief activities. For instance, in 2015, based on the estimate from nutrition and mortality survey conducted by MSF in Borno State, Nigeria, the agencies decided that the situation was not catastrophic, hence, the justification to scale back humanitarian activity in the region [77]. While in 2018, the Action Against Hunger stated that rationale for conducting a survey in Hajjah, Yemen was to inform the humanitarian response plan [236].

Researchers have used estimates from SMART surveys for understanding the relationships between humanitarian emergencies and public health indicators. Estimates from SMART surveys conducted in South Sudan were used to study the relationship between conflict intensity, displacement, food security and vaccination coverage and mortality[175]. In Ethiopia and Darfur data from SMART surveys were aggregated to study the effect of humanitarian emergencies such as conflict and drought on mortality [62, 176]. Studies based on the aggregation of small-scale surveys in Yemen were lacking despite the established practice of using of small-scale surveys for exploring the effect of humanitarian emergencies on the affected population and availability of such survey results from Yemen in CE-DAT and from UNOCHA.

The majority of reported mortality rates from SMART surveys conducted in Yemen between 2015 and 2019 suggest a stable mortality rate. These findings are contrary to expectations given the sustained conflict characterized by mass displacement and the moribund health facilities, infrastructure and social systems [46, 138]. Given the wide range of potential sources of bias, the accuracy of these surveys and the potential limitations of their use should be thoughtfully considered.

However, it maybe that the reported mortality rates truly reflect the health status of the population, and may reflect population-level resilience to the negative impacts of sustained violence given that the country and the Yemeni people are no strangers to conflicts. In addition, the explanation of the low overall mortality rates could be because the most afflicted people were not included in this study due to mass displacement and restricted access to unstable areas, resulting in an underestimation of mortality rates.

Furthermore, the activities of humanitarian agencies and other donor agencies may have ameliorated the impact of the conflicts on mortality. Irrespective of the underlying causes, the use of robust survey technique, the clear reporting of mortality data and sample size estimates should be encouraged (as suggested in chapter 3), to ensure that the minimum required standards for survey methodology are met. The survey reports should contain information required for the validation of results by operational agencies and researchers. These steps will not only encourage the use of SMART survey findings but will also give a robust and less contentious estimates needed for policymaking and effective aid targeting.

Interventions beyond statistical significance

We expected to find a significant number of excess deaths due to the ongoing conflict in Yemen and a strong relationship between conflict and crude mortality rate, but surprisingly, that was not the case. In chapter 4, we observed that between 2015 and 2019, the estimated avoidable deaths in Yemen were 168,212, and there was no significant difference between estimated conflict crude death rate and the estimated pre-conflict baseline rates. From a statistical point of view, the test and the samples used in the study do not provide sufficient evidence to conclude that there are excess deaths attributed to the conflict. Nevertheless, this does not negate the reports of death and hardship [18]. It rather reiterates the need for robust statistical methods and data. It is also imperative to consider the context and not solely the statistical significance while interpreting conflict related estimates.

The result obtained in chapter 4 is prone to double counting. Majority of the surveys used in the analysis indicated that some areas were excluded due to insecurity, and these surveys did not report the number of violent deaths. As a result, we included the violent deaths recorded in ACLED database. Due to the risk of double counting inherent in the method, we retrospectively compared the mortality values recorded in other databases to the estimate obtained from our method. If the number of deaths recorded in the five-year period (2010 – 2014) prior to the conflict was used as the baseline, the value of excess mortality estimated in chapter 4 is about 46% and 41% more than the values obtained from the World Bank data (90,948)[6, 161] and the World Population Prospects (WPP) (99,370) [307] respectively. On the other hand, if we use baseline values from the same period as in chapter 4 (we only have data from 2012 – 2014 for the pre-conflict period), the excess mortality from the World Bank data (371,488) is more than double the value obtained in chapter 4.

Furthermore, we found no significant association between the estimated conflict crude death rates and insecurity level during the period, though our estimated excess mortality was low compared to reported conflict mortality in Darfur, Iraq and DRC [48, 74, 176]. The disparity in excess mortality across these conflicts may be because of differences in population resilience, inflow of humanitarian aid, the nature of the conflicts and survey coverage.

The conflict in Yemen is characterized mainly by targeted air attacks on strategic locations that have occurred in all governorates. According to YDP data, military facilities are the most common single target, accounting for approximately 52% (excluding unidentified targets) of air targets from 2015 to 2019 [271].The dimensions of the conflict have shown some remarkable differences from the wars in Darfur, DRC and Iraq. For instance, unlike the war in Yemen, during the war in DRC, concerted efforts were made by rebel group to systematically exterminate the Bambuti in Ituri [308]. At the end of 2002 through 2003, over 60,000 were reported to have been killed in the north-eastern district of Ituri alone [309]. The complete disregards of human rights, the campaign of targeted mass murder of civilians and the involvement of neighboring states in the war in their bids to plunder the natural resources in DRC, expanded the scale of atrocities [308-310] and most likely contributed immensely to the high number of avoidable deaths recorded in the DRC war. As a result, more than 2 million excess deaths were recorded in the 32-month period after the war started [311]. Similarly, in 2003, the deliberate and indiscriminate killings of civilians in the war in Darfur with a strong ethnic and tribal undertone resulted in over 290,000 excess deaths [176, 312, 313] — this was official declared a genocide by the USA in 2004.

In Iraq, the conflict first aimed at displacing the tyrannical regime, later devolved into an occupation by the US and North Atlantic Treaty Organization (NATO) forces leading to a drawn-out, violent insurgency. Insurgents consistently targeted both military and civilians. For instance, amongst the single deadliest bombings by insurgent, are the coordinated suicides attacks with religious undertone that took place on 23 November, 2006, 18 April, 2007 and 14 August, 2007 , which claimed 281, 233 and 796 lives respectively [314, 315]. Simultaneously, more than 4,000 condolence payment were made by US-led coalition forces during the Iraq war from 2004 to 2008 [316], an indication of the scale of unintentional deaths and harms to civilians. The direct effect of the massive bombardment of facilities and infrastructures during the Iraqi war resulted in immediate civilian deaths and injuries. At the end of the war, nearly 100,000 excess deaths were reported over an 18-month period [74].

The studies in Iraqi and DRC were retrospective cross-sectional surveys [48, 75]. Given that the studies were conducted during a relatively stable period, the studies are most likely to have included areas that would have otherwise been inaccessible due to active conflict during the war. In effect, conducting the surveys in stable periods likely resulted in capturing of more deaths. Secondly, populations that were otherwise displaced in the height of the war and were difficult to find may have been easier to locate during the survey period. These considerations may have contributed to increased number of war-related deaths captured that are likely to be missed given the current situation in Yemen. However, the possibility of recall bias in the study may have also contributed to the increased number of reported deaths attributed to the conflicts for both DRC and Iraq. These are plausible, indirect explanations for Yemen's low excess deaths when compared to other long-term conflict zones but were not specifically investigated in this dissertation.

Irrespective of the differences in the nature of the conflicts and the resulting magnitude of the estimated number of avoidable deaths, violent direct deaths account for a large percentage of all deaths in some conflict settings. In Yemen, direct deaths accounts for 67.2% of the excess deaths (chapter 4) that occurred in the 5-year period. Similarly, in Iraq, violence and airstrikes from coalition forces accounted for 51% of the deaths [75]. In contrast, in Darfur, violence was not the main cause of deaths [176]. On one hand, the heavy reliance of the war in Yemen on airstrikes and isolated confrontation between warring parties may have increased the number of direct deaths. On the other hand, as opposed to direct deaths, the interventions from operational agencies may have mitigated the risks of mortality from indirect causes. However, in some conflicts, indirect deaths represent a major proportion of the recorded deaths. For example, in the DRC conflict, indirect deaths from preventable and treatable diseases accounted for the majority of deaths — less than 10% of all deaths were due to violence [22, 48].

Regardless of the body count, humanitarian organizations have worked diligently, even in the face of danger, to offer help to the Yemeni people since the 2015 turning point in the ongoing conflict. At the end of 2020, UNHCR provided emergency shelter kits to over 127,000 people and provided cash assistance to over 1 million IDPs and host communities [317]. Given the crumbling health system, the irregular payment of salaries to health workers and risks to lives of health workers, MSF and other aid organizations have provided incentives to 1,200 Ministry of Public Heath Population (MoPHP) staff and facilities across the country [318]. In addition, with the support of WHO, UNICEF and Gavi, the Vaccine Alliance and MoPHP, health care workers are working tirelessly to ensure that individuals across the country are vaccinated against preventable diseases [319].

Inequality in health status in protracted crisis

In chapter 5, we developed a simple method for the classification of security level in poor resource settings. We detected two subpopulations amongst children less than five years old for effective aid targeting and the relationships between these subpopulations and insecurity level. We observed that, in contrast to results from surveys that reported high number of under-five death rates, surveys reporting low numbers of under-five deaths were not associated with insecurity levels. We concluded that the relationship between patterns of under-five death rates and the level of insecurity is crucial in understanding the impact of protracted conflict on under-five mortality.

The pattern of violence and deaths in protracted conflicts are not homogeneous across the population, and this is important for the identification of the most affected areas. In humanitarian emergencies, states and non-state actors, as well as public health specialists, work together to identify vulnerable populations to ensure the effective and equitable distribution of aid. However, these efforts to ameliorate the impact of conflicts on the exposed population may not yield consistent outcomes amongst the affected. Therefore, understanding the heterogeneity of population-level impacts is vital for effective intervention.

The differences in the effect of conflicts across the subpopulations may reflect the intensity of the conflict, proximity of the population to the sites of armed conflict, prevailing health status, and inequitable access to health services and aid. Typically, the most vulnerable during protracted conflicts are women and children, but due to data constraints, we did not study gender disparity. Nevertheless, the disparity in mortality amongst children is evident between subpopulations of children less than five years old in Yemen. An increase in the number of deaths amongst children less than five years old was shown to be associated with high insecurity in Yemen (chapter 5). This association might be explained by the idea that populations living in high insecurity areas (closer to the battle front) have higher risk of dying. For instance, a 2018 study showed that children born within 50km of an armed conflict had a higher mortality rate than if there were no conflict in the area [259]. Security indicators might also reflect access to essential health care services and availability of consumer goods; high insecurity resulting in restricted access to essential services and the closure of businesses. For instance, in Yemen in 2019, the Houthi militias were reported to have looted shops and businesses in areas under their control forcing businesses to shut down [320]. The forceful closure of businesses and deprivation of affected populations of food aid might increase the already high prices of essential materials, hence, elevating malnutrition and its associated consequences such as increased mortality. This perpetuates the disparity in the effects of the conflict on the populations living in these areas when compared to relatively secure areas.

Further, insecurity can lead to inequity in the delivery of food aid and other life-saving medical treatments to people who are in desperate need. Due to significant insecurity and the destruction of transportation facilities, areas in need may be denied immediate care and be possibly cutoff from aid programs. For instance, a study of immunization coverage during conflict in 16 countries (including Yemen), indicated that insecurity and the destruction of health facilities contribute to delay and infrequent immunization program [321]. The provision of aid into Yemen has been severely complicated by the naval blockade and destruction of the airport in Sana'a [141].

The blocking of both aid and health workers from reaching certain parts of the population can further perpetuate health inequality and general suffering of the people. In Yemen, the denial of complete access to UN and other aid agencies to the affected population has worsened the hardship and exacerbated the spread of preventable diseases in the population [322]. Similarly, in 2008, in eastern DRC, aid workers were harassed, relief supplies seized and vehicles vandalized. Hence, critical humanitarian assistance was cut-off to a large number of vulnerable people living within the region [323]. Apart from the actions of rebel groups, Congolese and state actors used obstruction, starvation, coercion, and in some cases, totally banned NGOs from working in crucial areas as weapons to achieve military and political goals during conflict [324], endangering millions of lives.

Furthermore, the outright theft of aid material by fighting forces can lead to the loss of food aid meant for affected population, further aggravating malnutrition and exposing already vulnerable populations to opportunistic diseases. For instance, in 2020, UN food agency, reported the looting of food aid in the rebel-held areas of the northern province of Hajjah. This came on the heels of the partial suspension of food aid to insecure areas controlled by the rebel due to diversion of aid from the vulnerable population [325]. Despite the nationwide conflict, the difference in intensity, unequal access to health care and aid has invariably affected the population disparately. Hence, populations with restricted access to essential services and commodities and high exposure to insecurity are most likely to experience higher mortality rates than areas with relatively better access and less exposure to conflict-related insecurity.

6.2 Implication for the humanitarian community

Humanitarian assistance is expensive, and available resources for aid program are limited. Given the increasing number of prolonged crises, reliable data are essential for addressing the needs of the affected population. This study has substantial implications for efficient and effective aid targeting, as well as providing new insights into mortality patterns in conflict situations.

The main sources of data for public-health indicators are usually census, surveillance and household surveys. These are easily implemented in stable conditions but depend largely on existing infrastructures. In Yemen, in the 15 years leading to the conflict there were 3 household surveys and the last census was conducted 11 years prior to the conflict [78]. These are valuable sources of information on health-related events but are subject to the rapid change of the health status of the population, especially amongst populations experiencing crisis. Apart from the nationwide surveys the health surveillance system depends on the existing infrastructures which were in a precarious condition before the conflict [301]. The current deterioration of health facilities and the forced displacement of the population pose great challenges to the effectiveness of such a system. Consequently, local and international operational agencies rely on result from small-scale surveys designed for such settings as well as estimates from the surveillance system for assessment and monitoring.

For humanitarian and donor agencies like UNICEF, ACF and MSF that are mostly responsible for conducting surveys in humanitarian emergencies, efforts are geared towards ensuring that the recommended methodology is adhered to for the precise estimation of mortality indicators. Over-estimation of mortality rate may lead to the diversion of scare resources from other victims that would have benefitted from it. Under estimation may contribute to neglect and hence worsen the suffering of the affected population [77]. In terms of reporting, accurate reporting signifies legitimacy and provides observers and the research community with the opportunity to assess the quality of the surveys for future use and decision-making. The development of a checklist to ensure that these crucial steps are performed could assist in ensuring compliance.

During the course of this project, the majority of the small-scale survey from Yemen reported neither gender disaggregated mortality nor cause-specific mortality, unlike large scale surveys and health-surveillance system. Reporting male and female specific mortality rates may provide additional insight on the inequitable access to health services and resources [326]. Reporting cause-specific mortality rates would help reveal health challenges requiring priority during planning and implementation. Apart from the well-known factors such as gender, insecurity level, displacement status, and cultural practices [327], that could explain the disproportionate mortality outcome in crises, policymakers should take into account possible unobserved factors that could enforce disparity. This could lead to more targeted and efficient assistance for the affected community. In addition, the interaction of cultural practices and the aforementioned factors cannot be over-emphasized, as this interaction could also perpetuate inequalities that are likely to continue beyond the crisis.

6.3 Impact for the scientific community

This dissertation contributes to the scientific advances in humanitarian crisis and conflict epidemiology. One of the major contributions of this dissertation to the scientific community is the introduction of novel method of calculating avoidable mortality due to conflict. Our focus was the estimation of excess mortality and generating of baseline estimates based on estimates from several survey results. Our study highlighted the essence of developing methods that effectively combine several pieces of information considering their peculiarity.

In addition, this study provides an important insight into the on-going debate surrounding the interpretation of conflict mortality where attention is mostly on the statistical significance of estimates rather than the deteriorating condition of the affected population. To strengthen our estimate, we opted for an approach that provides levels of certainty around the baseline estimate. The implication of this approach is that it strengthens and gives more credibility to the estimate of excess mortality.

Small-scale surveys are usually meant for the decision making over a small-area and the extrapolation of such estimates is very difficult [57]. Our research is based on using aggregated results for inference at national level. This approach opens the door for further, even more informative studies. The integration of small-area data into large surveys like DHS with geographical mapping capability will provide aggregate results for the areas, display variables and estimates for each possible level, and provide the results on maps for easy interpretation and visualization. This offers the opportunity for conducting analyses which consider spatio-temporal [328] relationships based on a rich pool of data. For instance, such mapping techniques would give valuable information for understanding the level of mortality in rebel held areas or for assessing vaccination coverage or effectiveness of aid deployment in places that are worst hit by the crisis.

Our research presents a novel, parsimonious method for assessing insecurity in resource-scarce areas using readily available public data. Rather than relying on estimation techniques that requires vast array of data [252], that are usually not available in most crisis settings, our strategy uses fewer data that are easily accessible to the public. Furthermore, utilizing our strategy, we can identify at-risk areas that would not have been found using traditional modeling techniques. However, given that this study gives just the first approach, there is need for the extension of the method to include predictive capability for anticipating of the level of insecurity.

6.4 Conclusions

Conflicts are becoming increasingly complicated and prolonged [329], and they present significant harm to a large number of individuals. However, full examination of the influence on mortality in particular is scarce, and mortality information is primarily based on scattered data. Consequently, humanitarian decision- and policy-making based on such standalone information are not truly representative of the prevailing situation. Taking into consideration the methodological strengths and limitation of this dissertation, we posit that:

> The prolonged conflict may not have necessarily affected the implementation of surveys compared to periods before the conflict. However, there should be special consideration for the improvement of the estimation of death rates to capture the true extent of the crisis. Similarly, improving reporting methodologies would not only eliminate ambiguity in the interpretation of results but also would make it easier to integrate surveys as a credible data source in scientific studies.
>
> The ongoing conflict in Yemen has caused tremendous hardship to the people of Yemen. Given the wide confidence limits around the estimated avoidable deaths of over 100 000, it is uncertain whether there is a change in the number of estimated deaths between the conflict and the pre-conflict period. Nevertheless, children are disproportionately affected by the incessant conflict. On-going efforts should be made to scale-up mitigation efforts to address the suffering of the people.

6.5 Limitations

Scientific analyses are subject to limitations; hence, findings of this study should be interpreted considering both the limitations and strengths of the study. For this thesis, the limitations are broadly discussed under data quality type and statistical methodology.

The data used for this study are secondary data based on the results of retrospective nutrition and mortality surveys conducted in humanitarian settings. These surveys have certain limitations. One of the common biases of retrospective studies is recall bias. People may find it difficult to accurately remember events that happened in the distant past and/or may be more or less likely to report traumatic events such as family member deaths depending on their lived experiences.

To mitigate this bias, the SMART methodology recommended the use of recall period less than one year. A three-month recall period is recommended during acute emergencies as it allows estimation of death rate that are situationally and temporally sensitive When the goal is to document mortality, a long recall period of up to one year is permissible [59]. In addition, the beginning of the recall period should be a date known to the population, often marked by a population-level event or holiday. Most of the mortality surveys from Yemen used in the study have a recall period of 90 days. The starting day of the recall periods were based on a notable festive period like the day of the anniversary of the Prophet's birth in order to help respondents remember the period in which the events of survey interest occurred [59].

SMART surveys are designed to minimize recall bias, but once the data is collected, it is difficult to account for it. Most importantly the extent to which this influence mortality estimate from retrospective survey is difficult to quantify. The modified flashbulb method used in longitudinal survey studies [330] can be adapted to assess if the pattern of recall bias is influenced by intensity of conflict in small-scale surveys conducted in conflict settings. For instance, additional variables on events that are well known in the survey area have to be collected during the survey period. Using the method for classification of insecurity, the sample can be categorized as obtained in areas with high level of insecurity or areas with low level of insecurity. The idea is that since traumatic events are likely to affect recall, patterns observed in the statistical modeling of the data using these additional variables could be an indication of the presence or absence of possible recall bias. However, while this approach does not eliminate the recall bias it provides meaningful insights that can be used in drawing conclusions.

These surveys are also prone to selection bias — selection of affected population. The second stage of SMART surveys is the random selection of geographically-defined locations. In most cases, information about these areas is outdated and are inaccessible to enumerators due to conflict. If the mortality rate is higher in the excluded area (as expected in conflict settings), this could lead to underestimation of mortality rate. Most surveys used in this study explicitly stated when areas were excluded for security reasons. IDPs are frequently excluded from surveys, further driving estimates toward lower mortality rates. For this analysis, the impact of the exclusion of areas/clusters/regions and certain populations from some of the surveys is difficult to assess. However, it is possible to include the excluded area as missing data in modeling process. For instance, the mortality rate – which is the main outcome – can be considered missing for an area, but other variables collected independently of the survey such as insecurity level, food insecurity, access to healthcare, presence/absent of aid agencies can be included in the modeling process. Using Bayesian data augmentation approach, these other characteristics inform the estimation of the missing mortality rate measure [193].

Information provided by conflict event databases are prone to reporting bias, especially for fatality-related data. To minimize this bias, we cross-compared the number of events (air raids) in both YDP and ACLED to ensure consistency. The relevance of including political, economic, and existing security and military structures in the formulation of a security index cannot be overstated.

Furthermore, the method used in the computation of excess morality is prone to over-estimation of the number of excess deaths attributed to the conflict. The survey data I used in this study did not provide information on violent deaths and the majority of survey excluded insecure areas. The direct addition of the conflict data may lead to double counting, it is possible that some of the fatalities would have been captured in the survey data. Detailed data and methodological limitations pertaining to each study used in this thesis are discussed in chapter 3, 4 and 5.

6.6 Future perspectives

This thesis demonstrates the utility of combining publicly available data to better understand mortality in prolonged humanitarian crises. Further, it demonstrates the need for more insight on how best to integrate other sources of mortality data from conflict settings. Most mortality surveys do not provide detailed information on gender disaggregation of crude and child mortality or on causes of deaths. This information is usually collected via verbal autopsy and graveyard surveillance [80, 85]. It will be helpful to investigate the consolidation of mortality data from these sources of detailed mortality data collection and small-scale surveys to form an enriched pool of data [331]. For instance, a statistical methodology that allows each additional data source to borrow strength from the other and also capture the amount of heterogeneity introduced by each data source could be incredibly valuable. This approach would provide detailed and robust estimates for effective program implementation.

Furthermore, population size and composition are integral parts in the estimation of excess mortality in humanitarian emergencies. These variables can be outdated, missing some groups or areas and are difficult to measure accurately, especially if the population is experiencing forced migration and are in resource scare settings [332]. The bias introduced by these demographic variables is carried on to the assessment of the population health status. Methods that have been used in an attempt to tackle this problem in population based-study such as use of satellite imagery [333-335] and tracking via mobile phone [336] can be integrated into the statistical modeling of SMART surveys for robust estimation of mortality rates.

We proposed the estimation of baseline mortality with level of certainty, and this can be affected by the choice of prior. The DHS, MICS and health-surveillance system provide series of health-related information that can be sources of valuable prior information in the Bayesian framework. Depending on how recent the large study estimates are, they can serve as priors in modeling conflict mortality. For instance, the mean, variance or scale and shape parameters of informative prior can be determined from these alternative sources and used in the construction of prior information by transforming the estimates into the appropriate prior distribution. This will serve both as a sensitivity measure and a means of improving on the precision of the estimates.

A majority of countries experiencing prolonged humanitarian crisis are countries with very strong, conservative cultural practices. For instance, Yemen and Northeast Nigeria have a strong cultural belief that shape important aspects of everyday lives of the people. Data on cultural practices are mostly captured via qualitative research. The impact of the interaction of cultural and gender practices on mortality in protracted crisis can be investigated through the use of Bayesian methods for modeling mixed methods [337]. Understanding the interaction of quantitative and qualitative measures will provide a better understanding of how to minimize the effect of cultural complexities on direct and indirect mortality in these settings. Also, this knowledge could portend practices that perpetuate the drivers of mortality that occurs several years after the crises due to inequality inherent in these cultural practices.

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Appendix A

S1:Estimated standard error for CDR and U5DR based on reported confidence limits

YEAR	ST.SE.U5DI	EST.SE.CDR	CDR	LCL.CDR	UCL.CDR	U5DR	LCL.U5DR	UCL.U5DR
2012	0.4	0.09	0.27	0.14	0.51	0.71	0.27	1.84
2012	0.42	0.08	0.21	0.1	0.43	0.69	0.25	1.89
2012	0.01	0.09	0.25	0.12	0.49	0.6	0.18	0.2
2012	0.29	0.1	0.22	0.1	0.48	0.63	0.28	1.43
2012	0.31	0.07	0.17	0.08	0.37	0.31	0.07	1.27
2012	0.25	0.05	0.06	0.02	0.2	0.13	0.02	0.99
2012	0.24	0.06	0.18	0.1	0.32	0.25	0.06	0.99
2012	0.15	0.05	0.18	0.11	0.31	0.16	0.04	0.64
2012	0.26	0.05	0.16	0.09	0.28	0.42	0.15	1.18
2012	0.19	0.04	0.19	0.12	0.29	0.49	0.24	0.97
2013	0.16	0.06	0.27	0.18	0.4	0.16	0.04	0.66
2013	0.28	0.07	0.15	0.06	0.33	0.15	0.02	1.11
2013	0.25	0.19	0.33	0.19	0.95	0.13	0.02	1
2014	0.32	0.09	0.23	0.12	0.46	0.17	0.02	1.26
2014	0.26	0.08	0.27	0.16	0.48	0.14	0.02	1.03
2014	0.29	0.08	0.17	0.07	0.37	0.15	0.02	1.14
2015	0.27	0.09	0.19	0.09	0.43	0.14	0.02	1.07
2015	0.23	0.09	0.33	0.2	0.54	0.12	0.02	0.93
2016	0.27	0.06	0.26	0.17	0.39	1.21	0.78	1.84
2016	0.24	0.05	0.18	0.11	0.29	0.64	0.32	1.26
2016	0.09	0.02	0.04	0.02	0.09	0.09	0.02	0.36
2016	0.11	0.02	0.07	0.04	0.13	0.11	0.03	0.48
2016	0.37	0.05	0.21	0.13	0.33	1.14	0.53	1.97
2016	0.14	0.03	0.09	0.05	0.15	0.28	0.12	0.65
2016	0.19	0.05	0.16	0.1	0.28	0.4	0.17	0.92
2018	0.42	0.07	0.1	0.03	0.29	0.22	0.03	1.69
2018	0.36	0.14	0.36	0.18	0.71	0.37	0.09	1.52
2018	0.4	0.11	0.35	0.19	0.64	0.71	0.27	1.84
2018	0.49	0.08	0.21	0.11	0.41	0.78	0.27	2.2
2018	0.36	0.07	0.12	0.05	0.32	0.19	0.02	1.43
2018	0.39	0.09	0.12	0.04	0.41	0.38	0.09	1.6
2018	0.31	0.11	0.39	0.23	0.66	0.33	0.08	1.31
2018	0.25	0.05	0.13	0.07	0.25	0.14	0.02	1.01
2017	0.22	0.14	0.09	0	0.27	0.19	0.02	0.46
2017	0.77	0.24	0.48	0.3	0.77	0.7	0.27	1.81
2018	0.52	0.15	0.3	0.18	0.48	0.68	0.34	1.37
2018	0.46	0.09	0.12	0.06	0.24	0.24	0.06	0.97
2018	0.4	0.12	0.13	0.06	0.3	0.11	0.01	0.81
2018	0.99	0.24	0.45	0.27	0.74	0.65	0.19	2.16
2018	0.56	0.13	0.09	0.03	0.29	0.25	0.02	1.13

EST.SE.U5DR: estimated standard error for under five death rate
EST.SE.CDR: estimated standard error for crude death rate
LCL.CDR: lower confidence limit for crude death rate
UCL.CDR: upper confidence limit for crude death rate
LCL.U5DR: lower confidence limit for under five death rate
UCL.U5DR: upper confidence limit for under five death rate

Appendix B

Appendix B-1

Characteristics of surveys used in chapter 4

S.ID	GOVERNORATE	CLUSTER	YEAR	REPRESENTATIVE SAMPLE SIZE
1A	ADEN		2012	10442
2A	HAJJAH	HL	2012	4516
2B	HAJJAH	LL	2012	4948
3A	HAJJAH	IDP	2012	5175
4A	IBB	EHL	2012	8592
4B	IBB	WHL	2012	10032
5A	LAHEG	HL	2012	4970
5B	LAHEG	LL	2012	5489
6A	REYMAH		2012	576700
7A	TAIZ	TM	2012	4100
7B	TAIZ	TC	2012	4827
8A	ABYAN	CIDA	2013	8344
8B	ABYAN	CDA	2013	9176
9A	AL-MAHWEET	HL	2013	5854
9B	AL-MAHWEET	LL	2013	6831
10A	DHAMAR	EASTERN	2013	6442
10B	DHAMAR	WESTERN	2013	6916
11A	AL-HODEIDAH	HL	2014	3881
11B	AL-HODEIDAH	LL	2014	4905
12A	HAJJAH	LL	2014	4751
12B	HAJJAH	HL	2014	4631
13A	LAHEG	HL	2014	5489
13B	LAHEG	LL	2014	4516
14A	SAADAH	LL	2014	5072
14B	SAADAH	HL	2014	4596
15A	TAIZ	LL	2014	3468
15B	TAIZ	MZ	2014	3545
15C	TAIZ	MT	2014	4137
16A	ADEN		2015	2994
17A	AL-BAIDA		2015	3575
18A	AL-HODEIDAH	LL	2015	3738

19A	HAJJAH	MT	2015	3860
19B	HAJJAH	LL	2015	3441
20A	LAHEG	HL	2015	2809
20B	LAHEG	LL	2015	3877
21A	ABYAN		2016	631400
21B	ADEN		2016	890100
22A	AL DHALE		2016	4754
21C	AL DHALE		2016	688800
21D	AL JAWF		2016	680400
21E	AL-BAIDA		2016	780200
21F	AL-HODEIDAH		2016	3520800
21G	AL-MAHWEET		2016	795400
21H	AMANAT-AL-ASIMAH		2016	2606400
21I	AMRAN		2016	1251600
21J	DHAMAR		2016	2244600
21K	HADHRAMOUT		2016	1795210
21L	HAJJAH		2016	2140900
21M	IBB		2016	3333800
21N	LAHEG		2016	1095007
21O	MAREB		2016	351000
21P	REYMAH		2016	576700
23A	SAADAH	SHL	2016	3793
23B	SAADAH	SLL	2016	3817
24A	SANAA	SAD	2016	3448
24B	SANAA	SAT	2016	4070
21Q	SANAA		2016	1385500
21R	SHABWA		2016	85840
25A	TAIZ	TCITY	2016	2605
25B	TAIZ	THL	2016	3572
25C	TAIZ	TLL	2016	3371
26A	IBB	WHL	2017	10032
26B	IBB	EHL	2017	8592
27A	SHABWA	Plateau	2017	4102
27B	SHABWA	Lowland Coastal	2017	4246
28A	TAIZ	HL	2017	3884

29A	ABYAN	LL	2018	3501
29B	ABYAN	HL	2018	3650
30A	ADEN		2018	4613
31A	AL DHALE		2018	4754
32A	AL JAWF		2018	4426
33A	AL-BAIDA		2018	3576
34A	AL-MAHRA		2018	5906
35A	AMRAN		2018	4537
36A	HADHRAMOUT	CZ	2018	4929
36B	HADHRAMOUT	VDZ	2018	5691
37A	HAJJAH	LL	2018	3373
37B	HAJJAH	HL	2018	4663
38A	LAHEG	HL	2018	3521
38B	LAHEG	LL	2018	3031
39A	MAREB	RURAL	2018	3900
39B	MAREB	CITY	2018	3373
40A	SANAA	DZ	2018	3984
40B	SANAA	TZ	2018	3278
41A	SOCOTRA		2018	4808
42A	TAIZ	TLL	2018	2820
42B	TAIZ	THL	2018	2973
42C	TAIZ	TC	2018	3835
43A	AL-MAHRA		2019	3017
43B	SHABWA		2019	4797
44A	SOCOTRA		2019	2961

Appendix B-2

Distribution of air raids/drone attacks, associated direct deaths, and PCDR by Governorate Jan 2015 – Dec 2019

Governorates	Direct deaths[b]	Air & drone attacks[b]	PCDR [c]	Level of insecurity
Socotra[a]	0	0	0.12	1
Al Mahrah	0	1	0.12	1
Raymah	7	15	0.30	1
Hadramawt	169	43	0.26	2
Al Mahwit	27	65	0.16	1
Abyan	332	117	0.18	2
Dhamar	371	161	0.11	1
Ad Dali	464	166	0.25	2
Aden	325	213	0.34	3
Ibb	313	214	0.28	2
Lahij	420	317	0.13	2
Shabwah	507	319	0.17	2
Amran	359	378	0.22	1
Al Bayda	781	452	0.23	3
Al Jawf	660	752	0.26	3
Marib	885	1323	0.30	3
Amanat al A.	1197	1325	0.12	3
Al Hodeida	2639	1755	0.14	3
Hajjah	2176	1945	0.35	3
Taizz	2549	1978	0.18	4

Sana’a	979	2013	0.17	3
Sa’dah	3520	4932	0.22	4

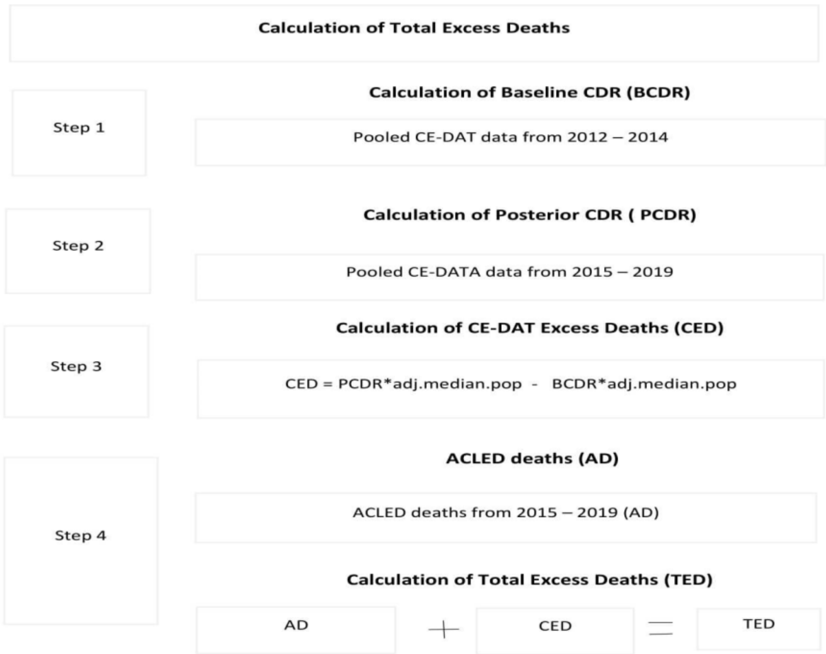
Appendix B-3

Test of association between four security levels and PCDR

	Degrees of freedom	Sum square	Mean Square	P-value
Security level (n=22)	3	0.02	0.01	0.41
Residuals	18	0.10	0.01	

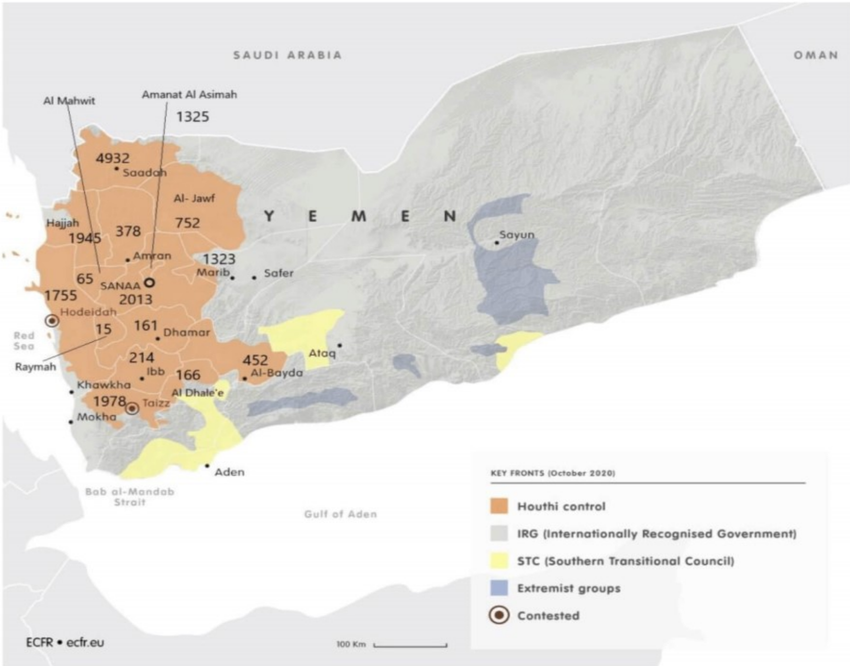
Appendix B-4

Step-by-step explanation of the calculation of excess deaths in Yemen 2015 - 2019



Appendix B-5

Distribution of air raid/drone strikes, 2015 – 2019, and indicative areas of control by different armed entities.

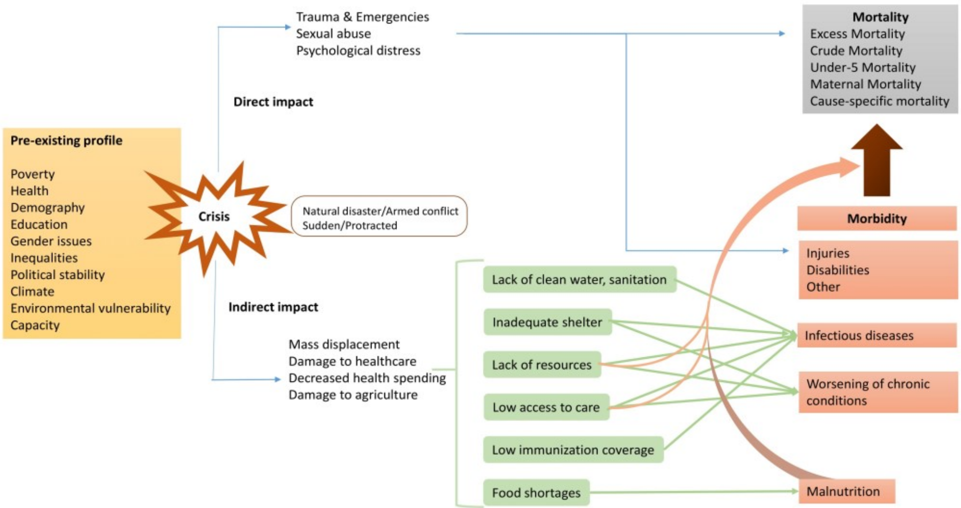


** The map of controlled area has been sourced from European Council on Foreign Relations website and has been adapted to include number of air raid/drone strikes. It should be considered indicative only and the page can be accessed by the link below: https://ecfr.eu/publication/talking_to_the_houthis_how_europeans_can_promote_peace_in_yemen/

Appendix C

Appendix C -1

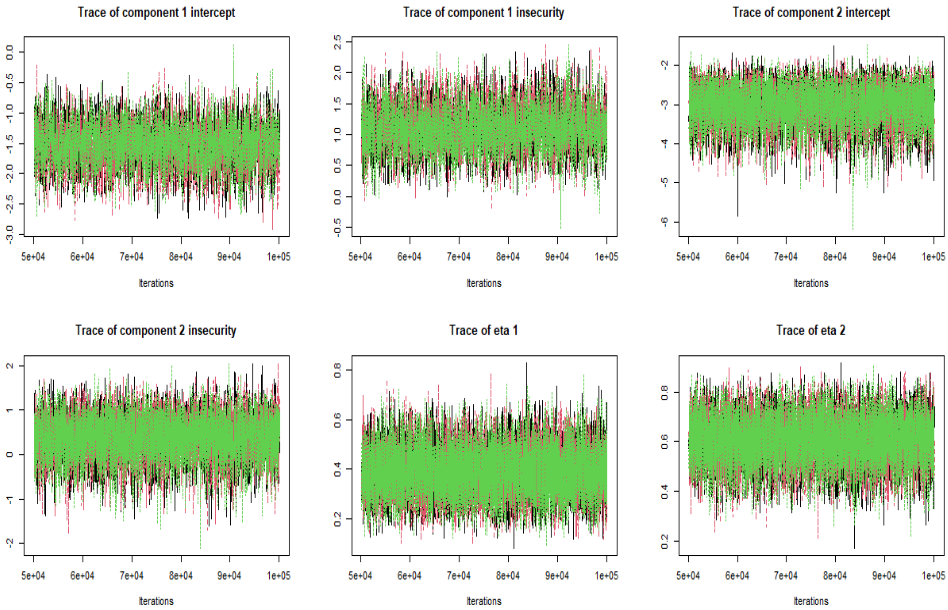
Framework showing the complex relationship between human insecurity due to armed conflict, and impacts on mortality and health status.



Adapted from Armed conflict and public health. A report on knowledge and knowledge gaps (Pg.14,26 &28), with permission from CRED.

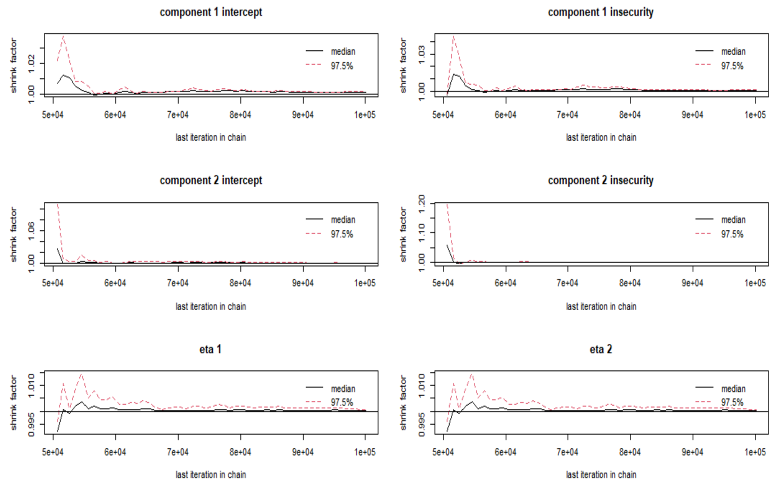
Appendix C-2

Trace plots of parameters for each component indicating convergence.



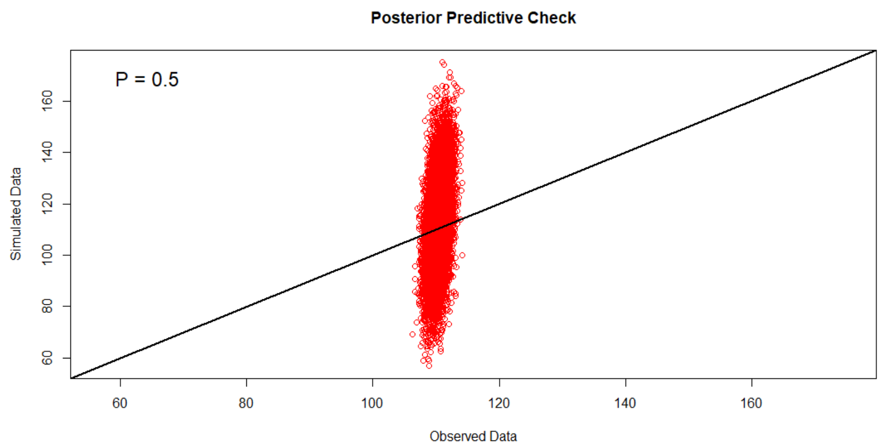
Appendix C-3

Gelman Rubin diagnostic plots for parameters of component 1 and component 2



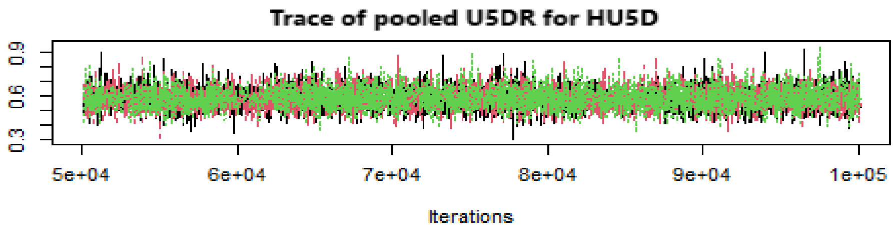
Appendix C-4

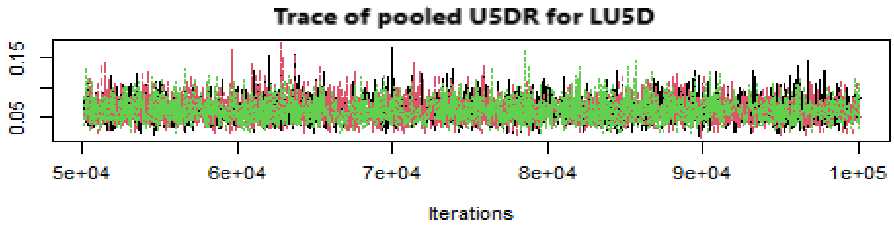
Posterior predictive check for Poisson finite mixture model.



Appendix C-5

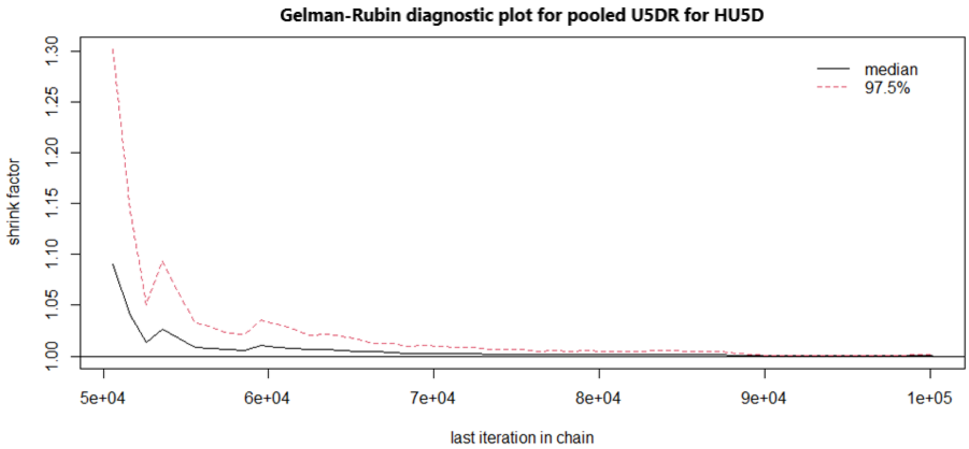
Trace plots of estimated pooled U5DR for subpopulation I and II

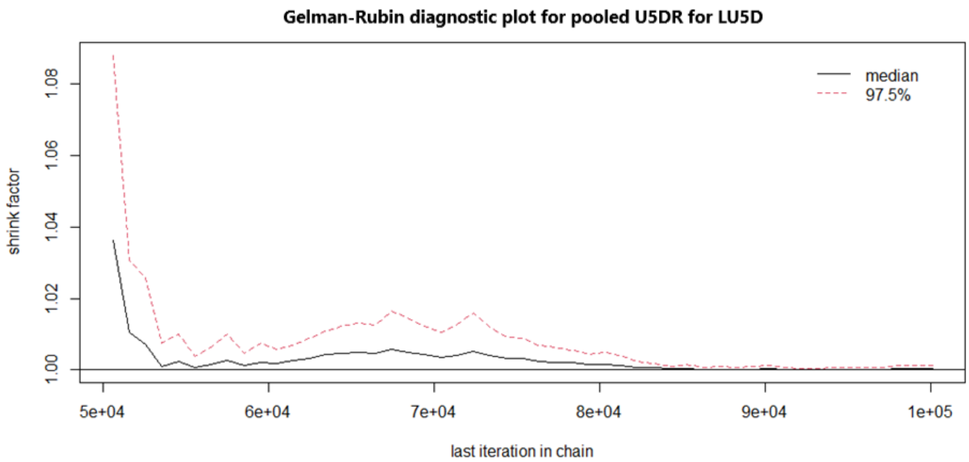




Appendix C-6

Gelman-Rubin diagnostic plots for Pooled U5DR estimate for subpopulation I (HU5D) and II (LU5D).





Appendix C-7

code for Bayesian Finite Mixture Model with the assumption that both components follow Poisson distribution

```
"model{
  for(i in 1:N){
  event[i] ~ dpois(lambda[i,S[i]])
  log(lambda[i,1]) <- alpha1[1] + alpha1[2]*sec_index[i]   + log(person_days[i])
  log(lambda[i,2]) <- alpha2[1] + alpha2[2]*sec_index[i]   + log(person_days[i])
  S[i] ~ dcat(eta)
  ##calculate probabilities using Stephen rules
  d[i] <- eta[1]*dpois(event[i],lambda[i,1]) + eta[2]*dpois(event[i],lambda[i,2])
  prob1[i] <- eta[1]*dpois(event[i],lambda[i,1])/d[i]
  prob2[i] <- eta[2]*dpois(event[i],lambda[i,2])/d[i]
  ### set up for ppc
  event.new[i] ~ dpois(lambda[i,S[i]]) #replicated
  res[i] <- event[i] - d[i]
  res.new[i] <- event.new[i] - d[i]
  }
  ###### priors
  ###########################
   b0 <- 1000
   for(m in 1:2){
  alpha1[m] ~ dnorm(0,1.0e-6)
  ## place restriction to control for identifiability
```

```
alpha2[m] ~ dnorm(0,1.0e-6*b0)T(,alpha1[m])
}
fit <- sum(res[])
fit.new <- sum(res.new[])
eta ~ ddirich(c(0.5,0.5))
}
```

Part B.2

R code for computing pooled U5DR for the overall data, for the LU5D and the HU5D groups.

```
model {
for (i in 1:N) {
event[i] ~ dpois(lambda[i])
lambda[i]<-theta[i]*person_time[i]
theta[i] ~ dgamma(alpha, beta)
res[i] <- event[i] - lambda[i]
new.event[i] ~ dpois(lambda[i])
new.res[i] <- new.event[i] - lambda[i]
}
mu~dgamma(0.001,0.001)
beta~dgamma(0.001,0.001)
alpha<-mu*beta
std <- sqrt(alpha/beta^2)
#parameter
fitted <- sum(res[])
```

```
newfit <- sum(new.res[])
}",
```

Appendix D

Details of the 91 small-scale surveys used for the analysis in Chapter 4

CDR = Crude death rate per 10 000 per day

Num.Deaths = Number of deaths estimated in the population

Survey ID	Governorate	Year	Recall Period	CDR	Num. Deaths	Person Days
A001	Aden	2012	90	0.18	1253	6959.22
A002	Hajjah	2012	90	0.13	6	46.15
B002	Hajjah	2012	90	0.22	1793	8150.3
C002	Hajjah	2012	90	0.25	2194	8777.25
A003	Ibb	2012	90	0.16	2210	13809.8
B003	Ibb	2012	90	0.19	1830	9629.4
A004	Laheg	2012	90	0.06	238	3962.22
B004	Laheg	2012	90	0.18	695	3861.06
A005	Reymah	2012	90	0.17	765	4500
A006	Taiz	2012	90	0.21	2591	12335.86
B006	Taiz	2012	90	0.27	3569	13216.99
A007	Abyan	2013	90	0.24	568	2367.5
B007	Abyan	2013	90	0.27	617	2285.96
A008	Al Mahweet	2013	90	0.15	411	2741.24
B008	Al Mahweet	2013	90	0.33	936	2836.22
A009	Dhamar	2013	90	0.19	1131	5952.74
B009	Dhamar	2013	90	0.27	2491	9226.18
A010	Al Hodeidah	2014	90	0.1	1248	12475.89
B010	Al Hodeidah	2014	90	0.18	2403	13350
A011	Hajjah	2014	90	0.15	1286	8572.62
B011	Hajjah	2014	90	0.23	1922	8354.93
A012	Laheg	2014	90	0.1	3969	39689.52
B012	Laheg	2014	90	0.17	6552	38543.26
A013	Saadah	2014	90	0.07	300	4286.02
B013	Saadah	2014	90	0.18	809	4492.58
A014	Taiz	2014	90	0.19	1801	9480.9

B014	Taiz	2014	90	0.24	1950	8124.9
C014	Taiz	2014	90	0.27	2146	7947.06
A015	Aden	2015	135	0.41	4280	10438.85
A016	Al Baida	2015	135	0.33	3232	9792.9
A017	Al Hodeidah	2015	135	0.19	7325	38551.95
A018	Hajjah	2015	150	0.17	2156	12681.03
B018	Hajjah	2015	150	0.3	5196	17320.8
A019	Laheg	2015	150	0.1	96	963.28
B019	Laheg	2015	150	0.23	288	1252.59
A020	Abyan	2016	90	0.22	1101	5004
B020	Aden	2016	90	0.44	3540	8046
A021	Al Baida	2016	90	0.15	1004	6696
A022	Al Dhale	2016	90	0.21	1319	6282
B022	Al Dhale	2016	90	0.39	2418	6201
A023	Al Hodeidah	2016	90	0.04	1115	27873
A024	Al Jawf	2016	90	0.22	1140	5184
A025	Al Mahweet	2016	90	0.16	975	6093
A026	Amanat-Al-Asimah	2016	90	0.12	3047	25392.01
A027	Amran	2016	90	0.07	655	9351
A028	Dhamar	2016	90	0.11	1843	16758
A029	Hadhramout	2016	90	0.21	2617	12463.37
A030	Hajjah	2016	90	0.63	11748	18648
A031	Ibb	2016	90	0.15	3750	25002
A032	Laheg	2016	90	0.13	1124	8649
A033	Mareb	2016	90	0.56	1657	2958.35
A034	Reymah	2016	90	0.3	1488	4959
A035	Saadah	2016	365	0.18	3440	19113.09
B035	Saadah	2016	365	0.26	4938	18992.91
A036	Sanaa	2016	90	0.15	1898	12650.99
B036	Sanaa	2016	365	0.04	759	18966.52
C036	Sanaa	2016	365	0.07	1567	22387.98
A037	Shabwa	2016	90	0.21	1170	5571
A038	Taiz	2016	365	0.09	3607	40077.7
B038	Taiz	2016	365	0.16	6066	37911.33
C038	Taiz	2016	365	0.21	7506	35744.97
A039	Ibb	2017	98	0.48	5578	11620.06
B039	Ibb	2017	105	0.17	3046	17915.94

A040	Shabwa	2017	90	0.16	460	2876.33
B040	Shabwa	2017	90	0.24	647	2694.67
A041	Taiz	2017	90	0.09	463	5146.95
A042	Abyan	2018	90	0.1	248	2483.53
B042	Abyan	2018	90	0.21	550	2617.78
A043	Aden	2018	123	0.11	1272	11559.54
A044	Al Baida	2018	145	0.2	2156	10778.81
A045	Al Dhale	2018	133.5	0.03	292	9746.57
A046	Al Jawf	2018	144	0.3	2544	8481.6
A047	Al Mahra	2018	116	0.04	71	1764.36
A048	Amran	2018	130.5	0.3	4242	14140.46
A049	Hadhramout	2018	98.5	0.39	3015	7729.83
B049	Hadhramout	2018	106.5	0.13	928	7142
A050	Hajjah	2018	93	0.26	2825	10867.3
B050	Hajjah	2018	93	0.36	3240	8999.48
A051	Laheg	2018	78	0.08	237	2965.88
B051	Laheg	2018	82.5	0.12	632	5264.71
A052	Mareb	2018	88	0.14	356	2545.77
B052	Mareb	2018	95	0.12	60	500.31
A053	Sanaa	2018	145	0.21	1979	9422.75
B053	Sanaa	2018	151.5	0.35	3166	9046.9
A054	Socotra	2018	118	0.12	93	771.17
A055	Taiz	2018	140	0.45	6348	14107.26
B055	Taiz	2018	147	0.13	2044	15724.17
C055	Taiz	2018	154	0.09	1440	15995.47
A056	Al Mahra	2019	191.5	0.16	474	2965.14
A057	Shabwa	2019	110.5	0.06	429	7151.21
A058	Socotra	2019	116	0	0	780.71

Appendix E

Details of the 56 small-scale surveys used for the analysis in Chapter 4

U5DR = under-five death rate per 10 000 per day.

Num. Deaths = Number of deaths among children less than five years old recorded within the recall period.

Survey ID	Governorate	Year	Recall Period	Num. Deaths	Sample size	U5DR
001A	Abyan	2016	90	1	531	0.21
002A	Abyan	2018	90	1	564	0.2
002B	Abyan	2018	90	0	513	0
003A	Aden	2015	135	0	370	0
004A	Aden	2016	90	0	562	0
005A	Aden	2018	123	0	532	0
006A	Al-Baida	2015	135	1	548	0.14
007A	Al-Baida	2018	145	6	587	0.71
008A	Al-Hodeidah	2015	135	1	717	0.1
009A	Al-Hodeidah	2016	365	0	688	0
009B	Al-Hodeidah	2016	90	0	542	0
010A	Al-Mahra	2019	191.5	0	617	0
011A	Al-Mahweet	2016	90	0	594	0
012A	Al Dhale	2016	90	0	575	0
013A	Al Dhale	2018	133.5	0	709	0
014A	Al Jawf	2016	90	1	558	0.2
015A	Al Jawf	2018	144	9	961	0.65
016A	Amanat-Al-Asimah	2016	90	1	477	0.23
017A	Amran	2016	90	2	649	0.34
018A	Dhamar	2016	90	1	621	0.18
019A	Hadhramout	2016	90	0	566	0
020A	Hadhramout	2018	98.5	2	638	0.32
020B	Hadhramout	2018	106.5	1	694	0.14

021A	Hajjah	2015	150	0	552	0
021B	Hajjah	2015	150	0	483	0
022A	Hajjah	2018	93	2	547	0.39
022B	Hajjah	2018	93	0	757	0
023A	Ibb	2016	90	2	529	0.42
024A	Ibb	2017	98	4	611	0.67
024B	Ibb	2017	105	0	581	0
025A	Laheg	2015	150	0	362	0
025B	Laheg	2015	150	0	474	0
026A	Laheg	2016	90	0	541	0
027A	Laheg	2018	82.5	1	599	0.2
027B	Laheg	2018	78	0	435	0
028A	Mareb	2016	90	4	623	0.71
029A	Mareb	2018	88	0	634	0
030A	Mareb	2018	95	2	565	0.37
031A	Reymah	2016	90	0	524	0
032A	Saadah	2016	365	22	523	1.15
032B	Saadah	2016	365	11	533	0.57
033A	Sanaa	2016	365	2	586	0.09
033B	Sanaa	2016	365	2	469	0.12
033C	Sanaa	2016	90	1	609	0.18
034A	Sanaa	2018	151.5	7	607	0.76
034B	Sanaa	2018	145	5	441	0.78
035A	Shabwa	2016	90	0	684	0
036A	Shabwa	2019	110.5	0	690	0
037A	Socotra	2018	118	2	684	0.25
038A	Socotra	2019	116	0	764	0
039A	Taiz	2016	365	13	404	0.88
039B	Taiz	2016	365	5	526	0.26
039C	Taiz	2016	365	8	574	0.38
040A	Taiz	2017	90	1	624	0.18
041A	Taiz	2018	147	1	534	0.13
041B	Taiz	2018	140	3	358	0.6

Appendix F
Scientific Curriculum Vitae

Jideofor Thomas Ogbu joined the Center for Research on the Epidemiology of Disasters as a research associate in October 2018. Before joining CRED, Thomas worked as an independent consultant in the financial and health sectors in Belgium and Nigeria. He holds a Bachelor degree in Statistics from the University of Nigeria, Nsukka. He also earned a Master of Science in Biostatistics in Hasselt University Belgium and a specialized Master in Public Health Methodology from Universite libre de Bruxelles-Belgium. His research focus is on improving health of affected population in protracted crises.

Lists of publications

Thomas Jideofor Ogbu, Debarati Guha-Sapir. "Strengthening data quality and reporting from small-scale surveys in humanitarian settings: a case study from Yemen, 2011-2019". Confl Health. 2021 May 3;15(1):33. doi: 10.1186/s13031-021-00369-2. PMID: 33941227; PMCID: PMC8091505.

Thomas Jideofor Ogbu, Jose Manuel Rodriguez-Llanes, Maria Moitinho de Almeida, Niko Speybroeck, Debarati Guha-Sapir, Human insecurity and child deaths in conflict: evidence for improved response in Yemen, *International Journal of Epidemiology*, 2022;, dyac038, https://doi.org/10.1093/ije/dyac038

Debarati Guha-Sapir**, Thomas Jideofor Ogbu**, Sarah Elizabeth Scales, Maria Moitinho de Almeida, Anne-Francoise Donneau, Anh Diep, Robyn Bernstein, Akram al-Masnai, Jose Manuel Rodriguez-Llanes, Gilbert Burnham. Civil war and death in Yemen: Analysis of SMART survey data, 2012 – 2019. **PLOS Global Public Health**.

Presentations

- **Thomas Jideofor Ogbu**, Debarati Guha Sapir, Fabian Gans & Miguel Mahecha. Analyzing the correlations in compound events between the EM-DAT and Earth System Data Lab databases. Presented at Max-Planck Institute for Biogechemistry, 2019.

- **Thomas Jideofor Ogbu**. Epidemiological evidence from secondary data. Presented at the Johns Hopkins School of Public Health Special seminar, 2019.

- **Thomas Jideofor Ogbu**, Jose Manuel Rodriguez-Llanes, Maria Moitinho de Almeida, Niko Speybroeck, Debarati Guha-Sapir. Pattern of Child Deaths and Armed Insecurity in Yemen: evidence from small-scale surveys. Presented at the "Doctoral Day", 2021, Louvain-la-Neuve, Belgium.

- **Thomas Jideofor Ogbu**, Jose Manuel Rodriguez-Llanes, Maria Moitinho de Almeida, Niko Speybroeck, Debarati Guha-Sapir. Pattern of Child Deaths and Armed Insecurity in Yemen: evidence from small-scale surveys. Poster presented at the virtual conference "14th European Health Conference', 2021, on-line.

- **Thomas Jideofor Ogbu,** Debarati Guha-Sapir. Counting the dead: the up and down-sides of measuring indirect mortality in conflicts. Present in Conference Boston University, 202, online.