And Then Comes Pestilence: Historical Geography and Epidemiology of Infectious Diseases after Natural Disasters

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ABSTRACT

This thesis examines the dynamic of infectious diseases after natural disasters. Methods from epidemiology and geography intersect in the nexus of this research to form new insights into the risk of infectious disease in the aftermath of natural disaster and catastrophe. In the past decades, natural disasters have increased in frequency and magnitude, and with climate change progressing as it is, this trend is expected to continue. It is thus important to gain a fuller understanding of the dynamic between natural disaster and disease, and challenge the persisting problems in disaster and disease response efforts.

Two approaches were taken to determine the risk of disease after disaster. Firstly, by pooling data from previously published literature, a form of meta-analysis was conducted to gain insight into risk patterns as well as to define relevant confounding factors that held significance in determining vulnerabilities of affected populations. For this analysis, a new tool was applied to identify relevant research, and this tool is expected to be useful in future study of the subject. Secondly, a set of empirical studies were conducted to determine the association between types of natural disasters, geographic region, and four distinct disease profiles. Cholera, malaria, tuberculosis, and the co-infection with HIV and tuberculosis served as examples for the types of diseases commonly observed after disasters (diarrhoeal diseases, vector-borne diseases, and acute respiratory infections). Logistic regression models were used to find the odds ratios for above average diseases at different tiers of disaster magnitude.

It was shown in this research that the relative risk of infectious disease after natural disasters was 3.45, indicating a higher probability of disease after disasters. Specific results show that disasters affecting higher numbers of the population typically lead to increases in new infections. Most interestingly, tuberculosis relapses showed significant increases after natural disasters, especially meteorological and hydrological disasters.

ACKNOWLEDGMENTS

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I want to express my sincerest gratitude to the Leverhulme Trust, who have supported me financially on a three-year studentship as part of their project grant, RPG-2012-736: *Humanitarian Crisis, Population Displacement and Epidemic Diseases, 1901-2010*.

I want to dedicate this thesis to the person who has supported and carried me through it all, the person who never stopped inspiring me, and never stopped believing in me: To my mother, Iris-Charlotte Fairley.

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Chapter 1: Introduction

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"To look back into the past only makes sense if it serves the future."

Konrad Adenauer

In an age of climate change, technological advances, population growth and urbanisation, the environment is constantly shifting and changing. This is by no means the first time human society has experienced, or caused, such shifts. As civilisations spread across the globe, with exploration, colonisation, and most recently globalisation, the environment has always been altered (Weiss & McMichael, 2015). Hand in hand with these changes come complex challenges to human health and safety.

Today, these challenges include urbanisation, population density, poverty, long distance air-travel and trade, political conflict usually affecting those most vulnerable, and the subject of much international debate: climate change (Weiss & McMichael, 2015). These new factors of the modern era affect the dynamics of infectious diseases and human hosts, leading to the re-emergence of old scourges but also to the appearance of apparently new pathogens (Weiss & McMichael, 2015). But there has also been a sharp, alarming increase in the frequency of disasters, both natural and technological, since about halfway through the last century (Leaning & Guha-Sapir, 2013).

None of these exist in isolation, but are linked by the environment and the culture we exist in. It is unlikely that the current trends in disaster frequency will plateau any time soon, and it is equally unlikely that we will stop seeing new infectious diseases emerge and re-emerge (Kouadio, 2012). To be better prepared for the future challenges in infectious disease epidemiology and disaster management, an understanding of what has come before is necessary. This research aims to provide a new perspective on the complex nexus between natural disasters and infectious diseases, and to improve the way they are dealt with in the future.

1.1 The challenges of a changing environment

1.1.1 A brief history of natural disasters

The Center for Research on the Epidemiology of Disasters (CRED), based in the School of Public Health of the Université Catholique de Louvain, Brussels, maintains records of some 22,000 disaster events – of all types – that have occurred worldwide since 1900. Of these, almost 13,000 (56%) are defined as 'natural disasters' (CRED, 2017). While in a time of leaps in technology, a vast number of disasters are caused by technological failures (37%), humanity remains vulnerable to the whims of nature (Table 1.1).

Table 1.1: Number of disasters recorded globally between 1900-2016 (CRED, 2017)

Disaster type	Global n of disasters
Biological n (%)	1494 (6.60)
Climatological n (%)	1113 (4.90)
Complex n (%)	14 (0.07)
Geophysical n (%)	1630 (7.20)
Hydrological n (%)	5432 (24.00)
Meteorological n (%)	4515 (20.00)
Technological n (%)	8402 (37.20)
Total	22600

With climate change becoming an increasingly serious issue, only aggravated by our own behaviour, natural disasters are expected to increase in the future – in both frequency and magnitude (Leaning & Guha-Sapir, 2013). Since its establishment in 1973, CRED has collected data on the global burden of disasters. Gathering data from recorded disasters back to the turn of the century, the database has now been collecting real-time data since the 1970s. A staggering, evidence-based, increase in the frequency of natural disasters can be observed in the 1980s and 1990s (Figure 1.1).

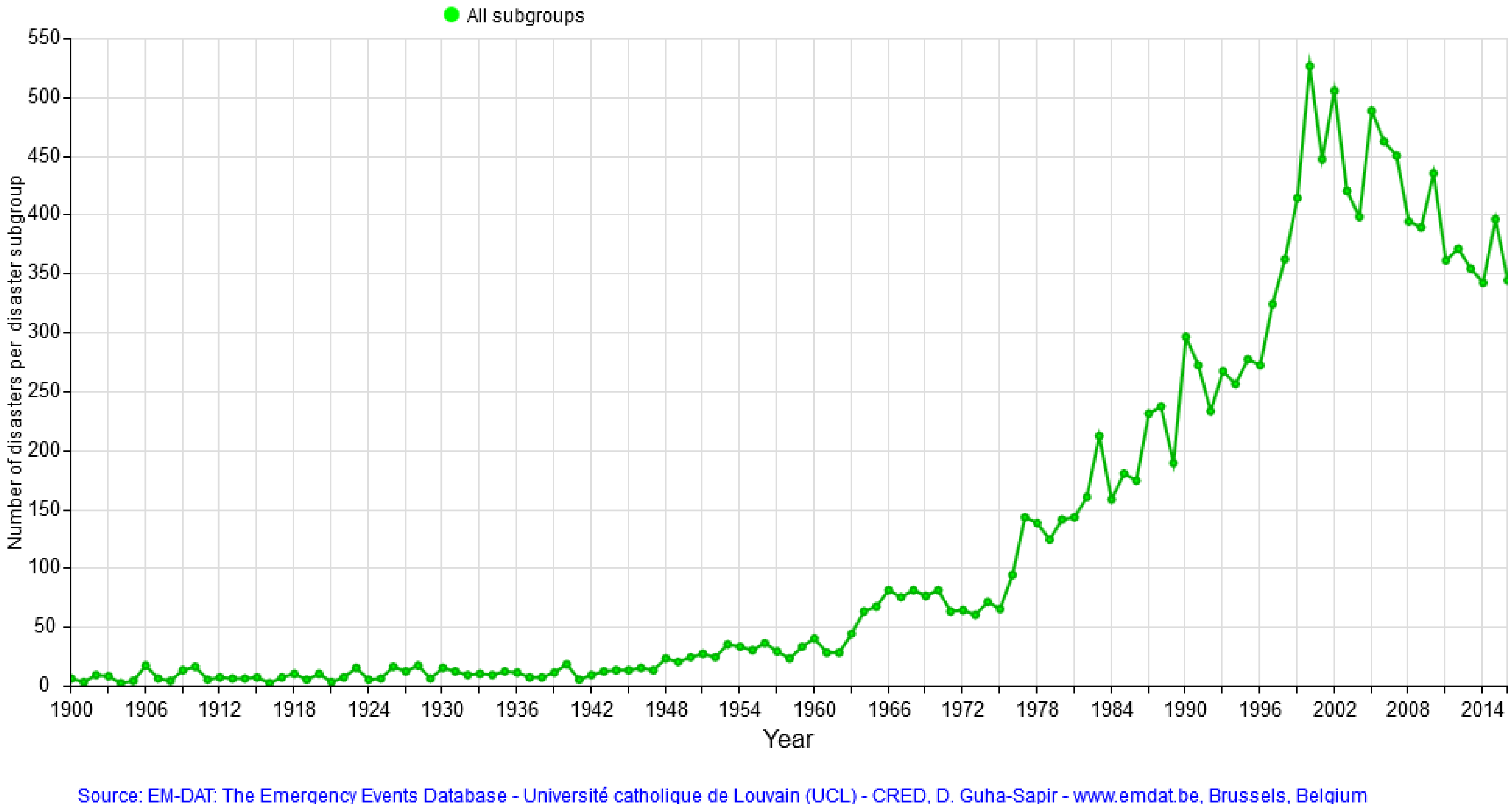


Figure 1.1: Natural disasters trend 1900-2016, constructed via EM-DAT.

Not only have natural disasters increased in their frequency, but also in their impact. Higher population densities mean that more people are affected when a disaster strikes, and while the mortality rate of natural disasters has decreased in past decades, the number of people who are affected – and subsequently struggle with the consequences of natural disasters – has dramatically increased (Kouadio, 2012). The latter are the people who will have to deal with the challenges of managing the aftermath of a natural disaster, who will have to survive in often harsh conditions of temporary shelters – exposed to overcrowding, malnutrition, poor access to hygiene and sanitation (Noji, 2005a). These are the people this research will focus on.

1.1.2 Emerging infectious diseases in the modern world: a summary

Just as natural disasters have seen a dramatic increase in recent history, a raft of apparently new infectious diseases have emerged in a changing environment. Recent reviews show that over 70% of emerging infectious diseases are zoonotic in origin (Taylor, Latham, & Woolhouse, 2001). Diseases such as Acquired Immune Deficiency Syndrome (AIDS), bovine spongiform encephalopathy (BSE), *Escherichia coli* infection, hantavirus pulmonary syndrome, and pandemic influenza have emerged due to changed interactions between humans and the environment (Weiss & McMichael, 2015). Infectious diseases remain among the leading causes of disability adjusted life years (DALY) – years of life lost due to disability, illness or death (WHO, 2008).

Changes in the environment and changes of culture and society influence the presence of infectious diseases. These changes resulted in a rise in drug resistance among pathogens, introducing multi-drug resistant strains of tuberculosis (WHO, 2014b) as well as hospital infections such as methicillin-resistant staphylococcus aureus (MRSA) (Boucher & Corey, 2008).

1.2 Introduction to the disaster and disease nexus

Given the importance of the physical environment to the dynamic of infectious diseases, it is to be expected that a drastic altercation of the environment – such as a natural disaster – will have an impact on this dynamic. That is the nexus where natural disasters and infectious diseases intersect, and create a new layer of challenges to take into consideration when preparing to manage either of the two. Despite this nexus being known for decades, the full extent of it and the complexity involved in the interaction between disasters and disease remains a subject of research and has not yet been fully understood (Kouadio et al., 2012). To determine the true risk of infectious disease after disasters, all factors of this interaction must be known – and the complexity of this issue creates obstacles to disease management after disasters.

A number of issues have persisted for decades when it comes to dealing with infectious disease after disasters. While a clear idea of which diseases can be expected after certain types of disasters exists (Linscott, 2007), in the acute response to disasters there remain issues that need to be addressed. The lack of clear communication and coordination between relief organisations was first raised as a problem 40 years ago (Lechat, 1976) but is still consistently brought up in recent research on disaster response (Kouadio et al., 2012; Leaning & Guha-Sapir, 2013; Noji, 2005b). Similarly, the transition from emergency response to routine care and infrastructure has been shown to be in need of improvement (Noji, 2005b) – especially in the light of findings that suggest some infectious disease outbreaks may be delayed for up to a year. A prime example for this is the cholera outbreak that struck Haiti over 9 months after the earthquake in 2010.

In this thesis, an in-depth look at the nexus between natural disasters and infectious diseases is taken, in order to gain insights into the dynamics of the two, and to offer understanding that may perhaps, in the future, facilitate response efforts to the threat of infectious disease in the aftermath of a disaster. A key concept in the understanding of this dynamic is risk, and the factors influencing this risk (Irwig, Irwig, Trevena, & Sweet, 2008). In the upcoming chapters, the analysis of disease risk after disasters will return, as well as an understanding of the factors influencing the risk and vulnerability of the people exposed to natural disasters.

1.3 Research aims

It is the overarching aim of this research to improve on current understanding of the intersection of natural disasters and communicable diseases outbreaks. Within this aim, the research objectives are established:

I. The identification of infectious diseases relevant to post-disaster management.

II. Understanding the factors influencing the dynamic of infectious diseases in the aftermath of disasters.

III. The construction of a database integrating natural disasters and infectious diseases.

IV. The development of a methodology to appropriately analyse the data.

V. An understanding of the differences in risk predictions for different diseases by type of disaster, disaster magnitude, and geographic region.

VI. To identify areas of future research towards an improved response to the threat of infectious diseases after natural disasters.

For this purpose, data have been drawn from a range of sources, including the CRED and the World Health Organization, as well as publications concerning recent disaster events and disease outbreaks, to integrate a large database on the effect of natural disasters on infectious diseases. Data were included from sources spanning the past century. The associated analysis has been approached from several directions, including geographical region, disaster magnitude, and different disease profiles including morbidity and mortality data over time. Diseases relevant after natural disasters have been identified through published literature.

With this data, systematic analysis have been performed, pooling existing findings to quantify the conditions of populations displaced by disasters. It is an aim to create profiles for different types of disasters in order to allow for improved preparedness in the future.

It is hypothesized that disasters of a larger magnitude and leading to population displacement into temporary shelters – leading to overcrowding – will have a quantifiable effect on incidence of certain infectious diseases in the population.

1.4 Thesis Outline

This is a thesis in two parts. The first part focuses on the published literature on infectious diseases after disasters in the recent past. Looking at the history of that nexus from the early 1900s, this first part aims to give insight into the existing knowledge on infectious diseases after natural disasters, as well as establish a first estimate of risk of disaster and disease in Chapter 3, which will serve to inform the second part of the thesis.

Chapter 2 contains an in depth, qualitative review of the existing literature and research on natural disasters and infectious diseases, to provide a context for understanding the results calculated in later chapters.

Chapter 3, the first empirical chapter, provides a quantitative approach to the literature, pooling data from previous research in a meta-analysis variant to estimate relative risks of disease after disasters and to identify factors influencing the effect of natural disasters and infectious disease on an affected population.

The second part (Chapters 4 through 8) of this thesis consists of empirical chapters investigating the statistical association between certain infectious diseases and natural disasters. Chapter 4 outlines the methodology utilised in the chapters following it, to determine the association between natural disasters and infectious diseases.

Chapter 5 through 8 then provide empirical evidence of the association between natural disasters and cholera (Chapter 5), malaria (Chapter 6), tuberculosis (Chapter 7) and the co-infection of Human Immunodeficiency Virus (HIV) and tuberculosis (Chapter 8).

In Chapter 9, the findings of this thesis will be discussed and placed in the context established in the literature review, providing reflections on the results as well as potential future actions and research possibilities in the context of disaster response. Chapter 10 will offer concluding recommendations and remarks to close this research and open up new potential direction for future research.

Chapter 2: Literature Review

Chapter Contents

2.1 Introduction

Natural disasters, over the course of the last century and earlier, have remained largely unpredictable in their occurrence. Whereas complex political emergencies occur under certain human-made circumstances, natural disasters can strike anywhere, at any time. Loss of property, internal displacement, physical and emotional injury and trauma, and damage to local infrastructure follow in the wake of such disasters, whether they strike in developing or industrialised regions. And while the acute effects of such disasters may pass quickly, the long-term effects of such events may last for weeks, months, or even years, and may affect millions of people. Recovery after natural disasters may be slow depending on the severity of the event, and relief efforts often end after only a few weeks – leaving the affected population alone and vulnerable in the struggle to rebuild the damaged infrastructure (Kouadio et al., 2012; Noji, 2005b).

There is a lasting public health effect of population displacement in consequence of natural disasters. This is rarely restricted to the displaced, but can lead to adverse health outcomes in the general population as well. The World Health Organization (WHO) has identified diarrhoeal diseases, acute respiratory infections (ARI), measles, malnutrition and malaria as the five most common causes of death after acute natural disasters (Linscott, 2007).

Populations displaced after disasters are at increased risk of epidemic disease. Displacement conditions such as overcrowded temporary shelters, poor quality water supply and sanitation facilities, and shortage of food are part of a long list of factors that adversely affect the health of such populations (Leaning & Guha-Sapir, 2013). Pre-disposing socio-economic factors such as vaccination coverage, access to clean water prior to the disaster (Wiwanitkit, 2010), access to regular healthcare and general knowledge about disease transmission and prevention (Connolly et al., 2004), as well as geographic factors such as climate, vector breeding grounds, extreme weather conditions, and frequency of disasters can further confound the health outcomes in the affected population (Watson, Gayer, & Connolly, 2007). This may facilitate the spread of communicable diseases within and beyond the displaced population. In some cases, this can lead to severe epidemics of communicable diseases with high levels of morbidity and mortality as the surrounding circumstances can hinder proper treatment for otherwise manageable diseases.

This chapter aims to review and summarise research at the intersection of natural disasters and infectious disease over the past century, setting the scene for the research conducted in the following chapters. Literature was identified via the US National Library of Medicine's PubMed, through use of the search terms 'natural disaster' AND 'epidemiology', 'communicable diseases', infectious diseases' and a number of diseases commonly mentioned in relation to natural disasters. The search terms used and the numbers of publications found are summarised in Appendix 1. The publications were read and the most relevant ones providing insight into the dynamics of disaster and disease were sampled for this review, and additional papers were identified through cross-references.

2.2 A world of natural disasters

Plate 2.1: natural disasters in Erice, Sicily, (Fairley, 2011). 'Pioggia' indicates strong rain; 'teremoto' literally translates to 'moving earth' or earthquake; 'idem' indicates 'same' so there were heavy rainfalls in 1792, in 1818, and in 1834; 'cholera' may refer to actual cholera, as this was only a few years after the second cholera pandemic, or it may be used as an umbrella term for a plague of severe diarrhoeal disease not necessarily caused by the same pathogen.

Natural disasters have always been a part of the human experience. Plate 2.1, captured in a church in the town of Erice on Sicily, shows a chronicle of events affecting the region over a number of years – listing major events such as heavy rainfall, earthquakes, and epidemics of cholera or cholera-like illness over time. Eventslike the eruptions like Mount Vesuvius that wiped out the culture of Pompeii (History, 1999) in 79 AD or the biblical flood widely hypothesised to be a dramatization of a flood from the Black Sea (Giosan, Filip, & Constatinescu, 2008) have often been considered as divine intervention, as outside of human control and thereby unpredictable (Steinberg, 2000). Since then, the study of natural disasters has progressed to acknowledge a human factor as confounder in the effect of natural disasters.

It has been argued that natural disasters are in fact not ‘natural’ in that they occur outside of human influence, but are culturally and historically constructed events that gain their status as ‘natural disaster’ because of their impact on humanity (Mauch & Pfister, 2009). This impact may be a direct result of a society’s choice to ignore the risk and deliberately settle in a region prone to disaster, building the risk of destruction themselves (Steinberg, 2000). It has become part of ‘disaster culture’ to settle in regions of natural hazards – like building our cities on the foot of active volcanos, or around rivers prone to flooding – for various reasons ranging from tradition to the fact that anywhere else seems even more hostile as an environment to settle in (Lechat, 1976). A nature event becomes a natural disaster only through its interaction with human society, when revealing “social vulnerability, and consequent damage to the physical and social fabric exceeds the ability of the affected community to recover without assistance” (Pelling, 2003, p.75). As such, natural disasters always have a social component to them and while they can strike everywhere, they will not have the same effect on the population of for example Tokyo as they will have on the population of Manila; even within one population, the effect may strongly differ (Pelling, 2003). A recent example of this may be the different effects of a tsunami in a socially relatively more vulnerable, rural setting in Indonesia, India or Thailand as compared with Japan’s more urbanized environment.

Natural disasters are treated in a very different way from wars and political conflict. While arguably just as many, if not more, people are affected by natural disasters — according to UN figures, 100 million people are affected by natural disasters on a yearly basis — our disaster memory is surprisingly short-lived (Mauch & Pfister, 2009). Over the course of history, perception of disasters has turned from a religious nature to a very practical nature, and at least in western cultures the affected populations go about their daily lives as soon as possible (Steinberg, 2000).

2.2.1 Natural disaster trends

Natural disasters are broadly grouped as geophysical, meteorological, hydrological, climatological, and biological disasters. The classification of disaster types most widely accepted and used has been proposed by the Center for Research on the Epidemiology of Disasters (CRED) in their Emergency Events Database (EM-DAT) (Table 2.1) (CRED, 2017) .

Table 2.1: General Classification of natural disasters (Source: CRED/Emdat).

Disaster Type	Definition
Geophysical	Events originating from solid earth
Meteorological	Events caused by short-lived/small to meso scale atmospheric processes (in the spectrum from minutes to days)
Hydrological	Events caused by deviations in the normal water cycle and/or overflow of bodies of water caused by wind set-up
Climatological	Events caused by long-lived/meso to macro scale processes (in the spectrum from intra-seasonal to multi-decadal climate variability)
Biological	Disaster caused by the exposure of living organisms to germs and toxic substances
Technological	Man-made disasters such as industrial and transport accidents
Complex	Major famine situations for which the drought was not the main causal factor

The CRED was established in 1973 to provide data and information on the impact of natural disasters on vulnerable populations (CRED, 2015). The EM-DAT database aims to provide an objective basis for analysis of vulnerability and disaster impact, to inform decision-making in disaster response. Over the course of the past 40 years, CRED has collected data on natural disasters worldwide – and integrated retrospective data from historical disasters as far back as the early 1900s. Figure 2.1 shows the trends of natural disasters over the past century, taken from EM-DAT, with a beginning increase of frequency in the 1960s, and a steep increase in all disaster types in the past 30 years. The figure shows the disaster subtypes, summarised in Table 2.1, showing upward trends of increasing natural disasters.

In part, this increase may be attributable to improvements in documentation – it is noteworthy that the sharp increases only began when EM-DAT was collecting disaster data in real-time, rather than integrating historic material. A reporting bias may be at play here, as EM-DAT could only collect historical data on disasters that were reported, and if no reporting was done, there was no full record of the events, hence only the most impactful disasters would find their way into the database prior to 1973. But that may only account for part of the effect. Contemporary disaster and climate change literature agrees that there has been an increase in disaster frequency in the recent past, compared to other historic periods (Leaning & Guha-Sapir, 2013). The increase in technological disasters may largely be due to technology's stronger role in recent history, the increase in the remaining disasters may relate to changes in climate, given that the disasters types displaying the strongest increase are climatological and hydrological in nature. A few interesting observations can be made upon examining Figure 2.1. A notable spike can be seen for geophysical disasters around 1907 – which likely signifies the San Francisco Earthquake of that year. Spikes of technological disasters can be seen in the years of World War II, 1939-1945. Other levels remained low throughout these early years of the database. The sharp spike in hydrological disasters occurring in 2005 may represent the South-East Asia tsunami.

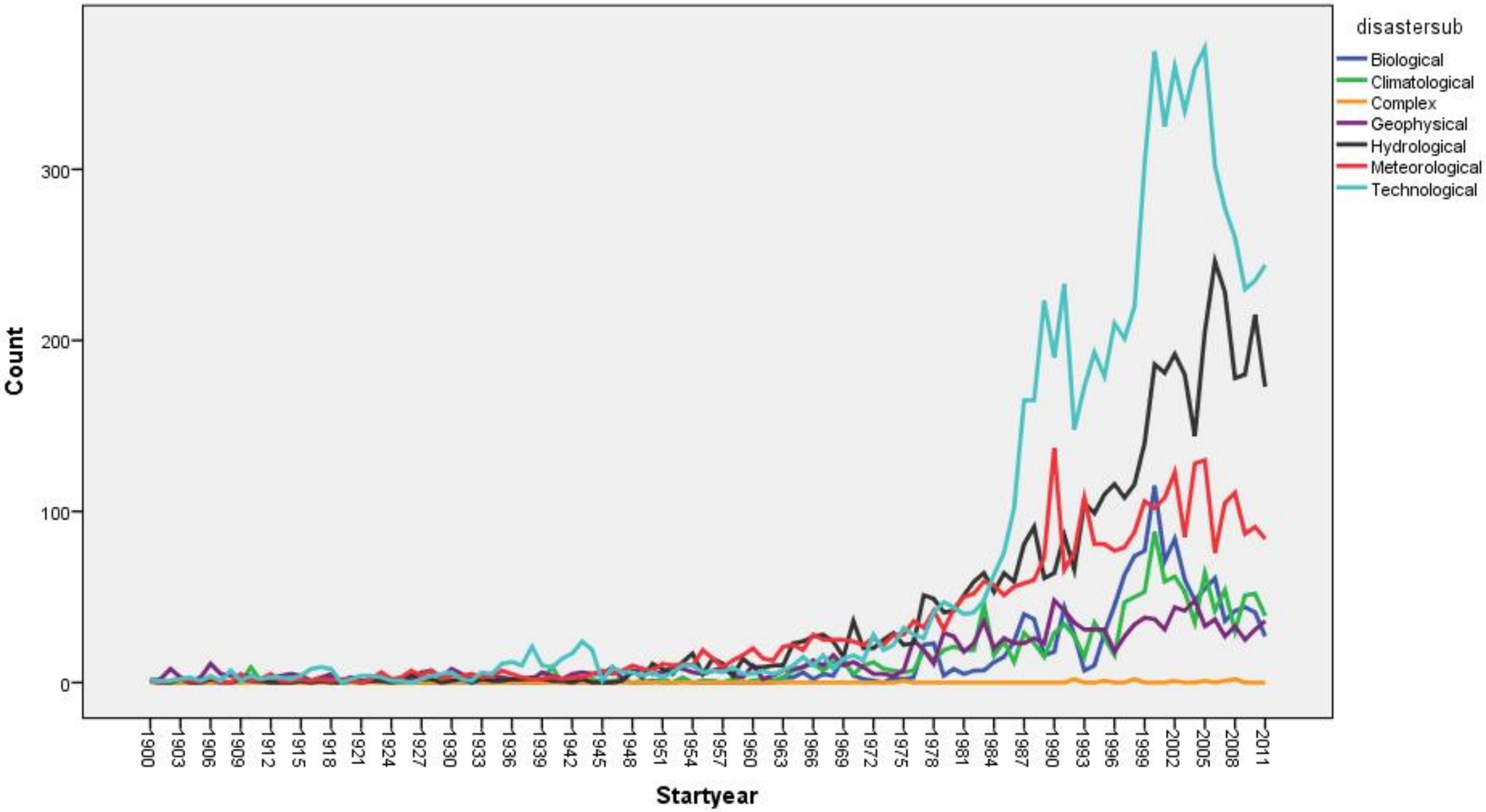


Figure 2.1: frequencies of natural disasters by subtype, 1900-2011, (source: EM-DAT).

For the purpose of this and the following chapters, disasters will be summarised by their subtype as proposed by EM-DAT. The present review does not aim to include every natural disaster, but focuses specifically on natural disasters that had a known outbreak of infectious disease in the aftermath, as the comparison between disasters with and without disease outbreaks will be the focus of chapters 3-8. An in depth investigation into the linkage between disaster and disease in the literature will be presented in sections 2.2.2 and 2.2.3.

Between 1900 and 2016, the database recorded a total of 22,600 natural disasters worldwide, gathering information on geographical location (country and area), economic impact, and affected population. 14,144 of these natural disasters were recorded from 1954 onwards. Disasters are included into the database, as per the definition on the EM-DAT website, if:

- Ten (10) or more people reported killed
- Hundred (100) or more people reported affected
- Declaration of a state of emergency
- Call for international assistance

(CRED, 2015)

An upward trend can be seen in Figure 2.2, the summarised figure of all natural disasters between 1900 and 2011 from the EM-DAT database (excluding technological disasters and complex emergencies). There has been a trend of disaster numbers almost doubling every decade since 1960, reaching a peak in the year 2000, with 526 natural disasters. After 2000, there has been a slow decline in the recorded number of natural disasters, and by 2016 the total had reduced to 344 – a level similar to 1997 and 1998. A disaster in the last century affected on average 973,038 people and killed an average 4,458.70 (Table 2.2). Interestingly, as Figures 2.3 and 2.4 show, the number of disaster-affected people has increased – likely due to increased population size and density – while the number of people killed by natural disasters has reduced dramatically, likely due to improved coping mechanisms, medical care, and disaster response. Globally, of the total number of disasters, 37% of disasters in the last century were technological in nature, and hydrological disasters were the second most common (23%) (Table 2.3). The following paragraphs will offer brief overviews of disasters throughout the past century, providing trends and frequencies of natural disasters. Technological and complex emergencies will be mentioned, but will not be reviewed in detail at this point.

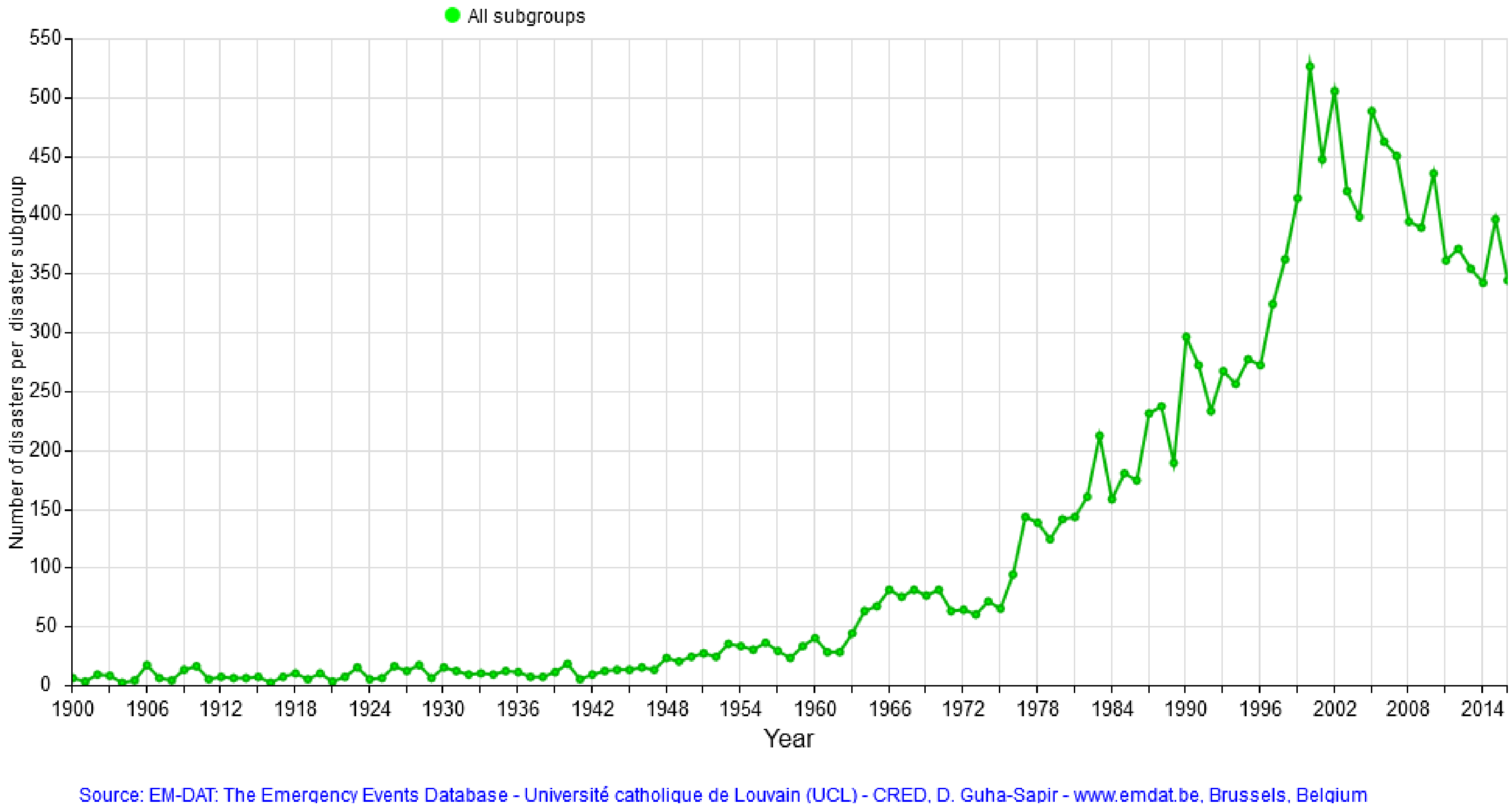


Figure 2.2: Natural disasters trend 1900-2016, constructed via EM-DAT.

Table 2.2: mean affected population and mortality per disaster for types of disasters, by geographical regions. Regions were defined by World Health Organization regions. (source: EM-DAT).

	Global	Africa	Americas	Eastern Mediterranean	Europe	South East Asia	Western Pacific
Disasters total							
Mean mortality	4,458.70	712.86	449.70	735.19	5,582.36	12,484.31	9,349.25
Mean affected	973,038.00	245,755.20	219,108.60	294,942.00	73,964.72	3,438,700.00	2,724,221.00
Biological							
Mean mortality	11,356.57	987.76	673.83	482.08	89,334.32	47,208.55	22,811.32
Mean affected	55,160.82	33,978.04	50,605.53	8,565.43	301,985.40	54,345.86	39,715.50
Climatological							
Mean mortality	55,882.60	14,732.37	36.70	17,263.73	23,542.67	280,005.60	106,212.80
Mean affected	4,406,369.51	1,626,063.00	820,441.40	2,204,936.00	404,567.60	29,834,511.00	6,358,571.00
Complex							
Mean mortality	2,805,000	---	---	---	5,000,000.00	610,000.00	---
Mean affected	1,514,316.46	598,750.00	7,750.00	2,018,607	3,500,000.00	2,946,133.00	900,000.00
Geophysical							
Mean mortality	3,195.92	167.86	2,279.48	2,822.78	2,338.44	3,127.01	6,528.27
Mean affected	240,393.13	37,737.36	168,862.60	116,096.30	73,901.99	491,483.00	529,817.50
Hydrological							
Mean mortality	3,139.88	53.09	152.38	175.22	80.48	515.15	18,921.70
Mean affected	1,533,900.00	109,292.20	108,739.62	435,359.90	54,393.87	4,414,884.00	6,106,654.00

Table 2.3: Disaster frequencies 1900-2016, by disaster type, by WHO region via EM-DAT (CRED, 2017).

	Global	Africa	Americas	Eeastern Mediterranean	Europe	South East Asia	Western Pacific
Biological n (%)	1494 (6.60)	799 (20.70)	174 (3.50)	150 (7.00)	74 (2.10)	182 (5.30)	115 (2.40)
Climatological n (%)	1113 (4.90)	299 (7.75)	303 (6.10)	65 (3.00)	163 (4.70)	84 (2.50)	199 (4.20)
Complex n (%)	14 (0.07)	4 (0.10)	2 (0.04)	2 (0.10)	2 (0.06)	3 (0.10)	1 (0.02)
Geophysical n (%)	1630 (7.20)	91 (2.35)	392 (7.90)	195 (9.10)	305 (8.80)	244 (7.00)	404 (8.50)
Hydrological n (%)	5432 (24.00)	833 (21.60)	1271 (25.70)	541 (25.30)	816 (23.50)	948 (27.80)	1023 (21.50)
Meteorological n (%)	4515 (20.00)	245 (6.35)	1377 (27.80)	130 (6.10)	753 (21.65)	534 (15.70)	1476 (31.00)
Technological n (%)	8402 (37.20)	1588 (41.150)	1432 (28.90)	1056 (49.40)	1365 (39.25)	1414 (41.50)	1546 (32.50)
Total	22600	3859	4951	2139	3478	3409	4764

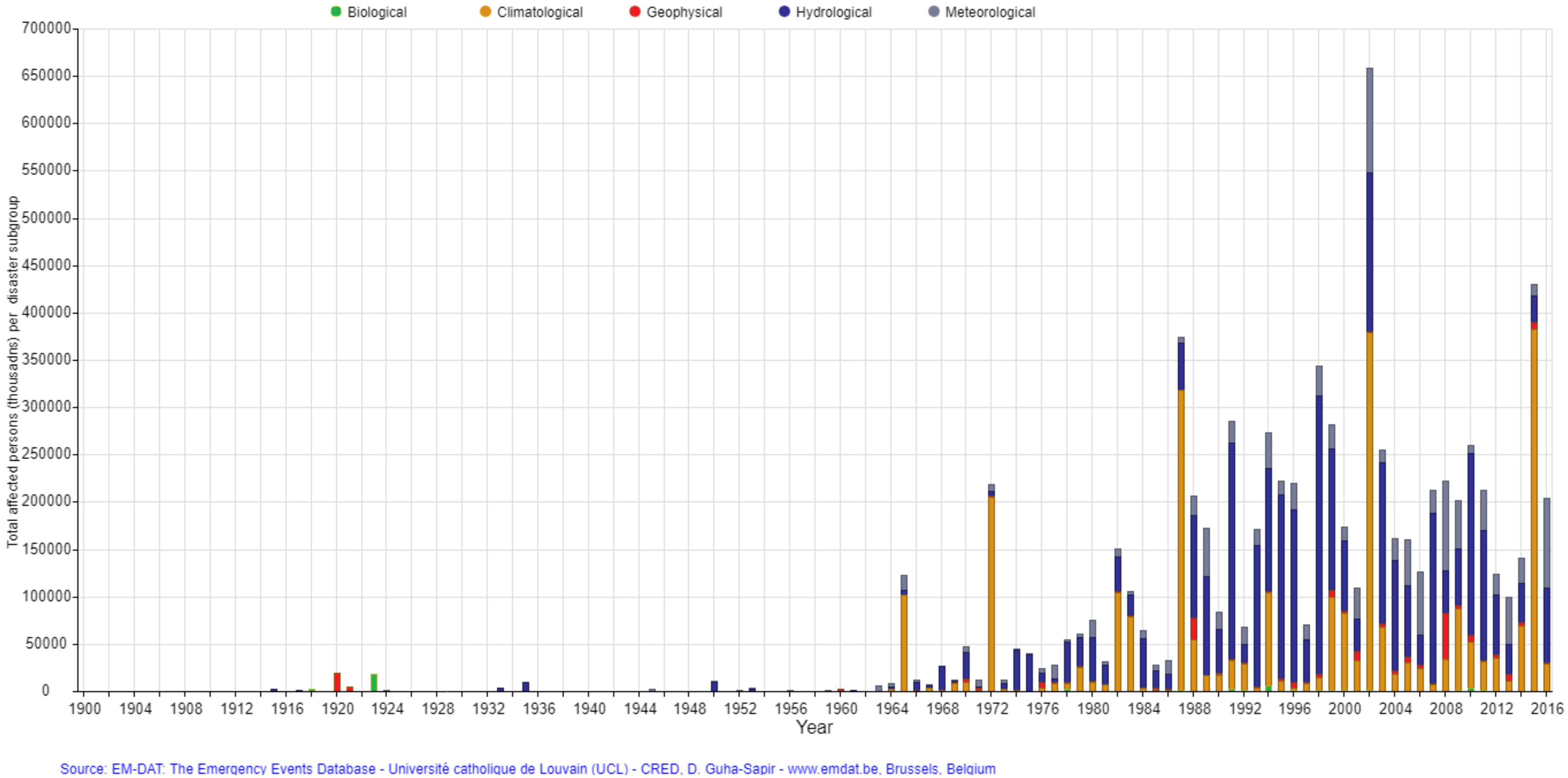


Figure 2.3: Total affected persons by natural disaster subgroups, 1900-2016, constructed via EM-DAT.

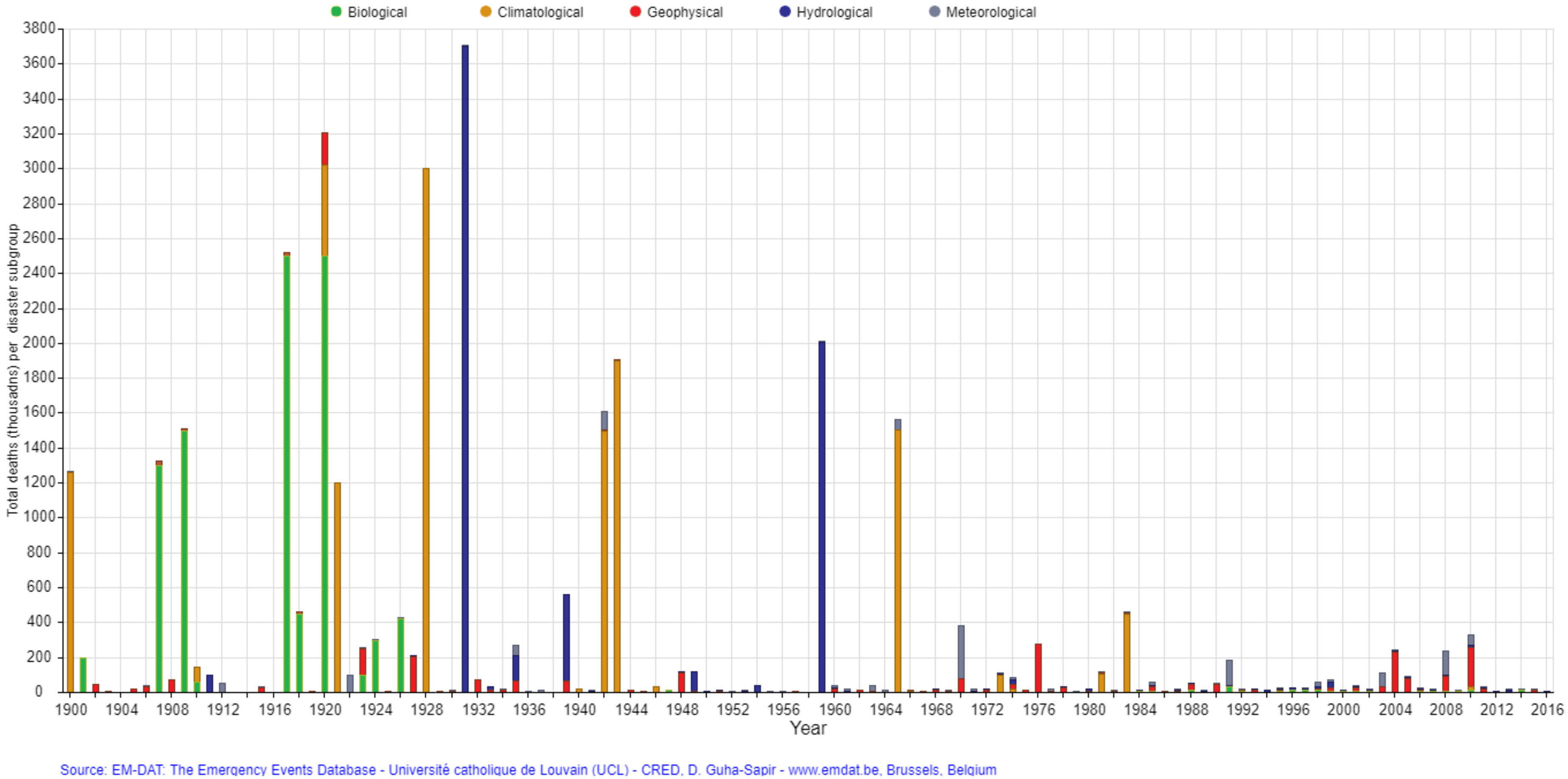


Figure 2.4: Total deaths by natural disaster subgroups, 1900-2016, constructed via EM-DAT.

Climatological disasters

Globally, about 5% of recorded natural disasters in the period 1900–2016 have been climatological in nature, including events caused by gradual changes in climate conditions (Table 2.3). This subgroup includes droughts, wildfires, and extreme temperatures, whereas such events as severe rains leading to flooding (i.e. monsoon rains, El Niño) are usually classed under hydrological disasters. In African countries as well as the Americas Region, up to 7% of disasters are climatological. Climatological disasters may be the result of long-term changes in climate, and may go on for extended periods of time, and are thus more complex to respond to than acute disasters (Wilhite, 1993). Despite the relatively small percentage of climatological disasters, these disasters have the most severe effects on the populations they strike. On average, a single climatological disaster affects almost 4.5 million people – causing food insecurity and the malnutrition that goes along with it, as well as infectious diseases discussed later in this chapter – and kills over 55 thousand people, often over the course of years (Stanke, Kerac, Prudhomme, Medlock, & Murray, 2013).

In the year 2000, there were 57 climatological disasters, the highest frequency to date (Figure 2.5). Spikes in climatological disasters can be seen in 1910, 1940, 1983, 2000, and 2015, and upon closer examination, the spikes are largely caused by severe droughts. The nine occurrences in 1910 were a drought affecting several countries in Africa (Burkina Faso, Cabo Verde, Chad, the Gambia, Guinea-Bissau, Mali, Mauritania, Niger, and Senegal) that lasted 4 years (Masih, Maskey, Mussá, & Trambauer, 2014), as well as a wildfire in Canada. A disaster that lasts for several years is only counted in the year it began. The same countries in the Africa Region were again affected by drought in 1940. In 1983, there were several drought events, affecting not only African countries, but also Asian countries in the summer monsoon (EMDAT). 2015 had mostly droughts as well, in African and South-East Asian countries. Still, climatological disasters are relatively rare in comparison to other disasters discussed in this section.

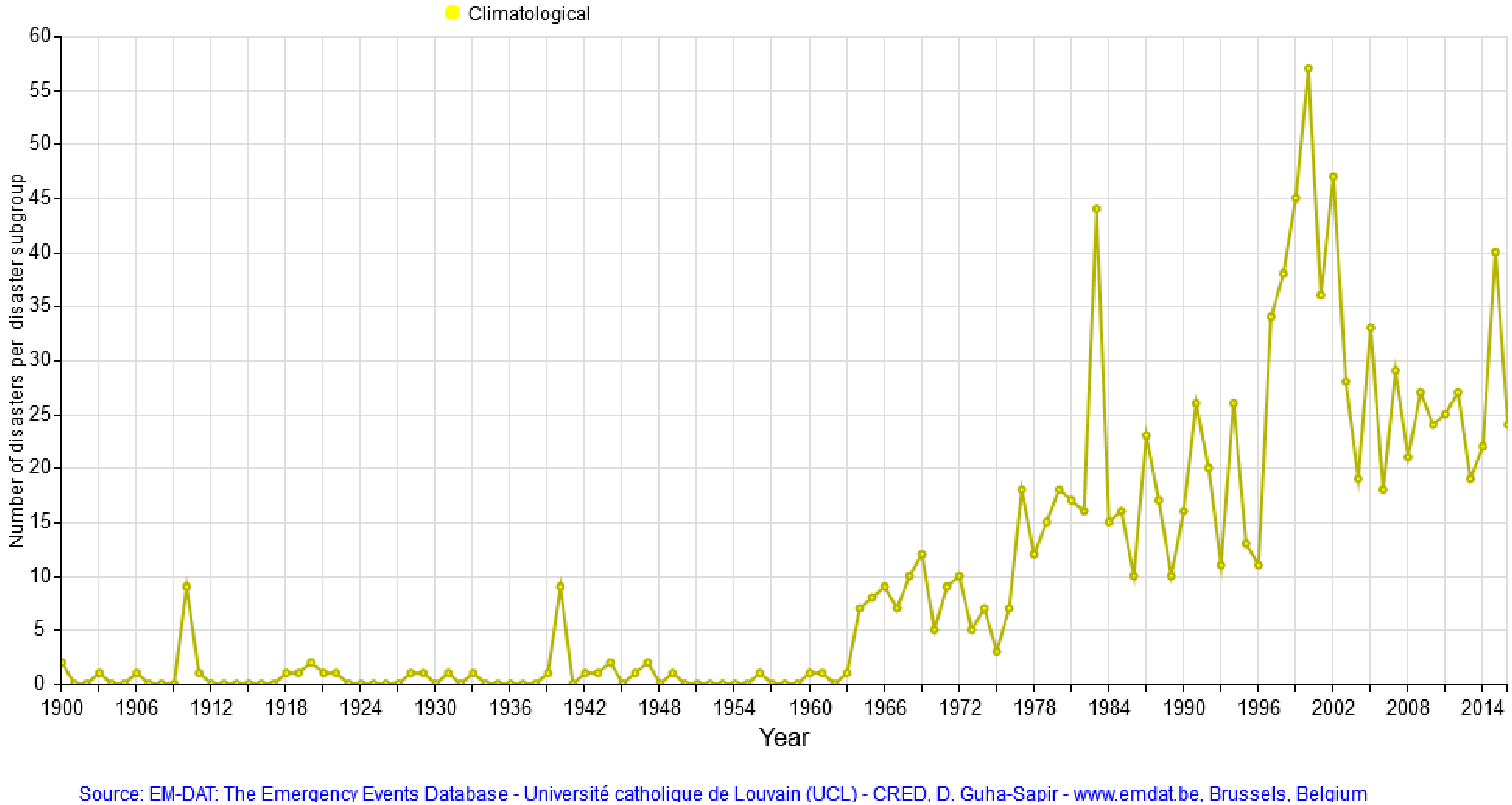


Figure 2.5: Climatological disasters trend 1900-2016, constructed via EM-DAT.

Geophysical disasters

As described in Table 2.1, geophysical disasters include earthquakes, volcanic activity, and tsunamis, as well as landslides, avalanches, rockfall and subsidence. Around 7% of natural disasters in the past century or so have been classified as geophysical (Table 2.3). The Africa Region has been least affected by this type of disaster, with only about 2% of events there being geophysical (Table 2.3). An average 240,000 people are affected globally per geophysical event such as an earthquake, and an average 3,000 persons are killed (Table 2.2). As shown in Figure 2.6, geophysical disaster frequencies have been relatively stable until the slow increase beginning in the 1940s and the sharp increases starting in the 1970s – leading to the levels we currently observe. In 1990 and later in 2004, there were spikes in geophysical disasters, with 48 events in these years respectively. In 1996, there was a drop in numbers to frequencies as low as 18 (the last time it was this low was 1981). In the past 5 years, levels have been fluctuating between 35 and 25 events per year.

The 2004 spike includes the earthquake and tsunami in the South-East Asian region late that year – separate events were recorded in the database for each country affected. The 1990 events were almost all earthquakes, affecting every region, with the exception of five events (two landslides, one avalanche, two volcanic activities leading to ash fall).

There were a few notable geophysical disasters in the recent past that will feature strongly in the chapters to come – namely the South-East Asia Tsunami of late 2004 that affected several countries including India, Indonesia, Thailand, and Sri Lanka, the Kashmir Earthquake in Pakistan 2005, the Haiti Earthquake of 2010, and the Great Japan Earthquake of 2011.

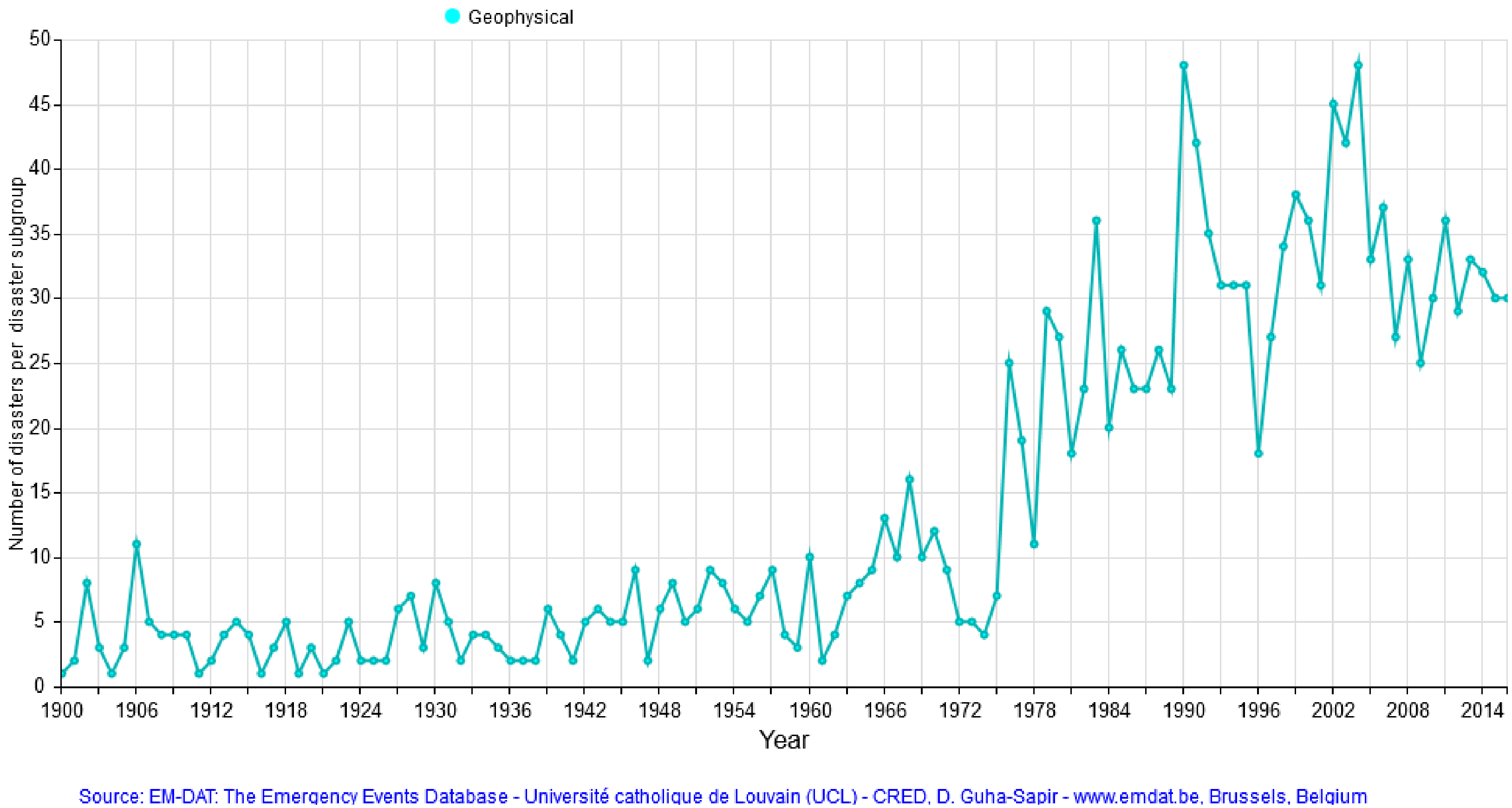


Figure 2.6: Geophysical disasters trend 1900-2016, constructed via EM-DAT.

Hydrological disasters

Hydrological disasters make up the majority of natural disasters, with 24% of the total global disasters in the period 1900-2016, only surpassed by 37% for technological disasters which are not 'natural' (Table 2.3). While for other disaster types, there seems to be at least one region where they are dramatically less or dramatically more relative to the total disasters, hydrological disasters make up around 25% of disasters in all regions, with relatively little fluctuation (Table 2.3). Hydrological disasters include all disasters that are caused by a 'deviation from the normal water cycle' (CRED, 2009), by either increased rainfall, snow melts, or overflowing bodies of water for any reason. As such, flood disasters are prone to cause a great deal of havoc where they strike, causing destruction to property and increased disease risks by altering environmental conditions in favour of disease spread (Ahern, Kovats, Wilkinson, Few, & Matthies, 2005; McCann, Moore, & Walker, 2011). On average, a hydrological disaster affects over 1,500,000 people – the second highest after climatological disasters – and kills 3,000 persons (Table 2.2).

The first real spike in hydrological disasters can be seen in 1926, with 6 events recorded in that year (Figure 2.7). Levels remained very low up until 1945, after which steady increases could be observed. This may relate to inconsistent record keeping prior to World War 2. In 2006, there were a total of 246 hydrological disasters, the peak of the curve, with slightly lower levels since, stabilising around 160 events per year (Figure 2.6). The events of 1926 were four river floods – in Germany, Belgium, India and Romania – and two wet landslides (as opposed to dry landslides, which are recorded as geophysical disasters) in Colombia and France. In 2006, 20 of the 246 events were landslides – the rest were floods, the vast majority of which were riverine.

Floods are regular events in monsoon affected regions in South-East Asia, and El Niño affected regions in South America. Severe flood events in recent history include the 2011 flood in Pakistan, the 2008 flood in Vietnam, and the 2000 floods in Mozambique that affected 5 million people.

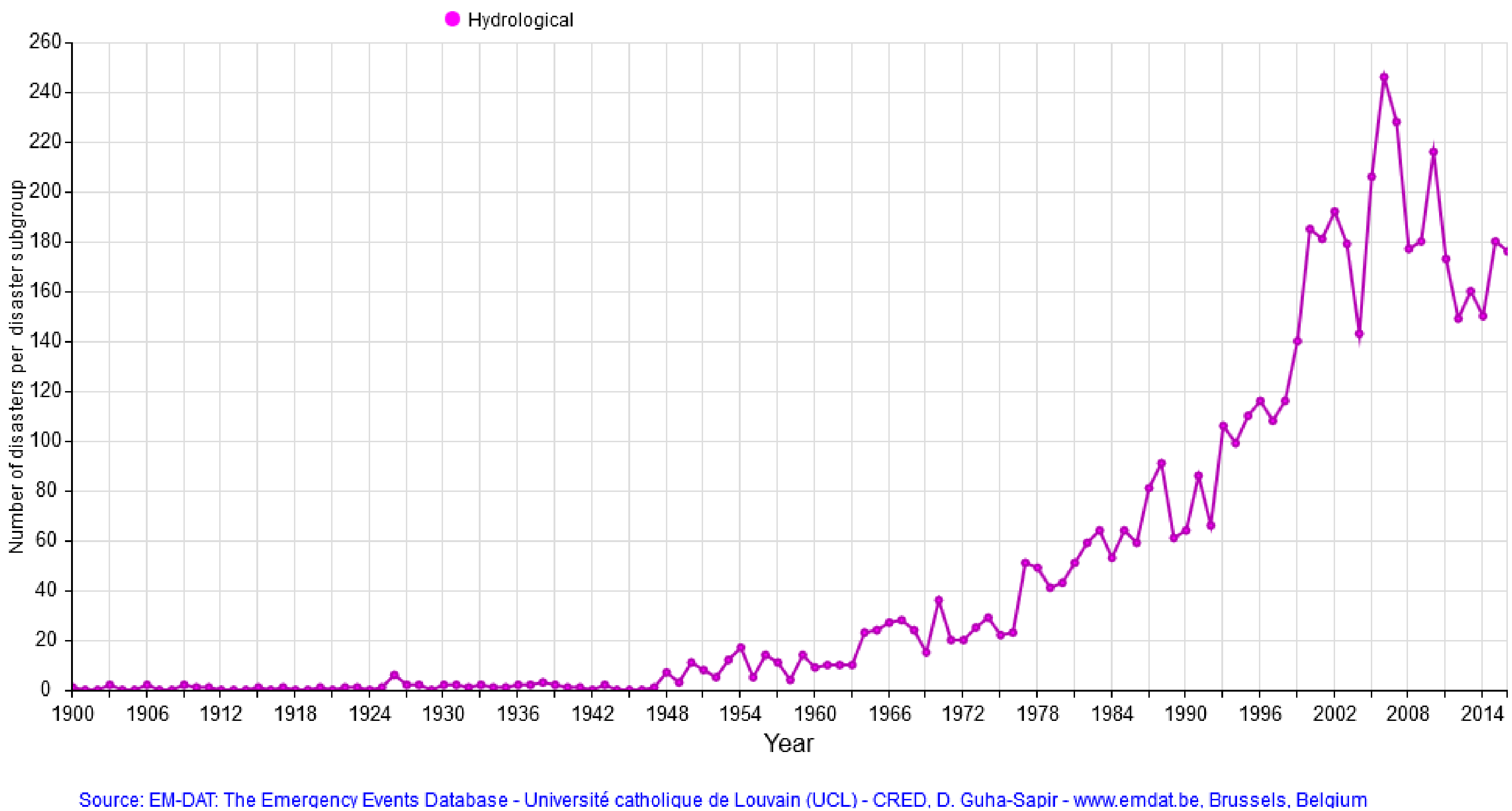


Figure 2.7: Hydrological disasters trend 1900-2016, constructed via EM-DAT.

Meteorological disasters

Meteorological disasters are the second most common type of natural disaster, accounting for 20% of all recorded disasters in the period 1900-2016 (Table 2.3). Between 1900 and 2016, 4,515 meteorological disasters were recorded worldwide. The Americas Region and the Western Pacific Region had higher relative numbers of meteorological disasters. In the Americas Region, almost 28% of disasters were meteorological, in the Western Pacific Region it was 31% of all disasters – in both regions counting over 1,300 events respectively. In the Africa Region on the other hand, only 6% of disasters were meteorological (Table 2.3). Globally, an average 859,032 people are affected per meteorological disaster, and about 900 are killed (Table 2.2). In the Western Pacific Region almost 2 million are affected, and in the South-East Asia Region over 1 million are affected and almost 5,000 killed per meteorological disaster (Table 2.2).

Meteorological disasters have been steadily increasing in frequency since 1945 (Figure 2.8). A first spike occurred in 1990, with 150 events, and has since been in numbers between 100 and 160 events per year.

In recent history, a number of meteorological disasters occurred that will feature in this thesis more strongly. Hurricane Katrina has of course received much attention when it struck New Orleans in 2005; cyclones Aila (India, 2009) and Nargis (Sri Lanka, 2008) also affected large numbers of people, to name only a few of the significant storms in these chapters.

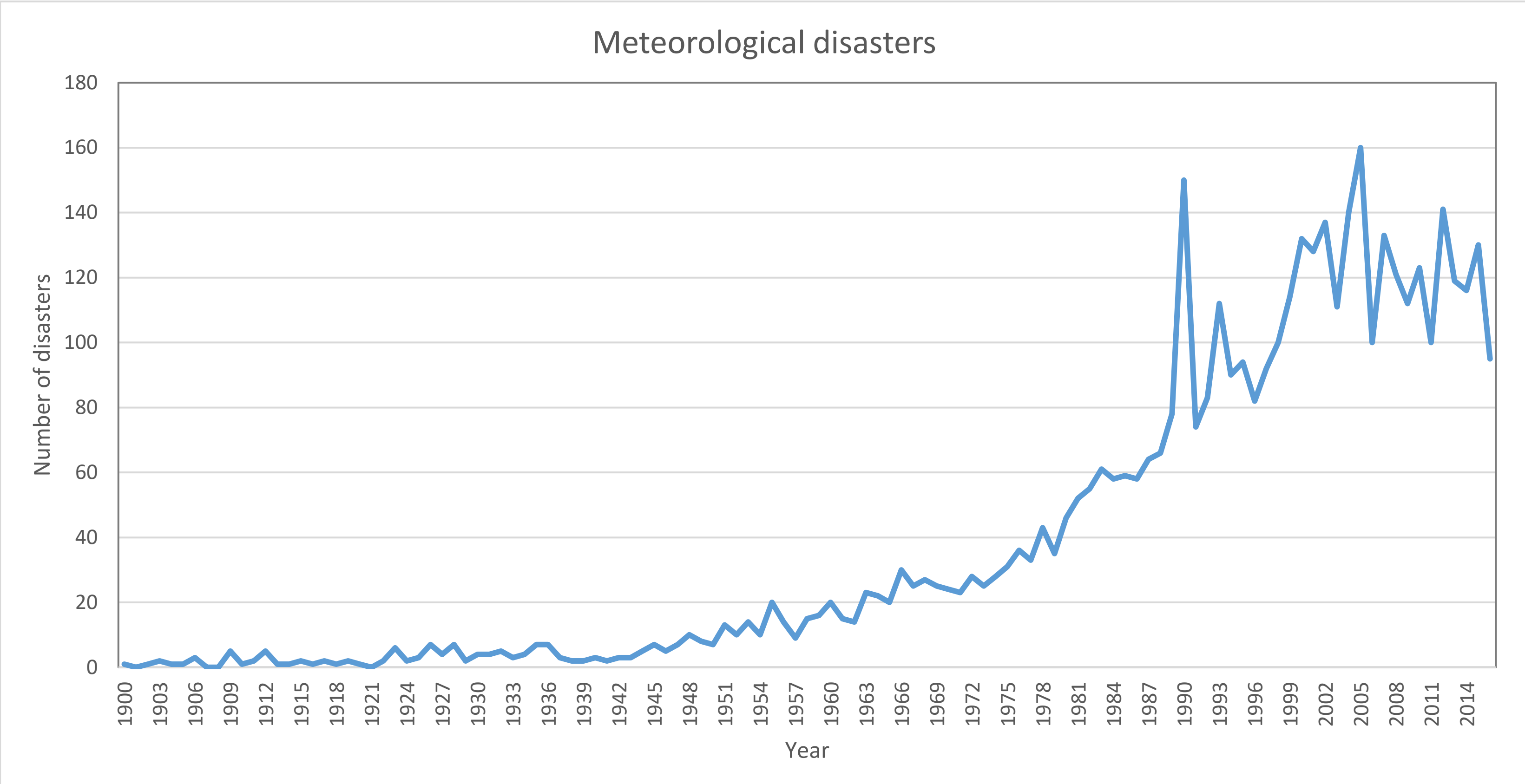


Figure 2.8: Meteorological disasters trend 1900-2016, constructed with EM-DAT data.

2.3 Introduction to infectious disease epidemiology

Much like natural disasters, infectious diseases have been a challenge to humanity for as far back as historic records will take us. What were, in the distant past, attributed to the workings of evil spirits, whims of Gods, or witchcraft, a modern understanding of disease reveals to be caused by microbial pathogens transmitted via various routes (Nelson & Williams, 2014). The history of epidemiology — the study of causes and patterns of disease among the people — in Western medicine begins as early as the 4th century BC. Hippocrates put forward the distinction between endemic and epidemic illness, and he dismissed the notion of evil spirits being responsible for illness, but instead attributed it to factors of the patient's environment (Duncan, 1988; Nelson & Williams, 2014). As will be shown later in this section, the role of the physical environment is still of major importance as a concept in epidemiology today.

The modern concept of epidemiology relies on a population approach to health and illness, rather than an individual perspective (Morabia, 2004). Thus, it allows for the study of disease at the population level, to discover the patterns of transmission. This shift in the view of epidemiology occurred with the advancement of population statistics in the 1600s (Nelson & Williams, 2014). Graunt made tabulations of mortality in London 1662, investigating cause of death, gender distribution, and environmental factors, such as urban vs. rural mortality (Graunt, 1665; Nelson & Williams, 2014). Over the coming centuries, research into causative agents of disease leapt forward, improving the understanding of human health. Starting in 1874, discoveries of such human pathogens responsible for tuberculosis (TB), cholera, diphtheria, tetanus, *E. coli*, botulism and the plague changed the understanding of disease (Nelson & Williams, 2014). Advances in microbiology allowed for the introduction of disease surveillance, using statistical methods to estimate burdens of disease and mortality.

The past century saw the introduction of disease surveillance, genetics, antibiotics and vaccination into the response to and treatment of infectious diseases. This was followed by a widespread euphoria and the belief that infectious diseases would be a thing of the past by the end of the 20th century (Nelson & Williams, 2014). However, just as methods of controlling infectious diseases have evolved, so have diseases (Weiss & McMichael, 2015). The AIDS crisis and the emergence of drug resistant disease strains puts new challenges before epidemiologists, microbiologists and physicians of the 21st century, and makes it clear that the eradication of disease as we know it still remains an objective to strive towards.

In the early 2000s, the WHO reported on the global burden of disease and found over 4,600 million episodes of diarrhoeal diseases worldwide in 2004, being the most common cause of illness (WHO, 2008). Over 400 million incident cases of lower respiratory infections, and over 200 million incident cases of malaria were the second and third most common cause of illness, far outranking any other infectious conditions such as human immunodeficiency virus (HIV), measles, or TB (WHO, 2008).

2.3.1 Risk factors of infectious disease

With advances in technology and medicine, and an increase in population size, an emergence of new infectious disease challenges has been observed in the past decades. With the understanding of the role of the environment in epidemiology, a number of factors can be identified to influence the risk of infection. They can be summarised in agent-host-environment interactions, also known as the Epidemiologic Triangle, a standard tool of infectious disease epidemiology that can be adapted to any disease under study (Miller, 2002). In this section, the triangle is used to provide a basic understanding of disease epidemiology and highlight some of the factors that will return in later sections. The epidemiologic triangle summarises the interaction between factors from three levels, which influence the spread of an infectious disease (Figure 2.9).

The three levels are the agent-level, the host-level, and the environment-level. As such, it can be used to identify risk factors for infectious diseases.

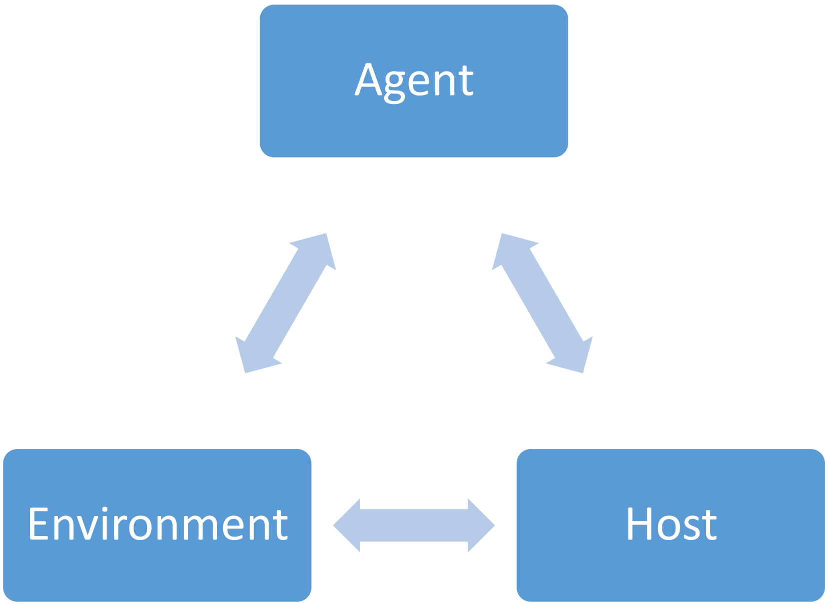


Figure 2.9: The Epidemiologic Triangle (Miller, 2002).

'Agent' in the triangle refers to the infectious agent or pathogen responsible for the disease. This can be, for example, bacteria or viruses. Factors relating to the agent have an impact on how well a pathogen is adapted to survive and how well an infection will spread because of it. This includes the pathogen's infectivity and virulence, it's susceptibility to antibiotics and other forms of pharmaceutical therapy, the availability of vaccines, and the ability to survive outside a host body (Rothman, 2002). For example, the influenza virus can survive outside a host for about 24 hours (Bean et al., 1982; Pirtle & Beran, 1991), while the tuberculosis bacteria can survive for weeks, sometimes months, outside a host body and retain its infectivity (Ghodbane, Mba Medie, Lepidi, Nappez, & Drancourt, 2014).

Interventions at this level are attempts at the eradication of an agent by targeted vaccination, quarantine, and therapy. With modern methods such as genetic manipulation, this may also be achieved. There are theories of malaria eradication by genetically altering the vector to make reproduction impossible, hence impacting the infectivity of the parasite (Alphey et al., 2002).

'Host' refers to the infected individual, or patient, and factors that influence susceptibility to disease as well as severity of disease and the potential spreading to other hosts. Host susceptibility to certain agents is altered by age, biological sex, genetic profile, as well as prior exposure to the disease, and the immune status of the individual (Miller, 2002; Rothman, 2002). For example, children are more vulnerable to measles, and immunocompromised patients – because of co-infection with HIV, or for genetic reasons – are at a greater risk of contracting infectious diseases and more likely to experience severe disease (Gandhi et al., 2010; Pineda et al., 2005). Similarly, behavioural factors can influence host susceptibility. These factors include religious practices, cultural customs, occupation, family background, dietary factors, sedentary lifestyles, and risk-taking behaviours (Miller, 2002). Safe sexual practices also fall under this second category of factors.

Interventions at the host level mostly have a medical approach – meaning treatment, isolation, and immunization campaigns – as well as a more behavioural approach, which blurs the line between host interventions and environmental interventions. These include promotion of healthier behaviours such as improved nutrition, encouraged physical activity, and education on safe behaviours.

Where medicine is typically the discipline working at the host and agent level, public health is concerned with the 'Environment' level of the triangle. Factors in the environment that alter the risk of infectious disease are complex, and can rarely be targeted with a single intervention. They range from climate- and geography-related factors such as temperature, humidity, altitude, location and accessibility of health care services as well as clean water and sanitation facilities, to factors of a social and cultural nature (Miller, 2002; Weiss &

McMichael, 2015). Political stability, urbanisation, population density, agricultural practices, poverty, and pollution all contribute to the environment in which an infectious disease exists and interacts with a host. In past decades, the environment in which humans and diseases exist has changed dramatically. New practices in agriculture, such as large scale farming and the use of pesticides, as well as growing populations requiring more land, encroaching on previously untouched wildlife, has exposed humans to newly emerging pathogens (Weiss & McMichael, 2015). Zoonotic diseases like avian influenza transmitted by domestic poultry, hantavirus transmitted by rodents, or bovine spongiform encephalopathy (BSE) are examples of recently emerged diseases posing new challenges (Weiss & McMichael, 2015). Similarly, changes in malaria and dengue vectors have been observed, such as resistance to insecticides but also change in vector distribution due to changing climates (Connolly, 2004; Weiss & McMichael, 2015).

At the environmental level, interventions are often just as complex. Disease prevention and health promotion and quarantine in the case of infections are public health concerns, but interventions such as improved housing, improved access to water and sanitation, city planning to control population growth and urbanization involve a large number of parties (Glasgow, Vogt, & Boles, 1999). Events that drastically and unexpectedly alter the environment – for example a natural disaster – can only be planned to some extent, and much of the work of keeping disease risk low happens in the response to such events. Political unrest and climate disasters such as droughts can increase poverty, malnutrition, poor hygiene, and may lead to large populations displaced from their homes and exposed to adverse conditions, exacerbating the risk of infection (Leaning & Guha-Sapir, 2013). Displacement of populations affected by such conflicts, whether it be across borders or within their own country, has always been associated with diseases and excess mortality (Smallman-Raynor & Cliff, 2004). In recent history, the plight of refugees has come to the attention of research, and the refugee crisis of the last decade has only been the tip of the iceberg. While there were 2 million refugees worldwide in 1974, by 2008 the annual number of refugees was as high as 15 million according to the UNHCR – while, if the number of internally displaced persons is included, it comes to likely more than 26 million (Kouadio, Kamigaki, & Oshitani, 2010).

All levels of the epidemiologic triangle interact in time to describe a disease dynamic. For example, TB re-emerged in recent decades because the bacterium formed resistance to the standard treatments (agent), because the HIV pandemic has made people vulnerable to co-infection (host), and large refugee populations in the recent crisis are exposed to adverse conditions that are favourable for an infection like TB (environment) (Sohail, 2006).

2.4 The intersection of disaster and disease

As per the section above, the environment in which host and agent exist strongly influences their relationship. In the event of a disaster – either natural, technological, or complex/political in origin – the environmental circumstances are often drastically changed. There may be reductions in water quality, access to sanitation, food and shelter, there may be overcrowding, all of which may impact the vulnerability of a population to infectious diseases.

The different characteristics of disaster types result in different disease profiles appearing in each scenario. Andrea Linscott (2007) summarised infectious diseases according to their typical occurrence after disasters (Table 2.4). According to her paper, wound infections and fungal contamination occurred commonly after earthquakes, tornados and hurricanes; floods were typically associated with diarrhoeal diseases and water-borne as well as vector-borne diseases; tsunamis, on the other hand, were commonly associated with respiratory tract infections, diarrhoeal diseases and wound infections; vector-borne diseases were uncommon (Linscott, 2007).

Reviewing literature on disasters and disease published in the past 40 years, an overview will be presented in the following section. The literature includes only natural disasters where at least one publication on infectious diseases in the aftermath of said disaster was found. The diseases mentioned most commonly in the literature were diarrhoeal and water-borne diseases, followed by vector-borne diseases, wound infections, and respiratory diseases (Table 2.4), and they will be discussed in further detail below. Literature on of infectious diseases was available for only a limited number of recent disasters. The gap in surveillance coverage (of several thousand disasters recorded in the EM-DAT database since 1901, barely a handful are thoroughly analysed in the literature, most of them in the last two decades) complicates conclusions about the impact of infectious diseases associated with disasters. This gap might be explained by insignificant numbers of cases of disease occurring in consequence of the majority of recorded disasters, as well as a likely lack of disease surveillance and media attention for the other events. An overview of natural disasters mentioned in relation to disease outbreaks in the sampled literature is given in Table 2.5, including the number of publications in which the disaster was mentioned. This illustrates the gap in coverage, with barely any mention of disasters in the first sixty years of the 20th century. The disasters that were mentioned are characterised by large numbers of affected populations and in some instances a great death toll. A breakdown of natural disaster types and infectious disease events is given in the following section.

Table 2.4: Diseases typically associated with certain disasters as taken from (Linscott, 2007).

Disaster	Diseases
Droughts	Vector-borne diseases;
Earthquakes	Wound infections (fungal and bacterial); diarrhoeal diseases
Floods	Water-borne diseases ; vector-borne diseases; diarrhoeal diseases; arboviruses (St. Louis encephalitis, west Nile encephalitis)
Hurricanes	Wound infections, vector-borne diseases, diarrhoeal diseases, mould contamination
Tornados	Wound infections
Tsunamis	Wound infections; diarrhoeal diseases; respiratory infections

Table 2.5: Natural disasters mentioned in the reviewed literature. Number of affected and mortality were taken from the EM-DAT database for the respective disaster, diseases were taken from literature presented in section 2.6. # indicates the number of articles reviewed in which the disaster was mentioned.

year	disaster	disaster specific	country	mortality	affected	diseases	#
1907	Earthquake	Includes San Francisco Fire	USA	1188			1
1918	Fire	Minnesota Fire	USA	1000			1
1931	Flood	Yellow River	China	3700000			2
1963	Cyclone	Flora	Haiti	5000			3
1964	Earthquake	Alaska	USA	131	1020		2
1970	Flood		Bangladesh		10000000		3
1970	Avalanche		Peru	66794	3000000		2
1970	Flood		India	627	10000000		2
1972	Hurricane	Agnes	USA	122			1
1972	Earthquake		Nicaragua	10000	720000		3
1975	Earthquake		Turkey	2385	53372		1
1976	Earthquake		China	242000	164000		1
1976	Earthquake		Guatemala	2300	5000000		3
1976	Earthquake		Italy	922	218222		1
1978	Earthquake		Iran	25000	40000		1
1979	Volcano		St Vincent	2	20000		1
1979	Hurricane	David	Dominica	40	72100	measles	2
1980	Volcano		USA	90	2500		2
1980	Earthquake		Italy	4689	407700		1
1981	Earthquake		Greece	22	80400		1
1983	Earthquake		Colombia	250	36200		1
1983	Flood		Ecuador		200000	malaria	1
1984	Tornado	Carolinas	USA		1400		1
1984	Volcano	Lake Monoun	Cameroon	37			1
1985	Earthquake		Mexico	9500	2000000		1
1985	Volcano		Colombia	21800	12700	infection	2
1986	Volcano		Cameroon	1746	10437		1
1988	Earthquake		Armenia	25000	2000000	infection	2
1992	Hurricane	Andrew	USA	44	250055		1
1994	Earthquake	California	USA	60	27000	mycosis	2
1998	Hurricane	Mitch	Nicaragua	3332	868228		2
1999	Earthquake	Marmaris	Turkey		103	E.coli, MRSA	2
1999	Earthquake	Kocaeli	Turkey	17127	1000000		2

2000	Flood		Mozambique	800	5000000	malaria	2

Table 2.5 (cont): Natural disasters mentioned in the reviewed literature. Number of affected and mortality were taken from the EM-DAT database for the respective disaster. Number of mentions indicates the number of articles reviewed in which the disaster was mentioned.

year	disaster	disaster specific	country	mortality	affected	Diseases	#
2004	Tsunami		India	16389	654512	malaria	10
2004	Cyclone	Jeanne	Haiti	2754	315594	malaria	1
2004	Tsunami		Sri Lanka	35399	1000000	malaria	9
2004	Flood	Hawaii	USA		105		1
2004	Tsunami		Indonesia	165708	532898	measles, tetanus,	8
2004	Tsunami		Thailand	8345	67007	pneumonia, MRSA,malaria	7
2005	Hurricane	Katrina	USA	1833	500000		5
2005	Hurricane	Rita	USA	10	300000		2
2005	Hurricane	Stan	El Salvador	69	72141		1
2005	Volcano		El Salvador	2	2000		1
2005	Earthquake		Pakistan	7338	5000000	measles, tetanus,	4
2008	Flood		Vietnam	99	600000	dengue	1
2008	Cyclone	Nargis	Sri Lanka	9	50000	cholera, tuberculosis, tetanus, malaria, dengue, rabies	2
2009	Cyclone	Aila	India	96	5000000	cholera	1
2010	Earthquake		Haiti	222570	4000000	cholera, malaria, rabies	8
2011	Flood		Pakistan	509	5000000		2
2011	Tsunami		Japan	19846	368820	pneumonia, influenza	5
2011	Tornado	Missouri Tornado	USA	11		mucormycosis	1
2012	Hurricane	Sandy	USA	286	215000		1

Geophysical disasters

Geophysical disasters include earthquakes, tsunamis, volcanos, rock falls, avalanches, landslides, and subsidence (Table 2.1). Of these, earthquakes are the most commonly mentioned disasters in the epidemiological literature. A total of 17 earthquakes have been mentioned, seven of these between 1970 and 1980 (Table 2.4). Of these events, an average of 1,220,472 million people were affected by an earthquake and about 36,874 casualties were accounted for. The earthquake in Pakistan in October 2005, known as the Kashmir Earthquake, and the earthquake that struck Haiti in January 2010 are the two disasters that received the most attention, both in the media and in epidemiologic research. These two events differ in their reporting in that most articles on the Haiti earthquake investigate the associated cholera outbreak (Hendriksen, 2011; Tappero, 2011; Abrams, 2013; Barzilay, 2013), while the Pakistan literature mostly looks at wound infections, the most commonly reported cause of disease after earthquakes (Baqir, 2012).

A total of six volcanic eruptions were mentioned in the literature as associated with disease outbreaks (Table 2.5). The eruption of Mount St. Helens (USA, May 1980) and the eruption of Nevado del Ruiz (Columbia, November 1985) were both mentioned in two different articles. The latter eruption displaced several thousand people and killed at least 21,000 (CRED, 2017). Lechat (1990) observed that approximately 70 people died of infection within two weeks after the Nevado del Ruiz incident, 39 of them from septic shock and 5 from tetanus. The Mount St. Helens incident on the other hand primarily raised concern about ambient ashes and the respiratory effects thereof (Bernstein et al., 1986; Lechat, 1990).

Major tsunami events struck in 2004 and 2011 (Table 2.5). The 2004 South-East Asia tsunami affected several countries, most notably India, Indonesia, Thailand and Sri Lanka. At least 226,000 people were killed by the wave in these countries and over 2 million were adversely affected by the consequences. A total of 34 articles reviewed investigate the 2004 tsunami catastrophe, making it the most covered event in recent history, an event that received media attention all across the globe, an overwhelming wave of solidarity, and a blockbuster movie (The Impossible, 2012: http://www.theimpossible-movie.com/). Given the extent of coverage, it is no surprise that disease surveillance is detailed in the aftermath of the tsunami. The more recent tsunami in Japan, resulting from the Tōhoku Earthquake in March 2011, while causing an equally large media impact, has been far less well documented in terms of communicable diseases, with a few articles investigating respiratory infections after the disaster (Daito et al., 2013; Ebisawa et al., 2011; Hatta et al., 2012; Tohma et al., 2012).

The two events also differ tremendously in the infrastructures they struck – with the 2004 tsunami hitting a more vulnerable population than the Great Japan Earthquake and following tsunami, which affected a highly developed region.

Crush injuries, skin lesions and wound infections are most commonly mentioned in association with earthquakes, more often than with any other type of disaster, while diarrhoeal diseases and vector-borne diseases find mention in the tsunami events, similar to regular flood events (Table 2.3).

Meteorological disaster

Meteorological disasters include tropical storms, extra-tropical storms, and local storms (Table 2.1). Of these, hurricanes, tornados and cyclones accounted for 14 events mentioned in the literature, the majority of which occurred in the last decade (table 2.4). What they all have in common is the large number of affected people. Most of these storms occur in the American and Pacific areas. An average of 900,000 people suffered in the aftermath of the meteorological disasters in the sampled literature, the largest impact attributed to cyclone Aila in India in May 2009 with 5 million people affected, and hurricane David in the Dominican Republic in August 1979, affecting 2 million.

Of the 14 events, the one mentioned most frequently in the literature is Hurricane Katrina that struck New Orleans in August 2005 (Table 2.5). This is perhaps surprising, considering the effect Katrina had in terms of casualties and affected population was below most of the other storms mentioned, but excessive media attention and disease surveillance coverage allows for far better documentation of the event than in most other cases. This also allowed for improved disease surveillance after the event compared to before Katrina (Ligon, 2006; Linscott, 2007; Watson et al., 2007).

Hydrological disasters

Hydrological disaster include floods and wet mass movements (Table 2.1). Of these, flood events are more difficult to systemise because they rarely have a fixed date, or even a fixed start and end point, but are quite literally more 'fluent' than other disasters. Floods occur regularly, depending on the weather conditions, and last comparably longer than an earthquake or a tsunami or a storm that strikes at a specific time and move on. Floods are a seasonal phenomenon in some regions (Ivers & Ryan, 2006; Schwartz et al., 2006). As floods may last from several days up to several weeks, their dynamic sets them apart from other events mentioned thus far. Geographically, the most notable floods occur in regions with monsoon rains or El Niño (Kovats et al., 2003; Costello et al. 2009), although there are examples in temperate latitudes where floods caused significant damage (Barredo, 2007).

Eight flood events were mentioned in the literature as specific events (Table 2.5), while several other articles treated floods as a collection of events and drew conclusions based on multiple events over time. The floods mentioned repeatedly are (i), the Yellow River Flood in China between July and November 1931 that killed nearly 4 million people (Lechat, 1976) and (ii), floods in 1970 in Bangladesh and India following cyclone Bhola in November 1970, that affected 10 million people each, causing substantial damage and disease (Lechat, 1976, 1990; Logue, Melick, & Hansen, 1981). Other floods mentioned in relative detail include the three large monsoon floods in Bangladesh in 1988, 1998, and 2004, in relation to diarrhoeal diseases (Schwartz et al., 2006).

As with other types of disasters, there are certain diseases more common during floods than during other events. These include especially diarrhoeal diseases, and vector-borne diseases more so than during tsunamis (Table 2.3).

2.5 Epidemiology's contribution to disaster research

Publications as recent as 2012 argue that "although there is a growing interest in disaster studies, few have provided a clear understanding of the concept of infectious disease occurrence following disasters" (Kouadio et al., 2012, p.96)

It is a common misconception — and one that has persisted for the past decades — that in a disaster event, any outside help is needed. Numerous articles agree that most disaster relief work remains horrendously unstructured and lacks adaptation to the specific needs within a certain population (Leaning & Guha-Sapir, 2013; Noji, 2005a; Noji, 2005b). Media panic after a natural disaster can trigger unnecessary public health measures (Kouadio et al., 2012; Watson et al., 2007) and the improper implementation of health education programmes (Myint et al., 2011). Difficulties and shortcomings with the transition from short-term to long-term relief work (Noji, 2005a) can exacerbate the problem, rather than improving the situation. While relief efforts are provided in good will, they may do more harm than good if communication between organisations falls behind enthusiasm.

Over the past 40 years, the use of epidemiologic concepts as an approach to health outcomes after disasters has been established by authors such as Michel F. Lechat (Lechat, 1976). Advocates of such techniques dismiss the notion that natural disasters result in severe chaos and leave the population in a helpless state. Noji (2005) criticizes international response efforts, their incapability to transition from acute to long-term assistance, and challenges the common misconception that disasters result in panic and reliance on outside help (Lechat, 1976; Noji, 2005b). Only medical personnel with skills otherwise unavailable in the affected region are necessary (Noji & Toole, 1997). It is argued that disaster response is burdened by "inappropriate donations, non-essential pharmaceuticals" (Noji & Toole, 1997, p.369) and a lack of logistic organisation, and that “A hasty response that is not based on an impartial evaluation only contributes to the chaos” (Noji & Toole, 1997, p.367) rather than improving the situation (Noji & Toole, 1997). The systematic approaches of epidemiologic research are believed to improve these response efforts. For instance, cluster sampling methods have been successfully used to assess risks and identify areas in need of assistance – because of diseases or other reasons (Leaning & Guha-Sapir, 2013; Noji, 2005b). It was recognised in the 1970, in consequence of a series of severe disasters, that epidemiologic methods may add value to relief planning (Leaning & Guha-Sapir, 2013). However, there are limitations to such methods and they may miss certain populations in need, depending on the type of disaster and geographical restrictions (Noji, 2005b).

Most relief workers, non-governmental organisations (NGOs) and the media leave a disaster-affected region after a short term, because of funding running out after initial attention is on a decline (Noji, 2005b). However, the consequences of disasters have been shown to last much longer. Outbreaks of diseases can be delayed up to several months, sometimes longer (Barzilay et al., 2013; Myint et al., 2011). The exacerbated risks of infection are often long term, such as disruption in surveillance, health programs, routine treatments, or the destruction of critical infrastructure that cannot possibly be re-established in a few weeks (Kouadio et al., 2012).

Long-term surveillance systems can provide valuable data to formulate models of outbreak risk and allow for better understanding of the dynamics of disaster and disease, and adequate disaster response (Logue et al., 1981). In order to understand the impact of disasters on public health, Logue and colleagues also propose the principle of host-agent-environment interaction (Figure 2.9) from infection epidemiology as a tool in disaster management. Relevant issues include the nature and impact of the disaster itself, the extent of the destruction (including collapsed buildings, flood waters, and debris), impact on nutrition, vector breeding grounds, demographics of the population, immunisation, education, response and intervention efforts, the timing of such efforts, as well as pre-existing social factors that have no direct link to the disaster itself (family, support networks, previous experiences with disasters, responsibilities in the community, role conflicts for those involved in for example health care or police).

This has provided insights into the conditions that favour disease outbreaks after natural disasters and what types of diseases are most likely to cause these outbreaks. Statistical methods have been used to standardise disaster patterns and tailor response needs to specific types of disasters.

A divide of disasters into a number of stages allows the identification of factors of concern during each stage of the disaster and enables more targeted responses. While there are differences in definitions of acute disaster phases, the literature agrees that communicable diseases become a concern in the phases after the disaster, when the acute effects of the event have already passed (Aghababian & Teuscher, 1992; Logue et al., 1981). Moreover, different diseases are of concern at different stages of a disaster (Aghababian & Teuscher, 1992; Baqir et al., 2012): wound infections occur during the acute stages, with blunt trauma affecting the population immediately after earthquakes or storms. Vector-borne diseases are of more concern at later stages, because of the delay in vector breeding times. Studies of malaria after natural disasters, especially tsunamis, have shown considerable delay in outbreaks due to the fact that vector breeding grounds are washed away by the initial flood waters and only re-established at later stages, with stagnant water and weak sanitation (Linscott, 2007; Watson, Gayer et al., 2007; Kumari et al. 2009; Myint et al., 2011)). Respiratory infections occur in temporary shelter conditions where people have been forced to abandon their homes due to disaster (Linscott, 2007).

2.6 Major disaster-related diseases

Only in rare instances are new pathogens introduced during or following disasters. Generally, it is endemic diseases of previously moderate or low prevalence that experience an increase after disasters due to changes in population susceptibility, overall adverse conditions, and increased exposure to pathogens (Aghababian & Teuscher, 1992).

The diseases most commonly mentioned in the literature can be grouped into diarrhoeal diseases, vector-borne diseases, wound infections, and respiratory infections. The following section will investigate these diseases commonly associated with natural disasters, their symptoms, and literature findings.

2.6.1 Diarrhoeal diseases

Diarrhoeal diseases occur in all types of disasters where water quality is affected, most commonly after flood-related disasters (Linscott, 2007). Contaminated fresh water sources, lack of personal hygiene, and unavailability of disinfectants are favourable conditions for a variety of microbes. The most common microbial causes for diarrhoeal disease are rotavirus, *Escherichia coli*, C*ryptosporidium*, and *Shigella* species causing the profile known as dysentery (Troeger et al., 2017; WHO, 2017a). While these are the most common causes of diarrhoeal disease on a daily basis, the overall conditions after natural disasters render the populations highly susceptible to a different spectrum of microbes related to clean water and sanitation. The diarrhoeal diseases emerging as relevant after natural disasters are summarised in Table 2.6.

Table 2.6: list of diarrhoeal diseases mentioned in the epidemiological literature in relation to disasters.

Diseases	Disasters mentioned	# of mentions
Cholera	Haiti earthquake (2010); cyclone Aila (2009); Bangladesh floods (1989, 1998, 2004); cyclone Odisha (1999), cyclone Nargis (2008)	9

E.coli	Tsunami Indonesia (2004), Wenchuan earthquake (2008), Izmit earthquake (1999), cyclone Odisha (1999)	6
Leptospirosis	Cyclone Odisha (1999), Mexico floods (2003)	5

Cholera:

Cholera is one of the most severe forms of diarrhoeal disease. Caused by the *Vibrio cholerae* bacteria, the disease is highly transmissible and is symptomatic with acute watery diarrhoea (described as 'rice water stool' for its characteristic appearance), abdominal cramps, nausea and vomiting, leading to severe dehydration, shock and eventually death. If left untreated, or treated inadequately, death may occur within 24 hours (Pfrimmer, 2010). Annual mortality is estimated at 100,000-120,000 (Bhunia & Ghosh, 2011).

Cholera spreads through contaminated drinking water or through the faecal-oral route, meaning the ingestion of food or water contaminated by human faeces containing *Vibrio cholera*. The bacteria have shown a significant increase in infectivity after passing through the human gastrointestinal tract, leading to hyper-infectivity often observed during epidemics after natural or man-made disasters (Hartley, Morris, & Smith, 2006; Schwartz et al., 2006). Humans may host the bacteria without expressing symptoms, however their faeces remain infectious for up to 14 days, presenting a high risk of infecting others (Pfrimmer, 2010).

Cholera was mentioned in 9 separate articles in the sampled literature (Table 2.6). An investigation among the population after cyclone Aila in May 2009 in India showed a 1.6 fold increase in risk of diarrhoeal disease compared to previous years. *Vibrio cholera* was the most commonly isolated pathogen (Panda et al., 2011). A second study of cyclone Aila found a cholera outbreak, involving 176 cases in three months, caused by contaminated water pipelines (Bhunia & Ghosh, 2011). A microbiological analysis of patients with diarrhoea after cyclone Odisha struck India in November 1999 identified cholera in over 70% of samples (Chhotray et al., 2002). A study in Bangladesh observed outbreaks of diarrhoeal disease, most notably cholera and rotavirus, after three consecutive floods (Schwartz et al., 2006).

Most recently, the cholera epidemic after the 2010 earthquake in Haiti gave rise to criticism. At the time of the earthquake, *Vibrio cholera* El Tor – the currently most common strain of cholera worldwide – had not been endemic in Haiti and therefore had to have been accidentally introduced from the outside, possibly by relief workers from Nepal (Hendriksen et al., 2011; Tappero & Tauxe, 2011). By November 2012 – two years after the initial earthquake – nearly 605,000 cases of cholera had been recorded in the surveillance programme (Barzilay et al., 2013). Also in the case of cyclone Nargis in Myanmar in May 2008, cholera rates were still elevated a year after the disaster compared to surveillance data from before 2008 (Myint et al., 2011). This stresses the long term consequences of natural disasters.

Due to the fact that temporary shelters facilitate the spread of the disease and disrupted access to clean water and medication may kill patients within a day, cholera and cholera prevention has often been central to arguments on whether or not emergency relief camps are the most appropriate solution for displaced populations (Van Damme, 1995). Unfavourable infrastructure and environmental conditions in temporary shelters make the otherwise relatively easy prevention of cholera near impossible (Pfrimmer, 2010).

Cholera will be studied in detail in Chapter 5.

***Escherichia coli (E.coli)*:**

Most commonly reported in the literature as occurring in the aftermath of tsunamis, *E.coli* is among the top five isolated pathogens after natural disasters (Hiransuthikul, Tantisiriwat, Lertutsahakul, Vibhagool, & Boonma, 2005; Linscott, 2007). The bacteria are harmless under normal circumstances; they are part of the natural gut flora (Heymann, 2015). However, given certain pathogenic strains and unfavourable circumstances, *E.coli* can lead to severe diarrhoeal diseases (Heymann, 2015).

Six articles mentioned *E.coli* (Table 2.6). A study in Indonesia after the 2005 tsunami found *E.coli* in 27% of samples of stored water in households. Chlorine treatment and water from improved sources were shown as factors preventing contamination (Gupta et al., 2007). *E.coli* has also been isolated in wounds after earthquakes. A study of 169 earthquake survivors in Wenchuan, China in May 2008, found wound infections with *E.coli* in 15.4% of cases (Wang et al., 2010). An investigation into hospital-acquired infections in Marmara after the Izmit earthquake in Turkey in August 1999 reported a 12% prevalence of *E.coli* among 630 trauma victims (Oncul et al., 2002). After cyclone Odisha in India (November 1999), 19.3% of diarrhoeal disease was caused by *E.coli*, the second most common pathogen after *Vibrio cholera* (Chhotray et al., 2002).

Leptospirosis:

Leptospirosis is a diarrhoeal disease caused by *Leptospira* bacteria found in rodent urine, contaminating water sources or through direct skin contact. It is endemic in most of South East Asia (Alderman, Turner, & Tong, 2012b). It is a waterborne disease and therefore most common in flood-related disasters, occurring in the acute phases of the disaster (Baqir et al., 2012; Linscott, 2007). Symptoms include sudden fever and chills, headaches, vomiting, and severe myalgia (Waring & Brown, 2005).

After cyclone Odisha in November 1999, 141 cases of leptospirosis were reported, including 11 deaths. However, the case-fatality ratio and attack rate were found to be lower than elsewhere (Jena, Mohanty, & Devadasan, 2004). In a study population in a rural area of Mexico at high risk of flooding, leptospirosis prevalence in 1,196 study subjects was 37.7%, exceptionally higher than anticipated and if compared to the rest of Mexico (Leal-Castellanos, Garcia-Suarez, Gonzalez-Figueroa, Fuentes-Allen, & Escobedo-de la Penal, 2003). Concerns about insufficient disease surveillance and the similar clinical presentation with dengue were raised (Leal-Castellanos et al., 2003).

2.6.2 Acute respiratory infections and airborne diseases

Infections of the respiratory tract are easily transmissible and therefore rank high among the most common cause of communicable disease outbreaks after disasters (Wisner & Adams, 2002). Pneumonia and influenza are among the most common causes of infection-related hospitalisation and death, followed by TB in low-income countries (Murray, Vos, Lopez, & Collaborators, 2016). Measles remains one of the leading causes of child mortality, and subject of widespread vaccination campaigns (WHO, 2017b). While the body of evidence for an association between natural disasters and respiratory infections is relatively small, a number of studies suggest an association with refugees after complex, political emergencies, indicating that population displacement events are indeed driving risk factors for ARI cases (Bellos et al., 2010). Overcrowding, poor housing conditions and cold, damp climate further such infections.

Table 2.7 lists the most common respiratory infections found after natural disasters, and they are further detailed in the upcoming section.

Table 2.7: Acute respiratory infections mentioned in the epidemiological literature in relation to disasters.

Diseases	Disasters mentioned	# of mentions
Measles	Hurricane David (1979), Hurricane Frederic (1979), Mt. Pinatubo eruption (1991), tsunami Indonesia (2004), Pakistan earthquake (2005)	9
Pneumonia	Tsunami Thailand (2004), Great Japan earthquake (2010)	6
Tuberculosis	Cyclone Nargis (2008)	2
Influenza	Great Japan earthquake (2010)	2

Measles:

Like malaria, measles ranks high on the WHO list of top five causes of mortality after disasters – despite being a vaccine-preventable disease (Wisner & Adams, 2002). Substantial effort is put into the control of measles because it most severely affects children aged under 5 years (Moss et al., 2006). Measles is an airborne viral disease, caused by a virus of the *Morbillivirus* genus. Symptoms include fever, cough, runny nose, and a characteristic skin rash (Kouadio et al., 2010). A vaccine has been available since 1959 and between 2000 and 2007, vaccination saw a worldwide decline in measles cases of 74%. It is still considered the most cost-effective, crucial prevention measure to be taken in post-disaster circumstances. However, in the aftermath of disasters, measles case-fatality ratios still reach up to 34%, while in the general population it can get as low as 2% (Kouadio et al., 2010). Overcrowded shelters, inadequate nutritional intake, and lack of vaccination coverage are the main risk factors for measles outbreaks after disasters (Kouadio et al., 2012).

Measles is mentioned in 9 articles of the sample (Table 2.6). After the 1979 Hurricane David in the Dominican Republic, measles was assumed to be one of the epidemic diseases directly linked to the event (Aghababian & Teuscher, 1992; Lechat, 1990). A study by Richard Bissell has shown a significant increase in measles cases in the three months following Hurricane David and Hurricane Frederic, two storms that hit the Dominican Republic within a month in 1979 (Bissell, 1983). Where the usual number of cases ranged between 20 and 100, there were 480 recorded cases in October 1979, the month after the hurricanes (Bissell, 1983).

After the eruption of Mt. Pinatubo in 1991 in the Philippines, 18,000 cases of measles were recorded in the unvaccinated population displaced by the disaster (Cook, Watson, van Buynder, Robertson, & Weinstein, 2008; Watson et al., 2007). More clusters of measles cases were recorded after the 2004 tsunami in Indonesia and after the Pakistan earthquake 2005 (Kouadio et al., 2012). However, the number of cases after the tsunami in Indonesia in 2004 were generally low due to rapidly implemented vaccination campaigns that were introduced in 1988 by the WHO (Toole & Waldman, 1988; Wilder-Smith, 2005). In Myanmar, on the other hand, no increase in measles cases was reported following cyclone Nargis in 2008 (Myint et al., 2011).

Pneumonia:

Pneumonia is a major concern after natural disasters (Waring & Brown, 2005). Pneumonia is a common condition caused by a variety of infectious agents, including bacteria such as *Klebsiella pneumonae* or *Streptococcus pneumonae*, but in rare cases it may also be viral and fungal in origin (Heymann, 2015). Commonly, pneumonia moves from the upper respiratory tract – where it is highly transmissible to others – deeper into the lower respiratory tract during the course of the disease (Ranganathan & Sonnappa, 2009). Pneumonia has a wide range of symptoms, strongly depending on what form of organism is causing it, but among the most common symptoms are productive coughs, chest pain, shortness of breath and fever (Hoare & Lim, 2006). Otherwise healthy individuals are not severely affected by the infection. However, pneumonia has been shown to appear as a hospital-acquired infection in already compromised patients and it is a very common secondary infection in immune-suppressed or otherwise weakened patients (Leach, 2009).

Pneumonia was mentioned in 6 articles (Table 2.6) and said to occur mostly in the post-disaster phases in the displaced population (Baqir et al., 2012; Ligon, 2006). It is found typically among tsunami victims (Linscott, 2007), likely due to the levels of destruction and subsequent population displacement. In support of this assumption, *Klesbiella pneumonae* was one of the most common organisms isolated from victims of the 2004 tsunami in Thailand (Hiransuthikul et al., 2005). After the Great Japan earthquake, 225 cases of pneumonia (mainly *Klesbiella pneumonae*, *Streptococcus pneumonae*, and *Haemophilus influenza*) were identified in the elderly hospitalised in the three months following the disaster, the majority being from nursing homes and from evacuation camps (Daito et al., 2013).

Tuberculosis (TB):

In some regions, TB may cause problems after natural disasters. The disease has experienced a resurgence in recent years after being considered on the way to elimination for many decades. Due to the fact that treatment for TB takes several months, a disaster can interrupt the course of treatment and thereby promote dangerous drug resistance and further spread of the infection. It was formerly advised to set up TB treatment as early as possible after disasters in regions of TB endemicity (Heymann, 2015), but recent WHO guidelines show lower priorities to TB management. Tuberculosis was mentioned in only 2 articles (Table 2.6), after cyclone Nargis hit Myanmar in May 2008. Investigations showed a *decrease* of detected TB cases after the event (Myint et al., 2011). The role of TB in the aftermath of disasters will be discussed in detail in Chapter 7.

Influenza:

Influenza is a viral disease associated with sudden high fever, cough, headache, general malaise, muscle and joint pain, and fatigue (WHO, 2014c). It spreads easily through droplet infection, especially in crowded conditions.

What is most noteworthy about influenza is its ability to mutate very easily (called antigenic drift and shift, meaning every seasonal virus strain is able to overcome antibodies of the immune system), calling for a new, adapted vaccine every year (Osterhaus, Fouchier, & Rimmelzwaan, 2011). Seasonal influenza returns annually in waves, usually in winter, while it can be prevalent in tropical regions throughout the year (WHO, 2014c). Pandemic influenza on the other hand is a severe event that occurs when a formerly zoonotic (most recent examples include avian influenza and H1N1 'Swine flu') strain of influenza adapts to infect humans. In such an event, the new, highly pathogenic virus can quickly infect thousands, spreading rapidly enough to cause a worldwide pandemic. Such has occurred three times in the 20th century (1918 'Spanish Flu'; 1957 'Asian Flu'; and 1968 'Hong Kong Flu) (De Jong, Rimmelzwaan, Fouchier, & Osterhaus, 2000), and – although far less deadly than its predecessors – most recently the first Pandemic of the 21st century: the 2009 'Swine Flu', 'Mexican Flu', or 'Novel Flu' incident.

Because of its high virulence, influenza is a potential threat in the aftermath of disaster, especially in crowded shelters. However, there have been virtually no reports of influenza occurring in epidemic numbers after disasters. It was mentioned in only two articles (Table 2.6). After the Great Japan Earthquake in March 2011, Tohma and colleagues detected 112 cases of seasonal influenza, 93 cases of Influenza B, and one case of H1N1 ('Novel Influenza') (Tohma et al., 2012). Hatta and colleagues found two small outbreaks in evacuees of the Great Japan Earthquake, one with a total of 25 patients over the course of nine days, a second one a month later with 20 patients (Hatta et al., 2012).

2.6.3 Wound infections

Wound infections are the most common and most immediate concern after natural disasters, being a result of direct physical trauma as opposed to other communicable diseases that occur at later stages and due to more indirect circumstances outlined elsewhere in this chapter. Flying, falling or floating debris, or severe destruction of buildings can cause major physical injuries that offer access ports for numerous kinds of bacteria or fungi, triggering a range of infections (Linscott, 2007).

About 20% of hospitalisations after earthquakes are due to bacteraemia, bacteria invading the blood through one way or another (Linscott, 2007; Porter, 2012). In Table 2.8 and the below section, the wound infections most commonly mentioned in the context of natural disasters are presented.

Table 2.8: Wound infections mentioned in the epidemiological literature in relation to disasters.

Diseases	Disasters mentioned	# of mentions
Tetanus	Pakistan earthquake (2005), Indonesia tsunami (2004), cyclone Nargis (2008)	5
Fungal infections	Nevado del Ruiz eruption 1985), Indonesia tsunami (2004), Joplin tornado (2011), Northridge earthquake (1994)	5
Drug-resistant infections	Thailand tsunami (2004), Armenia earthquake (1988), Izmit earthquake (1999)	6

Tetanus:

The most common concern of wound infections after natural disasters is tetanus, a blood infection with the *Clostridium tetani* bacteria acquired through cuts or open wounds of another source. The bacteria produce a toxin affecting skeletal muscles. The infection is characterised by muscle spasms and received its historical name – lockjaw – because the first symptoms usually involved spasms of the jaw before it can affect the rest of the body (CDC). Respiratory arrest is the most common consequence and cause of death in tetanus patients (Farrar et al., 2000). Despite vaccination programmes, tetanus still accounts for between 800,000 and 1 million deaths per year, usually in new-born's (Farrar et al., 2000). Tetanus can be prevented by immunisation that is obligatory in most western countries, but vaccination coverage is not universal. The WHO set a goal to eliminate neonatal tetanus by 1995 – but we are still far from achieving that goal by 2016 (WHO, 2014d). Tetanus is a prime example of a disease showing disastrous differences between developed countries and developing countries in terms of availability of vaccination and treatment (Farrar et al., 2000). Disasters involving physical trauma and injuries are at high risk of triggering tetanus outbreaks (Ligon, 2006) and it was mentioned in 5 articles (Table 2.7).

A tetanus outbreak was recorded in the aftermath of the earthquake in Pakistan in 2005 (Kouadio et al., 2012) and the 2004 tsunami in Indonesia(Watson et al., 2007). According to WHO figures, a spike of 106 cases of tetanus were recorded immediately after the tsunami, the case fatality ratio was nearly 19% (WHO, 2005). An increase in tetanus cases after cyclone Nargis in Sri Lanka in 2008 was detected, from between 0.49 and 0.55 per 100,000 population before the storm, to between 0.64 to 0.79 after the storm (Myint et al., 2011).

Fungal infections:

Mucormycosis is an infection with fungi that can manifest internally (e.g. in the lungs, gastrointestinal tract, or the brain) or externally (skin or soft tissue) (Spellberg, Edwards, & Ibrahim, 2005). Depending on severity and on availability of appropriate treatment, fungal infections can express with painful skin lesions, negatively affecting wound healing and can lead to the clinical picture of necrotising fasciitis (NF), leading to amputation or death (Andresen et al., 2005). Case fatality of mucormycosis, depending on its presentation, can range from 29% to as high as 83% (Kouadio et al., 2012). It has been occasionally reported after disasters that involve either the release of spores through disruption (for example after earthquakes of tornados) or after disasters involving stagnant water that promotes mould and the opportunity to infect hosts through wounds (Linscott, 2007).

Fungal diseases were mentioned in publications from the sample (Table 2.7). After the eruption of the volcano Nevado del Ruiz in November 1985 in Colombia, 35 cases of NF were reported, 8 of which had fungi isolated in the wounds, and 6 of these 8 patients died (Andresen et al., 2005).

Andresen and colleagues encountered a patient returning from the tsunami in Indonesia in 2004 presenting with similar clinical picture and warn that there were likely more patients that might have gone unnoticed due to the disease manifesting in a similar manner to bacterial NF, which is problematic because antibiotics show no effect against fungal infections (Andresen et al., 2005).

Fanfair and colleagues found 13 patients with mucormycosis in the aftermath of a tornado in Joplin, Missouri, in 2011. All patients had been injured directly by the tornado, having been recovered from the most catastrophically destroyed area in the path of the storm. Five of these patients did not survive the infection (Fanfair et al., 2012).

A similar instance occurred in 1994 in Northridge, California, where cases of coccidioidomycosis were reported after an earthquake-associated release of dust clouds of fungal spores to the atmosphere (Linscott, 2007). Coccidioidomycosis, also known as valley fever, is a fungal disease endemic to the western hemisphere and dispersed through the air as dry dust particles, the spores are inhaled and cause pulmonary disease (Hector & Laniado-Laborin, 2005).

Drug-resistance in wound infections:

A concern even more pressing in disaster situations than under regular conditions is that of drug-resistant bacteria. Resistant bacteria have evolved to be unresponsive to one or more antibiotics: such resistance usually occurs as a natural mutation of a few bacteria cells, and under normal circumstances, the body's natural defences can kill these bacteria. However if antibiotic treatment is not properly executed or is terminated too early, the resistant bacteria may survive and reproduce, creating more bacteria with the resistant mutation (Porter, 2012). Such infections are then difficult to treat properly and can severely harm the patient's health. Under disaster conditions, proper antibiotic therapy might be disrupted or problematic and patient compliance to treatment might be low due to more urgent concerns – such as finding shelter or family members (http://www.who.int/tb/features_archive/tsunami/en/). This breeds resistant bacteria.

Staphylococci and streptococci are the most common bacteria infecting wounds next to *Clostridium tetani*, and the perhaps best known example of a resistant strain is methicillin-resistant *Staphylococcus aureus* (MRSA) (Ligon, 2006). These bacteria can cause severe illness and can be lethal, depending on severity. To find the antibiotic treatment the strain is sensitive to is crucial in fighting the infection, but can be problematic in case the bacteria have become resistant to antibiotics. Furthermore, disaster situations can give rise to disease profiles that are otherwise very rare, difficult to identify and they may only become recognisable after weeks (Garbino & Garzoni, 2006).

Concern about drug resistant infections was raised in six reviewed articles (Table 2.8). In a clinical investigation of survivors of the 2004 tsunami in Thailand who were admitted to hospital with wound infections, 641 isolates were cultivated. Of these, 17 turned out to be associated with staphylococci, and two of those were MRSA (Hiransuthikul et al., 2005). Uckay and colleagues found seven cases of multi-drug resistant infections in nine patients transferred to their institution after the tsunami (Uckay, Sax, Harbarth, Bernard, & Pittet, 2008).

In the aftermath of the earthquake in Armenia in December 1988, between 80% and 100% of isolated bacteria were shown to be resistant to at least one of the six routinely used antibiotics (Nechaev, Kosachev, Kocherovets, & Epifanov, 1990).

Among trauma victims of the earthquake in Marmara, Turkey, in August 1999, MRSA was among the most common isolated strains (Bulut et al., 2005). Of the investigated patients, 32 (10.8%) died, 19 of those due to 'infection complications'. These included septic shock and acute renal failure (Bulut et al., 2005).

2.6.4 Vector-borne diseases

Vector-borne diseases are transmitted through an animal or insect vector, typically by way of a bite. Species most commonly associated with disease spread in disasters are mosquitos, ticks, rodents, and bats. Vector-borne diseases account for over a billion cases yearly, and account for about 17% of global infectious diseases (WHO, 2016b). The most common vector-borne diseases are malaria, dengue, and shistosomiasis, leishmaniasis, Chagas disease, yellow fever, and Japanese encephalitis (WHO, 2016b). In the following section, the typical vector-borne diseases relevant after natural disasters are summarised (Table 2.9).

Table 2.9: vector-borne diseases mentioned in the epidemiological literature in relation to disasters..

Diseases	Disasters mentioned	# of mentions
Malaria	Hurricane Flora (1963), after floods in areas of endemicity, hurricane Jeanne (2004), cyclone Nargis (2008), Sri Lanka and India tsunami (2004), Haiti earthquake (2010)	19
Dengue	Cyclone Nargis (2008), after floods in areas of endemicity, hurricane George (1998)	9
Rabies	Cyclone Nargis (2008), Haiti earthquake (2010)	4
St. Louis encephalitis	Dallas flooding	4

Malaria:

The most commonly mentioned disease threat after natural disasters is that of malaria. The body of available literature on malaria is therefore extensive compared to the majority of other diseases listed in this chapter here – it was mentioned in 19 articles in the sample literature (Table 2.9).

In malaria-endemic areas, malaria is among the five leading causes of death after disasters (Wisner & Adams, 2002). The disease is caused by species of the *Plasmodium* parasite and is transmitted by the *Anopheles* mosquitoes that breed in stagnant water. These mosquitoes are native in many parts of the world, but of the many species, only about 40 are able to transmit malaria (CDC). Malaria is only endemic in certain countries in the world where the right climate conditions exist (see Figure 2.10), and transmission is strongly linked to surrounding conditions that influence the breeding cycle of the vector (CDC).

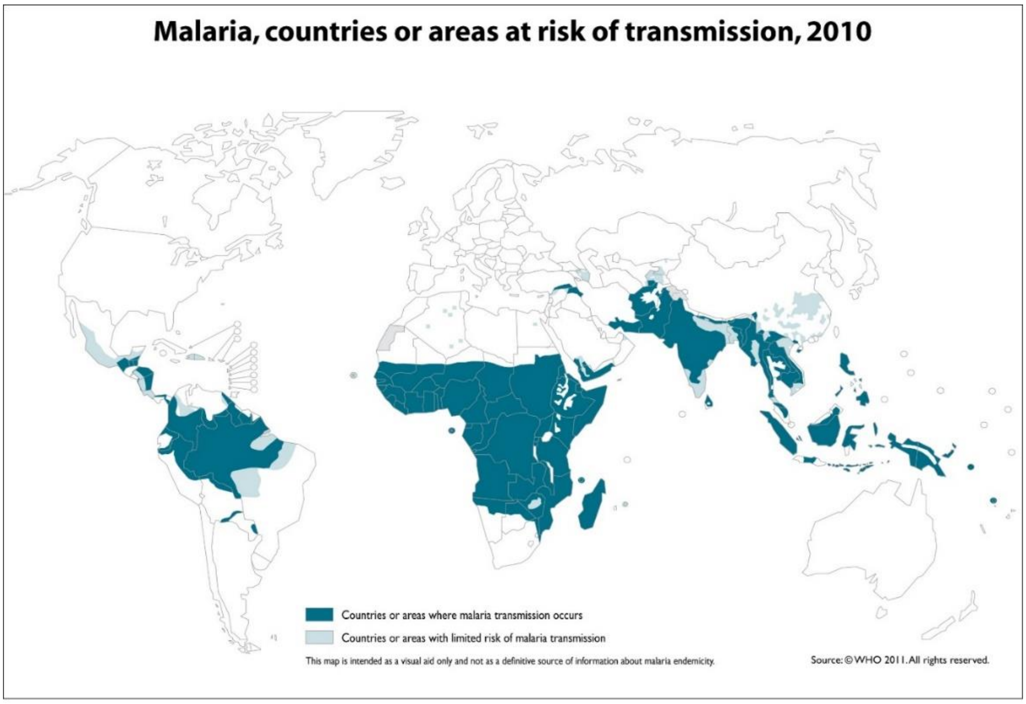


Figure 2.10: countries at risk for malaria transmission (source: WHO, 2011; http://gamapserver.who.int/mapLibrary/Files/Maps/Global_Malaria_ITHRiskMap.JPG?ua=1; last viewed: August 2016).

In Sri Lanka, for example, a steady increase in malaria was observed between 1996 and 2000, with seasonal peaks during January and lowest numbers during June and July (Briët, Galappaththy, Konradsen, Amerasinghe, & Amerasinghe, 2005).

Typically, malaria symptoms include fever, cold sweats, nausea, headaches, body aches and a general state of discomfort – signs typically described as 'flu-like symptoms' (Heymann, 2015). However, more complicated and severe malaria can lead to organ failure, anaemia and haemoglobinuria, abnormal coagulation, cardiovascular shock, and — if the brain is affected — seizures, behavioural changes, and coma (Ligon, 2006).

Malaria, along with other mosquito-borne diseases, is common during and after flooding, as the amassing water offers a larger breeding ground for the vector (Linscott, 2007). It typically occurs in the sub-acute phases of disasters, as the vector needs time to breed (Baqir et al., 2012). It has been shown that flooding initially will reduce the number of vectors, as the breeding grounds are effectively washed away by floodwaters, but as the flooding continues, the stagnant water provides ideal breeding conditions for the vector (Watson et al., 2007). Overcrowded temporary shelters and disrupted vector control measures also provide ideal conditions for the disease to spread (Kouadio et al., 2012; Waring & Brown, 2005).

A malaria epidemic was recorded in 1964 in Haiti, after hurricane Flora's devastation (Guha-Sapir & Lechat, 1986). Similarly, prolonged rainfalls resulting in flooding of the Guayas River in Colombia in 1982 caused an outbreak of malaria in the population displaced by these floods (Lechat, 1990). An increase in malaria cases was seen in the 1982 El Nino flooding in Colombia and Ecuador (Ahern et al., 2005) and an up to two fold increase was witnessed in Mozambique in 2000 (Morgan, Ahern, & Cairncross, 2005). In 2009, malaria was the second most common cause for medical consultations (18%) in Balochistan, Pakistan (Baqir et al., 2012). In Karachi in 2006, after torrential rains and flooding, an increase in cerebral malaria was detected by WHO surveillance (Baqir et al., 2012). Beatty and colleagues investigated patients in Haiti after Hurricane Jeanne, 2004, and found malaria to be the second most common diagnosis (29%) in 116 patients of their study. However, laboratory smears of only 3 patients were positive for malaria (Beatty et al., 2007). In the aftermath of cyclone Nargis in Myanmar, there was a spike in malaria cases in the year immediately following the storm, with a return to pre-cyclone levels thereafter (Myint et al., 2011).

Briët and colleagues conducted two investigations in malaria surveillance, one pre-tsunami in Sri Lanka and a second one a year after the tsunami in 2004. They mapped the declining trend of malaria in Sri Lanka and in their 2005 paper estimated that it would reach the lowest malaria prevalence yet (Briët et al., 2005). Looking at the figures after the tsunami, a further downward trend was noticed, however it was mentioned that malaria surveillance in the aftermath of the tsunami may have been disturbed – though it was not assumed to significantly impact the trend (Briët, Galappaththy, Amerasinghe, & Konradsen, 2006). Similarly, in a number of Indian coastal villages, while mosquitos were found breeding in a large number of water bodies after the tsunami, no marked increase of malaria was found (Gunasekaran et al., 2005). It was proposed that further study was necessary to confirm that cases might increase during the monsoon season (Gunasekaran et al., 2005). In contradiction, Krishnamoorthy and colleagues seemed less optimistic and warned of a high possibility of a malaria outbreak on Andaman & Nicobar Islands, India, due to an up to six-fold increase in vector breeding after the tsunami (Krishnamoorthy et al., 2005). These trends were confirmed in the island regions by Kumari and colleagues, who compared figures from before the tsunami (1996-2004) to figures of the year after and found up to 7-fold increases in confirmed malaria cases (Kumari, Joshi, Lal, & Shah, 2009).

As with wound infections, recent decades have seen a new problem arise: antimalarial drug resistance in the parasites that makes malaria increasingly difficult to treat and prevent (Baqir et al., 2012; Waring & Brown, 2005). A study of 19 malaria patients returning from Haiti after the earthquake in 2010 showed two cases of drug resistance and warns of the need for increased awareness of chloroquine-resistance (Gharbi et al., 2012). Another study of post-earthquake

Haiti found 79 confirmed cases of malaria and 5 resistant cases (Londono et al., 2009). Based on the increased development of resistance, it has even been argued that natural disasters and the malaria control actions taken after them may be counterproductive to malaria eradication efforts (Weinstein, Groff, & Skelly, 2010).

Chapter 5 will present a more detailed look into the association of natural disasters and malaria.

Dengue:

Dengue is a viral disease transmitted by mosquitos of the *Aedes aegypti* (and rarer transmitted by *Aedes albopictus and Aedes polynesiensis)* species (Ligon, 2006). Due to its rapid transmission, dengue is prone to cause epidemics in disaster conditions when control measures fail (Waring & Brown, 2005). Symptoms are usually flu-like and in most cases relatively mild. Dengue haemorrhagic fever however can lead to weakening of blood vessels and blood leaking into the surrounding tissue, circulatory failure, and shock, resulting in death in 12 to 24 hours if no appropriate volume replacement therapy is pursued (Ligon, 2006). Dengue incidence has seen a sharp increase over the last fifty years or so, and every year 50 to 100 million new infections occur (Duong et al., 2013). The conditions that improve breeding grounds for malaria (stagnant water, overcrowded shelters, disrupted vector control) also apply in the case of dengue. However, flooding has not been shown to increase vector breeding significantly but may coincide with the climatological, seasonal conditions that foster mosquito breeding (Watson et al., 2007).

Like malaria, dengue is endemic in Myanmar and was of concern in the aftermath of cyclone Nargis in May 2008, and a surge in cases was observed following the storm (Myint et al., 2011). In that incident, mass dengue control measures were undertaken to keep the mosquito population under control (Myint et al., 2011). A dengue outbreak was suspected in 1995 in Nicaragua, after a series of tropical storms, however the cases of fever-like illness turned out to be leptospirosis instead (Ahern et al., 2005). In a study in Hanoi after the 2008 flooding, 25 patients self-reported having been diagnosed with dengue within one month after the floods (Bich, Quang, Ha le, Hanh, & Guha-Sapir, 2011). A severe epidemic of dengue was recorded after the flood disaster in Brazil in 2008, with over 57,000 cases and 67 deaths (Kouadio et al., 2012). O'Leary and colleagues investigated dengue control in relief workers after hurricane George in Puerto Rico, 1998, but found no laboratory confirmed cases among the 204 participants of their study (O'Leary et al., 2002).

Rabies:

Rabies is a viral disease caused by the Lyssavirus. Nearly all mammals can become infected and most commonly in the wild, rabies is carried by racoons, foxes, bats, coyotes, and sometimes dogs and is transmitted through a bite (Ligon, 2006). Where such animals are encountered, risk of infection may be present. The virus does not express any symptoms from days to months after the infection. However, when the virus is able to enter the central nervous system, and becomes active there, symptoms start to show: initially flu-like symptoms will eventually turn to anxiety, confusion, agitation, abnormal and sometimes aggressive ('rabid') behaviour, delirium, and hallucinations (Ligon, 2006). Once symptomatic, treatment for rabies is no longer effective and the infection is always fatal (Ligon, 2006).

Rabies has been raised as a concern in the aftermath of natural disasters (Aghababian & Teuscher, 1992), but has rarely been documented in the literature (Table 2.9). Myint and colleagues found no significant increase in rabies cases after cyclone Nargis in Myanmar in 2008 (Myint et al., 2011). In Haiti however, where rabies prevalence is high, the disease may pose a significant threat and therefore strong rabies control measures (vaccinations and post-exposure prophylaxis) were undertaken after the 2010 earthquake (Schneider et al., 2012).

St. Louis encephalitis:

Like malaria and dengue, St. Louis encephalitis (SLE) is transmitted by the bite of mosquitoes. Specifically, St. Louis encephalitis is transmitted by *Culex* species (Ligon, 2006). Symptoms include headache, fever, general flu-like malaise, occasionally convulsions, tremors and spasms. Case fatality ranges from 3% to 30% and there is currently no specific treatment (Ligon, 2006).

SLE is associated with climatological events such as droughts, and with flooding, when the conditions of mosquito breeding are favourable (Linscott, 2007; McCann et al., 2011).

A 1972 study in a community living on a floodplain near Dallas found SLE antibodies in 13.9% of their 214 study participants, suggesting previous infection with SLE in these participants (Luby & Haley, 1972).

2.7 Discussion and Conclusion

Through reviewing the existing literature, a number of issues have come to attention.

The first lesson learned in reviewing the connection between disasters and disease outbreaks is that the very idea that 'natural disasters are connected to disease outbreaks' is inherently flawed (Kuadio et al., 2012). The disaster itself is a trigger, but not the cause, of disease outbreaks. The literature widely agrees that diseases occur – with very few exceptions such as wound infections from blunt trauma – so long after the acute event that they can barely be connected. Weeks, sometimes months (as in the case of cholera in Haiti), pass before outbreaks become visible, due to the delayed nature of many diseases and the surrounding circumstances after the disaster. Time is of the essence. If mosquitoes need three to four weeks to breed to a reasonably 'infectious' population after being washed away by a flood, the flood itself is not really what causes the malaria epidemic (Floret, Viel, Mauny, Hoen, & Piarroux, 2006; Krishnamoorthy et al., 2005). The causal relationship between disease and disaster is almost always mediated by the circumstances after the disaster – by whether or not a population had to be displaced into a shelter or not. Just as political conflict is not the direct cause of disease epidemics, the same applies with natural disasters. In many ways, the dynamics at work are the same. Large populations are confined to limited space, with limited resources, limited access to proper medical treatment, limited nutrition and fresh water – add an overexposure to pathogens through contaminated water or larger vector breeding grounds and you have the perfect cocktail for an epidemic (Noji, 2005a).

That does of course not justify ignoring the link between disasters and disease. More importantly, it demands a different approach to the connection. As Kouadio and colleagues have stated, there is a lack of understanding of the dynamics between disasters and disease (Kouadio et al., 2012). Much focus is placed on the short term effects of the disasters. It is no doubt true that in many cases, temporary shelters after natural disasters are by definition *temporary* and life returns to 'normal' after a relatively short period unless the circumstances are truly extreme. This differs from complex emergencies, where refugee camps may persist for months or even years (Floret et al., 2006). It is certainly true that in many instances, the threat of epidemics is sensationalised by the media (Noji, 2005b). However, the destruction after a natural disaster can still have long-term consequences for the population, even after the shelters, and epidemics such as cholera in Haiti, the measles epidemic in the Philippines in 1991 or the dengue epidemic after floods in Brazil illustrate this. It certainly also depends on the type of disaster, which diseases may or may not cause problems – as outlined previously in section 2.4 (Linscott, 2007). These long term consequences are often ignored. A number of authors have expressed their discontent with relief organisations and journalists leaving disaster-affected areas after just a few weeks – and some researchers investigating disease figures only for a similarly short time – and abandoning the affected population (Noji, 2005a; Kouadio et al.,2012). This poses the question: how many outbreaks did we miss, because no proper surveillance was in place and researchers left too early? Could this be a reason why the dynamics of diseases after disasters still pose so many challenges?

There is a misconception of non-endemic diseases being introduced into a vulnerable population from the outside, but this can usually be attributed to 'fear-mongering' in the media. With the exception of the highly unusual case of the Haiti cholera epidemic, where a pathogen was likely introduced by relief workers from the outside into a vulnerable population (Hendriksen et al., 2011), there is little evidence in the literature to suggest that non-endemic diseases gain a foothold during a disaster. Diseases with epidemic potential have been shown to almost invariably be endemic to the region beforehand.

There are very nearly 20,000 disasters listed in the EM-DAT database (section 2.2.1), yet it takes several months of combing through journals and archives to find information on disease outbreaks for even 1% of them. What happened with the other 99%? It is clear that not every disaster will bring disease outbreaks and epidemics in its wake. Also, the inclusion of a disaster in the database depends on a number of factors (>10 casualties; >100 affected; state of emergency declared; call for international assistance)(CRED, 2009). Epidemics and outbreaks are not automatically included in the database, because if they occurred in the aftermath of a disaster, they likely would not be separately included, while events such as the Cholera outbreak in Haiti are mentioned because they independently fulfil the criteria EM-DAT set out. And with EM-DAT relying on input from third parties, the data will never be completely neutral. At the same time, data on events before the late 80s and early 90s will always be biased for what was reported before a standardised definition was made, hence there is a large jump between disasters that happened before 1989 and after (see Figure 2.1).

The composition of surrounding factors – infrastructure, population density, displacement into temporary shelters, level of destruction, endemicity of diseases, availability of clean water and sufficient food, experience with disaster response – is what determines the probability of an outbreak in the disaster event (Kouadio et al. 2012). These variables differ from event to event and from location to location, taking the 'natural' out of the disaster in that it is the *manmade* factors surrounding the event that ultimately decide just how severe it will be. The Great Alaskan Earthquake in March 1964 is considered one of the most severe earthquakes in terms of magnitude (USGS, 2015), however, barely 115 people died in it, while the landslide in Ancash, Peru, in 1970 affected over 3 million and killed nearly 67 thousand – the difference between the two only in population density, a manmade condition (CRED, 2015).

Additionally, the availability of a functioning disease surveillance system is a key component of determining whether or not an outbreak is recorded as having occurred after a disaster. If surveillance was not routinely undertaken, there will be no possibility to access baseline disease figures and therefore no possibility to detect spikes that could indicate epidemics (Leaning & Guha-Sapir, 2013). Routine surveillance data is only available in very patchy patterns – areas highly prone to disasters have increasingly shown a good surveillance of baseline data, as preparedness and experience has established such systems in these areas. For example areas with monsoon flooding had usable surveillance data on many water-borne diseases available that allowed for baseline comparisons for post-tsunami figures. Kumari and colleagues for example inferred their baseline data from the prescription of malaria medication from 1995 onwards to estimate the number of malaria cases and compare them to newer figures (Kumari et al., 2009). Schwartz and colleagues could use a surveillance system that had been established in 1979 to obtain numbers for diarrhoeal diseases after three major flood events in Bangladesh – a surveillance system that was in place because of monsoon floods and the related consequences (Schwartz et al., 2006). In Pakistan, the disease early warning system (DEWS) has been monitoring a number of epidemic–prone diseases since shortly after the 2005 earthquake, to improve rapid response in the future and make figures available on a weekly basis (WHO, 2014a). It has facilitated response to outbreaks in more recent disasters, like floods in 2011, 2012, and 2013.

Another factor that may play into the lack of disease information surrounding certain events is the severity of the event and, linked to that very closely, the amount of media attention paid to it. As can be seen in Table 2.5, the disasters in recent history most mentioned in the literature, the disasters most studied and best investigated, are the 2004 South-East Asia Tsunami, Hurricane Katrina in 2005, closely followed by the 2005 Kashmir Earthquake, and the 2010 earthquake in Haiti. Possibly the 2011 earthquake in Japan would have produced similar numbers of mentions in scientific literature, if it were not for the language barrier of this author (there were more Japanese publications than English publications). Without exception, these are disasters that received massive media attention. Simply typing any of these into Google or an equivalent search engine will render millions upon millions of results. Picking a disaster from the list that accounted for equally devastating numbers in terms of affected populations or casualties, we come across cyclone Aila, for example. Aila struck India and Bangladesh in 2009 and was mentioned in two reviewed papers. Searching for Aila on google yielded barely 150 thousand results, instead of over 15 million for the 2004 tsunami or the 2010 earthquake in Haiti. But what about the severe floods in Mozambique in 2000? Search results are barely scratching the 900 thousand hits. Why? Both cyclone Aila and the floods in Mozambique disasters affected over 5 million people. The earthquake in Kocaeli, Turkey, in 1999, killed nearly ten times as many people as hurricane Katrina did. Why do we find so much more information on diseases, so much more scientific attention, for Katrina than any of the other events?

Media attention and the wider, global public interest in a disaster seems to have a large impact on what is being studied and to what extent.

Although two completely different dynamics, there are strong similarities in the epidemiology of refugee camps after complex emergencies and emergency shelters after natural disasters. The disease threats in both cases are the same, but the magnitude in which they strike differs. Generally, risk seems higher in refugee camps, although the surrounding conditions are the same with one critical exception: *time*. While there are still some struggles with management after natural disasters (see below), overall most acute problems are resolved in a timely fashion. Emergency shelters are temporary solutions and with few exceptions, life can return to something resembling normality in less than a year (Kouadio et al. 2012). In complex emergencies on the other hand, the exposure to camp conditions can last for years on end. This is another reason why camps may make things consecutively worse in the long term (Van Damme, 1995). Epidemics in refugee camps have a larger impact because the camp conditions are worse, on a long term, for a large number of people. Cholera after the Haiti earthquake may be a useful comparison. Many factors of this situation were unlike any other disasters reviewed here: after the initial earthquake in a setting with low infrastructure to begin with (Tappero & Tauxe, 2011), numerous other disasters struck in Haiti — from floods to storms to finally hurricane Tomas — that made the conditions worse, cumulating to enable the massive cholera outbreak in a community that had not previously dealt with cholera. This example highlights well that the conditions are what primarily determines the outcome, and that disaster magnitude is just one of these conditions.

Other diseases, such as TB and HIV/AIDS have a slower, more delayed impact and therefore are of less concern in acute natural disaster situations and become much more important in refugee camps (Connolly et al., 2004).

An issue that has been raised by a few articles reviewed is that of diagnosis in emergency conditions (Hashizume et al., 2006; Andresen et al. 2005; Ahern et al. 2005). In many instances, proper laboratories are unavailable, rapid tests are unreliable, and many diseases as described above can have very similar symptoms, making triage at an early stage difficult. Only as diseases progress do clinical pictures become more precise, and by that point it may well be too late for proper treatment (as is the case for rabies or wound infections). In Hashizume's study of malaria diagnosis after floods in Mozambique, about 75% of cases were correctly diagnosed using only clinical diagnosis by symptoms, while using a combination of rapid testing and clinical diagnosis performed about 12% better (Hashizume et al., 2006). Andresen and colleagues raised the issue of fungal infections clinically presenting with similar symptoms to bacterial infections, while requiring completely different treatment (Andresen et al., 2005). Prescribing the wrong course of treatment in such a case may cost a patient a limb or, in the worst case, their life. The same applies in cases where leptospirosis was suspected as cases of dengue because of the similar clinical picture. Dengue may be mistaken for leptospirosis in regions where it is relatively uncommon, conversely leptospirosis may be mistaken for dengue in areas where it is highly endemic – but both are treated very differently, as leptospirosis is a bacterial disease and dengue is a viral disease (Ahern et al., 2005). It is not the norm, as in most cases diagnosis appears to be reliable. However, when misdiagnosis occurs consequences can be severe, so all efforts should be made to improve rapid testing in emergency conditions.

With considerable research into disease outbreaks after disasters has already been undertaken, the question is raised: Why do we need to further study this? It has been estimated that between 19% and 35% of deaths in consequence of natural disasters are caused by infections of some sort (Uckay et al., 2008). Keeping in mind communicable diseases are – with the right prevention strategies and adequate treatment – 100% preventable, these are 35% of deaths that need not happen. For the past 40 years or so, problems with disaster preparedness and management of the aftermath have remained largely the same (Lechat, 1976; Noji, 2005b; Leaning & Guha-Sapir, 2013). Few issues have been solved, but for the most part, relief work still struggles with the same problems. Lechat brought to light in 1976 that pre-disaster preparedness needs to be improved as well as multi-disciplinary communication to manage post-disaster conditions in a more structured, smoother way. He warns that panic, unnecessary donations and uncoordinated relief efforts do more harm than good in the aftermath of disasters (Lechat, 1976). In 1996, Logue brought nearly the same issues forward – a need for improved city planning, risk assessment and safety measures before disasters strike, adequate preparation and inter-disciplinary coordination of relief work. He confirmed that improvements had been made in the past, but public health response after disasters was still lacking (twenty years after Lechat raised the issue) (Logue, 1996). In 1997, Noji and Toole again mentioned inappropriate donations and relief work not matching the risks and needs in the affected population (Noji & Toole, 1997). Noji, in 2005, further criticised that relief organisations left too quickly after disasters, mentioned lack of coordination on site and stated the transition from emergency care to routine care was insufficiently organised (Noji, 2005a, 2005b). Kouadio and colleagues raised the same issues – lack of coordination of relief work and lack of understanding of post-disaster dynamics (Kouadio et al., 2012). And finally, Leaning and Guha Sapir (2013) stated that public health response may indeed be much more rapid than it used to be, but coordination was *still* lacking between organisations and disciplines, and that the transition from relief work to local services was not working smoothly. These arguments still persist ten years after Noji raised the issues and nearly 40 years after Lechat. "Humanitarian relief will always be required, and there is a demonstrable need, as in other areas of global health, to place greater emphasis on prevention and mitigation." (Leaning & Guha-Sapir, 2013, p. 1841). Similarly, the rumours of corpses spreading diseases such as cholera have been devilishly persistent in the past decades and are still mentioned in almost all articles (and in all articles they are referred to as nothing but rumours and exaggerations) (Kouadio et al., 2012; Ligon, 2006; R. B. Sack & Siddique, 1998).

Because much of disease management after disasters is still largely dictated by rumours, media panic, and problems that have been persisting for the past decades, more research is needed to investigate the development of disaster and disease relationships, to offer new insights into mistakes made in the past to guide future improvements, taking into account everything we know and everything that is still buried in our data. An understanding of the past is needed to inform future decisions.

Chapter 3 - The Dynamics of Disaster and Disease: A Quasi-Meta-Analysis

Chapter Contents

3.1 Introduction

In Chapter 2, the disaster-disease nexus was approached from a qualitative angle, identifying key themes that emerge from the literature. In the present chapter, a more statistical approach is pursued, using data derived from biomedical research conducted over the past 40 years with a view to uncovering risk patterns, confounding factors and differences between disasters.

Since the early 1970s, epidemiological research methods have provided new perspectives on disaster preparedness and the understanding of infectious disease outbreaks after natural disasters (Lechat, 1976). Increased research into the complex link between disasters and disease over the past 40 years has helped identify those factors associated with elevated disease risks in populations that have been rendered vulnerable by natural disasters. Such factors may be internal to the host population (for example, vaccination status and pre-existing morbidities) and to the infective agent (drug resistance and endemicity), to pre-existing conditions (poverty, general health care coverage, education, previous disaster events and presence of disease vectors) as well as to factors associated with the external environment such as physical access to healthcare, geographic location, and climate (Connolly et al., 2004; Leaning & Guha-Sapir, 2013; Watson et al., 2007; Wiwanitkit, 2010). The operating conditions could be dramatically altered by the natural disaster, resulting in damaged infrastructure, temporary shelter conditions with poor hygiene, water supply, nutrition, disrupted health care coverage, overcrowding, and adverse climate conditions (Leaning & Guha-Sapir, 2013).

The links between disasters and disease have been approached from different angles by different researchers. Some have chosen more qualitative approaches, investigating anecdotal evidence and comparing disasters from a more socio-scientific angle (Berggren & Curiel, 2006; Noji, 2005a; Orellana, 2006). Others, from the more biomedical school of thought, have approached the subject using laboratory findings and clinical surveillance data to compare events (Andresen et al., 2005; Gharbi et al., 2012; Hendriksen et al., 2011).

This chapter will investigate the existing literature on disaster and disease, pooling quantitative data from different sources to make a first estimate of the risk of infectious disease after natural disasters and determine potential factors that influence this risk relationship. The aim of this chapter is to compare morbidity and mortality across natural disasters, arising both from the direct effects of the disaster itself and indirectly from infectious diseases in the aftermath of the disaster. The chapter will examine population demographics for the studied population and quantify reported risk factors.

3.2 Methodology

While the systematic literature review in Chapter 2 focuses on the qualitative nature and narrative discussion of disasters and disease, in this chapter a quasi-meta-analysis will be conducted in order to gain more quantitative insights into the dynamics of disaster and disease as presented in published literature. The purpose of a meta-analysis is to:

> "contrast and combine results from different studies, in the hopes of identifying patterns among study results, sources of disagreement among those results, or other interesting relationships that come to light in the context of multiple studies."
> [p.652 (Greenland & O'Rourke, 2008)]

The insights provided by the two forms of review are complementary, contributing to a more comprehensive picture of the disaster-disease nexus in the last century.

3.2.1 Search strategy

As with every systematic review, the selection of which studies to include is most crucial in constructing a meta-analysis.

As a first step, biomedical publications were broadly searched via PubMed; see Section 2.1 for details. The applied search terms were combinations of '(x) AND infectious disease', with 'x' being the different disaster types: earthquake;

flood; volcano; storm (tropical storm, cyclone, hurricane, typhoon); extreme climate conditions (extreme temperature, heat wave, cold wave, snow, blizzard). These disaster classifications were established by the Centre for Research on the Epidemiology of Disaster (CRED), described in detail in Section 2.2.1.

This identified a total of 393 publications, the earliest of which were published between 1971 and 1980. The emergence of interest in disasters and disease in this period is described in more detail in Section 3.5, as well as in Chapter 2. Each publication was reviewed for relevance, including information on the occurrence of infectious disease after disasters and mention of statistical research data that could be utilised for the present analysis. This process reduced the number of relevant publications to 215 for detailed review.

3.2.2 Review strategy: PICOS

Originally, PICOS and PICO were developed by the Cochrane collaboration in 1995 as a strategy to form a research question for clinical research that would make the question answerable and to facilitate literature search on basis of the question (O'Connor, Green, & Higgins, 2011). It was later extended to become a valuable tool for systematic literature review, as the PICOS strategy effectively summarises all elements relevant when reviewing clinical studies (Schardt, Adams, Owens, Keitz, & Fontelo, 2007).

PICOS stands for five elements of clinical research:

- **P**atients, representing the population under investigation, for example patients suffering from a given disease or condition.
- **I**ntervention looks at the treatment, drug, or therapy under investigation.
- **C**ontrols/comparators summarises the control population, for example those patients who did not receive a treatment of interest.

- **O**utcome represents the results of the investigation, the outcome of the new treatment versus the old, the comparison between the patient and control group after intervention.
- **S**tudy design refers to the type of study under investigation. Traditionally, this would only be randomised controlled trials, the 'gold standard' of evidence-based practice, and therefore the S was originally left out (PICO). When the biomedical community came to recognise that randomised trials were not a 'one size fits all' solution for evidence-based practice (Straus & McAlister, 2000; Altman et al. 2001), different study designs to answer different research questions emerged. Thus, study design became a relevant element of review, as studies of different designs could not be compared without biased results, leading to the inclusion of the S in PICOS.

These elements are commonly used in the context of clinical research and while the application of PICOS to other areas of research has been contested (Huang, Lin, & Demner-Fushman, 2006) it is considered a helpful tool to summarise reviewed studies in a systematic manner (Liberati et al., 2009).

3.2.3 Operationalisation of PICOS in this study

For the purpose of the present analysis, the elements of PICOS were uniquely modified to fit the need to identify and summarise publications relevant for the research of infectious diseases and natural disasters, as follows:

(1) *Patients* was taken to refer to the disaster-affected population. Where concrete numbers for this population were unavailable in the publication itself, data provided by the EM-DAT database of the Centre for Research on the Epidemiology of Disasters (CRED) was used (Chapter 2);

(2) *Intervention* was taken to describe the disaster itself, the event 'intervening' with the affected population;

(3) Controls. Instead of 'controls/comparators', the present review used *'confounders'*. This described a number of variables that may contribute

to, or may explain, the effect a disaster has on the population's vulnerability to infectious diseases. This included factors such as the presence of vector breeding grounds, the time of the year in which the event struck (e.g. seasonality), the socio economic status (SES) of the affected population as measured by gross national income, average age of the population, life expectancy, gender balance of the population, and whether or not the population was displaced into emergency shelters after the disaster. These factors have been identified through the comprehensive literature search in the previous chapter and the use of the Epidemiologic Triangle (Section 2.3.1, Section 2.4, and Section 2.5) and were considered as factors relevant to drawing country profiles for the risk of disease after a disaster. Where possible, a control figure was included. This showed numbers of hospitalisations or confirmed cases of a disease under investigation, independent of a natural disaster (i.e. at the same time of year prior to the event) in order to compare the 'typical' situation to the out-of-the-ordinary event of a natural disaster.

(4) *Outcome* was taken as a measure of the strain of the disaster on the population. Variables included: the number of people affected (which usually consists of people injured or rendered homeless by the disaster); the number of casualties; disease morbidity (new cases of disease after the event); and disease mortality (number of deaths due to infectious disease after the event).

(5) Study design. The 'study design' element of the PICOS acronym did not feature in this analysis. It was considered irrelevant for this particular purpose, as restricting it to a particular type of study would highly limit the number of available publications and make the analysis pointless.

After reviewing the publications using this approach, only 55 were identified as providing the information required for the next stage of analysis.

3.2.4 Statistical considerations

For this review, a number of variables were selected to compare the effect of different disasters on vulnerability to infectious disease. The most basic factors to be considered were the dependent or outcome variables defined in Section 3.2.3 above:

- *Disaster affected population*
- *Disaster mortality*
- *Disease morbidity after disaster*
  - *Disease incidence per 100,000 population (after disaster)*
  - *Disease incidence per 100,000 population (before disaster)*
- *Disease mortality after disaster*

Incidence rates were calculated from absolute numbers as reported in the publications (see below). The independent variables are summarised in Table 3.1.

Basic descriptive statistics were used to explore connections, trends and differences between disaster types and disease incidence. Publications were grouped by disaster type to in order to identify differences in numbers of disease by type of disaster.

Table 3.1: independent variables used in multiple linear regression to identify variables significant to infectious disease after natural disasters.

Variable name	Code	Source of data
Type of disaster	1 = earthquake, 2 = extreme climate conditions, 3 = storms, 4 = tsunami	From the article
Month of disaster	1 = January, 2= February, 3= March, 4 = April, 5 = May, 6 = June, 7 = July, 8 = August, 9 = September, 10 = October, 11 = November, 12 = December	From the article
Year of disaster	i.e. 1999	From the article
Diarrhoeal disease	1 = yes, 0 = no	From the article
Acute respiratory infection	1 = yes, 0 = no	From the article
Vector borne disease	1 = yes, 0 = no	From the article
Wound infection	1 = yes, 0 = no	From the article
Disease controls	(incidence/hospitalisation if unaffected by disaster event)	From the article

Table 3.1 (cont.): independent variables used in multiple linear regression to identify variables significant to infectious disease after natural disasters.

Variable name	Code	Source of data
WHO region	1 = Africa, 2= America, 3 = Eastern Mediterranean, 4 = Europe, 5 = South East Asia, 6 = Western Pacific	Country taken from the article, relevant WHO region identified through WHO website (http://www.who.int/about/regions/)
Country	1 = Brazil, 2 = China, 3 = France, 4 = Haiti, 5 = India, 6 = Indonesia, 7 = Italy, 8 = Japan, 9 = Mozambique, 10 = Pakistan, 11 = Philippines, 12 = Puerto Rico, 13 = Solomon Islands, 14 = Sri Lanka, 15 = Sweden, 16 = Taiwan, 17 = Thailand, 18 = Turkey, 19 = United States of America	From the article
Vector breeding ground	1 = yes, 0 = no	If not mentioned in the article itself, WHO data was consulted (statistics of the Global Health Observatory http://apps.who.int/gho/data/node.imr)
Population displacement in consequence of disaster	1 = yes, 0 = no	From the article
Age	Total population median	WHO data (http://www.who.int/about/regions/en/)
Gender balance	% female in total population	World Bank (http://data.worldbank.org/indicator/SP.POP.TOTL.FE.ZS)
Life expectancy	Average life expectancy in total population	WHO Global Health Observatory (http://apps.who.int/gho/data/node.imr)
Income	Gross national income per capita	World Bank (http://data.worldbank.org/indicator/NY.GDP.MKTP.CD)

Linear regression analysis

To test for significant associations between dependent and independent variables, and therefore identifying predictors for disaster effect, a number of multiple linear regression analyses were performed. Calculations were made using IBMs statistical software SPSS 21. This was performed for each of four outcome variables: disaster affected population; disaster mortality; disease morbidity; and disease mortality. Relevant statistics for the general model are the *F*-statistic, which indicates whether or not the overall null-hypothesis can be rejected. This overall null-hypothesis dictates that there is no statistically significant difference between infectious disease after disasters and infectious diseases without natural disasters correlated with the independent variables. If the F-statistic is statistically significant with a *P*-value below 0.05, the hypothesis can be rejected. The adjusted *R*-square shows how much of the variance in the outcome variable can be explained by the independent variables. For example, an *R*-square of .324 indicates that about 32.4% of the variance for disaster affected population can be explained by the model (see Table 3.6).

The β-value states that if the value of the independent variable increases by one unit, the outcome variable will be increased (if the association is positive) or decreased (if the association is negative) by that value. And lastly, the *t*-statistic for each independent variable is necessary to determine if the 0-hypothesis stating that the variable has no effect on the outcome can be rejected, again if the significance level *P* is below 0.05.

Relative Risk

In order to determine a link between natural disasters and infectious diseases, the most straightforward estimate is to calculate the relative risk of infection after natural disaster. Relative risk (RR) is calculated with the presence of an outcome when there was exposure (A) divided by the total population exposed, and the presence of the same outcome if there was no exposure (C) divided by the total unexposed population. For the present analysis the number of infectious disease hospitalisations after a natural disaster and the number of infectious disease hospitalisations with no natural disaster were used to calculate relative risk. A cross-tabulation was performed using the following format:

Table 3.2: cross-tabulation template for relative risk.

	Disease present (incidence per 100,000)	No disease present (-incidence per 100,000)	Total
Exposed to disaster	A	B	A+B
Not exposed to disaster	C	D	C+D

Using the relative risk formula derived from this table, **[A/(A+B)/C/(C+D)]** equals the relative risk for developing disease depending on exposure status. RR > 1 indicates the risk is higher in the exposed group, whereas RR < 1 indicates that the risk is lower in the exposed group, i.e. what might be called a 'protective effect' of the exposure. RR = 1 indicates no difference between exposure and non-exposure.

Disease incidence rates per 100,000 population were calculated using the data obtained from the publications. If not otherwise specified in the reviewed article, the disaster-affected population was used as the denominator. Incidence when unexposed was calculated by collecting surveillance data for the disease, ideally from at least a year before the disaster. If data from that period was unavailable, the data nearest to that time point before the disaster was used instead. If at all avoidable, it was attempted not to use surveillance data from after the disaster, as the long-term effects of the event may have a sustained impact on disease figures. Where pre-disaster incidence rates could not be found, the assumption was made that there was no difference in incidence, taking the same rate as presented in the disaster.

3.3 Results

The 55 publications identified by the search strategy and included in the present analysis were published between 1982 and 2014. They included a total of 29 different disasters (Appendix 2). As the table shows, the Haiti Earthquake in January 2010 and the Indian Ocean Tsunami in December 2004 being the two most frequently mentioned, followed by the Great East Japan Earthquake in 2011 and the 2008 Earthquake in Sichuan, China. Overall, earthquakes were the most commonly covered disasters (26 publications), followed by storms (15 publications), extreme climate conditions (7 publications) and tsunamis (7 publications). The publications covered all 6 geographic regions of the World Health Organization, with a total of 19 countries mentioned (see Appendix 2 and 3).

Of the 29 disasters, an average 3,925,547 people were affected and 49,850 were killed (Table 3.3). The 2008 earthquake, with its epi-centre in the Wenchuan county of Sichuan, China, had the highest estimated effect, with 46,240,000 affected people (Wang et al., 2010; Yang, Yang, Luo, & Gong, 2009; Zhang et al., 2012), whereas the Haitian earthquake in 2010 was arguably the deadliest, with an estimated 230,000 casualties (EM-DAT)(Abrams et al., 2013; Barzilay et al., 2013; Brown, Ripp, & Kazura, 2012; Gharbi et al., 2012; Mung et al., 2010; Neuberger et al., 2012; Stratton, 2013; Tappero & Tauxe, 2011). An average of 148,336 cases of infectious disease were recorded per disaster, ranging from 2 cases of tetanus after floods in Nimes, France in 1988(Duclos, Vidonne, Beuf, Perray, & Stoebner, 1991) to 5,618,902 cases of infectious disease recorded after floods in Pakistan in 2010 (Shahpar et al., 2012). In Haiti, 7,436 deaths were recorded in the cholera epidemic after the 2010 earthquake (Stratton, 2013), accounting for the highest number of deaths by infectious disease in the covered sample. On average, 1,033 lives were claimed by disease (Table 3.3).

Table 3.3: average impact of disasters across sample.

	Mean	Std. dev.
Disaster affected population	3,925,547.0	10,508,817.7
Disaster mortality	49,849.9	77,880.9
Disease morbidity	148,335.8	764,342.8
Disease mortality	1,033.5	2,494.5

As described in Chapter 2, infectious diseases of concern in natural disasters can generally be grouped into four categories: diarrhoeal diseases; acute respiratory infections; vector-borne diseases; and wound infections. Diarrhoeal diseases were mentioned in 26 of the sampled publications and are the most common type of reported disease, followed by vector borne diseases (14), acute respiratory infections (13) and wound infections (11); see Table 3.4. Earthquakes, floods and cyclones were associated with more disease outbreaks than other types of disaster. Cholera and malaria were the two most commonly mentioned diseases (11 and 13 mentions respectively) – although it has to be considered that the frequent mention of cholera is largely a result of the repeated coverage of the epidemic in Haiti.

Disaster types affected the populations they struck in different ways (Table 3.5). Earthquakes affected the largest number of people, on average 6,861,878 in the affected population versus tsunamis affecting the least (308,127). Extreme weather conditions had the highest incidence of infectious disease, which is likely due to the strong impact of the Pakistan flood in 2010, where the country-wide disease surveillance systems recorded over 5 million cases of infectious diseases, while the other disaster types counted only average numbers of patients ranging from 13 in the tornado in Joplin, Missouri, in 2011 (Fanfair et al., 2012) to an average of 83,360 for earthquakes in general. Earthquakes recorded the highest average disease-related mortality, killing about 2,304 patients.

Table 3.4: disease groups by disaster type.

	# of mention
Diarrhoeal disease	26
Earthquake	*8*
Extreme weather conditions	*6*
Storms	*9*
Tsunami	*3*
Acute respiratory infection	13
Earthquake	*7*
Extreme weather conditions	*2*
Storms	*3*
Tsunami	*1*
Vector borne disease	14
Earthquake	*5*
Extreme weather conditions	*1*
Storms	*4*
Tsunami	*4*
Wound infection	12
Earthquake	*7*
Extreme weather conditions	*0*
Storms	*2*
Tsunami	*3*

Table 3.5: average impact of disaster types on population.

	Population affected (mean)	Casualties (mean)	Disease morbidity (mean)	Disease mortality (mean)
Earthquakes	6,861,878.77	89,688.12	83,360.58	2,304.17
Extreme weather conditions	2,528,441.33	434.17	803,191.43	0.75
Storms	1,082,877.00	11,129.07	23,814.13	25.44
Tsunami	308,127.00	27,209.00	1,655.86	11.00

3.3.1 Multiple linear regression

The results of the linear regression analysis using four different response variables (disaster affected population, disasters casualties, disease morbidity, disease mortality) are summarised in Table 3.6. As the table shows, the analysis yielded no statistically significant association when disease morbidity after natural disasters was entered as the dependent variable.

With disaster-affected population entered as the dependent variable, the linear regression found three significant associations (female population, disaster type, and median age). This means that there is statistical evidence that the independent variables do influence the outcome (see Table 3.6).

Disaster mortality was negatively associated with month of disaster, average life expectancy, and disaster type. Although month of disaster does not present as statistically significant in the model including all three variables, it was statistically significant if entered on its own (P=.001) and if entered in a model with life expectancy (P=.002).

The analysis furthermore found average life expectancy, month of disaster and global WHO region negatively associated with disease mortality.

Table 3.6: Linear regression model statistics.

	Adjusted R-square	**F-statistic (p)**	**β**	**t-statistic (*P*)**
disaster affected population model	0.324	8.971 (.000)		
female%			-5097907.114	-4.610 (.000)
disaster type			-2629305.173	-2.398 (.021)
median age			358794.083	2.334 (.024)
disaster mortality	0.310	12.234 (.000)		
month of disaster			-4796.242	-1.761 (.085)
average life expectancy			-3910.174	-3.465 (.001)
disaster type			-21323.550	-2.395 (.021)
disease mortality	0.558	10.670 (.000)		
average life expectancy			-113.349	-2.125 (.046)
month of disaster			-277.930	-2.838 (.010)
WHO region			-556.398	-2.144 (.044)

3.3.2 Overall relative risk

Disease incidence was available for calculation from 40 publications. Using a cross-tabulation of the average incidence of disease and health in the population exposed to the disaster against the population not exposed (Table 3.7), an estimate of risk could be calculated. It was estimated that the relative risk of disease in the aftermath of a disaster is 3.45 (95% CI: 3.13–3.82; $P<0.0001$).

3.3.3 Relative risk by disaster type

Separate relative risks were calculated for the four disaster types. On the basis of the results in Table 3.7, the relative risk of infectious disease after earthquakes is 6.04 (95% Confidence Interval: 5.51-6.64; $P<0.0001$). The RR after tsunamis is 2.94 (95% CI:2.66-3.27; $P<0.0001$) and therefore disease is more likely after tsunamis, whereas the impact of storms on the risk of infectious disease was insignificant, accounting for a relative risk of 1.24 (95% CI: 1.09-1.41; $P=0.0012$). Lastly, the RR of disease after extreme weather conditions is 0.91 (95% CI: 0.82-1.01; $P=0.09$).

Table 3.7: Cross-tabulation for relative risk, constructed from Table 3.2.

	Disease present (incidence per 100,000)	No disease present (incidence per 100,000)	Total	Relative risk
Overall				**3.45 (95% CI: 3.13–3.82; *P*<0.0001)**
Exposed to disaster	1715.10	98284.9	100000	
Not exposed to disaster	496.98	99503.02	100000	
Earthquakes				**6.04 (95% CI: 5.51-6.64; *P*<0.0001)**
Exposed to disaster	3091.40	96908.60	100000	
Not exposed to disaster	511.65	99488.35	100000	
Tsunamis				**2.94 (95% CI:2.66-3.27; *P*<0.0001)**
Exposed to disaster	1415.42	98584.58	100000	
Not exposed to disaster	480.94	99519.06	100000	
Storms				**1.24 (95% CI: 1.09-1.41; *P*=0.0012)**
Exposed to disaster	507.18	99492.82	100000	
Not exposed to disaster	409.91	99590.09	100000	
Extreme weather conditions				**0.91 (95% CI: 0.82-1.01; *P*=0.09)**
Exposed to disaster	629.42	99370.58	100000	
Not exposed to disaster	691.43	99308.57	100000	

3.4 Discussion

3.4.1 Introductory observations

Although most of the results presented in Section 3.3 are estimates and are subject to a number of assumptions, they offer insights into the dynamics of disaster and disease that can influence the current understanding of this association.

As described in Chapter 2, the connection between disaster and disease has found an increasing interest in the scientific community since the mid-1970s, with attention being drawn to the matter by the writings of Michel Lechat in 1976 and James Logue in 1981 (Lechat, 1976; Logue et al., 1981). The introduction of epidemiological concepts into the study of disasters opened the field to a new audience and contributed to the sharp increase in biomedical literature on the matter in recent decades. Between 1990 and 2010, the average number of mentions of disasters and disease in the epidemiological literature increased from 5 publications to 24 (Chapter 2), illustrating this new interest in disaster epidemiology. This has greatly enabled research into the nexus of disaster and disease. Still, previous literature reviews (Ahern et al., 2005; Alderman, Turner, & Tong, 2012a) have noted significant shortcomings, both caused by lack of research conducted in the field and by data limitations. The research comes with numerous such limitations that — if progress is to be made in the field over the upcoming decades — need to be addressed. Such progress in a field that is so multidisciplinary cannot come from change in just one side, but has to be pushed from all involved disciplines.

The present research aims to inform such progress and offer new insights into the dynamics of disaster and disease. While great care was taken to ensure data is reliable, there were both strengths and obstacles to what could be performed and they will be highlighted in the following sections.

3.4.2 Meta-analysis selection process

Starting at the earliest stages of selection, I was aware of possible bias while selecting abstracts from the 393 initial publications. While it was attempted to be as inclusive as possible when selecting the abstracts, it has to be assumed that publications may have gone unnoticed in the selection process based on different expectations of abstract content. It can be assumed that the standard format of abstracts for epidemiological research provides a certain level of certainty that all relevant publications have been included, but it must still be considered as a sample. The results of this study therefore should not be considered a 'final' product, but a work in progress to be expanded as new evidence becomes available. Another problem with the selection of studies was that many publications reported on specific diseases or groups thereof, rather than the cumulative numbers of all infectious disease cases. Running separate analysis for individual diseases would have resulted in numbers too small to present viable results, but at the same time the data may lose generalisability due to measuring different variables.

However complicated a final selection of studies is, the approach used in this study to select relevant publications can be adapted for any type of biomedical research and should be considered to offer a new systematic approach to research in the disaster disease nexus. Standardisation issues that occurred during data collection do not reflect errors in the approach, but rather reflects the difficult landscape of biomedical publications investigating disaster and disease dynamics being unstandardized to a point where comparison becomes nearly impossible. It should be aimed to standardise research in the field of disaster epidemiology, in order to enable future comparisons and strengthen the evidence for disaster preparedness efforts.

This chapter applied a prototype search strategy based on the Cochrane Collaboration PICOS system, an approach that has been applied in clinical trials previously to pool data for meta-analysis, but has not been used in this particular context before. It remains a comprehensive approach to obtain relevant data and with future research can be improved for more informative comparisons.

3.4.3 Discussion of data

A number of assumptions were made about the data for the present analysis. Where the affected population used in the publication was not mentioned by the authors, data was taken from the EM-DAT database listing the total number of persons affected. This might have influenced the incidence calculations. Assuming an incidence of x cases for the entirety of the affected population of a disaster may be very different from an incidence of x cases for a specific population of, say, a single hospital or a single town. This was a possibility that had to be accepted in the instances where data was not available through the publication itself.

Of course, it has also been observed that using average incidence to calculate RR is not always accurate. The incidences calculated here often result from different surveillance periods, ranging from a week to several months, therefore being non-standardised. Baseline data were matched, whenever possible, to control for variance in seasonality. In some instances, it was possible to calculate the incidence over the exact same time period a year prior to the event. But this was the exception. In most cases, only annual incidence was available, and mostly these were national statistics, as opposed to data from the specific region where the disaster struck. This may bias the results, as incidence can greatly differ from one region to another and the national average may not be completely representative for these internal variances.

It also has to be noted that to assume the baseline data taken is a 'true' baseline unaffected by outside events must be treated with caution. While the incidence may not be affected by the disaster event in question, there may be numerous other factors that influence the cases of diseases at any time. These factors may be political, economic, or the occurrence of other disaster events (Lechat, 1976;

Schwartz et al., 2006). Data was not obtained from a clinically sterile environment that was independent of outside influences. It was attempted to correct for such factors, but to assume it could be entirely avoided would be optimistic.

Another assumption was made that, where the baseline incidence was missing there had been no effect of the disaster on the incidence of the disease. This is, of course, a risky assumption. However, after thorough consideration, it was decided that it was the most neutral solution. To clarify, the basis of the assumption was that if there had been a significant, noticeable change in the disease incidence, there would have been a report of it in some capacity, even if it was just one mention in one publication. Of course, the problematic availability of surveillance data prior to major events further complicates the inclusion of baseline data. Choosing, however, to take an average change in incidence based on available data from other publications would falsify the results, as the effect a disaster has on disease is largely determined by the exterior circumstances surrounding the event and these vary by country or region. Therefore it was decided to assume no change in incidence and only figure into the calculations the actual observed changes, instead of manufactured difference.

Spatial differences influence the dynamics of disaster and disease in that different geographic regions are differently affected. Numbers of affected people and economic damage differ by region with nations with high infrastructure and coping capabilities being less affected (Kouadio et a. 2012). Similar trends can be observed in the data from this review, where regions with weaker infrastructure and a lower gross national income per capita are more severely affected than higher income countries. China, arguably the most densely populated area, had the highest number of affected populations in the country comparison, accounting for a total of 35,798,298 affected. Haiti was shown to be severely affected by the Cholera epidemic following the 2010 earthquake, because of its pre-existing conditions of poor health and infrastructure, compared to its direct neighbour (Tappero & Tauxe, 2011). Such factors influencing the effect of disaster on disease have been noted previously, and it was argued that general conclusions cannot be drawn without great awareness of these geographical and socio-economic differences (Alderman et al., 2012a).

Results may also have been affected by the problem that a number of major disasters were the subject of multiple studies, while other disasters may have been completely neglected in biomedical literature. The inclusion of disasters of the severity of the Haiti Earthquake and its consequences multiple times in the calculations may skew the results, possibly accounting for the large RR evidenced for earthquakes in section 3.3.2.

3.4.4 Discussion of results

Multiple linear regression was chosen as a means to measure associations in this study (section 3.3.1). The approach was selected for the continuous outcome variables, while a logistic regression would have been chosen for a binary outcome (as presented in Chapter 4). With only 55 useable publications and wide confidence intervals, the results of the regressions presented above cannot be generalised without paying close attention to each individual scenario.

However, the results presented do give rise to interesting arguments. A population with a higher percentage of the female gender, and disaster type have been negatively associated with the disaster affected population. The association with disaster type seems straightforward: earthquakes appear to cause more damage to infrastructure and affect more people than extreme weather, storms, and tsunamis. Less straightforward is the association with a higher percentage of females in the population. It can possibly be seen as an indicator for overall development of the population – populations with a higher economic infrastructure have lower maternal mortality (Hogan et al., 2010) – meaning a higher development has a protective effect against natural disaster.

Median age on the other hand is associated with a larger affected population. This indicates that an older population is more vulnerable to natural disaster.

Disaster mortality is negatively associated with the month of disaster, the average life expectancy, and the disaster type. An interesting observation here is that, if month of disaster is the only variable in the model or paired with average life expectancy, the effect is statistically significant indicating that a later month in the year leads to lower disaster mortality (a surprising outcome in itself). But if disaster type is added to the model, month of disaster becomes insignificant. It can be assumed that the effect of disaster type negates the effect of the disaster timing. This may be related to disaster seasonality (i.e. monsoon seasons, or hurricanes that appear seasonal), but further research is necessary.

The association with average life expectancy makes sense in that a higher life expectancy is indicative of a healthier population (Molla et al., 2001), better infrastructure and health care, essential elements to preventing mortality both from disaster and from disease.

Statistically less significant is the association of disease mortality with average life expectancy, month of disaster, and WHO region, but the same considerations apply.

Subject to data limitations, the relative risk analysis in Sections 3.3.2 and 3.3.3 yields some noteworthy results. While extreme weather conditions were shown to have the highest number of disease cases (Table 3.5), when calculating RR it was shown that there was no significant difference between pre- and post-disaster incidence. Inspecting the available data, it is shown that the extreme weather events differ in economic context, in geographical context, and in temporal context. The only factor they have in common is that, with the exception of the floods in Pakistan in 2010 (Shahpar et al., 2012), none of these events resulted in significant population displacement to temporary shelters (Glass et al., 1979; Duclos et al., 1991). This confirms the hypothesis made in Chapter 2 that the most important factor determining disease risk after disaster is not the disaster itself, but the circumstances following the event. The resulting RR of disease is 6 times higher for disasters where displacement took place.

It also has to be considered that cases of disease after disasters might have gone undetected because of surveillance periods and differences in disease incubation periods. For example, it has been shown in previous publications that the reported incidence of vector-borne diseases decrease significantly in the immediate aftermath of floods as the breeding ground is washed away by the initial floodwaters (Watson et al., 2007) leading to a delay in the emergence of cases of vector-borne diseases. This might have influenced the data in the case of extreme weather conditions and contributed to the low RR (= 0.91) for these events.

3.4.5 Limitations

While the results presented in this chapter provide interesting insights into the association of natural disasters and disease within space and place, there were limitations to what could be done and to how the findings must be interpreted.

A meta-analysis would have yielded the most reliable results. However, due to the substantial heterogeneity of the data, the methodology was not feasible and would not have yielded informative results. In routine epidemiological studies, each 'case' for the analysis is recorded, measured and included using the same methodology. In a meta-analysis however, each 'case' represents an individual study or publication, meaning each case was reported and measured with a different underpinning methodology. There is no guarantee that two studies measure exactly the same. This heterogeneity of the data and a lack of standardisation makes direct comparison impossible. Attempting to standardise the data retrospectively would lead to a loss of information, as it would mean cutting away potentially valuable data that would not fit with the new standard. The source of this heterogeneity comes from the fact that all articles focus on different approaches. Strictly biomedical publications focus on genetic subtypes of disease, on laboratory testing, and less on the source of the samples under investigation. They barely report information about patient outcomes, and patients are excluded if they are not 'laboratory confirmed', leaving patients that may still be hospitalised and ill out of their reported numbers. Adversely, there are publications that focus more on the social implications of the disease events and not on the clinical, looking at sources of infection but again providing limited information on outcome itself. The unstandardized reporting is also reflected in large variations of methodology. Sample sizes vary greatly, with some studies looking at the entire population, others just looking at cases within a single hospital or health care centre. Timing of data collection also influences the data; some studies collect data over several months, while others look only at a short period of maybe two or three weeks, some even less. Although it is possible to extrapolate the data, there is a large amount of uncertainty involved in this approach. It has been argued by Alderman and colleagues that the health outcome categories seen in publications do not necessarily "illustrate the full extent of the potential direct and indirect health impacts" (Alderman et al., 2012a), and this is a limitation applicable in this study as well. The only way to avoid such losses in the future is to set clearer standards for data collection beforehand and make data comparable in that way.

With surveillance coverage being patchy at the best of times, assumptions had to be made in order to derive incidence rates for diseases used to calculate relative risk. Data was taken from various sources, presented in largely varying formats and were brought into a format that would allow for comparison, but bias and data noise is very likely and unavoidable. In order to enable future research and aid preparedness for disease outbreaks, disease surveillance – on a global scale – needs to undergo significant improvement. The surveillance system introduced in Pakistan and a number of other countries in the last ten years (Checchi et al., 2011) presents a great example of good disease surveillance and the approach should be adopted in all WHO countries.

This chapter has been previously presented at the 2016 Annual Meeting of the American Association of Geographers (AAG) in San Francisco (Fairley, 2016b).

Chapter 4 - Methodology of Chapters 5-8

Chapter Contents

4.1 Background

Chapters 2 and 3 provided insight into the association between natural disasters and infectious diseases, using evidence from previously published literature over the past decades. In chapter 5-8, a quantitative investigation is taken, utilising WHO data in an ecological study of infectious disease and disaster over a period of 14 years. The following sections will outline the rationale of these four chapters, along with an overview of the data used and the methodology applied.

4.1.1 Background: The study of Sumner et al.

In a seminal study published in Prehospital Disaster Medicine in 2013, Sumner and colleagues presented a landmark investigation into the association between cholera and one category of geophysical disasters, namely earthquakes (Sumner, Turner, & Thielman, 2013). The longitudinal study spanning 15 years most notably found that earthquake events affecting more than 10,000 people were associated with a 2.26 odds of having a higher than average cholera rate in that year. The paper included data for cholera and for earthquakes between 1995 and 2009. Disease data were coded in a binary variable as 1 (> average cholera rates) and 0 (≤ average cholera rates), where the average was calculated over the 15 years for every country individually. Disaster data were coded into a series of binary variables looking at the number of affected population by an earthquake per country-year (for example, the variable ≥10,000 affected coded as 1=yes and 0=no). Additional covariates were included to account for their potential effect on cholera rates. Statistical association between earthquakes and cholera was calculated using a fixed effect model logistic regression to allow for time-invariant factors that may affect cholera rates, as well as factors that would affect all countries, such a global climatic change. There was no mention in the publication of alternative methodologies that might have been considered.

The results of Sumner and colleagues – while not reaching statistically significance – identified an increasing odds of cholera with the size of the population affected by the earthquake. Pure coincidence is ruled out, although the underlying relationship could not be identified in the study. Weaknesses of the study design, discussed in the paper's results, come from bias in the data. The possibility was considered that reporting of cholera cases may have been more thorough in the aftermath of earthquakes. Furthermore, data were available only on a national level, and a selection bias in the initial decision which countries to include limited the results of the study. However, the results were considered as a stepping stone to further research, providing a first estimation and new insights into the relation between cholera and earthquakes.

The three authors – Steven A. Sumner, MD; Elizabeth L. Turner, PhD; and Nathan M. Thielman, MPH – are part of the Global Health Institute at Duke University, North Carolina, and work in the Duke University departments of Medicine, Biostatistics and Bioinformatics, and Infectious Diseases and Geographic Medicine respectively.

4.1.2 Extending the work of Sumner et al.

Drawing on the methodology of Sumner and colleagues, Chapters 5 – 8 of this thesis seek to gain a quantitative insight into disaster and disease in the recent years, looking at data between 2000 and 2013. Instead of looking at cholera exclusively in relation to earthquakes, a broader approach will be taken, by looking at groups of disasters in association with four diseases representative of diseases types commonly considered significant in the aftermath of natural disasters. The aim of the upcoming chapters is to gain new insights into the dynamics of these diseases in disaster-prone countries, and in some cases to investigate the links between the diseases, and the implications the disease has on the conditions surrounding the disaster.

This chapter outlines the general methodology applied in the four chapters: the disease selection, data collection for disasters and diseases, and the statistical analysis performed.

4.2 Disease selection

As has been outlined in Chapter 2, the four types of diseases most commonly observed after natural disasters are 1) diarrhoeal diseases, 2) acute respiratory infections (ARI), 3) wound infections, and 4) vector-borne infections (Linscott, 2007). Selection of diseases for the following chapters was performed with these types in mind. In Chapter 2, the most common diseases were introduced. Among the diarrhoeal diseases were leptospirosis, *E.coli*, and cholera. Cholera was chosen for analysis in Chapter 5, because numbers of cholera have been well recorded, and its role after disasters has already been proven in other publications – such as Sumner et al. 2013. The common vector-borne diseases of concern after natural disasters are malaria, dengue, rabies, and St. Louis encephalitis. Malaria was chosen as a vector-borne diseases, given its significance in areas of endemicity. The common acute respiratory infections listed in Chapter 2 were measles, pneumonia, influenza, and tuberculosis. Measles is mostly documented in children and with figures of vaccination coverage, which is beyond the scope of these chapters. Pneumonia and influenza have not seen much attention in post-disaster situations, despite the implication that they can become an issue in overcrowded emergency shelters. Tuberculosis has received the least attention in the aftermath of disasters, despite the recent emergence as a research priority due to drug resistance. It was therefore chosen to fill a gap in current research, by focusing on the role of tuberculosis after natural disasters in Chapter 7. Chapter 8 investigates the co-infection of HIV and tuberculosis. HIV – and sexually transmitted diseases in general – have not been shown yet to be affected by natural disasters, and play a more dominant role in complex emergencies that force people to displace for prolonged periods of time.

Wound infections were not considered in these chapters, as they have a very different dynamic from the other types: Wound infections occur in the acute aftermath of the disaster – by contamination of wounds sustained by, for example, flying debris. These diseases have been extensively studied, whereas diseases that appear outside of the acute disaster are less well understood.

Standard overviews of the nature, transmission and clinical courses of the selected diseases are provided by Heymann (2015) and the summaries that follow are based on that source.

Chapter 5 - Cholera

Cholera was chosen to represent diarrhoeal diseases. It is one of the best understood diseases in current research. Cholera is a bacterial infection transmitted through contaminated drinking water and was identified in the literature as one of the most significant threats in disaster situations (Panda et al., 2011; Schwartz et al., 2006; Sumner et al., 2013).

Historically, cholera has dramatically impacted the world, causing six global pandemics in the 19th century spreading from the Gulf of Bengal, and a seventh pandemic in the 20th century (Heymann, 2015). Cholera rates have decreased in recent years, and this has been credited to improved sanitation and hygiene. In 2011, about 58% of global cholera cases could be attributed to the severe epidemic in the aftermath of the earthquake in Haiti, a country where the disease was not endemic prior to the outbreak (Barzilay et al., 2013). However, it is considered likely that true figures of cholera are higher than records show, due to limited and unstandardized surveillance (Bhunia & Ghosh, 2011).

As disruptions in infrastructure, temporary shelters with poor water quality and sanitation are risk factors for cholera, it has been a high priority for disaster management in the last two decades at least (Pfrimmer, 2010).

Chapter 6 - *Malaria*

Malaria was selected not only for its nature as a vector-borne disease, but also because of its significant role as a major killer in countries where it is endemic (Wisner & Adams, 2002). Carried and transmitted by the Anopheles mosquito, the parasitic disease affects roughly 200 million people yearly and poses a specifically high risk to young children (Heymann, 2015).

Malaria is no longer endemic in most temperate zones, but is the leading cause of morbidity and mortality in tropical regions. In 2010, malaria was reported from 99 countries in tropical regions (Heymann, 2015). Disease prevention is limited to insecticide laced mosquito nets distributed in homes, but there is concern about improper application of these measures (Minakawa, Dida, Sonye, Futami, & Kaneko, 2008) and it may be problematic to control after a natural disaster (Waring & Brown, 2005). A recent rise in insecticide resistance among mosquitoes further complicates malaria control efforts (Weinstein et al., 2010).

In the aftermath of natural disasters in endemic regions, malaria control has been a priority issue for the past decades. Where natural disasters alter the environment, possibly in favour of vector breeding, malaria becomes a threat that may manifest months after the actual disaster. There is a large body of research on the occurrence of malaria after natural disasters in endemic regions, especially in the aftermath of the South East Asia Tsunami in 2004 (Balaraman, 2005; Briët et al., 2005; Gunasekaran et al., 2005; Hashizume et al., 2006; Krishnamoorthy et al., 2005; Kumari et al., 2009; Weinstein et al., 2010)

Chapter 7 - Tuberculosis

Tuberculosis (TB) was favoured as a respiratory illness over influenza, because of the lack of research conducted on its dynamics after natural disasters. Tuberculosis is a bacterial disease commonly affecting the lungs, but potentially spreading to other parts of the body (extra-pulmonary tuberculosis). It is treated by a chemo-therapy course devised by the WHO. This directly observed treatment short-course (DOTS), if supervised by a medical professional, takes roughly 2-3 months to complete, and if not directly supervised may take up to 6 months to complete. The nature of this lengthy treatment makes it prone to interruption, leading to disease relapse and an increased risk of drug resistance (WHO, 2015b).

Tuberculosis occurs worldwide, with an estimated 9 million cases of ‘open’ TB (TB that is symptomatic as opposed to latent TB that is present in a patient but does not show symptoms) per year (Heymann, 2015).

Considering the possibility of a natural disaster disrupting health infrastructure, it was assumed there could be an impact of natural disaster on tuberculosis numbers. However, existing research has found little to no evidence of natural disasters affecting tuberculosis (Myint et al., 2011). However, there has been no research into tuberculosis relapse, so the dedicated chapter in this thesis seeks to fill this research gap.

Chapter 8 - HIV & Tuberculosis Co-infection

In addition to the tuberculosis chapter, a separate chapter will investigate tuberculosis as a co-infection of HIV. Sexually transmitted diseases were not identified as an issue in the aftermath of natural disasters in previous research, but have been shown as problematic among displaced populations in complex emergencies (Connolly et al., 2004). Due to its long incubation period, identifying an association between time spent in a disaster shelter and symptomatic HIV disease is challenging, however there is a possibility to investigate co-infection with tuberculosis. Tuberculosis is a common complication in the course of AIDS (Heymann, 2015). As HIV patients are immuno-compromised, being exposed to a higher risk of infection in the aftermath of disaster may be quantifiable with data on co-infections available from WHO.

4.3 Data

For each of the four diseases considered in Chapter 5 – 8, data on natural disasters and disease occurrence has been collected in a systematic manner to insure comparability and reproducibility. Data was geocoded and analysed according to WHO regions (Figure 4.1). This section details the nature of the data utilised in the analysis.

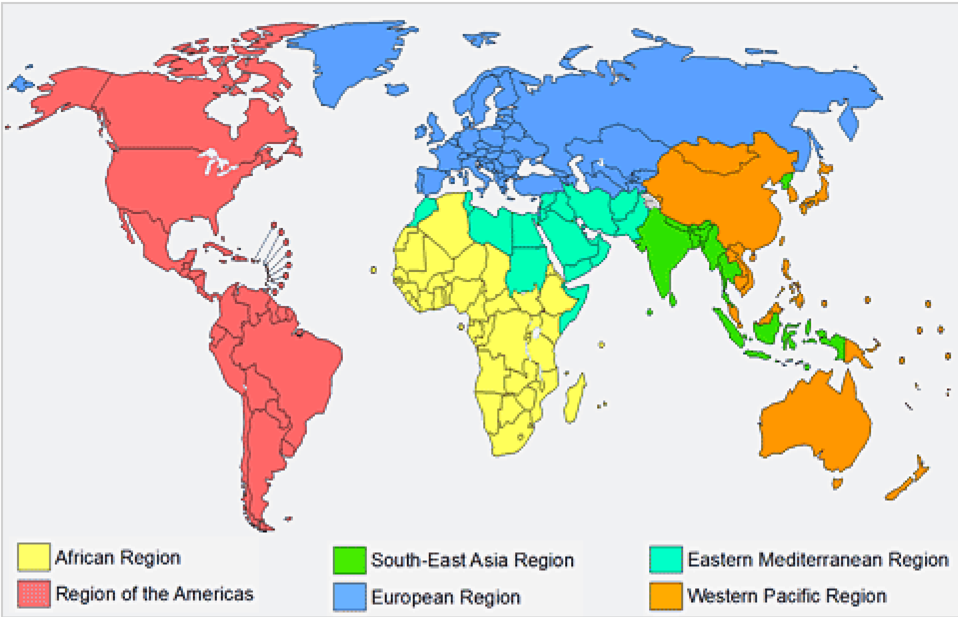


Figure 4.1: map of WHO regions (WHO, 2017c).

4.3.1 Disease data

Surveillance data for each of the infectious diseases in Section 4.2 was obtained from the World Health Organization Global Health Observatory data repository (WHO, 2016a). This database, categorised by a large set of indicators of global health, provides epidemiologically relevant data on numerous diseases, including the four selected for analysis. The Global Health Observatory includes morbidity and mortality data, case fatality rates where available, and relapse cases where relevant. Data were extracted for the years between 2000 and 2013, because data were most comprehensive for these years. Prior to the year 2000, surveillance was largely incomplete, with large gaps of years without recorded data, and changing, standardised case definitions, which would lead to complications for the intended analysis. Sumner et al. (2013) chose a period between 1998 and 2009, in order to avoid inclusion of the Haiti cholera epidemic, as it would likely bias the data. However, considering the following chapters investigated diseases other than cholera as well, it was decided to include a different time interval in favour of more comprehensive data surveillance.

Table 4.1 summarises the disease data extracted from the Global Health Observatory. There were different considerations made for the different diseases and they will be outlined below.

Table 4.1: variables used in the analysis of chapters 5-8 (source: http://apps.who.int/gho/data/node.main#ndx-M, last accessed: October 2016).

DISEASE VARIABLES	*DEFINITION*	*SOURCE*
Cholera		
reported cholera cases	cases confirmed by laboratory, epidemiology, or clinically	Reported to WHO by national authorities
reported cholera deaths	Confirmed cholera deaths	Reported to WHO by national authorities
Malaria		
reported confirmed cases	Confirmed by microscopy	Submitted to WHO by national malaria control programs
reported malaria deaths	Deaths from confirmed and probable malaria cases	Submitted to WHO by national malaria control programs
Tuberculosis		
notified cases of tuberculosis (new and relapse)	Pre-2013 TB data includes new TB cases (pulmonary, extra-pulmonary, laboratory confirmed); retreatment after relapse or treatment failure; and treatment status unknown	Routine surveillance data from TB control programs
Notified cases of tuberculosis (only relapse)	Pulmonary smear/culture positive TB retreatment after relapse	Routine surveillance data from TB control programs
HIV and TB coinfection	Number of TB incident (new and relapse)in HIV positive patients	National surveillance systems

Disease data were collected for a total of 194 countries. However, there were variations between diseases in terms of which countries could be included. Listed in Appendix 4 are all countries for which data were available (and disease-specific exceptions). Not all countries were included in the malaria analysis, as malaria is only endemic in a number of countries, whereas cholera, tuberculosis, and HIV may occur in any country. A total of 86 countries were therefore excluded from the malaria chapter because there was no case of malaria recorded over the period of 14 years (2000-2013). This was done to avoid bias in the data by including countries where malaria is not endemic.

Similarly, data on tuberculosis and HIV co-infections was available only from 2007 onwards and this dictated the time bracket for investigation (2007-2013), thereby avoiding data bias by excluding years where data was inconsistently recorded.

As presented by Sumner and colleagues(2013), in order to run a logistic regression analysis, the data under investigation had to be re-coded into binary variables. A loss of data when simplifying into binaries has to be accepted in that case. However, this may also be advantageous. It is doubtful that case reporting was complete for any country-year period, and by instead using a binary variable for above or below average, it does not necessarily matter if surveillance caught every last case, so long as it is clearly above or below the 14 year average.

Disease data were dichotomised. National averages of the measures of disease occurrence in Table 4.1 were calculated over the 14 year period for each country to reach r_i, where r represents the 14 year average number of cases and i represents the country. Following this, the annual number of disease cases t was compared to the national average r_i. If t was larger than r_i, the country-year was coded as 1, if y was equal to or smaller than r_i, it was coded as 0.

Where no data was available in a year, it was assumed to be a ‘below average’ year. It was assumed that if there had been a noticeable increase in disease cases, the surveillance would have picked up on it retrospectively.

4.3.2 Disaster data

Information on natural disasters over the 14 years under investigation was extracted from the EM-DAT database. As described in detail in chapter 2, the database includes data on over 18 thousand disasters from 1901 onwards, providing among other things information on the date of events, geographical location, number of affected people, number of people killed, and the economic impact of the disaster (http://www.emdat.be/). The disasters are categorised into main types that can again be categorised into 7 overarching groups (see table 2.1). For the purpose of the present analysis, extra-terrestrial disasters were excluded as a group because they have only recently been added as a category and not much data was available, and biological disasters were excluded because these include disease epidemics and would therefore bias the data. This variable could be used in future research as an interesting variable to discern if the recorded epidemics are reflected in the WHO disease data.

This narrows disaster data down to four categories – Geophysical disasters (including earthquakes), meteorological disasters (including storms), hydrological disasters (including floods), and climatological disasters (including droughts), as well as a fifth category for total disasters, including all of the above.

Magnitude tiers

Sumner and colleagues used a system of 5 tiers to determine disaster magnitude:

≥ 100 people affected (yes/no)

≥ 2,500 people affected (yes/no)

≥ 5,000 people affected (yes/no)

≥ 7,500 people affected (yes/no)

≥ 10,000 people affected (yes/no)

No statistically significant results were found in their analysis, and in an attempt to broaden the analysis, an additional tier was added for the analysis presented in Chapter 5 – 8. Specifically, a tier including disasters affecting above 100,000 people was added based on the assumption that different types of disaster will likely affect larger numbers of the population. Flood disasters often affect several millions at once, and of the 1341 disasters that were recorded in the four groups together over the 13 years, 478 have been shown to affect more than 100,00 of the population – 279 alone in the hydrological disasters group. With only 54 such large events in the geophysical disasters group, it would have made no sense to include the category in Sumner's study, but for the present analysis it could make a difference. Inspecting the average magnitude of natural disasters across geographic regions throughout the EM-DAT database (Table 2.2), a large number of disaster types is shown to affect far more than 100,000 of the population.

Additionally, as Sumneret al. (2013) tiers of disaster magnitude rendered no significant results in their analysis, a second set of analysis will be conducted in the following chapters, in which the data for everything below 10,000 will be pooled in one magnitude tier. The disaster magnitude tiers for the upcoming Chapters 5-8 are summarised in Table 4.2.

Table 4.2: disaster magnitude tiers for country (i) and year (t)=2000, 2001, 2002,..., 2013 used in chapters 5-8.

6-tier analysis:
100-2,499 people affected in i_t
2,500-4,999 people affected in i_t
5,000-7,499 people affected in i_t
7,500-9,999 people affected in i_t
10,000-99,999 people affected in i_t
≥ 100,000 people affected in i_t
3-tier analysis:
≤10,000 people affected in i_t
10,000-99,999 people affected in i_t
≥ 100,000 people affected in i_t

Disaster magnitude was measured in affected population rather than mortality, as the affected survivors are the population at increased risk of disease (see Chapter 3).

The analysis will not look at individual disasters, which means that to some extent, the effect of consecutive events can be interpreted in the results, as countries that have no disaster of a type in one year will have less data input than countries prone to disasters.

4.3.3 Covariates

To gain insight into the surrounding context that may influence disease levels after disasters, a number of covariates were included in the analysis. The covariates are proxy indicators of the baseline conditions of the affected country. They measure the infrastructure and, to some extent, the impact a disaster had on that infrastructure. They, too, have an influence on the dependent variable in the logistic regression analysis. The covariates included and data sources are summarised in table 4.3.

Table 4.3: Covariates for data analysis

Covariate	Definition	Source
Gross Domestic Products	GDP per capita per year	World Bank (http://databank.worldbank.org/data/reports.aspx?source=2&series=NY.GDP.PCAP.CD&country=)
<5 child mortality	Probability of dying before the age of 5, per 1000 live births	Global Health Observatory, Household surveys, national census data
Access to clean water source	% of population with access to clean water	World Bank (http://databank.worldbank.org/data/reports.aspx?source=2&series=SH.H2O.SAFE.ZS&country=)
Access to improved sanitation	% of the population with access to improved sanitation facilities	World Bank (http://databank.worldbank.org/data/reports.aspx?source=2&series=SH.STA.ACSN&country=)

4.4 Data Analysis

Data was analysed using SPSS 21. Basic frequencies were calculated to describe the dataset. Data is summarised in country-years, meaning the total number of years (14) multiplied by the number of countries, arriving at a total of 2716 country-years. An overview of counts of above average numbers for each disease are presented in Table 4.4, including a breakdown by WHO region. These numbers represented the data available for analysis in the upcoming Chapters 5 through 8.

Table 4.4: Total country-years and country-years with above average disease events (source: Global Health Observatory, WHO).

	Country-years above average/total country-years	Country-years African Region (above average/total)	Country-years Americas Region (above average/total)	Country-years South-East Asian Region (above average/total)	Country-years European Region (above average/total)	Country-years Eastern Mediterranean Region (above average/total)	Country-years Western Pacific Region (above average/total)
Cholera cases	228/2716	127/658	24/490	12/154	15/742	22/294	28/378
Cholera deaths	180/2716	128/658	7/490	9/154	2/742	17/294	17/378
Malaria cases	495/1512	173/616	120/308	57/140	44/126	50/182	51/140
Malaria deaths	484/1512	228/616	82/308	50/140	13/126	49/182	62/140
Tuberculosis cases	1025/2716	261/658	171/490	64/154	272/742	115/294	142/378
Tuberculosis relapse	452/2716	137/658	77/490	29/154	103/742	52/294	54/378
HIV+ TB co-infection cases	561/1848	177/506	82/386	24/110	124/429	45/231	52/187

The main statistical tool used to measure the association between disaster and disease in the four chapter was binary logistic regression. The basic model used in the analysis is as follows:

$$\ln[Y/(1-Y)] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n,$$

(Equation 4.1)

Where Y represents the probability of the response variable being 1 (above average). The response variable differs for each chapter. In Chapter 5, the two separate response variables are 'cholera cases' and 'cholera deaths'; in Chapter 6 'malaria cases' and 'malaria deaths'; in Chapter 7 'tuberculosis cases' and 'tuberculosis relapse'; and in Chapter 8 'HIV+TB co-infection cases. Predictor variables (the magnitude tiers described in section 4.3.2) are represented by X1,…,X_n, and B1,…,β_n represents estimated coefficients assigned to each predictors. The constant estimated by the model is represented as β_0. Odds ratios are estimated by calculating the difference between the probability of event 1 and event 0 – specifically the difference between the probability of response variables being above average and below average. If odds ratios are above 1, the probability of the response variable reaching above average numbers is increased. If odds ratios are below 1, it suggests that the probability of the response variable not being above average is increased.

To estimate reliability of the outcome, 95% confidence intervals were calculated, and *P*-values were calculated to determine statistical significance at $P<0.05$.

Sumner and colleagues restricted the analysis to in-phase data, meaning that cholera data were associated with disaster data for the same year *t* (Sumner et al., 2013). For the purpose of the upcoming chapters, an additional analysis was preformed, taking into account a time lag, both in surveillance data coming through due to disruption in infrastructure, as well as delayed outbreaks of diseases. The diseases under investigation are prone to have delayed presentation (see Section 2.3 for details on infectious diseases). The cholera epidemic in Haiti took almost a full year to manifest after the disaster (Barzilay et al., 2013), malaria outbreaks may be delayed due to disturbed vector breeding grounds, and broken down health infrastructure may show an effect on tuberculosis case management.

To take the potential effect of a time lag into account, the additional binary response variables were created, linking disasters of year 0 with disease data from year +1 for cholera and malaria, as well as +2 for tuberculosis and HIV+TB co-infections, as these diseases have longer incubation periods.

4.4 Discussion

4.4.1 Discussion of Methodology

Sumner and colleagues provided an interesting insight into the dynamics of cholera and earthquakes. The results of that study opened up the possibility for future research, and the chapters following here will attempt to expand upon these findings.

Sumner and colleagues used five magnitude tiers to determine severity of disasters in a year, but found no significant associations across earthquakes in their time period (Sumner et al., 2013). The decision was made for the present analysis to use a different distribution of magnitude tiers, pooling data of everything affecting up to 10,000 in the population, in order to have larger data quantity available for analysis.

A magnitude tier was included to account for large scale disasters affecting over 100,000 people, in addition to the tiers proposed by Sumner et al.

As was stated in Section 4.3.2, Sumner and colleagues choice of their magnitude tiers made sense for exclusively earthquake oriented analysis. However, for the analyses proposed in this Chapter, larger numbers of affected populations needed to be taken into account.

It was further expanded upon the basic methodology of Sumner at al. by including all types of disasters. While the analysis of earthquakes and cholera rendered no significant findings (Sumner et al., 2013), the present analysis seeks to offer a wider scope and understanding of the context of natural disasters and infectious diseases. This led to the analysis of infectious diseases in relation to all natural disasters, and further attempted to associate infectious diseases with different types of natural disaster as outlined in section 4.3.2.

The final adaptation of the original methodology by Sumner and colleagues was the inclusion of an analysis of time lag, to account for the possibility of delays in disease outbreaks after disasters. The dimension of time has barely been considered in the research of natural disasters and infectious disease so far. While it is often mentioned that the risk of disease in the acute phase of a disaster is negligible (Floret et al., 2006), there is little evidence of research into the post-acute disaster phase. Still, it was assumed for the diseases that will be studied in the following chapters that a time effect might influence the numbers of infectious diseases. While Sumner et al chose to omit the Haiti earthquake, the time effect might have occurred in other instances in the same way it did for cholera in Haiti, so it would have been a worthwhile measure to take lag times into account. Therefore it might have made sense for Sumner and colleagues to consider an analysis to that effect.

4.4.2 Limitations

The chapters described here will attempt to compare area level data for natural disasters and disease, and make statements on wider associations between the two. This methodology essentially describing an ecological study, the limitations of such studies becomes evident here – and in future chapters. While being a useful tool, ecological studies have a drawback that becomes evident in these future chapters: The ecological fallacy (Piantadosi et al., 1988). Ecological fallacy occurs when population data is used to infer associations to individuals. In the case of this study, this covers the assumption that, in case of above average disease numbers, the population where this data was obtained were in fact the people affected by disaster, and not completely unrelated data from a different region in the country. With the available data, it is impossible to determine in retrospect if this fallacy occurred. To prove the presence of ecological fallacy, it would be necessary to analyse the individual data of the disaster affected population (Idrovo, 2011).

Still, even if assuming ecological fallacy was present in the analysis, the results hold epidemiological value (Diez-Roux, 2002). It was not claimed that the results presented in chapters 5-8 are to be taken without deeper examination. Rather, they are a first attempt to grasp the complex relation between natural disasters and disease, and to inform future research.

Chapter 5 –Natural disaster and Cholera

Chapter Contents

5.1 Introduction

As described in Chapters 2 and 4, epidemiology emerged as a distinct area of disaster management in the late 1970s. Lechat first introduced an epidemiologic perspective into disaster preparedness and disaster management in 1976, in the aftermath of a number of severe disasters, and over the following decades, its role saw a steady increase in importance for disaster response (Lechat, 1976). In the 1980s, the application of epidemiologic methods had become the norm in order to improve disaster preparedness and response (Glass, O'Hare, & Conrad, 1979; Leaning & Guha-Sapir, 2013). Although much progress has been made by introducing cluster sampling into needs assessment after disasters (Malilay, Flanders, & Brogan, 1996; Noji, 2005b), in many instances it has been shown that issues still persist since Lechat and Logue first pointed them out (Leaning & Guha-Sapir, 2013; Lechat, 1976; Logue et al., 1981; Noji & Toole, 1997).

The coordination of relief work in the aftermath of disaster has been burdened by unnecessary donations of pharmaceuticals and sometimes hasty, unstructured disaster response informed by assumptions and panic, rather than evidence (Leaning & Guha-Sapir, 2013; Noji & Toole, 1997). Already as early as 1976 and 1981, these issues have been identified, and suggestions for improvements by using epidemiologic research methods to identify risks were made (Lechat, 1979; Logue et al., 1981). Yet reviews of disaster management as recent as 2013 state that 'coordinating health-needs assessment by multiple groups is still weak' [p.1840, Leaning & Guha-Sapir, 2013] – suggesting that there is still progress to be made (Leaning & Guha-Sapir, 2013).

With the role of epidemiology increasing in disaster management, there is a need for new insights into the dynamic relationship of disaster and disease. Events such as the earthquake in Bam, Iran, in 2003 (Sharifi, Aflatoonian, Aflatoonian, & Kermanizadeh, 2015), the Great East Japan earthquake of 2011 (Tokuda et al., 2014) and typhoon Haiyan in the Philippines of 2013 (Aumentado et al., 2015) are only a few examples of recent disasters where epidemiological research was conducted to identify disease-related setbacks to post-disaster management and to provide approaches for improvement in future events.

Cholera has been identified as one of the main disease-related concerns in the aftermath of disasters (Section 2.6.1). Its most prominent occurrence in recent history is, without question, the severe epidemic in Haiti after the earthquake in 2010 (Tappero & Tauxe, 2011). Cholera's highly contagious nature in conditions of poor sanitation has historically led to seven pandemic events to date – with cholera spreading globally and becoming the first infectious disease requiring reporting to health authorities as early as 1866 (Azizi & Azizi, 2010; D. A. Sack, Sack, Nair, & Siddique, 2004). Cholera experienced a continuous increase starting in the 1950s, to being endemic in many countries of the world by the early 2000s (Figure 5.1).

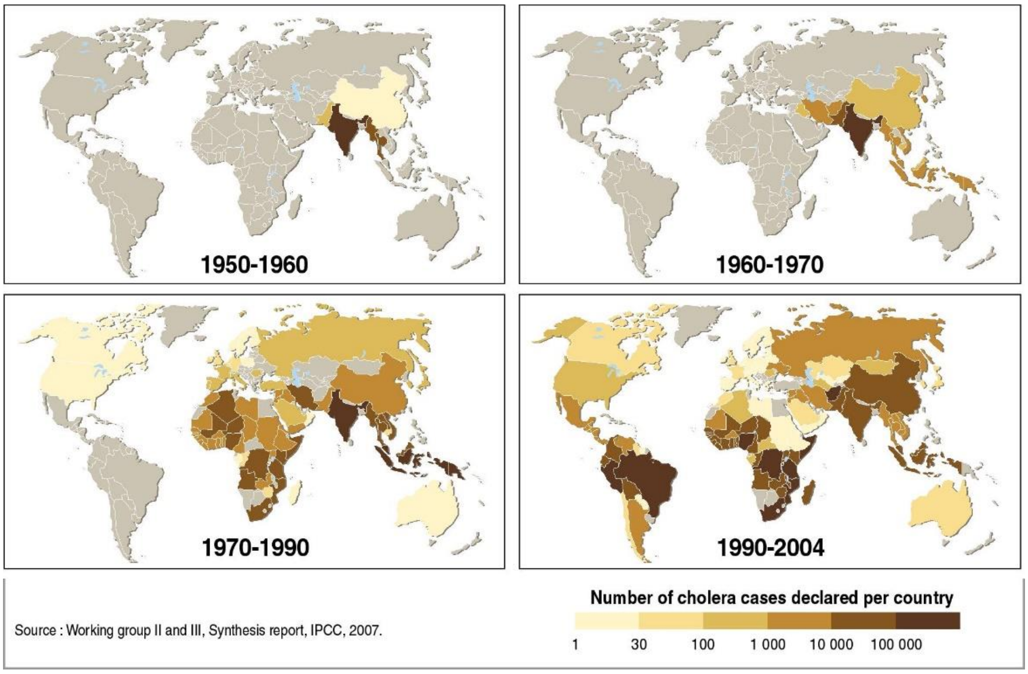


Figure 5.1: Global cholera distribution between 1950-2004 (http://www.grida.no/graphicslib/detail/the-spread-of-cholera-1950-2004_1471).

In 1990, a new serotype of cholera surfaced, further complicating the understanding of cholera (Chhotray et al., 2002). Because of its highly virulent nature and its link to contaminated water (Sack, 2004; Hartley, 2005) — as may occur after natural disasters — cholera control has been identified as a priority in post-disaster situations (Abrams et al., 2013; Bengtsson, Lu, Thorson, Garfield, & von Schreeb, 2011). There have been studies investigating cholera outbreaks after specific disasters (Chhotray et al., 2002; Panda et al., 2011; Schwartz et al., 2006) and cholera rates across countries for a specific type of disaster (Sumner et al., 2013). The present chapter will investigate global cholera rates in association with natural disasters over 14 years, by four different types of disaster and for increasing disaster magnitudes.

5.2 Methodology

The basic methodology of data collection and analysis is described in Chapter 4. Disease data were collected for a total of 194 countries for the six WHO regions (see Figure 4.1) from the WHO Global Health Observatory. This accounted for 2716 country-years (one entry per year over 14 years for 194 countries). It amounted to a total of 2,925,502 cases of cholera and 60,087 fatalities, with large numbers in the African and American Region (Table 5.1).

Table 5.1: Regional frequencies of disease.

	cholera cases	cholera deaths
Global	2,925,502	60,087
Africa	1,711,263	41,740
Americas	751,156	9,644
South-East Asia	51,641	231
Europe	998	9
Eastern Mediterranean	336,429	6,323
Western Pacific	74,015	2,140

5.2.1 Cholera data

The Global Health Observatory collected the following cholera variables:

(1) 'confirmed cholera cases', defined as cholera cases confirmed 'clinically, epidemiologically, or by a laboratory investigation'; and
(2) 'cholera deaths' defined as death as outcome of cholera (WHO, 2016a)

For the purpose of this chapter, cholera cases were coded into a binary variable. The average cases of cholera were calculated for each country (Let r represent the average cholera cases and i the country) r_i. Subsequently, the annual numbers of cases t was compared to the national average r_i. So, if t was larger than r_i, the year was coded as (1) in the variable, if t was equal to or below r_i, it was coded as (0).

As shown in table 4.4, over the 2716 country-years, there were a total of 228 years with above average cholera rates, and 180 years with above average numbers of deaths from cholera.

The WHO recognises that absolute cholera case counts need to be examined carefully when assessing the true burden of disease, due to common challenges to national disease surveillance (WHO, 2016a). With disease surveillance possibly challenged in the aftermath of disaster, it is likely that cases may have gone undetected, making the actual count of cholera cases an unreliable measure. However, by coding cholera morbidity and mortality as binary variables, the effect of incomplete reporting may be reduced. Even if the exact numbers of cases may not be found, it is likely a surveillance system will pick up on whether or not there are more or less cases of a disease than usual. Binary variables are recommended in situations where the only relevant information to the analysis is whether or not a value is above or below a pre-defined threshold (Pasta, 2009). In the present analysis, the use of binary variables reduces the level of uncertainty involved in disease surveillance. Thus, the analysis will be more forgiving in years where reporting was incomplete, as the exact numbers will not weigh in the results. The assumption is made that – in the event of a severe outbreak – surveillance would be more vigorous, and that would be reflected in the data as an 'above average' year. Whether or not the numbers are perfectly accurate in these cases will not have a major effect on the outcome.

Additionally, an analysis of 1-year-lag was introduced to enable a comparison of disaster magnitude in one year with cholera activity in the following year. This was done to account for disease outbreaks related to disasters that might occur with delay. One year lag was chosen for cholera in light of the Haiti earthquake in 2010, where it took almost exactly a year for the severe cholera outbreak to manifest in the population (Tappero & Tauxe, 2011).

Further expanding on Sumner and colleagues paper, the data were disaggregated according to WHO region (Figure 4.1), to discover possible regional differences in the association between disaster and disease (Sumner et al., 2013).

5.2.2 Disaster data

Disaster data for the regression analysis was obtained from the EM-DAT database. Date were split into five categories (total, geophysical, meteorological, hydrological, and climatological) with 6 tiers each for analysis (affected population ≥100, ≥2,500, ≥5,000, ≥7,500, ≥10,000, ≥100,000) as described in more detail in the main Methodology chapter 4. The first 5 tiers were taken from Sumner et al., while the ≥100,000 tier was added for the present analysis in order to account for higher magnitude disasters affecting a larger number of the population. This was done based on the assumption that hydrological disasters (such as the 2005 South East Asia tsunami) tend to affect a much larger population and it was considered likely that at higher affected populations, there would be more insights that might be missed if the data was pooled into the ≥10,000 tier. After running the 6-tier regression as per the study if Sumner et al., a second set of analyses was performed with coarser intervals of magnitude (at affected population of ≤10,000, 10,000-100,000, and ≥100,000). In this 3-tier regression, the effects of lower magnitude disasters were pooled together to identify associations that might not have been visible in the 6-tier analysis and have a different approach to larger scale disasters.

5.3 Results

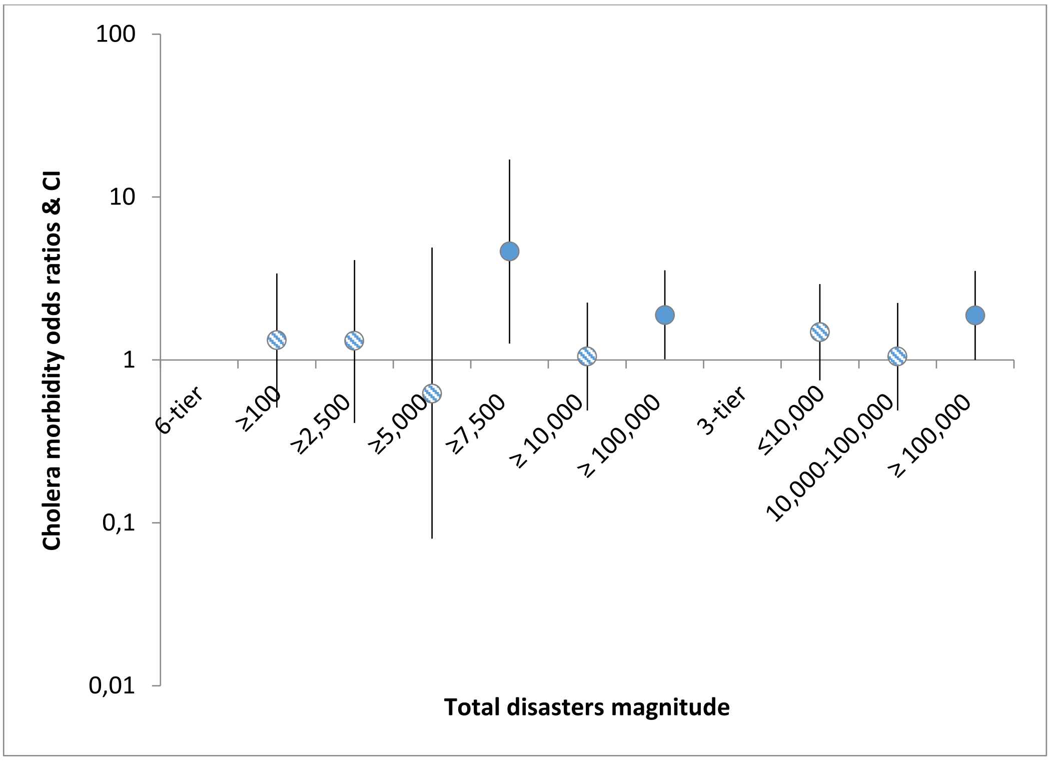
It has previously been a challenge to show statistically significant association between cholera activity and disasters (Sumner et al., 2013), and the results presented in this section offer unprecedented insights into the relationship. Tables 5.2 – 5.6 present odds ratios, confidence intervals and significance levels (*P*-value) for cholera cases and cholera deaths of each disaster subgroup.

5.3.1 Natural disasters and Cholera

In tables 5.2 – 5.6, odds ratios and confidence intervals are shown for cholera morbidity and cholera mortality. Specifically, Table 5.2 presents the results of cholera morbidity and mortality for all disasters combined. Table 5.3 presents the disaggregated data for geophysical disasters, Table 5.4 the meteorological disasters, and table 5.5 and 5.6 present hydrological and climatological disasters respectively. Both the 6-tier analysis and 3-tier analysis are presented. The tables are arranged by disaster type, and statisticallysignificant results are highlighted. For visual representation, the results were summarised in Figure 5.2 – 5.6, showing odds ratios and confidence intervals on a logarithmic scale. Significant results can be recognised at a glance by the solid fill, insignificant results are patterned, and the whiskers represent the confidence interval.

Table 5.2: Odds ratio and confidence interval of average confirmed cholera morbidity and mortality for disasters, adjusted for sanitation, water access, GDP and under 5 child mortality.

	Cholera morbidity			Cholera mortality		
Total affected	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	1.32	0.51-3.40	0.57	0.54	0.12-2.48	0.43
≥2,500	1.31	0.41-4.11	0.65	1.42	0.42-4.80	0.57
≥5,000	0.62	0.08-4.91	0.61	/	/	/
≥7,500	4.64	1.26-17.01	0.02	3.22	0.74-14.09	0.12
≥ 10,000	1.05	0.49-2.25	0.90	0.53	0.20-1.41	0.20
≥ 100,000	1.89	1.01-3.55	0.05	1.47	0.73-2.93	0.28
3-tier analysis						
≤10,000	1.48	0.75-2.92	0.26	0.99	0.42-2.29	0.96
10,000-100,000	1.05	0.49-2.24	0.91	0.53	0.20-1.40	0.20
≥ 100,000	1.88	1.0-3.52	0.05	1.45	0.73-2.91	0.29



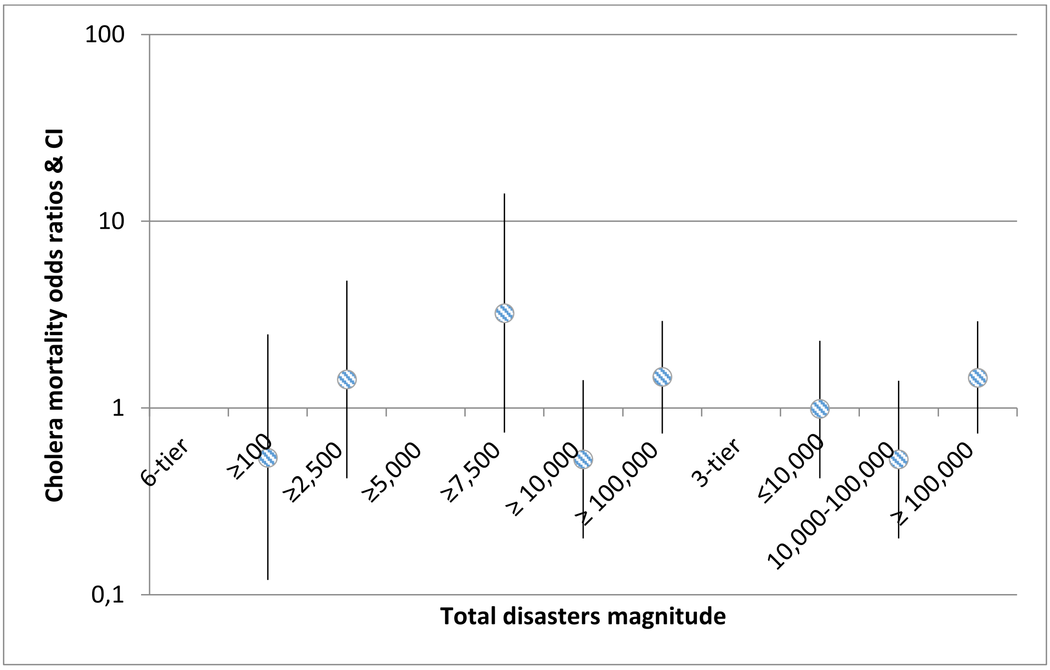


Figure 5.2: graphic representation of odd ratio and confidence intervals of average cholera morbidity (top) and mortality (bottom) for total disasters magnitude.

Overall, natural disasters impacting a higher number of people are shown to have a significant increase in risk of above average cholera morbidity. Disasters affecting between 7,500 and 10,000 show a 4 times increase in odds of cholera outbreaks. For disasters affecting more than a 100,000 odds are almost twice as high (Table 5.2). While the confidence interval for the 7,500-9,999 magnitude tier is wide, suggesting the result may not necessarily be reliable, the CI in the higher magnitude tier is narrow and suggests a level of certainty that the associations are correct based on the observations. No significant results were found for increased cholera mortality.

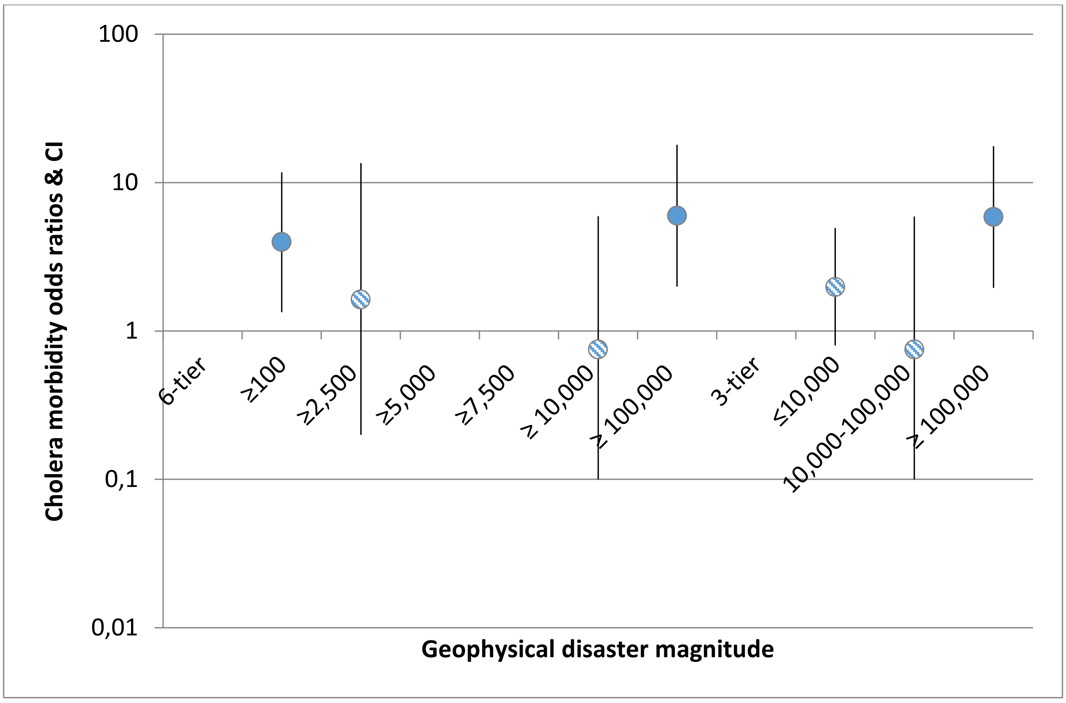
In the 3-tier analysis, the measure of the affected population was changed. This shows the odds ratio for more than 100,000 of the population affected remains robust (Table 5.2a).

Geophysical disaster

In geophysical disasters, there is a highly significant change in odds for disasters affecting more than 100,000 of the population, for both cholera cases and cholera mortality (Table 5.2b). Cholera morbidity for geophysical disasters affecting over 100,000 of the population presented a nearly 6 fold increase in odds, which coincides with findings of relative risk in Section 3.3.3). This remained robust in the 3-tier analysis. A significant result of OR=3.98 (95% CI 1.34-11.71, P=0.01) for disasters affecting between 100 and 2,500 people suggests that some smaller scale disasters may lead to an increase in disease cases, which could be an indication for something other than disaster magnitude to affect the average disease cases.

Table 5.3: Odds ratio and confidence interval of average confirmed cholera cases and mortality for geophysical disaster, adjusted for sanitation, water access, GDP and under 5 child mortality.

	Cholera morbidity			*Cholera mortality*		
Geophysical disaster: affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	3.98	1.34-11.71	0.01	0.95	0.19-4.70	0.95
≥2,500	1.63	0.20-13.51	0.65	/	/	0.99
≥5,000	/	/	/	/	/	0.99
≥7,500	/	/	/	/	/	0.99
≥ 10,000	0.75	0.10-5.94	0.79	1.35	0.15-11.96	0.79
≥ 100,000	5.98	1.99-17.99	0.001	8.97	2.83-28.44	0.001
3-tier analysis						
≤10,000	1.98	0.80-4.95	0.14	0.47	0.10-2.15	0.33
10,000-100,000	0.75	0.10-5.91	0.78	1.36	0.15-12.01	0.78
≥ 100,000	5.87	1.95-17.63	0.002	8.92	2.81-28.27	0.001



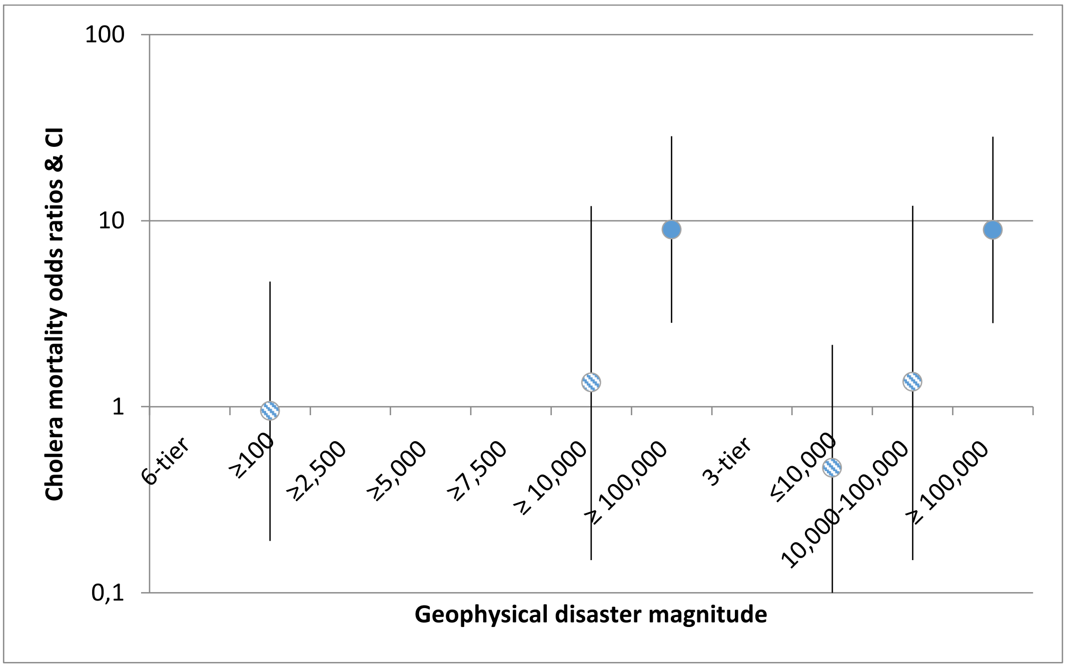


Figure 5.3: graphic representation of odds ratio and confidence intervals of average cholera morbidity (top) and mortality (bottom) for geophysical disaster magnitude.

Meteorological disaster

Table 5.4 summarises the results of logistic regression for meteorological disasters and cholera morbidity and mortality. Figure 5.4 presents the results graphically, where a solid fill represents statistically significant results and a patterned fill represents insignificant results. The whispers represent the confidence interval. At 100,000 affected population, meteorological disasters display significantly increased odds of cholera cases – and a near significantly increased odds of cholera death. No other significant associations were found.

Table 5.4: Odds ratio and confidence interval of average confirmed cholera cases and mortality for meteorological disasters, adjusted for sanitation, water access, GDP and under 5 child mortality.

	Cholera morbidity			***Cholera mortality***		
Meteorological disasters: affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	1.27	0.42-3.84	0.67	0.91	0.20-4.17	0.9
≥2,500	/	/	0.99	/	/	/
≥5,000	1.56	0.17-14.41	0.70	/	/	/
≥7,500	1.94	0.21-18.11	0.56	2.58	0.24-27.82	0.43
≥ 10,000	1.79	0.70-4.59	0.22	0.69	0.15-3.10	0.63
≥ 100,000	3.46	1.48-8.08	0.004	2.52	0.91-6.93	0.07
3-tier analysis						
≤10,000	1.15	0.46-2.86	0.77	0.77	0.22-2.67	0.67
10,000-100,000	1.79	0.70-4.59	0.22	0.69	0.153-3.11	0.63
≥ 100,000	3.48	1.48-8.08	0.004	2.50	0.91-6.89	0.08

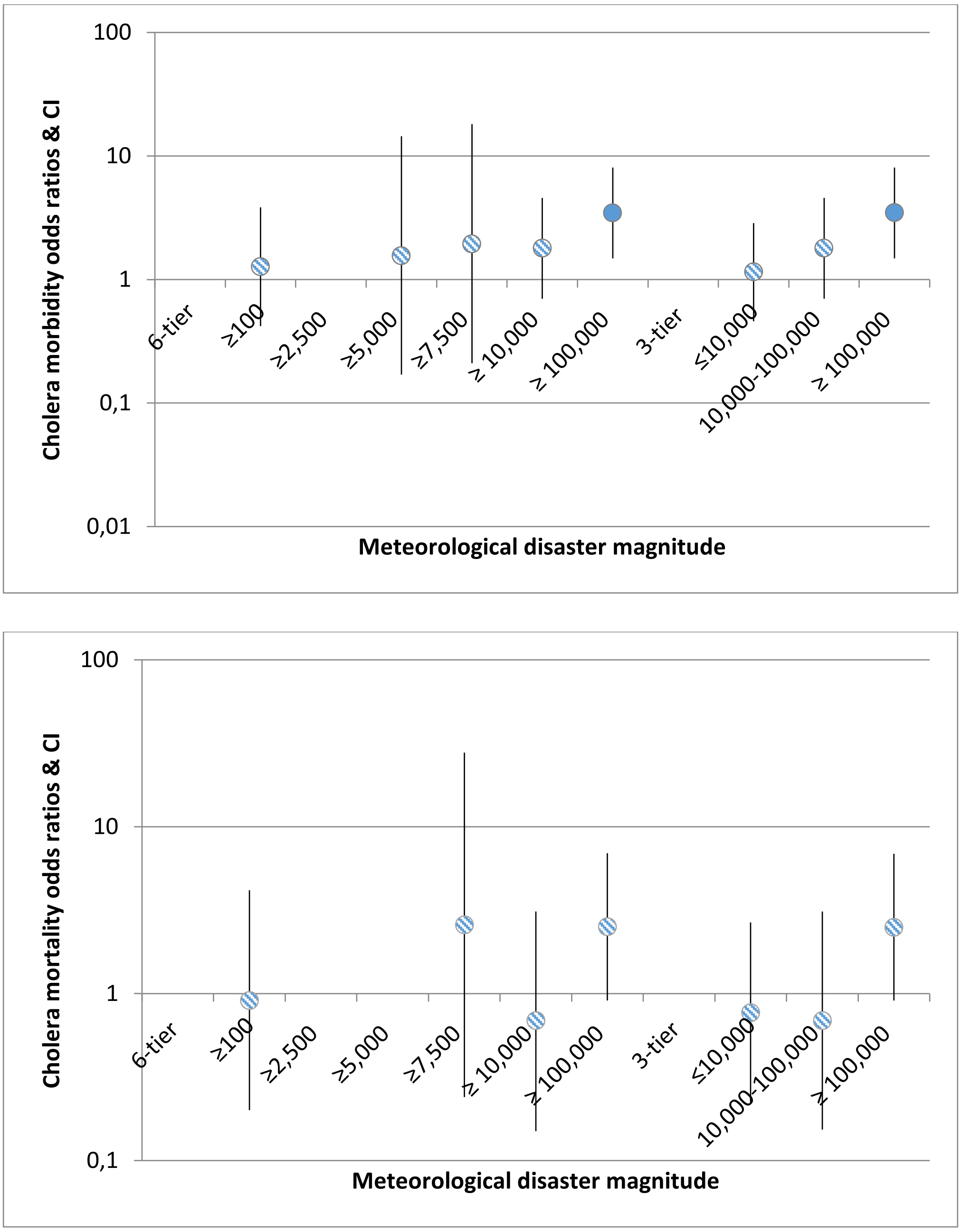
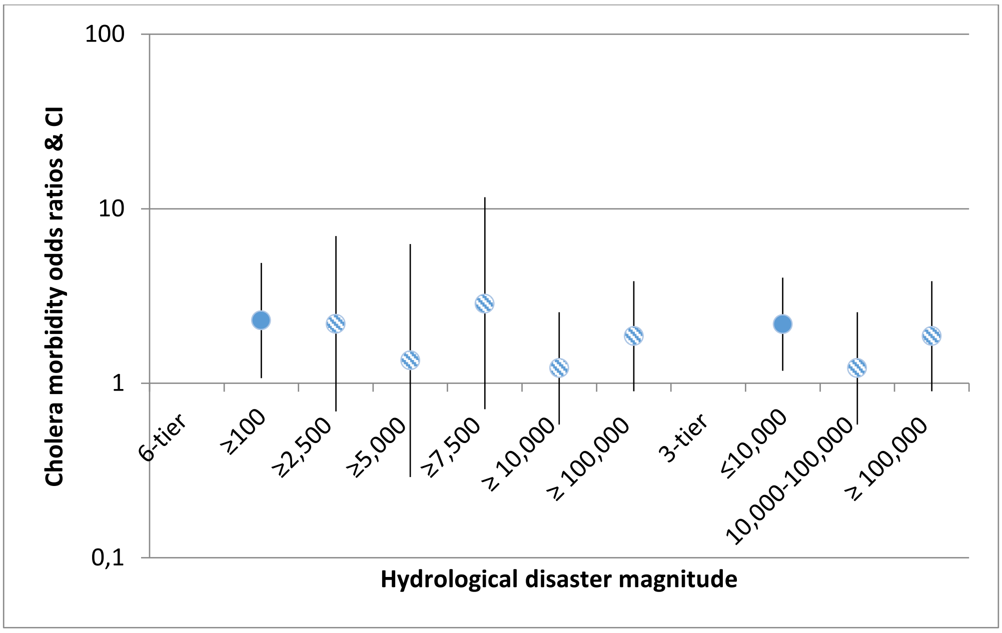


Figure 5.4: Graphic representation of odds ratio and confidence intervals of average cholera morbidity (top) and mortality (bottom) for meteorological disaster magnitude.

Other disasters

Hydrological disasters affecting between 100 and 2,500 of the population have a significant increase in cholera odds (Figure 5.5 and Table 5.5), reminiscent of the association of small scale disasters and disease averages in geophysical disasters. The strength of the association leads to a highly significant increase in odds of cholera for the adjusted below 10,000 affected population in the 3-tier analysis. At between 2,500 and 5,000 affected, cholera mortality odds are significantly increased, yet with no effect on the adjusted affected population variables in the 3-tier analysis.

No significant results were found for climatological disasters.



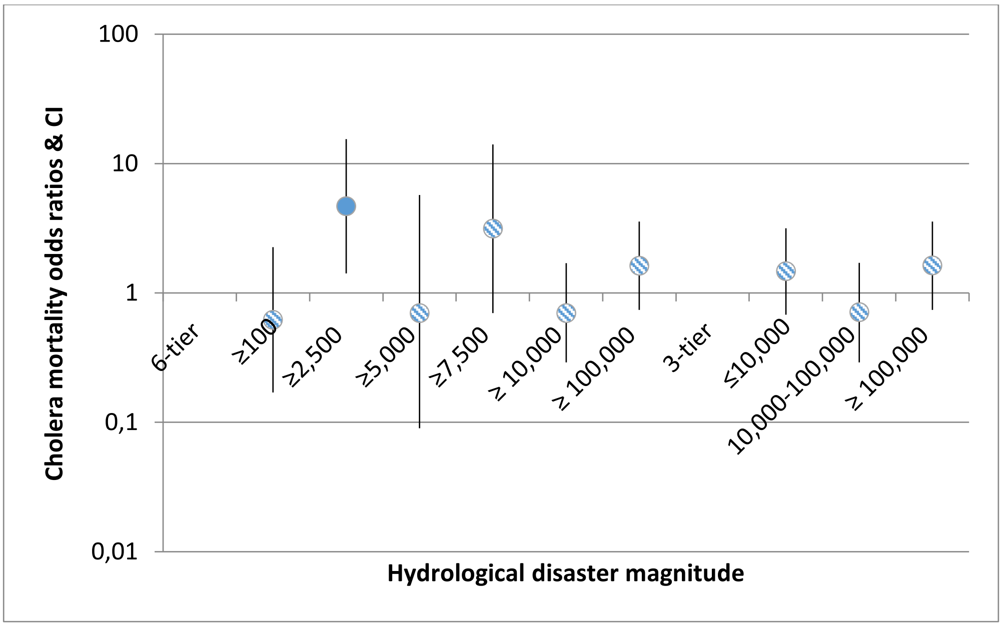


Figure 5.5: Graphic representation of odds ratio and confidence intervals of average cholera morbidity (top) and mortality (bottom) for hydrological disaster magnitude.

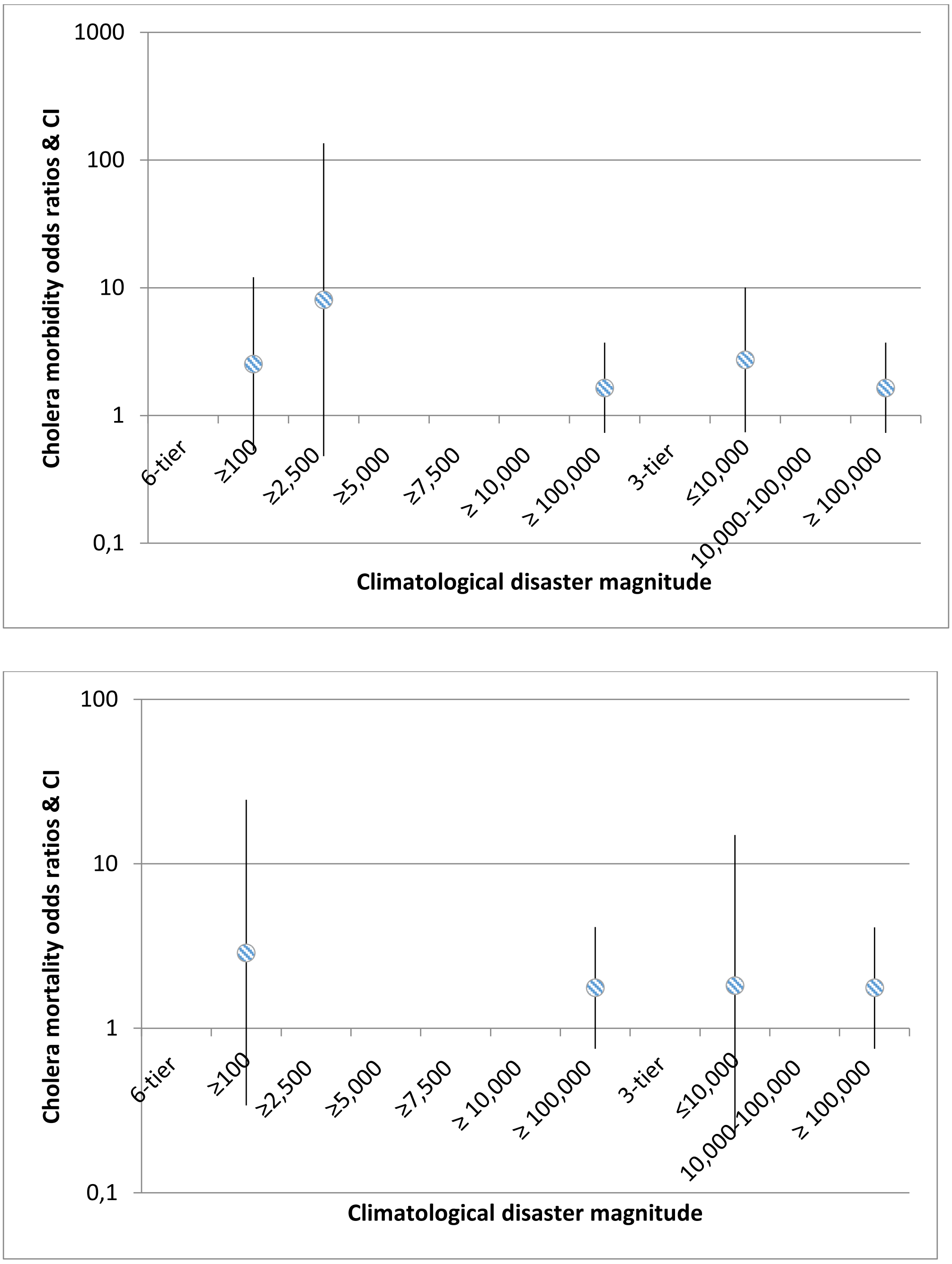


Figure 5.6: Graphic representation of odds ratio and confidence intervals of average cholera morbidity (top) and mortality (bottom) for climatological disaster magnitude.

Table 5.5: Odds ratio and confidence interval of average confirmed cholera morbidity and mortality for hydrological disasters, adjusted for sanitation, water access, GDP and under 5 child mortality.

	Cholera morbidity			Cholera mortality		
Hydrological disaster: Affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	2.29	1.07-4.89	0.03	0.62	0.17-2.26	0.47
≥2,500	2.19	0.69-6.97	0.18	4.68	1.42-15.45	0.01
≥5,000	1.35	0.29-6.27	0.71	0.70	0.09-5.73	0.74
≥7,500	2.86	0.71-11.64	0.14	3.14	0.70-14.03	0.43
≥ 10,000	1.22	0.58-2.55	0.61	0.70	0.29-1.70	0.43
≥ 100,000	1.86	0.90-3.85	0.10	1.62	0.74-3.56	0.23
3-tier analysis						
≤10,000	2.18	1.18-4.03	0.01	1.47	0.68-3.17	0.32
10,000-100,000	1.22	0.58-2.55	0.61	0.71	0.29-1.71	0.44
≥ 100,000	1.86	0.90-3.85	0.09	1.63	0.74-3.57	0.23

Table 5.6: Odds ratio and confidence interval of average confirmed cholera cases and mortality for climatological disasters, adjusted for sanitation, water access, GDP and under 5 child mortality.

	Cholera morbidity			Cholera mortality		
Climatological disaster: Affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	2.53	0.53-12.07	0.24	2.87	0.34-24.52	0.34
≥2,500	8.03	0.48-135.36	0.15	/	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	/	/	/	/	/	/
≥ 100,000	1.64	0.73-3.71	0.23	1.76	0.75-4.12	0.19
3-tier analysis						
≤10,000	2.73	0.74-10.06	0.13	1.81	0.22-14.97	0.58
10,000-100,000	/	/	/	/	/	/
≥ 100,000	1.64	0.73-3.71	0.23	1.76	0.75-4.11	0.19

5.3.2 Regional analysis

The results of the regional logistic regression are presented in figures 5.7 – 5.11. The visual depiction shows odds ratios and confidence interval for all disasters on a logarithmic scale, for the 6-tier and 3-tier analysis. Significant results are indicated by a solid fill, while insignificant results present with a patterned fill. No results were found for the South East Asian region due to low data quantity preventing the analysis from being run. A complete summary of the regional results – including a breakdown by disaster type – can be found in Appendix 5.

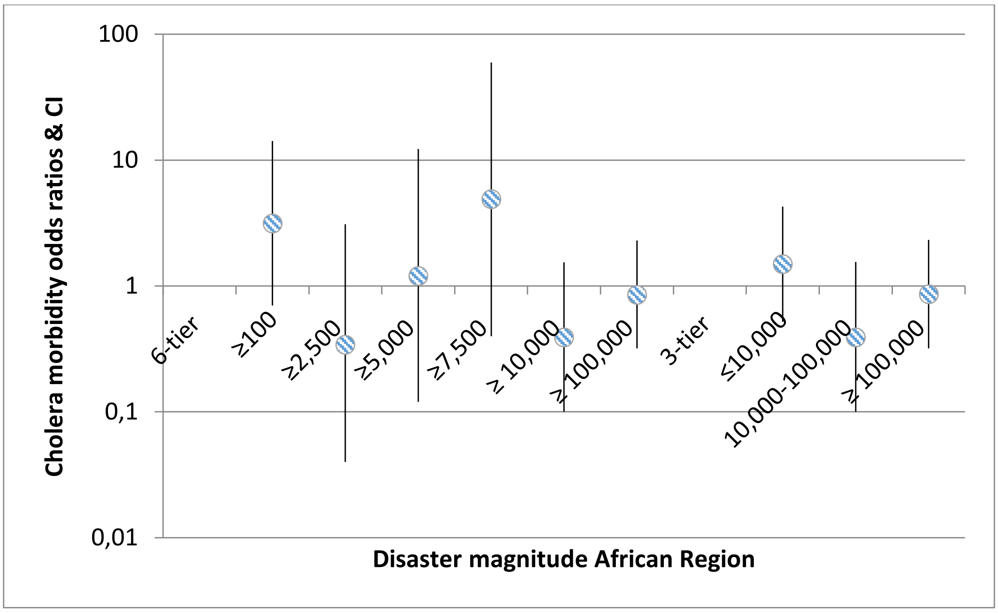


Figure 5.7: Graphic representation of odds ratio and confidence intervals of average cholera morbidity in the African region.

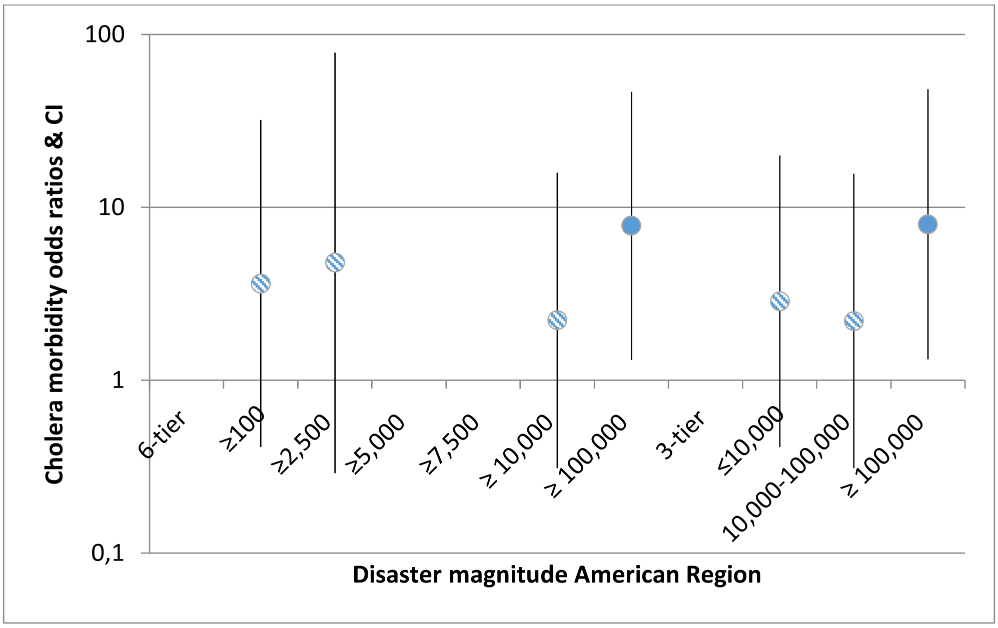


Figure 5.8: Graphic representation of odds ratio and confidence intervals of average cholera morbidity in the American region.

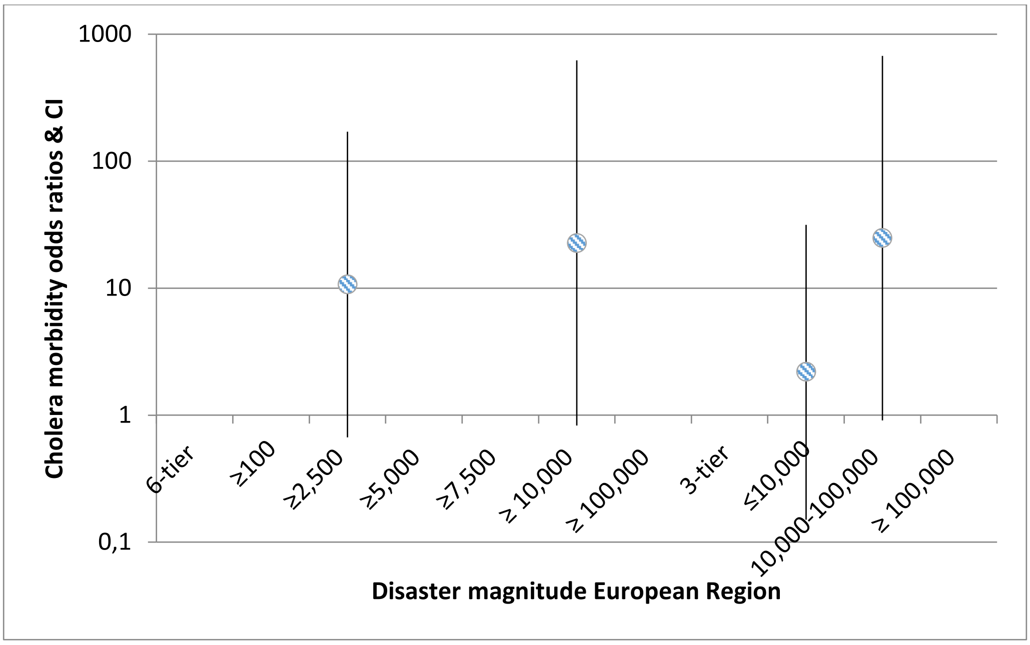


Figure 5.9: Graphic representation of odds ratio and confidence intervals of average cholera morbidity in the European region.

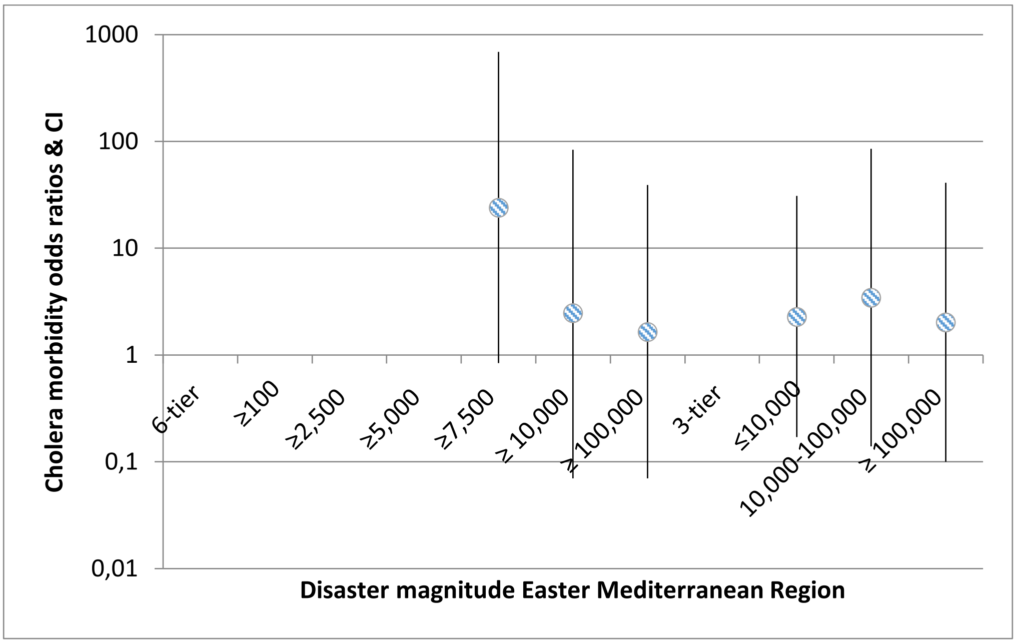


Figure 5.10: Graphic representation of odds ratio and confidence intervals of average cholera morbidity in the Eastern Mediterranean region.

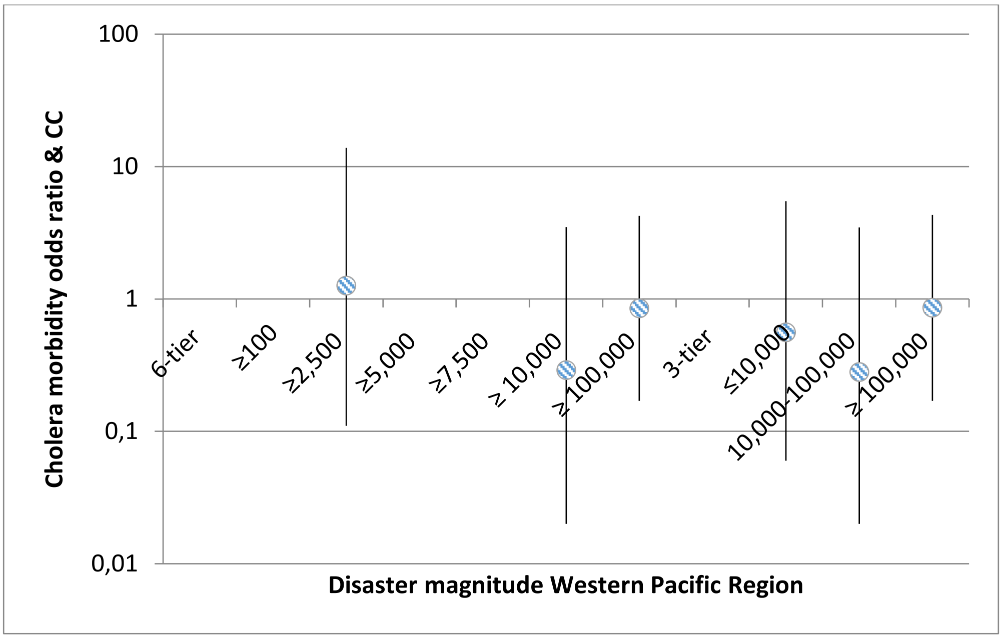


Figure 5.11: Graphic representation of odds ratio and confidence intervals of average cholera morbidity in the Western Pacific region.

Very few significant results emerged from the regional analysis. Looking at the data from a regional perspective, there are a few near significant results. A significant increase in average cholera cases for disasters affecting over 100,000 of the population was found in the American Region (*P*=0.02). Disasters affecting between 10,000-99,999 of the population in countries in the European region reach near significance (*P*=0.07-0.06), as do disasters affecting between 7,500-9,999 of the population in countries of the Eastern Mediterranean Region (*P*=0.06 in the 6-tier analysis). The remaining associations were insignificant, and no association was found for the South-East Asian region.

Although not displayed here, significant results were found for geophysical disasters in the American (100-2,499 magnitude tier: OR=27.46; 95%CI=1.37-549.84; *P*=0.03; >100,000 magnitude tier: OR=14.73; 95%CI=2.07-104.94; *P*=0.01) and the Eastern Mediterranean region (<10,000 magnitude tier: OR=16.85; 95%CI=1.03-274.92; *P*=0.05), for meteorological disasters in the European region (10,000-99,999 magnitude tier: OR=44.51; 95%CI=1.88-

1051.77; *P*=0.02), and for hydrological disasters in the American region (2,500-4,999 magnitude tier: OR=19.77; 95%CI=1.68-232.79; *P*=0.02; >100,000 magnitude tier: OR=14.58, 95%CI=2.04-104.50; *P*=0.01). The complete results for this analysis can be found in Appendix 5.

5.3.3 1-year lag analysis

Results of the 1-year lag analysis for cholera morbidity are presented in Table 5.7 and figures 5.12 – 5.16. As before, odds ratios and confidence intervals of cholera morbidity are shown, with significant results presented with solid fill, and insignificant results patterned. The complete tabulation of odds ratios, 95% confidence intervals, and *P*-values for disaster types and magnitude tiers can be found in Table 5.7.

Table 5.7: Odds ratio and confidence interval of average confirmed cholera morbidity, compared to one year after natural disaster.

	Cholera morbidity, same year			**Cholera morbidity, following year**		
	odds ratio	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
total disasters 6-tier						
≥100	1.32	0.51-3.40	0.57	1.81	0.53-6.14	0.34
≥2,500	1.31	0.41-4.11	0.65	1.32	0.27-6.45	0.73
≥5,000	0.62	0.08-4.91	0.61	1.38	0.16-11.91	0.77
≥7,500	4.64	1.26-17.01	0.02	1.66	0.18-15.53	0.66
≥ 10,000	1.05	0.49-2.25	0.90	1.82	0.72-4.59	0.21
≥ 100,000	1.89	1.01-3.55	0.05	2.06	0.89-4.76	0.09
Total disasters 3-tier						
≤ 10,000	1.48	0.75-2.92	0.26	1.58	0.61-4.08	0.35
10,000-100,000	1.05	0.49-2.24	0.91	1.82	0.72-4.59	0.21
≥ 100,000	1.88	1.0-3.52	0.05	2.06	0.89-4.78	0.09

Table 5.7 (cont.): Odds ratio and confidence interval of average confirmed cholera morbidity, compared to one year after natural disaster.

	Cholera morbidity, same year			**Cholera morbidity, following year**		
	odds ratio	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
Geophysical disasters 6-tier						
≥100	3.98	1.34-11.71	0.01	0.64	0.08-5.29	0.68
≥2,500	1.63	0.20-13.51	0.65	4.25	0.49-36.83	0.19
≥5,000	/	/	/	3.08	0.30-31.78	0.35
≥7,500	/	/	/	/	/	/
≥ 10,000	0.75	0.10-5.94	0.79	4.73	1.10-20.37	0.04
≥ 100,000	5.98	1.99-17.99	0.001	1.26	0.15-10.68	0.83
Geophysical disasters 3-tier						
≤ 10,000	1.98	0.80-4.95	0.14	1.23	0.33-4.55	0.76
10,000-100,000	0.75	0.10-5.91	0.78	4.6	1.08-19.65	0.04
≥ 100,000	5.87	1.95-17.63	0.002	1.24	0.15-10.48	0.84
Meteorological disasters 6-tier						
≥100	1.27	0.42-3.84	0.67	2.1	0.63-6.98	0.23
≥2,500	/	/	0.99	3.49	0.38-32.23	0.27
≥5,000	1.56	0.17-14.41	0.70	/	/	/
≥7,500	1.94	0.21-18.11	0.56	/	/	/
≥ 10,000	1.79	0.70-4.59	0.22	3.44	1.15-10.32	0.03
≥ 100,000	3.46	1.48-8.08	0.004	2.27	0.62-8.33	0.22
Meteorological disasters 3-tier						
≤ 10,000	1.15	0.46-2.86	0.77	1.72	0.59-4.96	0.32
10,000-100,000	1.79	0.70-4.59	0.22	3.43	1.15-10.30	0.03
≥ 100,000	3.48	1.48-8.08	0.004	2.28	0.62-8.36	0.22

Table 5.7 (cont.): Odds ratio and confidence interval of average confirmed cholera morbidity, compared to one year after natural disaster.

	Cholera morbidity, same year			Cholera morbidity, following year		
	odds ratio	95% CI	*P*-value	odds ratio	95% CI	*P*-value
Hydrological disasters 6-tier						
≥100	2.29	1.07-4.89	0.03	3.35	1.33-8.43	0.01
≥2,500	2.19	0.69-6.97	0.18	2.66	0.65-10.81	0.17
≥5,000	1.35	0.29-6.27	0.71	2.43	0.47-12.54	0.29
≥7,500	2.86	0.71-11.64	0.14	1.21	0.13-11.03	0.87
≥ 10,000	1.22	0.58-2.55	0.61	1.27	0.50-3.22	0.61
≥ 100,000	1.86	0.90-3.85	0.10	1.23	0.46-3.30	0.68
Hydrological disasters 3-tier						
≤ 10,000	2.18	1.18-4.03	0.01	2.75	1.27-5.97	0.01
10,000-100,000	1.22	0.58-2.55	0.61	1.28	0.51-3.25	0.60
≥ 100,000	1.86	0.90-3.85	0.09	1.25	0.47-3.33	0.66
Climatological disasters 6-tier						
≥100	2.53	0.53-12.07	0.24	/	/	/
≥2,500	8.03	0.48-135.36	0.15	17.03	1.03-282.40	0.04
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	/	/	/	/	/	/
≥ 100,000	1.64	0.73-3.71	0.23	1.68	0.67-4.24	0.27
Climatological disasters 3-tier						
≤ 10,000	2.73	0.74-10.06	0.13	1.82	0.23-14.59	0.57
10,000-100,000	/	/	/	/	/	/
≥ 100,000	1.64	0.73-3.71	0.23	1.68	0.67-4.25	0.27

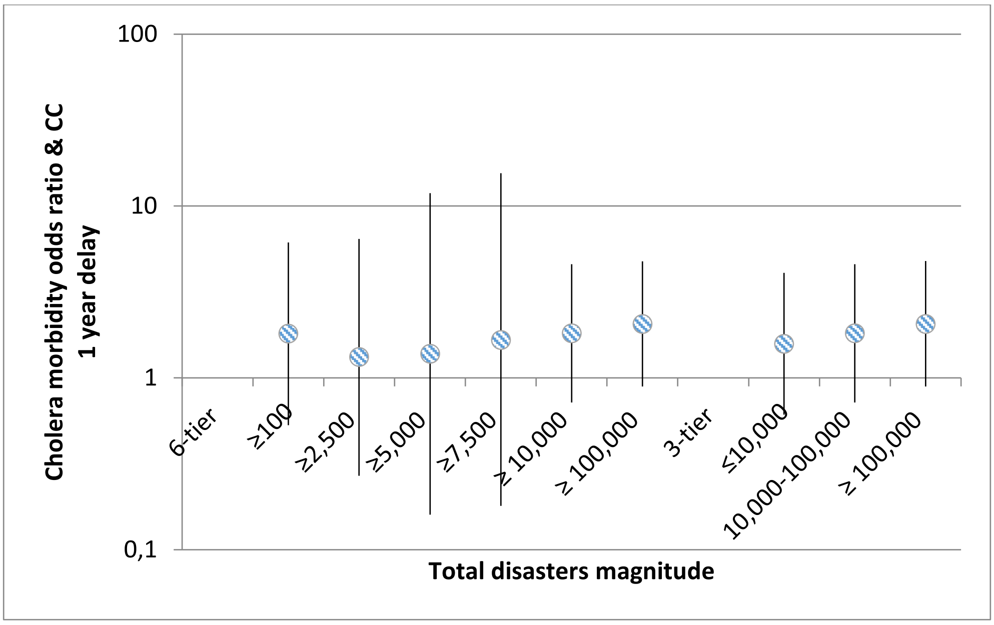


Figure 5.12: Graphic representation of odds ratio and confidence intervals of average cholera morbidity with a 1-year delay for total disasters.

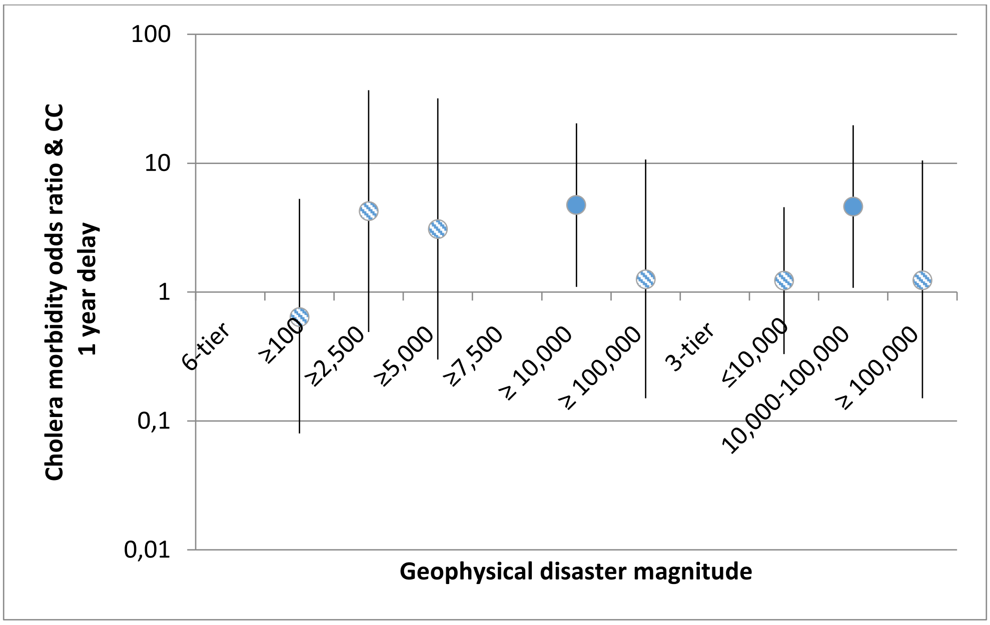


Figure 5.13: Graphic representation of odds ratio and confidence intervals of average cholera morbidity with a 1-year delay for geophysical disasters.

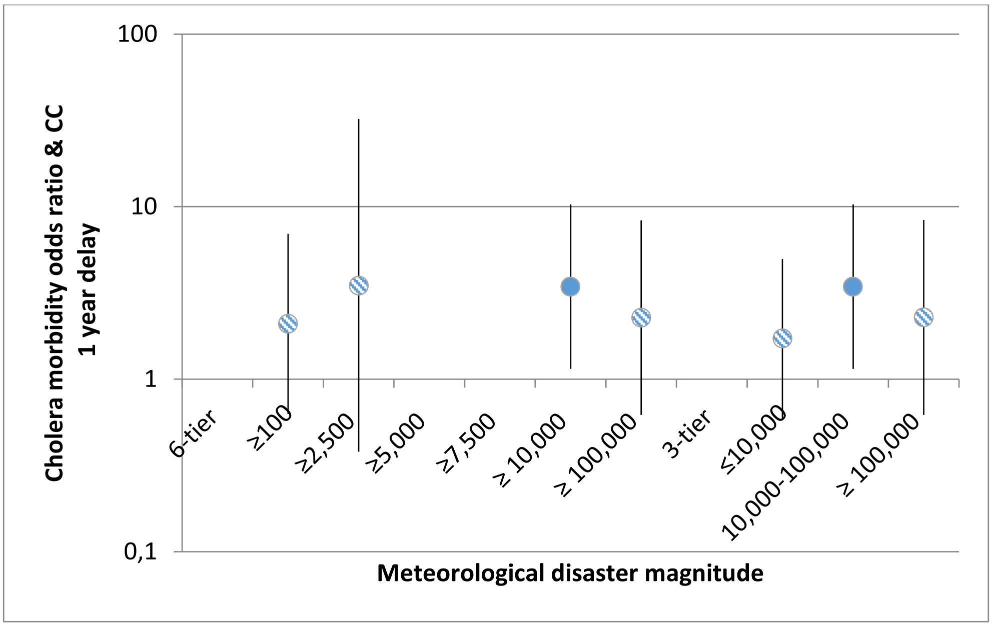


Figure 5.14: Graphic representation of odds ratio and confidence intervals of average cholera morbidity with a 1-year delay for meteorological disasters.

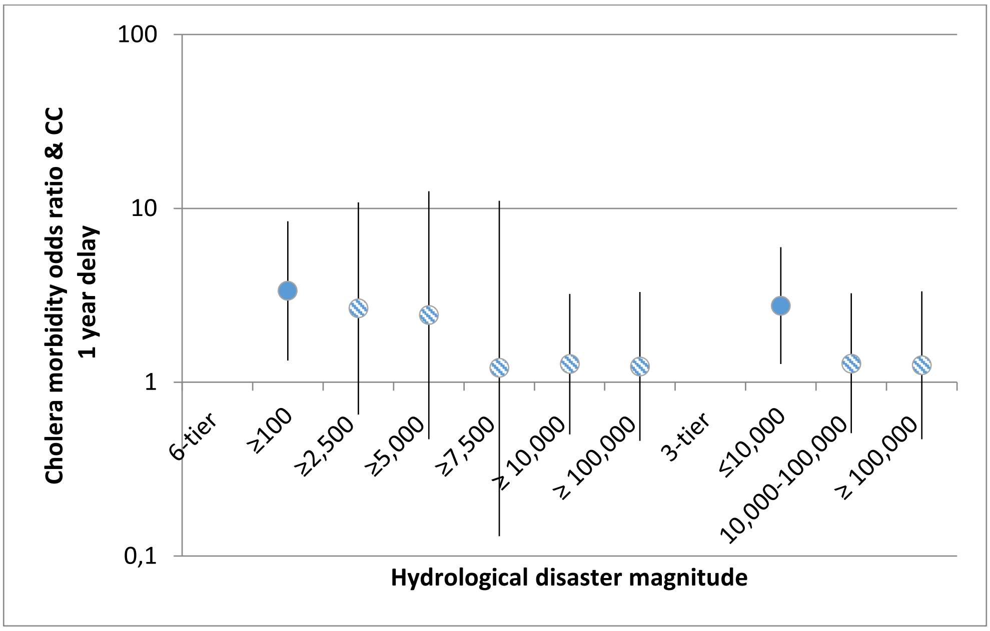


Figure 5.15: Graphic representation of odds ratio and confidence intervals of average cholera morbidity with a 1-year delay for hydrological disasters.

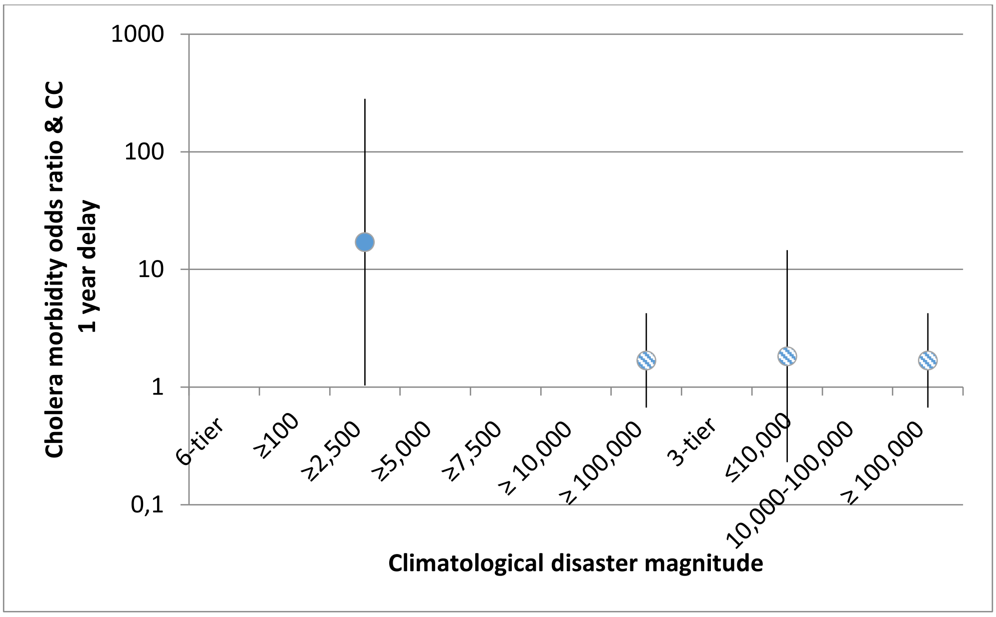


Figure 5.16: Graphic representation of odds ratio and confidence intervals of average cholera morbidity with a 1-year delay for climatological disasters.

The one-year lag association of natural disasters with cholera morbidity offers some interesting new insights when compared to the results of the in-phase analysis (Figures 5.2 to 5.6). While for total disasters, no significant results were found, when looking at specific disaster types the effect of disasters shows some shifts (Table 5.4). One year after geophysical disasters, the odds for above average cholera cases was found to be significantly increased if the disaster affected between 10,000 and 100,000 of the population. The same effect occurred in meteorological disasters, where disasters affecting over 100,000 had a highly significant effect (*P*=0.004) in the same year, while disasters affecting between 10,000 and 100,000 have a significant effect (*P*=0.03) on cholera cases in the following year. For hydrological disasters however, the effect remains stable. Both within the same year and the year after, cholera case averages are affected by disasters in under 10,000 of the population.

Interestingly, only in the analysis of cholera cases one year after the disasters do climatological disasters (affecting between 2,500 and 5,000 of the population) show a significant increase (*P*=0.04). This is the only significant result for climatological disasters found in this analysis.

5.4 Discussion

5.4.1 Discussion of findings

The present analysis supports the notion that an increase in cholera activity may not follow in the immediate aftermath of disaster events (Shears, 1991), with only relatively few years in which above average numbers of cholera were detected (228 country-years out of 2716). The results presented in section 5.3 show that disasters which affect small numbers of people rarely have an effect on the odds of above average disease at all. For total disasters, it was only at above 7,500 people affected that an increase in odds was found significant with an OR=4.64 (95%CI=1.26-17.01; P=0.02) and at above 100,000 people affected with OR=1.89 (95%CI=1.01-3.55; P=0.05) (Table 5.2). The confidence interval for the smaller magnitude tier is wider compared to the higher magnitude tier, which suggests the latter result is more robust. Similar figures are shown for the remaining disaster types. This confirms the hypothesis that large scale disasters have a stronger effect on infectious disease figures. For climatological disasters, no significant effect on odds was found at all (Table 5.6).

Where significant results were found in years with disasters affecting very few people (2,500 or less), it is quite possible that the present analysis did not account for all factors influencing disease risk, and further investigation is necessary. It seems unlikely that earthquakes affecting between 100 and 2,500 of the population render the same effect on cholera as earthquakes affecting over 100,000 of the population. It is more probable that surrounding factors – for example socio-political circumstances making the population more vulnerable, or a pre-existing cholera outbreak unrelated to the natural disaster – led to the above average cholera numbers. To gain insight into the possible dynamics of these smaller events, the analysis will need to be refined further in follow up.

For geophysical disasters and, to a somewhat lesser extent, meteorological disasters as well, both cholera morbidity and cholera mortality are affected by large scale disasters. In Table 5.3, odds of above average cholera morbidity are significantly higher in geophysical disaster-affected populations of ≥100,000

(OR=5.98; 95%CI=1.99-17.99; *P*=0.001), and a similar increase was found for cholera mortality (OR=8.97; 95%CI=2.83-28.44; *P*=0.001). Meteorological disasters in Table 5.4 showed a significant increase in odds of morbidity at above 100,000 people affected (OR=3.46; 95%CI=1.48-8.08; *P*=0.004), and while mortality results were not statistically significant, the *P*-value is approaching significance (OR=2.52; 95%CI=0.91-6.93; *P*=0.07).

Unlike geophysical and meteorological disasters, hydrological disasters there was only limited evidence for increased cholera odds (Table 5.5), and these findings appeared in smaller magnitude tiers. There was a significant increase in odds of cholera morbidity in hydrological disasters affecting between 100 and 2,499 people (OR=2.29; 95%CI=1.07-4.89; *P*=0.03) and mortality for disasters affecting between 2,500 and 5,000 people (OR=4.68; 95%CI=1.42-15.45; *P*=0.01). This challenges the notion that cholera is most prevalent in disasters related to water (Linscott, 2007). This may be considered an unexpected finding, considering cholera's relation to contaminated water, but it may reinforce arguments that state that contaminated water is not the only source of cholera infection (Sack et al., 2004). It suggests that disasters which tend to have a more severe effect on the surrounding infrastructure (i.e. earthquakes and severe storms), leaving sanitation facilities damaged, have a more significant effect on cholera rates.

Disaggregating the data into 6 separate geographical regions, available data for individual analysis was limited and confidence in the findings was reduced. However, inspecting the regional results for cholera morbidity presented in Figures 5.7–5.11, significant findings were made for disaster-related cholera increases in the Americas region at above 100,000 people affected (PR=7.81; 95%CI=1.31-46.70; *P*=0.02). The most likely explanation for this is the Haiti earthquake and subsequent cholera epidemic in 2010 factoring in the results and introducing a level of bias (see Chapter 3). In order to eliminate that potential bias, Haiti would have to be excluded from the analysis. Interestingly, while the results were stable between the 6-tier analysis and the 3-tier analysis in almost all regions, this was not the case in Eastern Mediterranean region, with noticeably different results for above 10,000 and 100,000 of the population affected between the two analyses. As not enough data was available for most of the 6-tier analysis to yield results, it can be assumed adjusting the disaster magnitude into 3-tiers may have stabilised the results to some extent.

With the introduction of the 1-year lag into the analysis, a new layer of insight was added to the findings (Table 5.7). For total disasters, the analysis shows no above average cholera morbidity one year following the disasters. For geophysical and meteorological disasters however, statistically significant odds of higher cholera morbidity was found at 1-year lag (geophysical: OR=4.73; 95%CI=1.10-20.37; *P*=0.04, and meteorological: OR=3.44; 95%CI=1.15-10.32; *P*=0.03). Similar to the in-phase analysis, hydrological disasters affecting between 100 and 2,499 people were shown to have a lasting effect on cholera morbidity, with an even stronger effect after one year (OR=3.35; 95%CI=1.33-8.43; *P*=0.01). Interestingly, a statistically significant result was found for climatological events after 1 year (OR=17.03; 95%CI=1.03-282.40; P=0.04). The confidence interval was very wide, but the finding still bears some significance for future research, especially with climatological disasters expected to increase in the future.

Sumner and colleagues, whose paper on cholera and earthquakes inspired this chapter, found no significant results in their analysis. However, when designing their analysis, the upper tier of the magnitude classification was set at ≥10,000 – whereas the present chapter set the upper tier at ≥100,000. Interestingly, that is where significant results were mostly found. It could be argued that if the analysis on earthquakes was repeated as conducted by Sumner et al. but including an additional category of ≥100,000 population affected, their study might have yielded significant results.

5.4.2 Natural disasters and the risk of cholera

Despite a number of issues persisting in post-disaster management that potentially increase the risk of infectious diseases, studies of disasters have previously shown a minimal impact of disasters on infectious disease activity (Ahern et al., 2005; Shears, 1991; Watson et al., 2007; Wilder-Smith, 2005). However, it has been noted that diseases may increase in later phases after the disaster, and should not be neglected entirely (Shears, 1991).

McCann et al. (2011) listed a number of misconceptions concerning the 2004 tsunami in South Asia, including an overestimation of epidemic risk and an adverse effect of excessive medical voluntarism (McCann et al., 2011). This is in line with the assessment made by Wilder-Smith in 2005. Ahern and colleagues conducted a review of numerous flood-related studies, and found only limited evidence of increased disease risk (Ahern et al., 2005). Sumner and colleagues, in their paper on cholera and earthquakes, found no statistically significant increase in odds of above average cholera rates (Sumner et al., 2013).

The argument that the impact of infectious diseases may rise significantly after the disaster event occurred has been addressed by Shears and Wilder-Smith (Shears, 1991; Wilder-Smith, 2005). The data presented in this chapter confirms the lag in infectious disease activity as an issue to be considered. Not only are increased odds of cholera found after a year (Table 5.7), but they are also found in climatological disasters, which would have gone unnoticed had the analysis focused entirely on the same year of the disaster. This supports the assumption that infectious disease concerns can occur long after the disaster event itself.

Opposing opinions and research show increases in diarrhoeal or gastrointestinal disease cases, including cholera. Panda and colleagues, among others, argue that there is an association between outbreaks of diarrhoeal disease and disasters, and support their argument with data from the aftermath of cyclone Aila in 2009 (Panda et al., 2011). Wade and colleagues found an increase in gastrointestinal complaints after the flooding of the Mississippi River in communities in Minnesota, Wisconsin, North Dakota, Iowa, and Illinois via results from the Water Evaluation Trial (WET) along the river in

2001 (Wade et al., 2004). Furthermore, Schwartz and colleagues found V*ibrio cholerae* to be the main pathogen causing outbreaks in the aftermath of three flood disasters in Bangladesh, in 1988, 1998, and 2002 respectively (Schwartz et al., 2006).

The findings of this chapter and, by extension, Chapter 3, are in line with these arguments. There is currently limited evidence for an association between natural disasters and cholera, but when disaster magnitude is large enough and long-term observations are made, rather than short term analysis of the acute post-disaster phase, statistically significant results can be found. It becomes evident that certain characteristics need to be met for disasters to have an impact on disease, and disaster magnitude can be considered an important factor in this dynamic.

The findings in this chapter, in showing statistical evidence for the role of cholera in the aftermath of large scale disasters as well as highlighting the importance of time lag in the emergence of epidemics, provides support for endeavours to move disaster management forward. As was suggested as early as 1991 (Shears, 1991), and was still proven relevant as recently as 2013 (Leaning & Guha-Sapir, 2013), in the acute post-disaster management phase of medium-sized disasters, supplies should focus on providing improved shelter where necessary, reliable sanitation, and food and clean water provisions. Treatment supplies can take a secondary concern at least when it comes to challenging cholera in the acute post-disaster phase – measures to prevent cholera from becoming an issue in the first place are important at this stage. Infectious diseases become an increasing problem in later phases, cholera being a concern up to a year after the event, as was evident in the case of Haiti, and in disasters that affect very large numbers of people simultaneously (Kouadio et al., 2012). The establishment of a reliable disease surveillance system in order to be alerted immediately of an increase in disease incidence is a crucial issue to counter the emergence of infectious diseases in the long term effect of a disaster and should be set up as swiftly as possible, alongside disaster management that will carry over into routine care, once initial relief organisations have left the affected area (Leaning & Guha-Sapir, 2013).

5.4.3 Limitations

The main limitations of this analysis relate to the available data included. The inclusion of the earthquake in Haiti of 2010 in this analysis may have biased the results for geophysical disasters. In Sumner's analysis, it was deliberately chosen to not include data from 2010 to avoid the inclusion of the Haiti earthquake for that reason. In the present analysis, it was – after careful consideration – elected to include the data. The data period as defined in Section 4.2 was standardised for the four chapters for reasons of data availability and comparability. As the bias from the Haiti earthquake would not be present for any disease other than cholera, it was decided to keep the data in, while being aware that there might be a bias. In the future, a separate analysis with the data excluded could be conducted to investigate the difference in outcome.

5.5 Conclusion

Cholera is one of the most studied, best understood diseases in the aftermath of natural disasters. This is largely due to its dramatic role after the Haiti Earthquake in 2010. This chapter aimed to expand on the findings of Sumner and colleagues by including different disaster types. Also, by including a 1-year time lag, a layer was added to existing findings on the effect of natural disasters on cholera incidence. While Sumner and colleagues did not find statistically significant results in their analysis, by expanding on their methodology, a number of significant results could be found in this chapter. It has been shown that numbers of cholera are significantly above average in disasters affecting larger numbers of the population, especially for geophysical and meteorological disasters, and for hydrological disasters after 1 year.

Chapter 6: Natural Disaster and Malaria

Chapter Contents

6.1 Background

As described in Section 4.2, malaria is a disease caused by the *Plasmodium* parasite (mostly *P. falciparum* and *P. vivax*) and transmitted by the bite of the female *Anopheles* mosquito. Once bitten, the parasite is injected into the bloodstream. Common symptoms of malaria are waves of sudden coldness followed by fever and cold, occurring every few days, as new parasitic cells are produced in the bloodstream in waves. New mosquitoes are infected by feeding on infected humans, and carry the parasite along to their next blood meal. Severe forms of malaria – typically caused by *P. falciparum* – manifest in neurological symptoms as severe as seizures and coma (Heymann, 2015).

In areas where it is endemic (Figure 2.10), malaria is one of the leading causes of morbidity and mortality. Malaria is endemic in tropical regions, where Anopheles mosquitos breed (Wisner & Adams, 2002; CDC). A major risk factor for malaria is the presence of standing waters, as they provide ideal breeding conditions for mosquitos. Globally, WHO estimates that around 200 million patients are infected with malaria, and around 500,000 people die of malaria – these estimates are between 2010 and 2015 (Global Health Observatory, 2016).

In the aftermath of disasters, in endemic areas, conditions may lean towards a high risk, high exposure scenario for malaria. Breeding conditions for mosquitos may be changed favourably by disasters, and populations are made more vulnerable due to temporary shelters, overcrowding, and the breakdown of health infrastructures (Gunasekaran et al., 2005; Heymann, 2015; Krishnamoorthy et al., 2005; Kumari et al., 2009). Malaria control is recognized as a priority issue in the aftermath of natural disasters, and has contributed largely to keeping numbers of malaria low in the emergency phase (Kumari et al., 2009). However, there are also arguments indicating that there may be no or limited increase of malaria after disasters (Briët et al., 2006; Briët et al., 2005; Floret et al., 2006), or that the current approach to malaria control after disasters may negatively affect malaria eradication efforts (Weinstein et al., 2010).

Drawing on the methodology outlined in Chapter 4, the present chapter will investigate the association between recorded levels of malaria activity and natural disasters, to potentially reveal statistical changes over time.

6.2 Methodology

6.2.1 Disease Data

In accordance with Section 4.3, data for malaria infections were gathered from the Global Health Observatory at WHO (http://apps.who.int/gho/data/node.main.A1362?lang=en). The two categories in question were 'Reported confirmed cases' and 'Reported deaths'. Reported confirmed cases are cases of malaria that are confirmed by microscopy slide and/or by malaria rapid diagnostic tests (RDTs). Reported deaths includes both confirmed and probable deaths due to malaria, based on data submitted by national malaria control programmes. Countries were excluded from the analysis if no case of malaria was reported within the 14 year period (2000-2013). For these countries, the assumption was that malaria is not endemic, which made the country irrelevant to this particular analysis. These exclusions brought the country-years for this chapter down to a total 1512. Countries that would not regularly have endemic malaria, but had reported cases due to importing, were included in the analysis, even if malaria was not naturally endemic there.

Over the 14 year period specified in Section 4.3.1, a total of 255,412,515 cases of malaria were confirmed. Likewise, 1,809,358 malaria deaths were reported. Table 6.1 shows the majority of cases and deaths due to malaria occur in the African region of the World Health Organization, and the lowest numbers were recorded in the European region – where malaria is only endemic in nine countries.

Table 6.1: Regional distribution of malaria cases and deaths, regions as defined by WHO (see figure 4.1).

	malaria cases	malaria deaths
Africa	191,288,714	1,719,916
Americas	10,784,753	3,186
South-East Asia	34,023,872	47,020
Europe	116,642	45
Eastern Mediterranean	14,732,607	21,967
Western Pacific	4,465,927	17,224
Global	255,412,515	1,809,358

The disease data were dichotomised into above and below average cases and deaths. To do so, the national average *ri* of cases and deaths over the 14 years under investigation was calculated for each country *i* included. The annual number *t* of cases or deaths was then compared to *ri*. Years where *t* was below or equal to *ri* were coded as 0, and years with *t* above *ri* were coded as 1, as was outlined previously in section 4.3.1.

Of the above mentioned 1512 country-years, above average numbers of malaria cases occurred in 495 country-years and above average malaria deaths in 484 country-years (see Table 4.4).

6.2.2 Data analysis

To determine the association between malaria and natural disaster magnitude, logistic regression analyses were carried out with the disaster magnitude tiers previously described in detail in Chapter 4. The model of logistic regression as well as a breakdown of the elements of the analysis is provided in Section 4.4 and Equation 4.1.

Aside from global confirmed cases and deaths from malaria, regional analysis was performed as well as analysis by type of disaster. Following the method described in Section 4.4, a logistic regression with a one-year time lag was conducted. In that case, natural disasters were associated with malaria figures from one year later, to account for a time lag in disease data. A lag may occur due to surveillance systems picking up cases and deaths retrospectively, but also because malaria infection is highly dependent on seasonality and vector breeding, so looking into data from a later stage, after a breeding cycle has passed, was considered a logical approach. One year lag was chosen in accordance with literature reviewed in section 2.6.4, investigating malaria figures a year after the South-East Asian Tsunami (Briët et al., 2006).

6.3 Results

Summarised in this section are the results of logistic regression analysis estimating the association between malaria cases and deaths after natural disaster. Section 6.3.1 shows the results for global analysis by disaster type, section 6.3.2 presents regional results, and section 6.3.3 presents the global one-year-lag analysis. The tabular information presents odds ratios, *P*-values, and 95% confidence interval (CI) of the analysis for each tier of disaster magnitude. The graphic representation is on a logarithmic scale, showing the odds ratio for each analysis as a circle, and the 95% CI as whiskers. Statistically significant results are marked by solid filled circles, whereas insignificant results have patterned circles.

6.3.1 Natural disasters and malaria

The results for global malaria cases and deaths for disasters of all types are summarised in Table 6.2. Reviewed literature suggests that disasters affecting a larger number of people may result in an increase in malaria figures. In the overview of total natural disasters (Table 6.2) it is confirmed that years in which large numbers of people are affected by disaster (≥100,000 people) lead to increased odds of above average malaria cases (OR=1.80, 95% CI=1.05-3.09, *P*=0.03). There was a two fold increase in odds for above average death from malaria in years where between 10,000 and 100,000 people were affected by disasters (OR=2.22, 95% CI=1.15-4.31, *P*=0.02).

Table 6.2: Global odds ratio and confidence interval of average confirmed malaria cases and deaths for disasters, adjusted for sanitation, water access, and under 5 child mortality, between 2000 and 2013.

	malaria cases			**malaria deaths**		
Total affected	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	1.31	0.53-3.28	0.56	1.05	0.37-2.95	0.93
≥2,500	1.19	0.45-3.17	0.73	1.68	0.61-4.65	0.32
≥5,000	1.06	0.25-4.46	0.94	1.47	0.33-6.49	0.62
≥7,500	1.05	0.29-3.77	0.94	2.57	0.71-9.28	0.15
≥ 10,000	1.29	0.69-2.43	0.42	2.22	1.15-4.31	0.02
≥ 100,000	1.80	1.05-3.09	0.03	1.58	0.88-2.83	0.13
3-tier analysis						
≤10,000	1.19	0.63-2.25	0.60	1.51	0.77-3.00	0.23
10,000-100,000	1.30	0.70-2.43	0.42	2.21	1.14-4.29	0.02
≥ 100,000	1.80	1.05-3.09	0.03	1.57	0.88-2.82	0.13

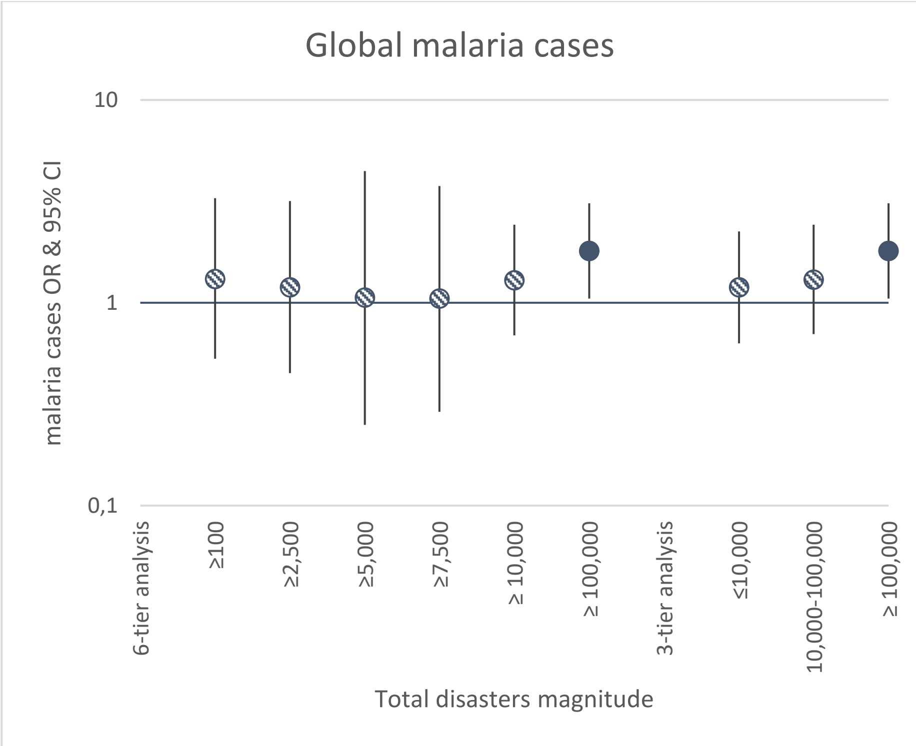


Figure 6.1a: Graphic representation of odds and 95% CI of above global average malaria cases for total disasters, between 2000 and 2013.

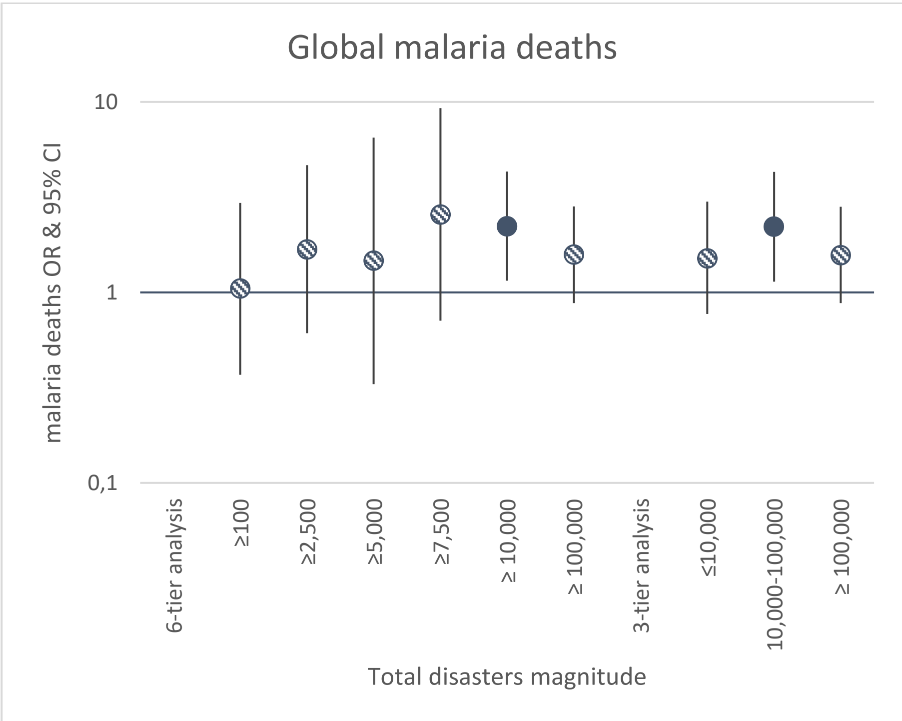


Figure 6.1b: Graphic representation of odds and 95% CI of above global average malaria deaths for total disasters, between 2000 and 2013.

Hydrological disasters

No statistically significant results were found for hydrological disasters and malaria cases. However, significantly increased odds were found for malaria deaths at between 2,500 and 5,000 people affected (OR=3.72, 95%CI= 1.15-12.01, *P*=0.03) and at 100,000 or more people affected (OR=2.01, 95%CI= 1.07-3.77, *P*=0.03). The results hold up in the three-tier analysis as well, where years in which less than 10,000 people were affected by disaster show a two fold increase of odds (OR=2.37, 95%CI=1.27-4.43, *P*=0.01).

Table 6.3: Global odds ratio and confidence interval of average confirmed malaria cases and deaths for hydrological disasters, adjusted for sanitation, water access, and under 5 child mortality, between 2000 and 2013.

	malaria cases			malaria deaths		
Hydrological disaster affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	1.61	0.74-3.47	0.23	2.03	0.89-4.63	0.09
≥2,500	1.34	0.42-4.32	0.62	3.72	1.15-12.01	0.03
≥5,000	1.03	0.29-3.63	0.97	1.72	0.48-6.17	0.40
≥7,500	1.13	0.31-4.13	0.85	3.13	0.82-11.99	0.10
≥ 10,000	1.02	0.58-1.93	0.86	1.68	0.89-3.15	0.11
≥ 100,000	1.46	0.81-2.65	0.21	2.01	1.07-3.77	0.03
3-tier analysis						
≤10,000	1.36	0.76-2.35	0.30	2.37	1.27-4.43	0.01
10,000-100,000	1.06	0.58-1.93	0.86	1.68	0.89-3.15	0.11
≥ 100,000	1.47	0.81-2.65	0.21	2.00	1.07-3.77	0.03

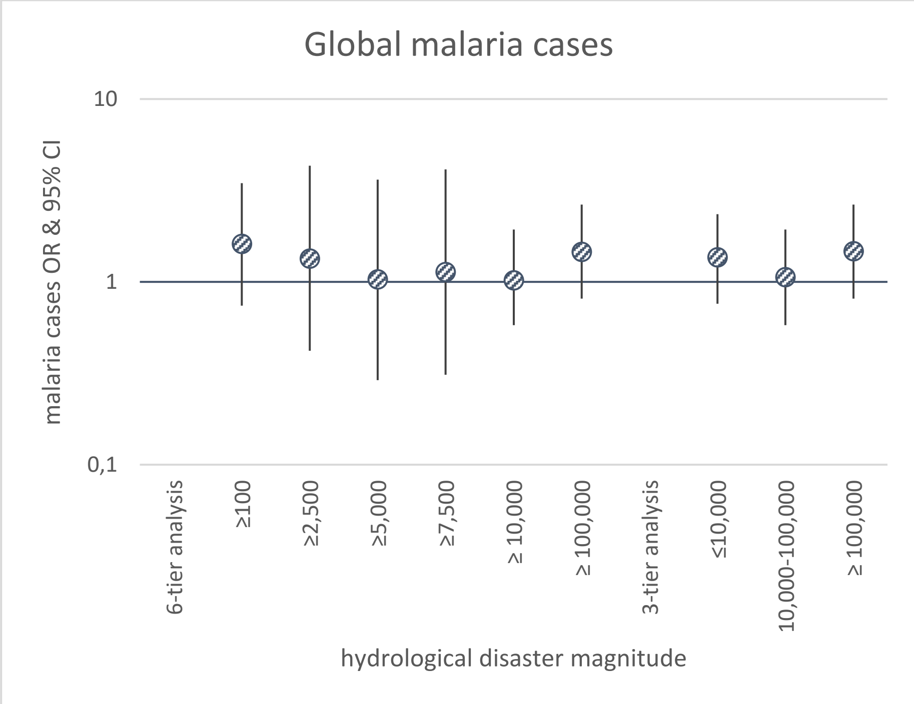


Figure 6.2a: Graphic representation of odds and 95% CI of above global average malaria cases for hydrological disasters, between 2000 and 2013.

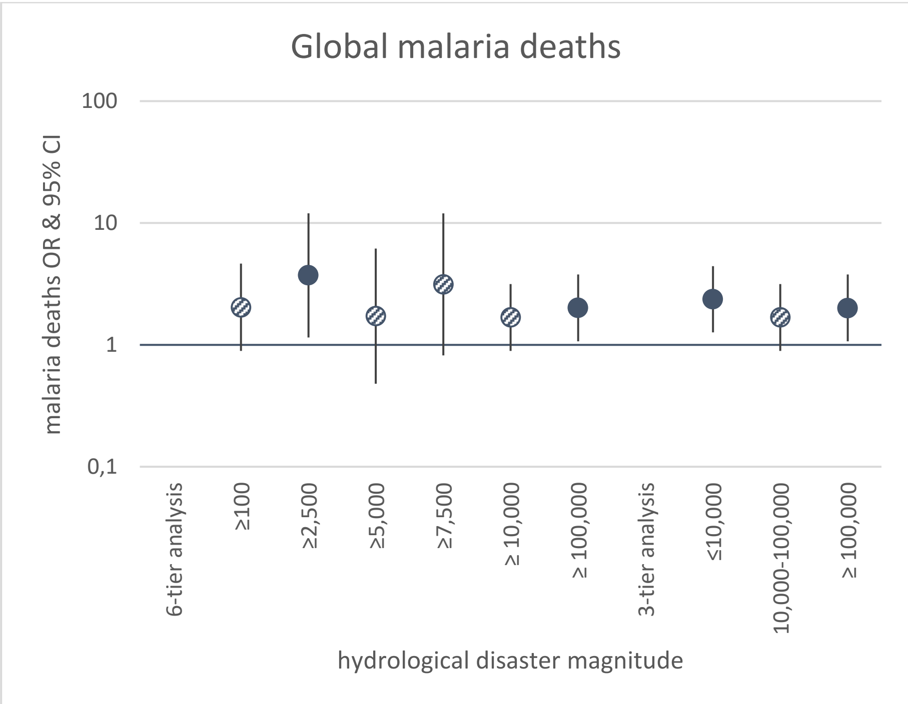


Figure 6.2b: Graphic representation of odds and 95% CI of above global average malaria deaths for hydrological disasters, between 2000 and 2013.

Other disaster types

This section presents the tabulated results for geophysical disasters (Table 6.4), meteorological disasters (Table 6.5), and climatological disasters (Table 6.6). No statistically significant results were found for these types of disasters on a global level, for either malaria cases or malaria deaths.

Table 6.4: Global odds ratio and confidence interval of average confirmed malaria cases and deaths for geophysical disasters, adjusted for sanitation, water access, and under 5 child mortality, between 2000 and 2013.

	malaria cases			**malaria deaths**		
Geophysical disaster affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	0.80	0.24-2.68	0.71	0.82	0.24-2.80	0.75
≥2,500	0.69	0.13-3.56	0.65	/	/	/
≥5,000	5.34	0.57-50.01	0.14	5.33	0.55-42.04	0.15
≥7,500	0.76	0.07-8.64	0.83	/	/	/
≥ 10,000	0.85	0.21-3.48	0.82	0.79	0.15-4.26	0.78
≥ 100,000	1.24	0.41-3.79	0.71	0.84	0.25-2.84	0.78
3-tier analysis						
≤10,000	1.05	0.47-2.35	0.90	0.74	0.31-1.83	0.53
10,000-100,000	0.85	0.21-3.51	0.82	0.81	0.15-4.39	0.80
≥ 100,000	1.25	0.41-3.82	0.70	0.84	0.25-2.85	0.78

Table 6.5: Global odds ratio and confidence interval of average confirmed malaria cases and deaths for meteorological disasters, adjusted for sanitation, water access, and under 5 child mortality, between 2000 and 2013.

	malaria cases			**malaria deaths**		
Meteorological disaster affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	2.43	0.92-6.41	0.07	1.49	0.49-4.56	0.47
≥2,500	0.88	0.16-4.81	0.88	2.51	0.51-12.26	0.26
≥5,000	2.14	0.28-16.53	0.46	0.97	0.08-11.20	0.98
≥7,500	0.66	0.06-7.08	0.73	0.88	0.07-11.53	0.92
≥ 10,000	1.95	0.85-4.46	0.12	1.43	0.59-3.47	0.44
≥ 100,000	1.00	0.42-2.38	1.00	1.31	0.53-3.22	0.56
3-tier analysis						
≤10,000	1.70	0.80-3.64	0.17	1.52	0.65-3.54	0.33
10,000-100,000	1.95	0.85-4.46	0.12	1.43	0.59-3.46	0.44
≥ 100,000	1.01	0.42-2.40	1.00	1.31	0.53-3.23	0.56

Table 6.6: Global odds ratio and confidence interval of average confirmed malaria cases and deaths for climatological disasters, adjusted for sanitation, water access, and under 5 child mortality, between 2000 and 2013.

	malaria cases			malaria deaths		
Climatological disaster affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	1.13	0.19-6.60	0.89	0.86	0.09-8.19	0.90
≥2,500	/	/	/	/	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	0.36	0.04-3.45	0.38	1.22	0.17-8.59	0.85
≥ 100,000	0.83	0.40-1.69	0.60	0.90	0.43-1.88	0.79
3-tier analysis						
≤10,000	1.37	0.30-6.15	0.68	0.54	0.06-4.80	0.58
10,000-100,000	0.37	0.04-3.45	0.38	1.22	0.17-8.59	0.84
≥ 100,000	0.82	0.40-1.69	0.60	0.90	0.43-1.88	0.79

6.3.2 Regional results

This section summarises the results for malaria cases and deaths (OR, 95% CI, and *P*-value) by WHO world region (Figure 4.1) for total disasters. For a full, tabulated breakdown of regional malaria cases by disaster type, refer to Appendix 6.

Only two significant results were found for the regional analysis of malaria cases. For disasters affecting over 100,000 people in the WHO Africa Region (Figure 6.3), a significant increase of odds of above average malaria was found (OR=2.70, 95%CI=1.17-6.22; *P*=0.02). In the European Region, disasters affecting more than 100,000 of the population saw a significant increase in malaria cases (OR=29.76; 95%CI=1.25-708.90; *P*=0.04). No other significant results were found for the regions.

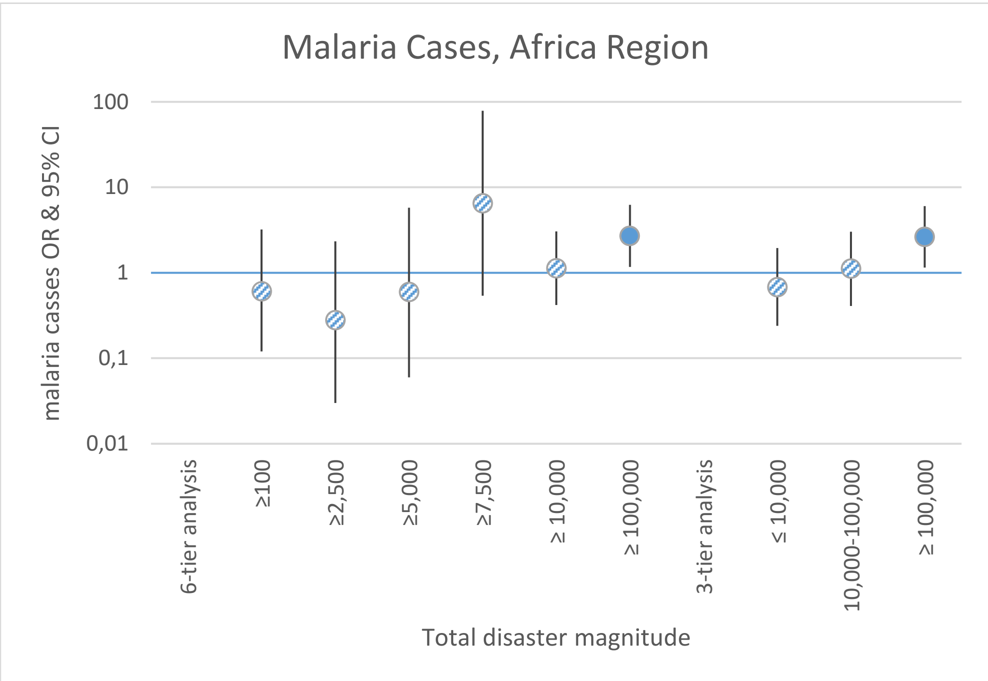


Figure 6.3: Graphic representation of odds and 95% CI of above global average malaria cases for disasters in the WHO Africa region (Figure 4.1), between 2000 and 2013.

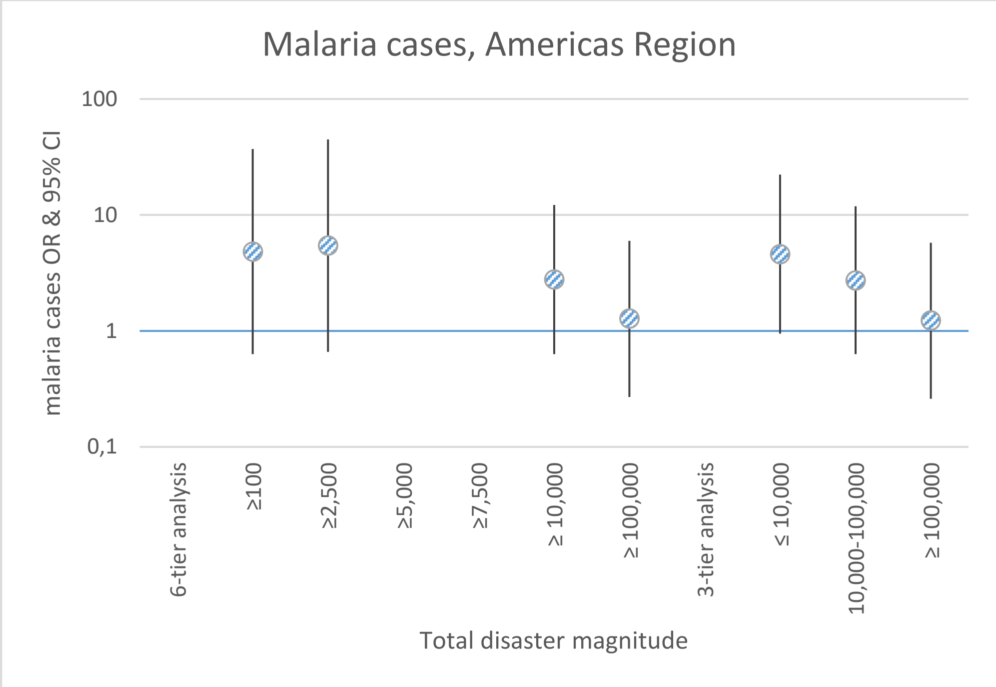


Figure 6.4: Graphic representation of odds and 95% CI of above global average malaria cases for disasters in the WHO Americas region (Figure 4.1), between 2000 and 2013.

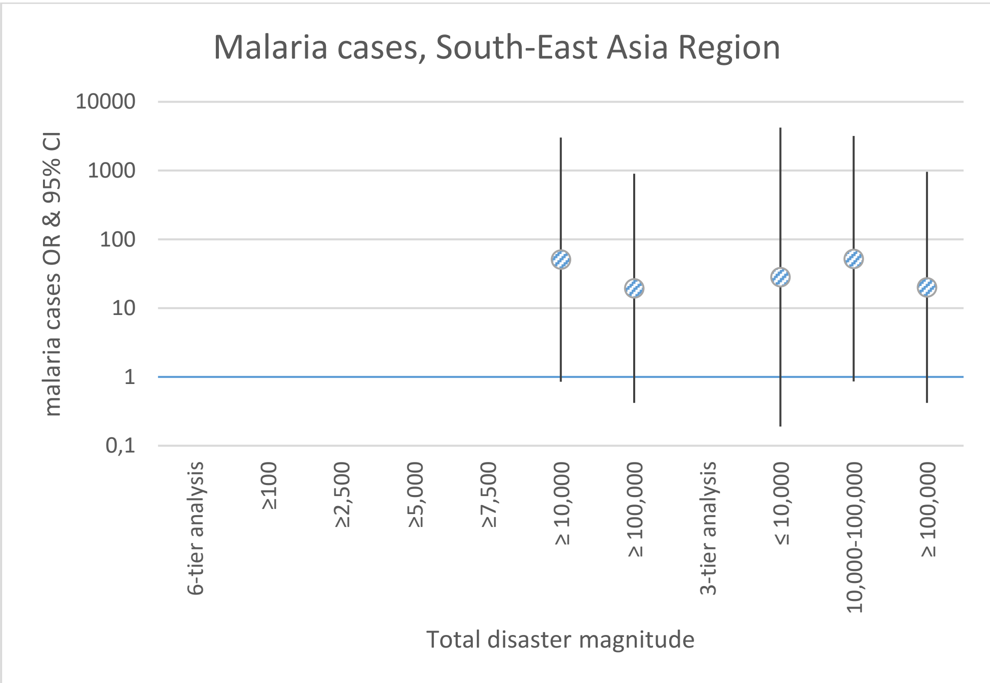


Figure 6.5: Graphic representation of odds and 95% CI of above global average malaria cases for disasters in the WHO South-East Asia region (Figure 4.1), between 2000 and 2013.

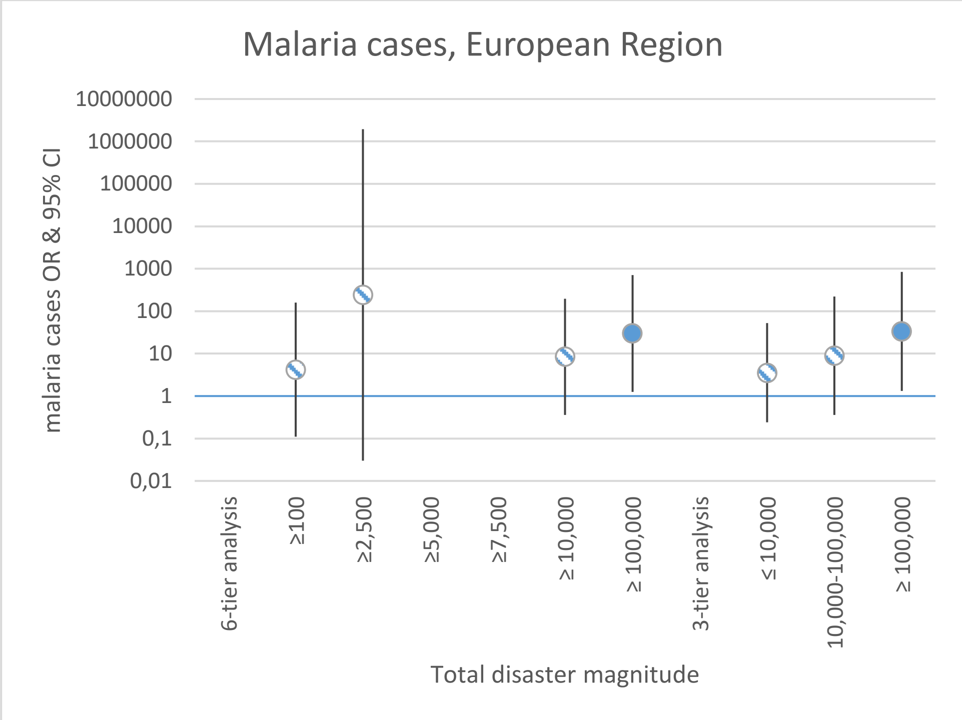


Figure 6.6: Graphic representation of odds and 95% CI of above global average malaria cases for disasters in the WHO European region (Figure 4.1), between 2000 and 2013.

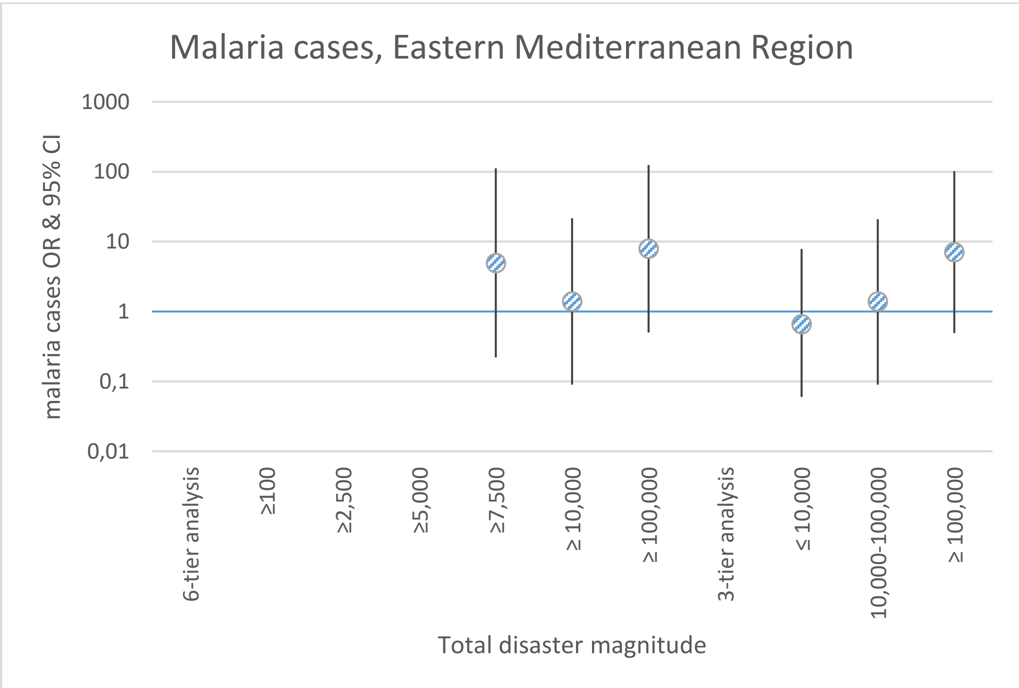


Figure 6.7: Graphic representation of odds and 95% CI of above global average malaria cases for disasters in the WHO Eastern Mediterranean region (Figure 4.1), between 2000 and 2013.

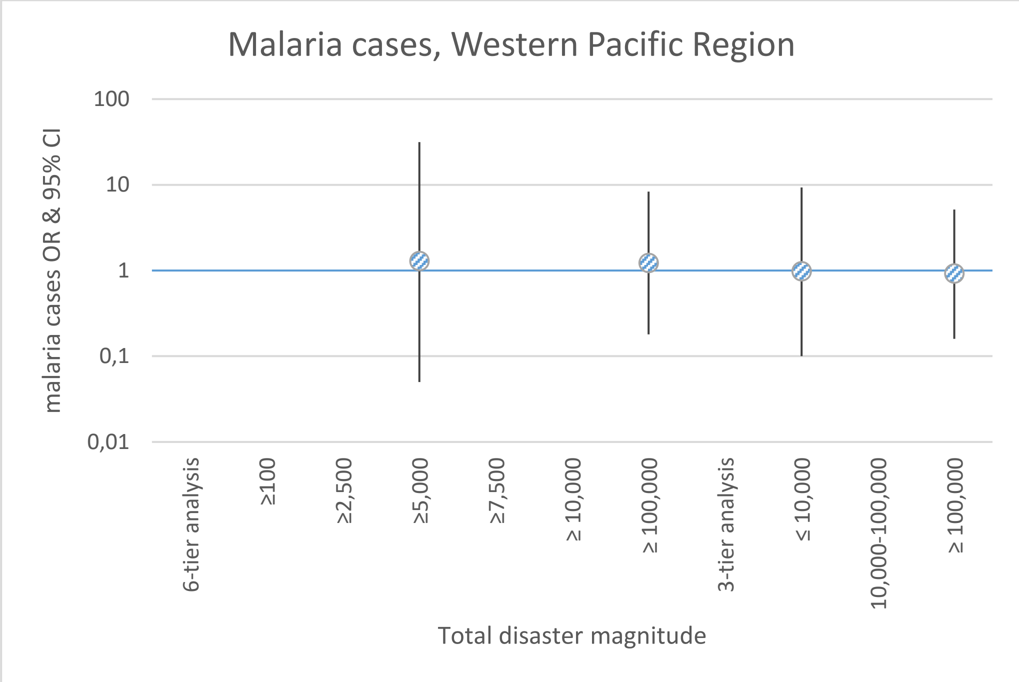


Figure 6.8: Graphic representation of odds and 95% CI of above global average malaria cases for disasters in the WHO Western Pacific region (Figure 4.1), between 2000 and 2013.

6.3.3 1-year lag analysis

This section presents the results of the lag analysis. Data will only be presented in graphic representation (Figures 6.9 – 6.14), for a full tabulation of the results – including malaria cases and malaria deaths – refer to appendix 7 and 8.

There was an increase in total malaria deaths at between 10,000 and 100,000 affected people for total disasters (OR=2.01, 95%CI=1.05-3.85, *P*=0.04) at 1-year lag, as seen in Figure 6.10 and no significant results for all malaria cases.

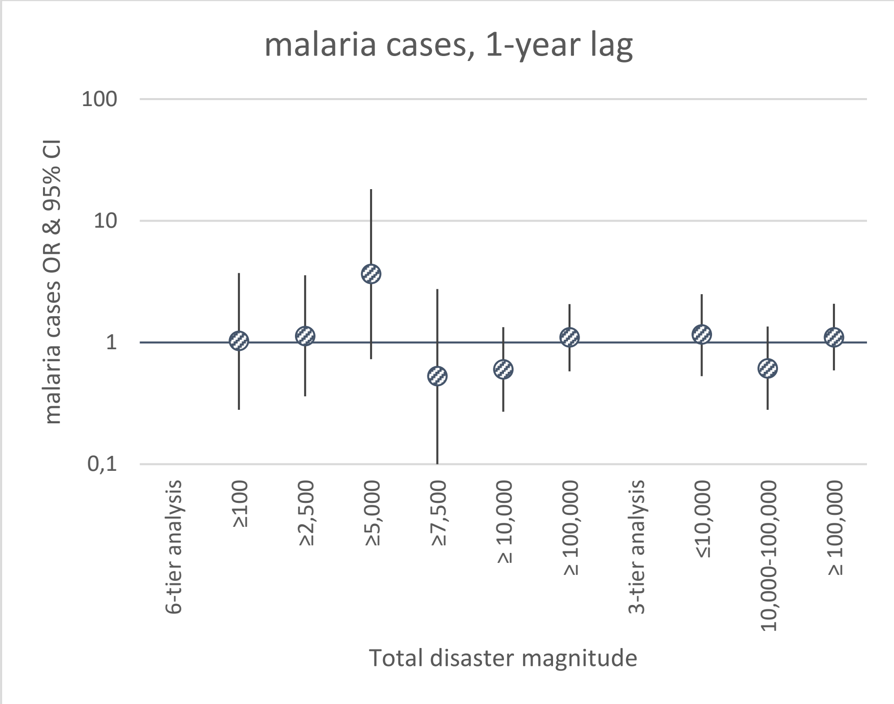


Figure 6.9: Graphic representation of odds and 95% CI of above global average malaria cases for all disasters at 1-year lag, between 2000 and 2013.

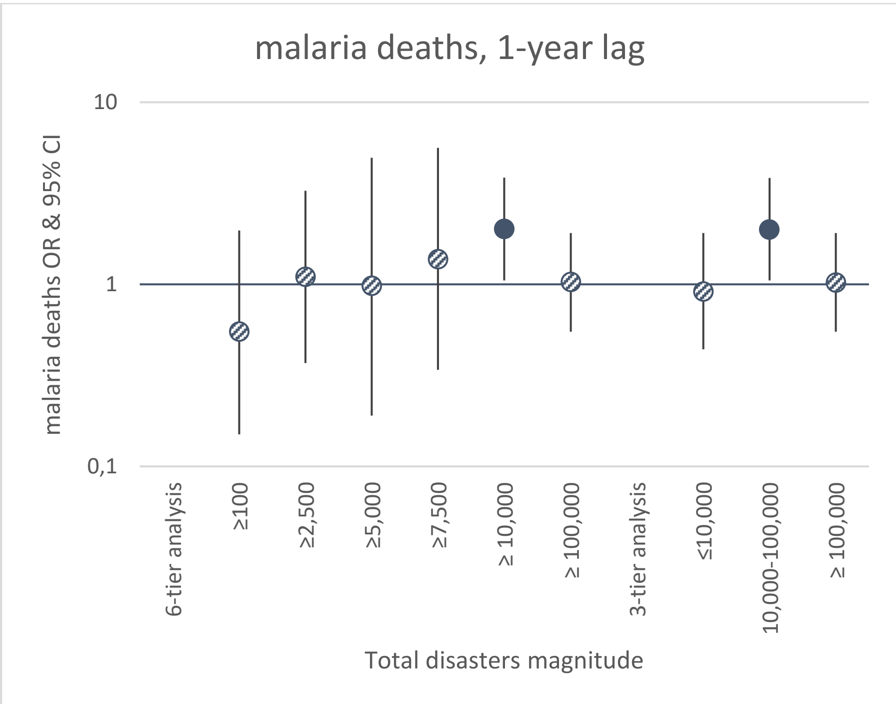


Figure 6.10: Graphic representation of odds and 95% CI of above global average malaria deaths for all disasters at 1-year lag, between 2000 and 2013.

Meteorological disasters

At a 1-year lag, significant results appear in the 3-tier analysis for meteorological disasters in years when over 100,000 people are affected by the disasters (OR=2.86, 95%CI= 1.08-7.57, *P*=0.03). This is in line with previous assumptions about the effect of large scale disasters. The significant result found for the magnitude tier of 100-2,499 people affected (OR=5.33, 95%CI=1.43-19.00, *P*=0.01) is open for debate due to the large confidence interval. The effect also was not present in the 3-tier analysis (Figure 6.11). No results were found for malaria deaths.

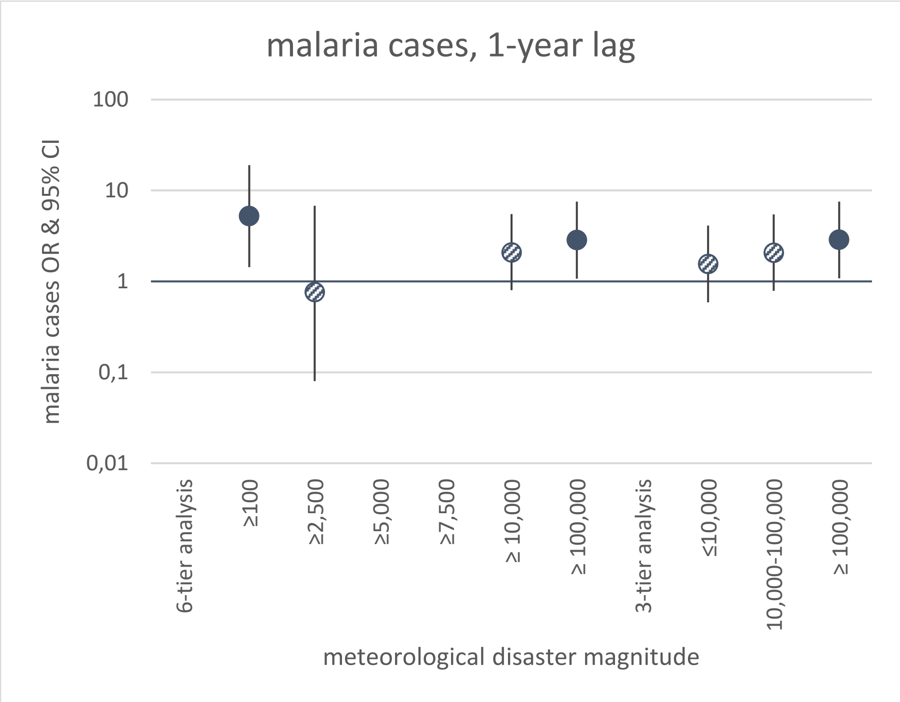


Figure 6.11: Graphic representation of odds and 95% CI of above global average malaria cases for meteorological disasters at 1-year lag, between 2000 and 2013.

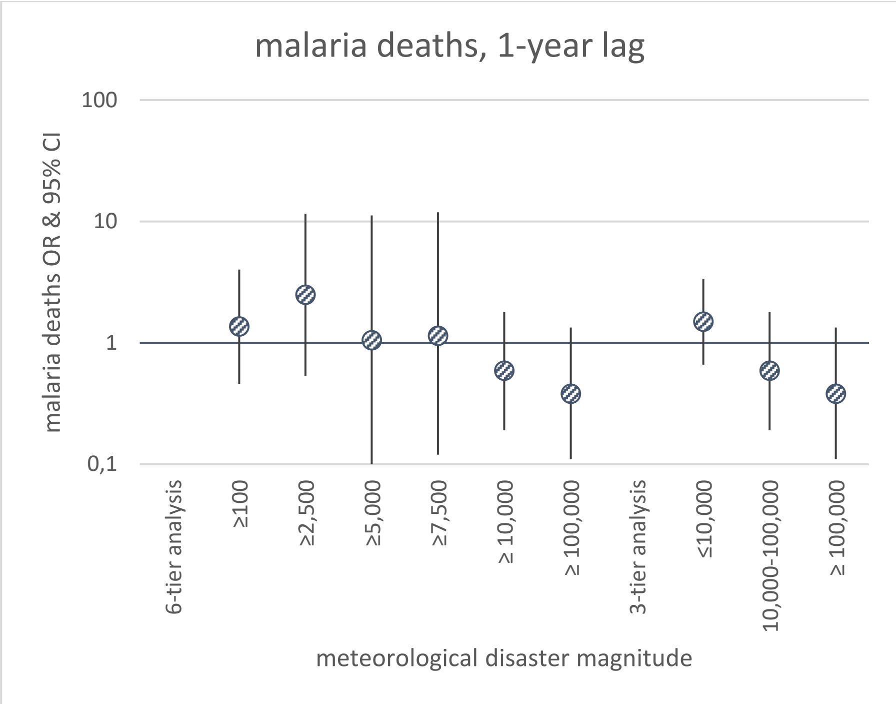


Figure 6.12: Graphic representation of odds and 95% CI of above global average malaria deaths for meteorological disasters at 1-year lag, between 2000 and 2013.

Hydrological disasters

For hydrological disasters affecting between 10,000 and 100,000 people, the association with malaria cases appears negative (Figure 6.13) – meaning after a year, the likelihood of recording above average malaria cases are in fact slightly lower than found for the acute disaster year (OR=0.47, 95%CI=0.23-0.98, *P*=0.04).

While malaria cases appear reduced 1 years after hydrological disasters, a highly significant increase in malaria deaths was found in Figure 6.14 at between 10,000 and 100,000 people affected (OR=2.43, 95%CI=1.32-4.49, *P*=0.004).

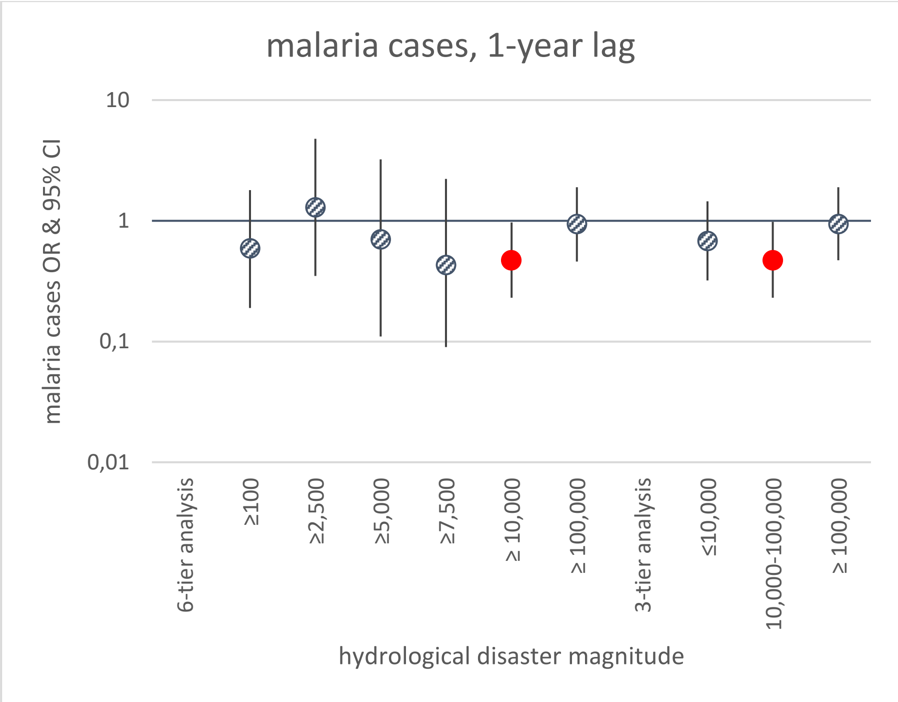


Figure 6.13: Graphic representation of odds and 95% CI of above global average malaria cases for hydrological disasters at 1-year lag, between 2000 and 2013.

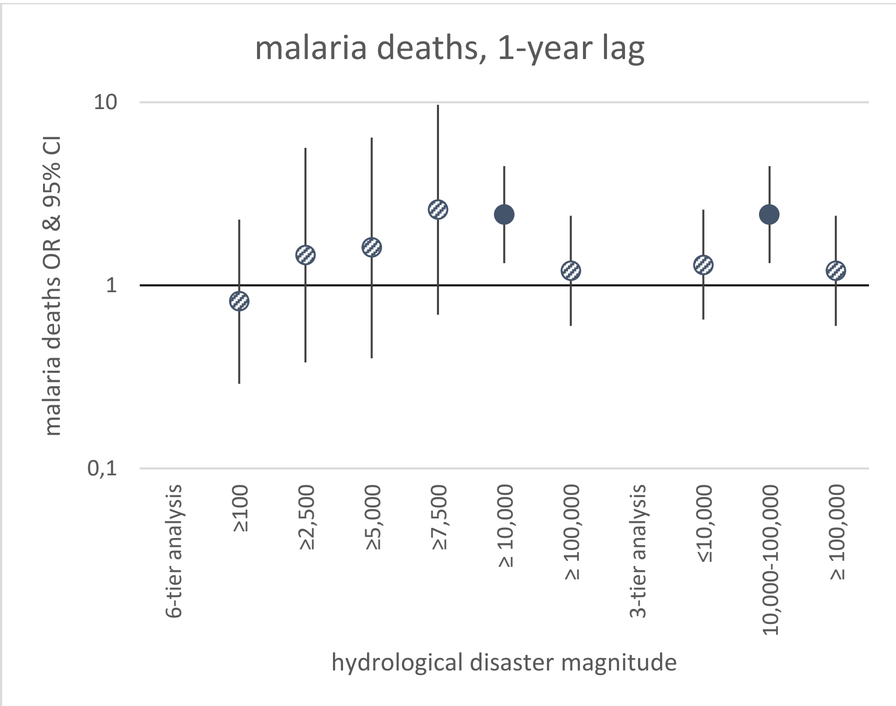


Figure 6.14: Graphic representation of odds and 95% CI of above global average malaria deaths for hydrological disasters at 1-year lag, between 2000 and 2013.

6.4. Discussion

6.4.1 Discussion of findings

Overall, very few statistically significant results could be found in the analysis presented in section 6.3, indicating a limited effect of natural disasters on malaria rates. This may speak in favour of well-established malaria prevention methods, a tool that is among the basic response efforts of NGOs in emergency situations. For hydrological disasters, an increase in malaria deaths was identified for between 2,500 and 4,999 population affected (OR=3.72, 95%CI= 1.15-12.01, P=0.03) and above 100,000 population affected (OR=2.01, 95%CI= 1.07-3.77, P=0.03). This finding is intuitive, as it would be expected that hydrological disasters have a stronger effect on malaria dynamics (Morgan et al., 2005). The increase in deaths may be explained by the post-disaster situation causing the disruptions of preventive anti-malarial supply. The improper use of malaria prevention measures such as bed nets and insecticide may breed resistance in both the vectors and the parasites, leading to complications with malaria treatment (Weinstein et al., 2010).

No effect was found for geophysical, meteorological, and climatological disasters. In the instance of climatological disasters, this might be due to a shortage of data – in the 485 country-years with above average malaria deaths, climatological disasters occurred in 68 country-years, compared to 279 country-years with hydrological disasters. For the other types of disasters, a lack of effect could be explained because neither are directly related to water, the main risk factor for increased malaria (Linscott, 2007; Morgan et al., 2005).

In the regional analysis, the only significant result was found in the African Region at ≥100,000 of the population affected (OR=2.40, 95%CI= 1.17-6.22; P=0.02). This can be explained by the fact that malaria is highly endemic in African countries, and a major issue even outside of disaster situations. The other significant result – in the European Region – is paired with a very wide confidence interval, suggesting low confidence in the finding. No other significant results were found. As noted by Briët and colleagues, collapsing disease surveillance systems are a problem in emergencies, and may lead to detection problems for malaria (Briët et al., 2005). Another possible explanation may be a bias in numbers. Much more data was available for the African Region than for the South-East Asia region, Europe region, Eastern Mediterranean region, and Western Pacific region – rendering analysis largely impossible for these regions and causing wide confidence intervals in cases where analysis was possible. The Africa region had data available for 616 country-years (Table 4.4), about twice as much data than what was available for the Americas region. The general imbalance in numbers may skew the results. Further investigations are necessary to consider the findings conclusive.

A significant negative association was found in the 1-year lag analysis for hydrological disaster. This is an interesting finding given the general conflicting opinions on the effect of flood disasters on malaria. One school of thought assumes flooding may initial wash away existing mosquito breeding grounds, leading to a decrease in malaria cases in the months immediately after the disaster (Floret et al., 2006). Such theories are supported by research findings in parts of Sri Lanka affected by the tsunami in 2005 (Briët et al., 2006; Briët et al., 2005). Another theory suggests floods lead to increased pools of standing water, offering more opportunity for mosquitos to breed, increasing malaria vectors. This is supported by a number of flood studies, most of them as well after the 2004 South-East Asia tsunami (Gunasekaran et al., 2005; Krishnamoorthy et al., 2005), but also after other flood events, such as severe flooding in Mozambique in 2000 (Morgan et al., 2005).

While there was no significant increase in malaria cases for hydrological disasters for the in-phase analysis, there was an increase in malaria deaths. This suggests that while malaria incidence did not increase, the ability to properly respond to incoming patients may have been hampered by the disaster. But the lower probability of above average malaria cases for the year after a disaster is interesting, as it is in line with the theory that temporary standing water – a risk factor for increased vector breeding (Watson & Gayer, 2007) – disappears over time and thus reduces vector breeding.

6.4.2 Natural disasters and the risk of malaria

An issue that was not investigated in this chapter, but may hold strong significance for future research of malaria after disasters, is the role of drug resistance. It has been argued that measures taken in the aftermath of disasters breeds more resistant vectors, which will eventually hinder efforts to reduce the disease burden (Weinstein et al., 2010). While most argue that malaria vector control efforts post-disaster are effective in keeping the new patients numbers low (Kumari et al., 2009), it would be a worthwhile project to investigate also the numbers of insecticide resistant vectors before, and after a disaster. Data for such an analysis is not readily available as of yet, and it would therefore be advised to conduct a detailed observation on resistance among mosquitos after a disaster, to be able to target malaria control in such a way that it will not only provide acute relief , but also support long term goals of malaria eradication.

6.5 Conclusion

This chapter sought to provide insight into the dynamic of malaria after natural disasters. Malaria is one of the most problematic diseases in countries where it is endemic, and poses a risk after natural disasters as well. In this chapter, malaria death was shown to be a major issue after hydrological disasters, and for both meteorological and hydrological disasters within a year after the disaster. This serves as an indication of malaria being dependent on seasonality and the availability of vector breeding grounds (Watson & Gayer, 2007; Baqir et al., 2012). Malaria – perhaps more so than with the other diseases in this research – is highly sensitive to changes in the physical environment. Furthermore, factors of drug resistance may provide a new insight, and require further study in the future.

Chapter 7 – Natural disasters and tuberculosis

Chapter Contents

7.1 Introduction

While there has been substantial research into the relationship between natural disasters and diseases such as malaria and cholera, scientific evidence for the relationship with most respiratory infections (including influenza, pneumonia, measles, and tuberculosis) remains limited. Of the four most concerning respiratory infections identified by the literature, tuberculosis (TB) has the least evidence for its role after natural disasters for a lack of published studies on the subject. Perhaps surprisingly, there even is anecdotal evidence suggesting that notified cases of tuberculosis may reduce in the aftermath of natural disasters (Myint et al., 2011). The present chapter aims to present empirical evidence of the role of TB in the aftermath of natural disaster.

Background on the choice of tuberculosis was given in Section 4.2. Tuberculosis is a bacterial disease of the lungs. Throughout history, it has been known as consumption, or 'the moths' for its presentation on X-ray imagery. A vaccine to protect against TB was first introduced in 1921 (Comstock, 1994) – the *Bacille Calmette-Guerin* (BCG) vaccine – and has been widely used in the period since World War II (Luca & Mihaescu, 2013). Active TB is treated by antibiotics. While cases were reduced after the introduction of the BCG vaccine, recent increases in drug resistant TB have caused an increase in infection, diminishing the likelihood of the planned elimination of TB (WHO, 2014b). Tuberculosis remains one of the most common infections in the world, with large numbers of cases being recorded in economically less developed countries (Figure 7.1).

Tuberculosis treatment requires a long term therapy with antimicrobial drugs. The Directly Observed Treatment Short course (DOTS) was defined by the World Health Organization in their Stop TB Strategy, and requires 6 months of supervised drug treatment (WHO, 2006). Due to the length of treatment, an interruption in the course can have severe consequences – from disease recurrence to the development of drug resistant bacteria strains that have, in recent years, increased the difficulty of TB eradication efforts (WHO, 2014b).

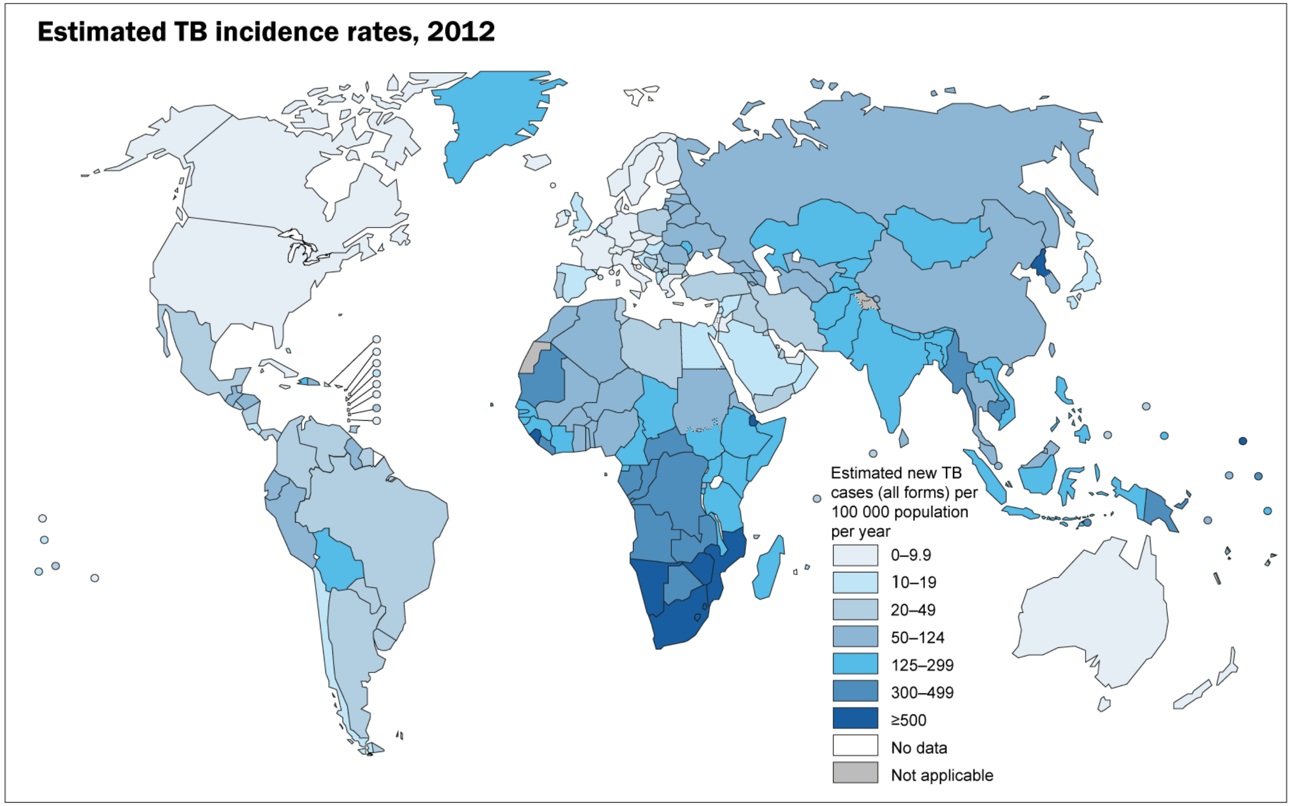


Figure 7.1: Global estimated TB incidence rates for 2012, as presented by WHO (http://gamapserver.who.int/mapLibrary/Files/Maps/Global_TBincidence_2012.png, 2013).

Previous research in the role of TB after natural disasters has looked at new infections with the disease (Myint et al., 2011), and as previously stated found no evidence to that effect. The present chapter will take a different approach. While data on new infections will be included as well, they will be contrasted with data on recurrences of TB – an approach that has been previously neglected. Recurring TB was considered more relevant in the context than new infections, as it serves as an indicator for treatment interruptions, and – by extension – disruptions in health infrastructure in the aftermath of natural disaster (Noji, 2005a).

7.2 Methodology

7.2.1 Tuberculosis data

Data on tuberculosis was gathered via the Global Health Observatory of WHO (WHO, 2016a). The first relevant data category was 'Total number of notified TB cases'. This summarised all notified cases, including new infections, relapse infections, and cases with unknown tuberculosis history. The second category was 'Relapse cases', which measured re-treatment after relapse (returned, previously treated TB infection). In the majority of countries, complete surveillance coverage of tuberculosis according to WHO standards was only available from 2001 onwards, specific surveillance of relapse within the WHO definition was available from 2007 onwards.

Over the 14 year period specified in Chapter 4 section 4.2, the Global Health Observatory included a recorded total of 64,635,491 cases of tuberculosis, and 1,707,096 relapses. Large regional differences in number of tuberculosis cases and relapse are summarised in table 7.1.

Table 7.1: Regional numbers of tuberculosis incident and relapse, over 14 year period.

	Tuberculosis incidence	Tuberculosis relapse
Global	64,635,491	1,707,096
Africa	14,933,760	332,417
Americas	2,580,213	60,796
South-East Asia	23,719,351	763,591
Europe	4,544,704	148,451
Eastern Mediterranean	3,946,834	65,604
Western Pacific	14,879,007	336,237

As described in Section 4.3.1, the data was dichotomised by determining above and below average cases and relapse. For that purpose, the national average of cases/relapse over the 14 year period studied *r* was calculated for each country *i*. The yearly reported numbers *t* were then compared to r_i. Where *t* exceeded r_i, the reported numbers were above the national average and thus coded as 1, whereas *t* lower than or equal to r_i were coded as 0. There were a total of 1,025 country years of above average tuberculosis cases, opposed to 1,691 below average. For relapse cases, 452 country years had above average numbers and 2,264 below average country years.

7.2.2 Data analysis

To determine the association between tuberculosis and natural disaster magnitude, a number of logistic regression analyses were performed for the different tiers of disaster magnitude described in detail in Section 4.3.2. The basic model of logistic regression was used in accordance with Equation 4.1 and Section 4.4.

The method was conducted for a number of analyses. Aside from a straightforward approach of associating global cases and relapses with disasters, this chapter investigated regional associations, as well as performing logistic regression with time-lagged data. In the latter case, natural disasters were associated with disease figures from one year in the future and two years in the future, to account for a time lag in disease data appearing in the surveillance system as well as time delays caused by incubation. Two years were selected especially with the relapse cases in mind, as a way to adjust for a potential delay caused by treatment interruption.

7.3 Results

This section presents the results of logistic regression analysis for tuberculosis cases and relapse, after natural disasters. Section 7.3.1 covers the basic summary, 7.3.2 the regional breakdown of results, and section 7.3.3 the lag analysis. Analyses were performed in accordance with Chapter 4 for the 6 tiers of magnitude and 3 tiers of magnitude, measuring the number of people affected by disasters in a year. The tables present odds ratios, 95% confidence interval, and *P* values, and the data is furthermore visualised in figures 7.2 through 7.15. The graphs are plotted on the logarithmic scale, with the x-axis showing the different tiers of disaster magnitude, and the y-axis showing the scale of odds ratios and confidence intervals. Circles represent odds ratios and whiskers the confidence interval. Solid fill signifies a statistical significance a P value= 0.05 or lower, patterned fill signifies insignificant results.

7.3.1 General results for tuberculosis cases and relapse

Table 7.2 displays the results of the logistic regression for total disasters – which includes all types of disasters – and tuberculosis cases as well as tuberculosis relapse. For relapse cases, significant associations were found for natural disasters affecting more than 10,000 people (OR: 1.06, CI: 1.19-3.55, *P*=0.01) and more than 100,000 people (OR: 2.03, CI: 1.20-3.43, *P*=0.01). The data on total tuberculosis cases revealed no significant associations, and the implications of that will be discussed in further detail in section 7.4 of this chapter.

Table 7.2: Odds ratio and confidence interval of average confirmed tuberculosis cases and relapse for disasters, between 2000 and 2013.

	Tuberculosis cases			Tuberculosis relapse		
Total affected	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	0.80	0.43-1.46	0.46	0.54	0.21-1.45	0.22
≥2,500	1.97	0.93-4.17	0.08	0.84	0.30-2.54	0.76
≥5,000	1.61	0.61-4.27	0.34	0.71	0.16-3.23	0.66
≥7,500	0.92	0.27-3.09	0.89	1.69	0.44-6.48	0.44
≥ 10,000	1.1	0.69-1.76	0.70	2.06	1.19-3.55	0.01
≥ 100,000	1.41	0.90-2.20	0.14	2.03	1.20-3.43	0.01
3-tier analysis						
≤10,000	1.15	0.74-1.78	0.54	0.76	0.40-1.44	0.39
10,000-100,000	1.09	0.68-1.75	0.71	2.05	1.19-3.53	0.01
≥ 100,000	1.39	0.90-2.18	0.15	2.01	1.19-3.40	0.01

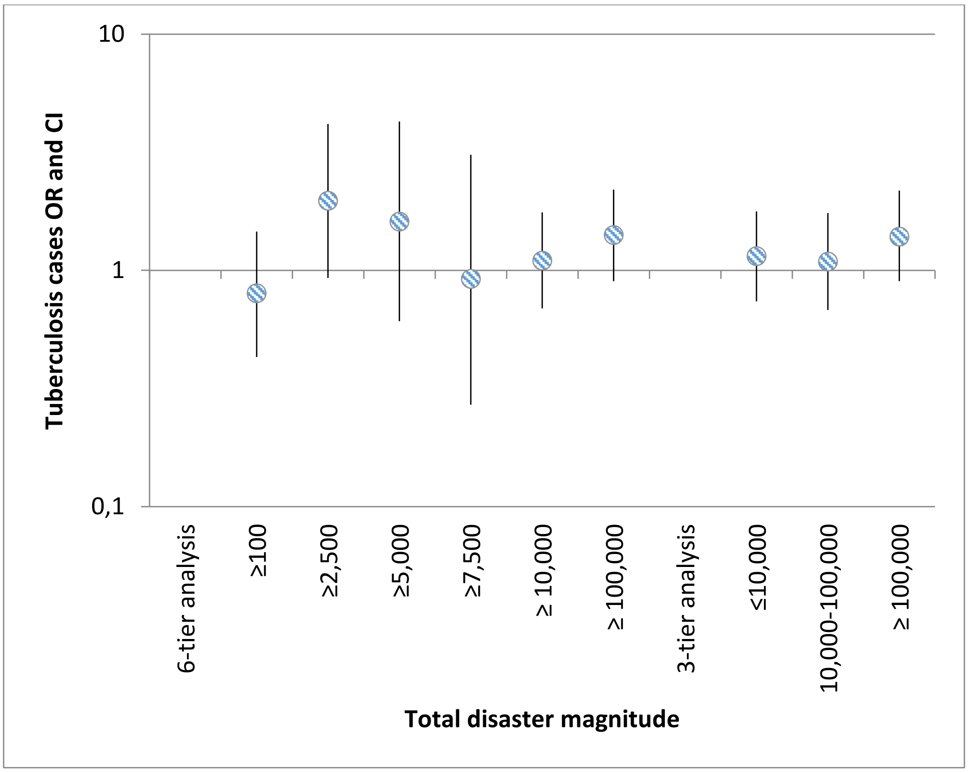


Figure 7.2a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases and total natural disasters, between 2000 and 2013.

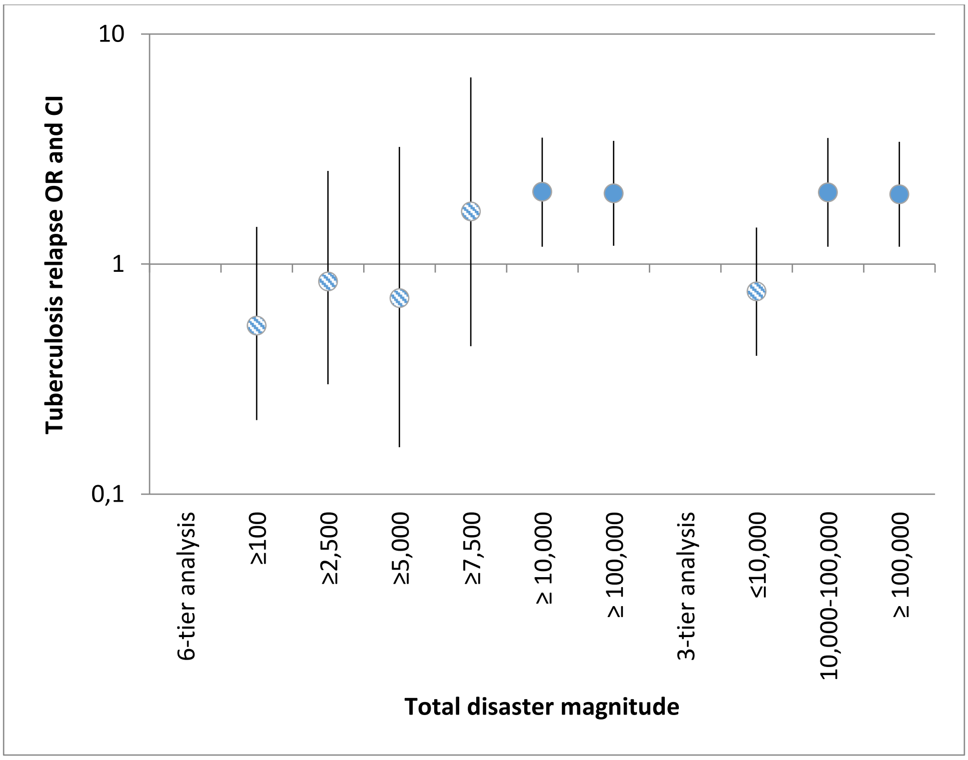


Figure 7.2b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse and total natural disasters, between 2000 and 2013.

Meteorological Disaster

When disaggregating by disaster type, significant results could be observed in meteorological disasters. As seen in table 7.3 and figures 7.4 and 7.5, at above 100,000 people affected, meteorological disasters show a significant and positive association with increased odds of above average number tuberculosis cases (OR=2.12; 95%CI= 1.04-4.27, *P*=0.04). For relapse cases, meteorological diseases affecting between 10,000 and 100,000 people mark a significant increase (OR=2.20; 95%CI=1.06-4.57, *P*=0.03). There are a few near significant odds for above average tuberculosis cases in disasters affecting above 10,000 people, and for relapse cases in small scale disasters affecting between 100 and 2,500 people.

Table 7.3: Odds ratio and confidence interval of average confirmed tuberculosis cases and relapse for meteorological disasters, between 2000 and 2013.

	Tuberculosis cases			**Tuberculosis relapse**		
Meteorological disaster affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	0.75	0.37-1.52	0.42	0.30	0.88-1.05	0.06
≥2,500	2.75	0.63-12.07	0.18	1.49	0.28-7.99	0.65
≥5,000	0.49	0.09-2.57	0.40	1.24	0.23-6.69	0.81
≥7,500	2.72	0.60-12.36	0.20	2.14	0.41-11.28	0.37
≥ 10,000	0.49	0.23-1.07	0.07	2.20	1.06-4.57	0.03
≥ 100,000	2.12	1.04-4.27	0.04	1.58	0.68-3.66	0.29
3-tier analysis						
≤10,000	1	0.57-1.74	0.99	0.67	0.31-1.46	0.32
10,000-100,000	0.49	0.23-1.06	0.07	2.18	1.05-4.53	0.04
≥ 100,000	2.09	1.03-4.23	0.04	1.56	0.67-3.60	0.30

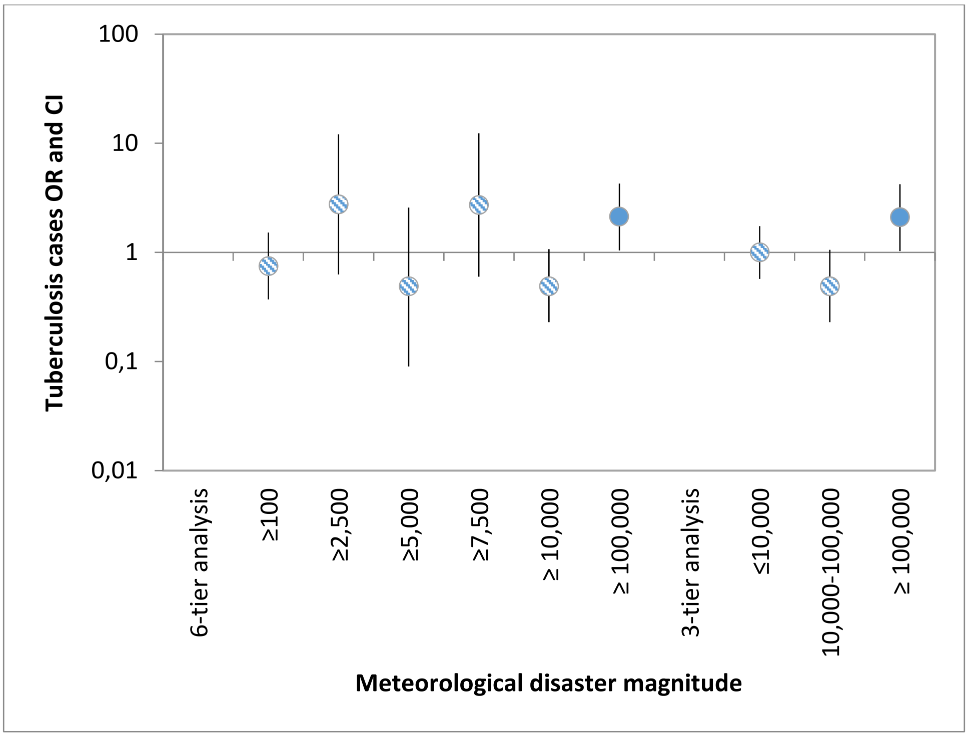


Figure 7.3a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases and meteorological disasters, between 2000 and 2013.

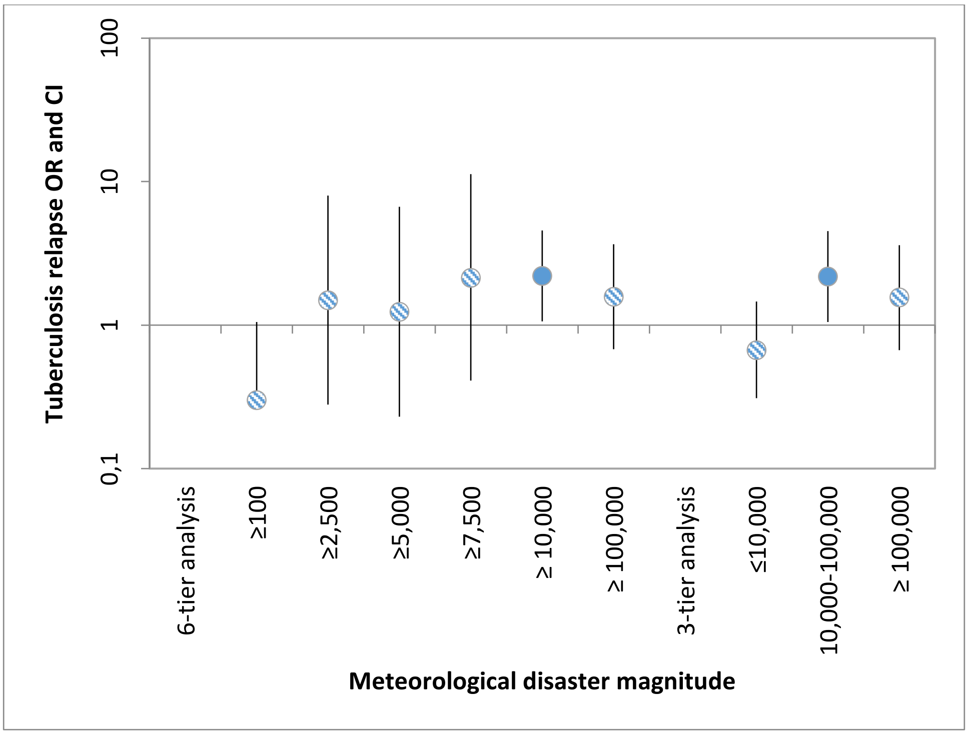


Figure 7.3b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse and meteorological disasters, between 2000 and 2013.

Hydrological disasters

For hydrological disasters, significantly positive odds ratios were found for between 10,000 and 99,999 (OR=1.84; 95%CI=1.05-3.23; *P*=0.03) and above 100,000 affected people (OR=1.93; 95%CI=1.06-3.53; *P*=0.03) when looking at tuberculosis relapse cases (Table 7.4). No significant results were found for overall tuberculosis cases.

Table 7.4: Odds ratio and confidence interval of average confirmed tuberculosis cases and relapse for hydrological disasters, between 2000 and 2013.

	Tuberculosis cases			**Tuberculosis relapse**		
Hydrological disaster affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	0.92	0.52-1.61	0.77	0.61	0.27-1.44	0.27
≥2,500	1.46	0.66-3.23	0.36	0.6	0.17-2.10	0.42
≥5,000	0.73	0.25-2.12	0.56	1.36	0.42-4.34	0.61
≥7,500	0.87	0.26-2.92	0.82	2.21	0.65-7.39	0.21
≥ 10,000	1.45	0.89-2.37	0.14	1.84	1.05-3.23	0.03
≥ 100,000	1.51	0.89-2.59	0.13	1.93	1.06-3.53	0.03
3-tier analysis						
≤10,000	0.99	0.64-1.52	0.94	0.86	0.48-1.53	0.60
10,000-100,000	1.46	0.89-2.38	0.13	1.83	1.04-3.20	0.04
≥ 100,000	1.52	0.89-2.60	0.13	1.92	1.05-3.50	0.03

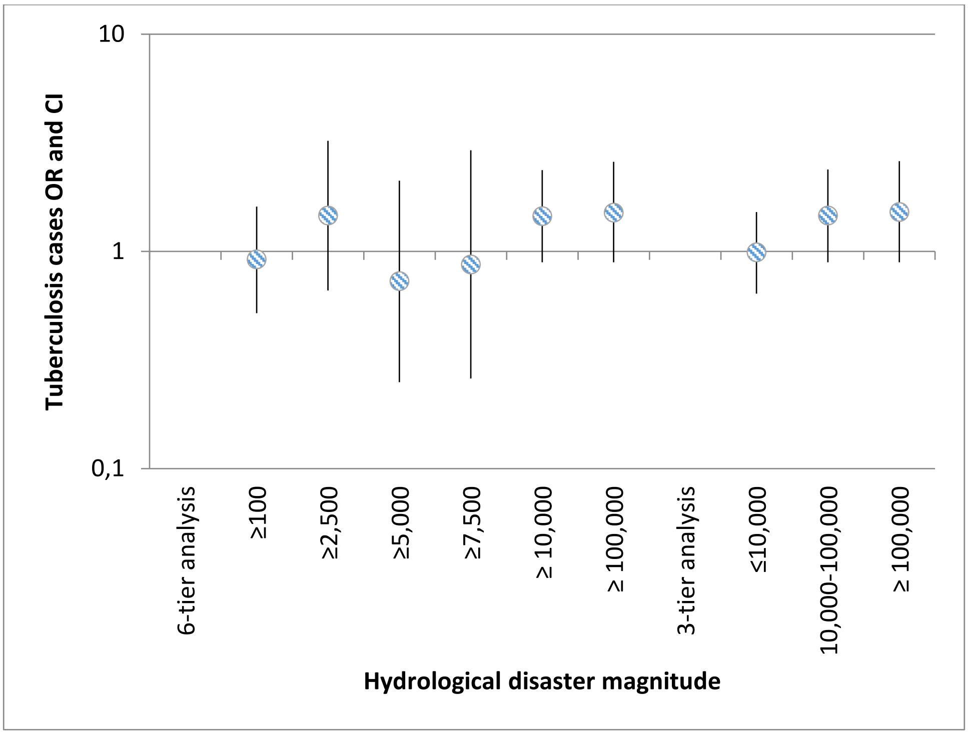


Figure 7.4a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases and hydrological disasters, between 2000 and 2013.

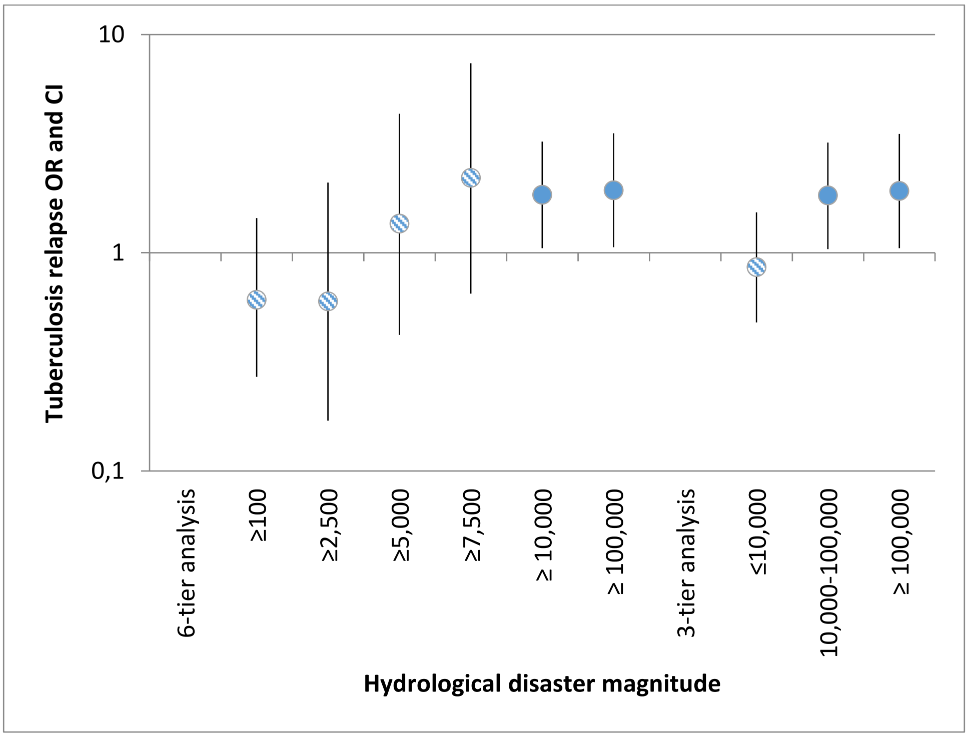


Figure 7.4b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse and hydrological disasters, between 2000 and 2013.

Other disasters

In the case of geophysical disasters, no significant results were found for either tuberculosis cases or relapse (Table 7.5). The closest to significant was for relapse cases in disasters affecting between 7,500 and 9,999 people (OR=8.73; 95% CI=0.76-100.85; *P*=0.08), all remaining results were clearly insignificant. Similar to geophysical disasters, no significant associations were found for climatological disasters (Table 7.6).

Table 7.5: Odds ratio and confidence interval of average confirmed tuberculosis cases and relapse for geophysical disasters, between 2000 and 2013.

	Tuberculosis cases			**Tuberculosis relapse**		
Geophysical disaster affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	0.65	0.22-1.88	0.43	1.25	0.39-3.95	0.71
≥2,500	1.64	0.43-6.26	0.47	0.69	0.09-5.64	0.73
≥5,000	0.53	0.06-4.92	0.58	/	/	/
≥7,500	4.06	0.35-47.06	0.26	8.73	0.76-100.85	0.08
≥ 10,000	0.98	0.35-2.79	0.96	1.38	0.41-4.62	0.61
≥ 100,000	0.53	0.16-1.72	0.29	0.54	0.12-2.51	0.43
3-tier analysis						
≤10,000	0.98	0.47-2.03	0.95	1.18	0.49-2.82	0.72
10,000-100,000	0.97	0.34-2.78	0.95	1.37	0.41-4.61	0.61
≥ 100,000	0.53	0.16-1.73	0.29	0.54	0.12-2.52	0.43

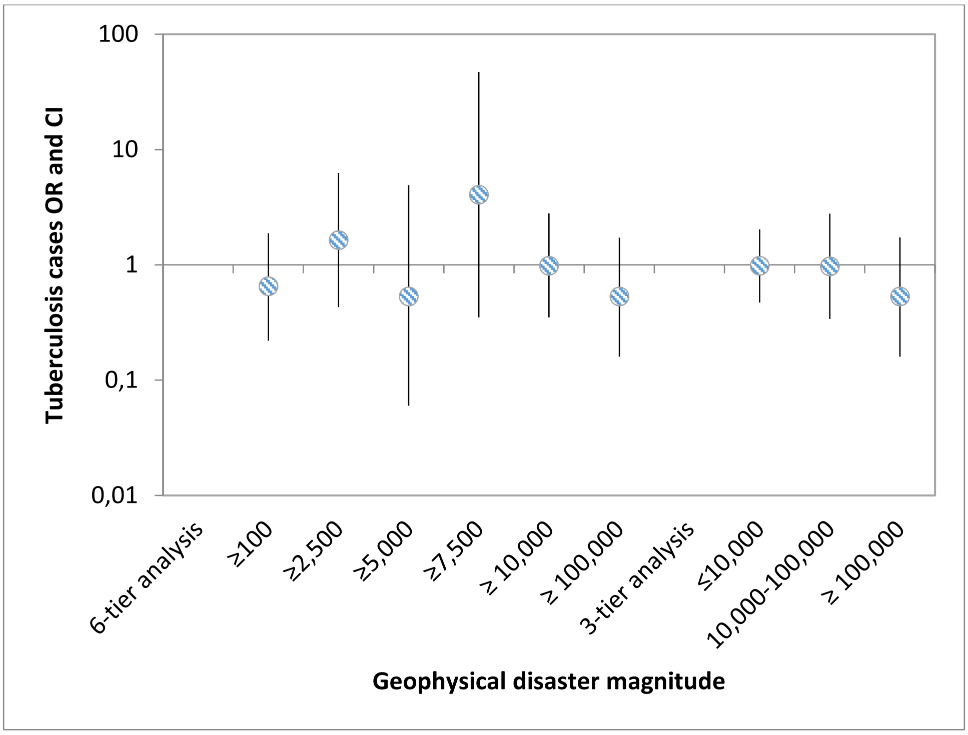


Figure 7.5a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases and geophysical disasters, between 2000 and 2013.

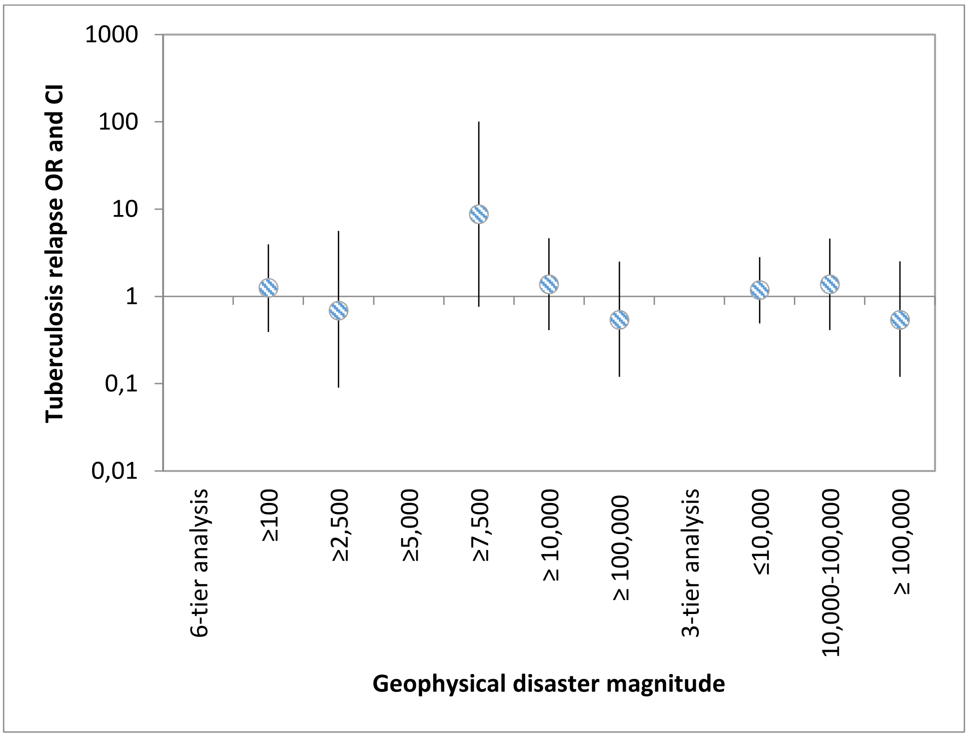


Figure 7.5b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse and geophysical disasters, between 2000 and 2013.

Table 7.6: Odds ratio and confidence interval of average confirmed tuberculosis cases and relapse for climatological disasters, between 2000 and 2013.

	Tuberculosis cases			Tuberculosis relapse		
Climatological disaster affected population	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	0.84	0.25-2.86	0.79	0.48	0.06-3.81	0.49
≥2,500	1.2	0.07-19.34	0.90	/	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	/	/	/	0.77	0.09-6.57	0.81
≥ 100,000	0.63	0.31-1.27	0.20	1.31	0.63-2.73	0.48
3-tier analysis						
≤10,000	0.73	0.25-2.14	0.57	1.20	0.33-4.34	0.78
10,000-100,000	/	/	/	0.77	0.09-6.58	0.81
≥ 100,000	0.62	0.31-1.27	0.20	1.31	0.63-2.74	0.47

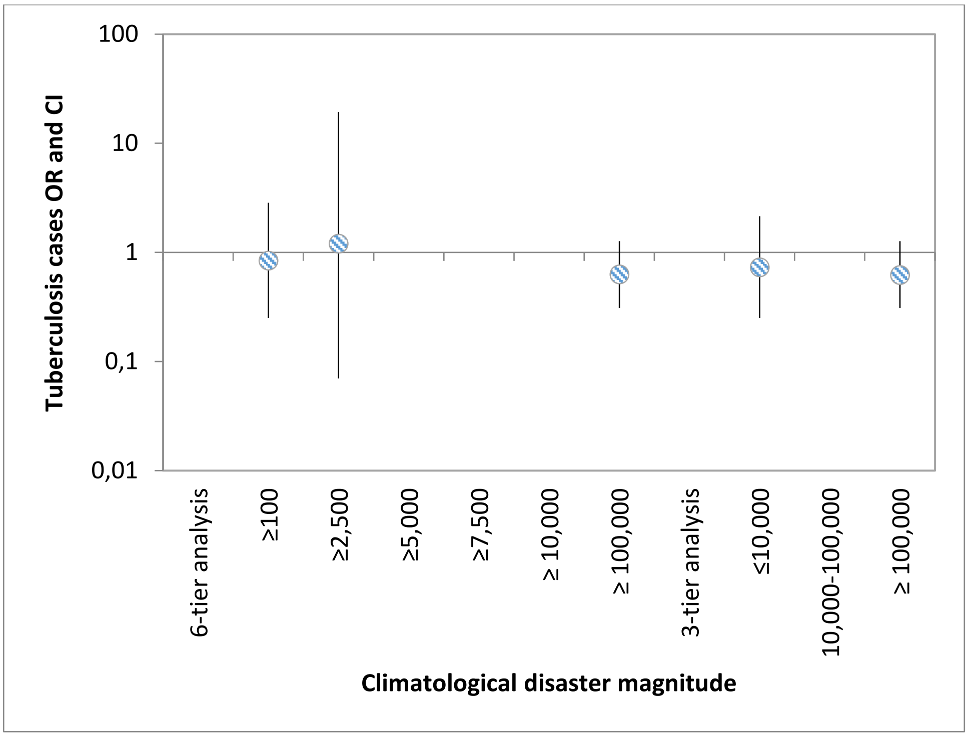


Figure 7.6a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases and climatological disasters, between 2000 and 2013.

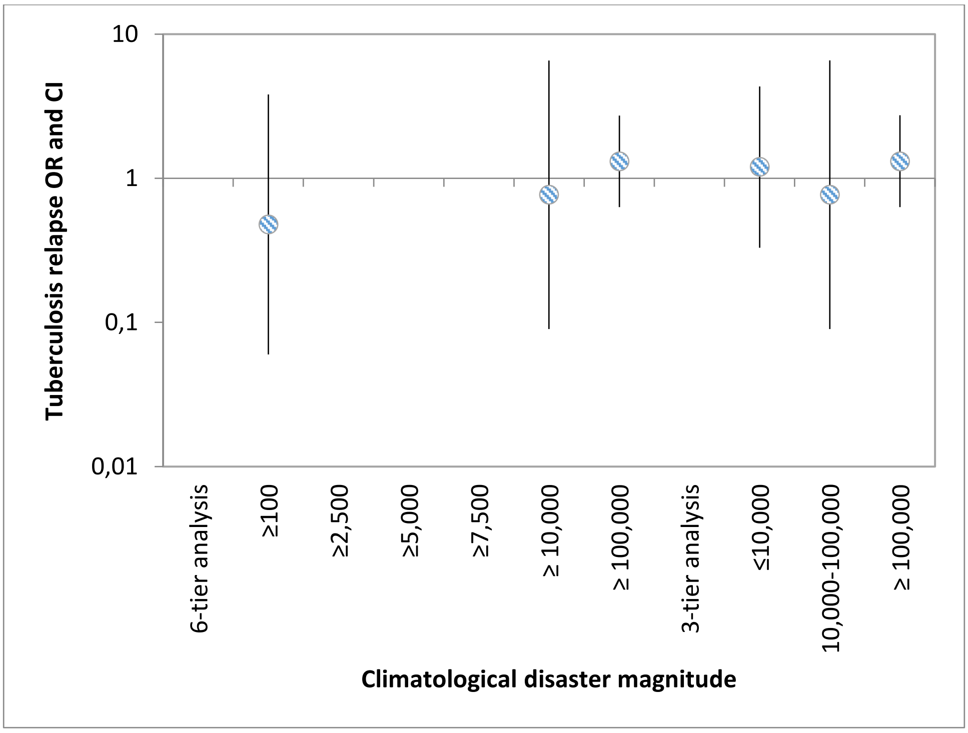


Figure 7.6b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse and climatological disasters, between 2000 and 2013.

7.3.2 Regional results for tuberculosis cases and relapse

The results of the regional binary logistic regression are presented in Figures 7.7 – 7.12. The data was split in six WHO regions in accordance with Figure 4.1. The results are visualised on a logarithmic scale, with odds ratios shown as circles and the confidence interval as the whiskers. Solid filled circles indicate statistically significant associations between above average tuberculosis cases or relapse and total natural disasters. For a complete, tabular overview of regional results and disaster types, consult appendix 9 total tuberculosis cases and 10 for tuberculosis relapse.

Significant increases in tuberculosis cases can be found for years with disasters affecting more than 100,000 people in the African Region (OR= 3.24; 95%CI= 1.34-7.84; *P*=0.01) in Figure 7.7a. For tuberculosis relapse no significant results were found (Figure 7.7b).

African Region

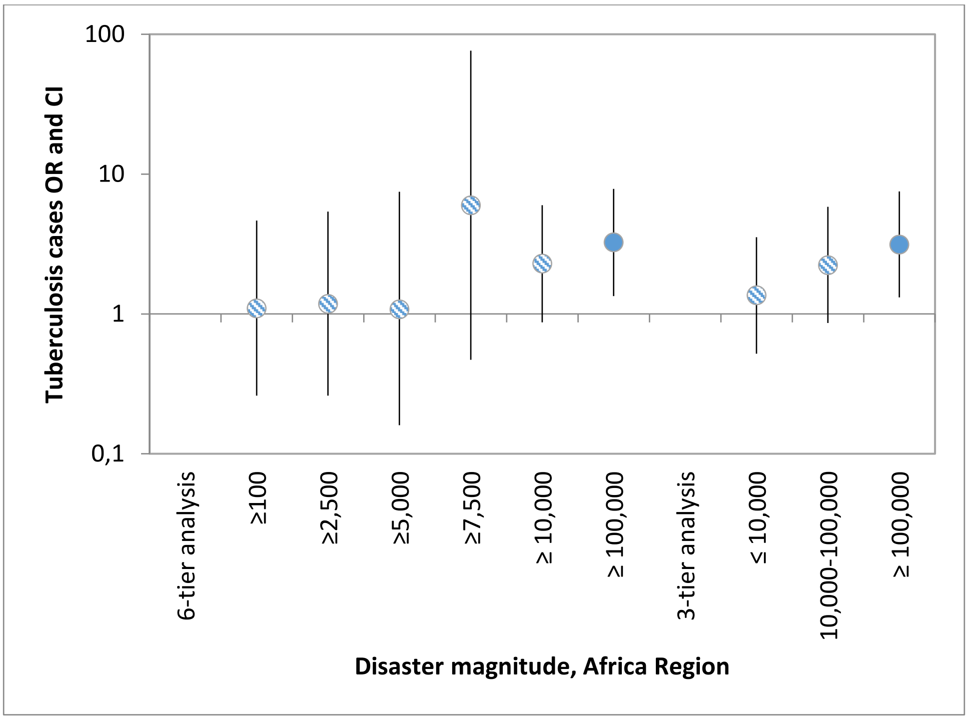


Figure 7.7a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases in the African Region, between 2000 and 2013.

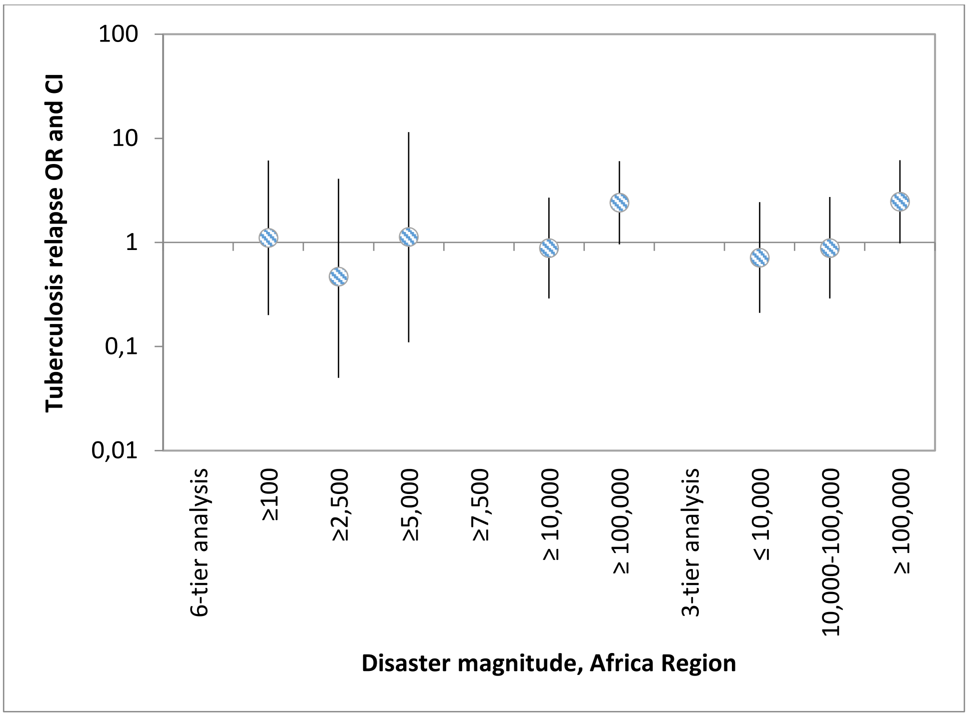


Figure 7.7b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse in the African Region, between 2000 and 2013.

American Region

In the American Region, significant increases in tuberculosis cases were identified in years with between 2,500 and 5,000 people affected by natural disasters (OR=12.48; 95%CI=1.17-132.89; *P*=0.04) in Figure 7.8a. No significant results were found for tuberculosis relapse (Figure 7.8b).

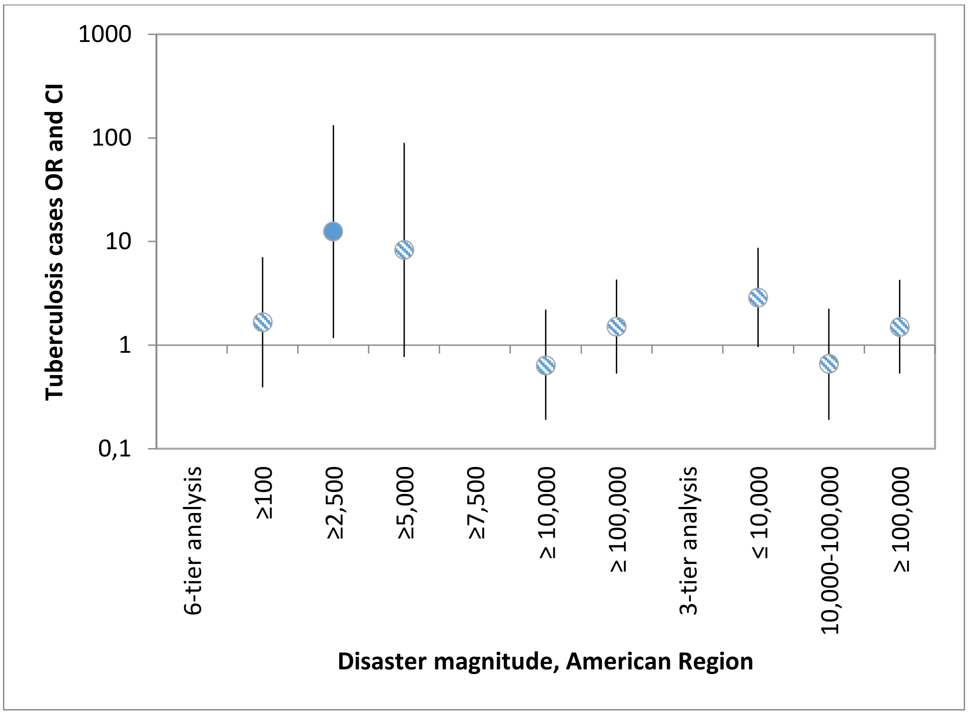


Figure 7.8a: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse in the American Region, between 2000 and 2013.

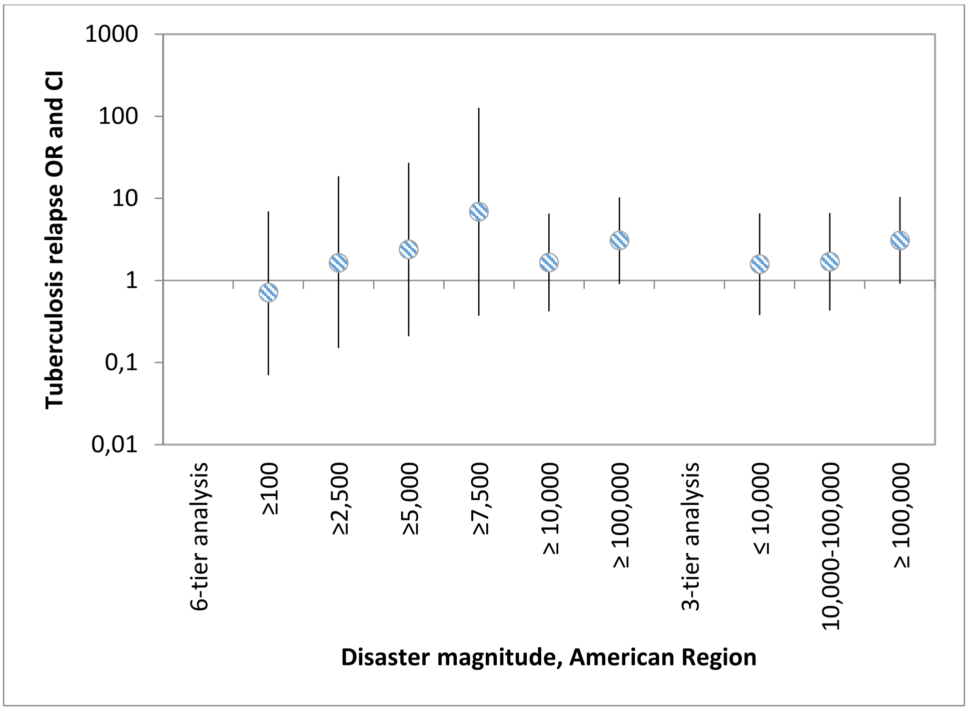


Figure 7.8b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse in the American Region, between 2000 and 2013.

European Region

Data for tuberculosis relapse in the European region was relatively limited. Still, positive significant results were found for years with natural disasters affecting between 10,000 and 100,000 people (OR=4.53; 95%CI=1.25-16.65; P=0.02) in Figure 7.9b for tuberculosis relapses. No significant results were found for overall cases (Figure 7.9a).

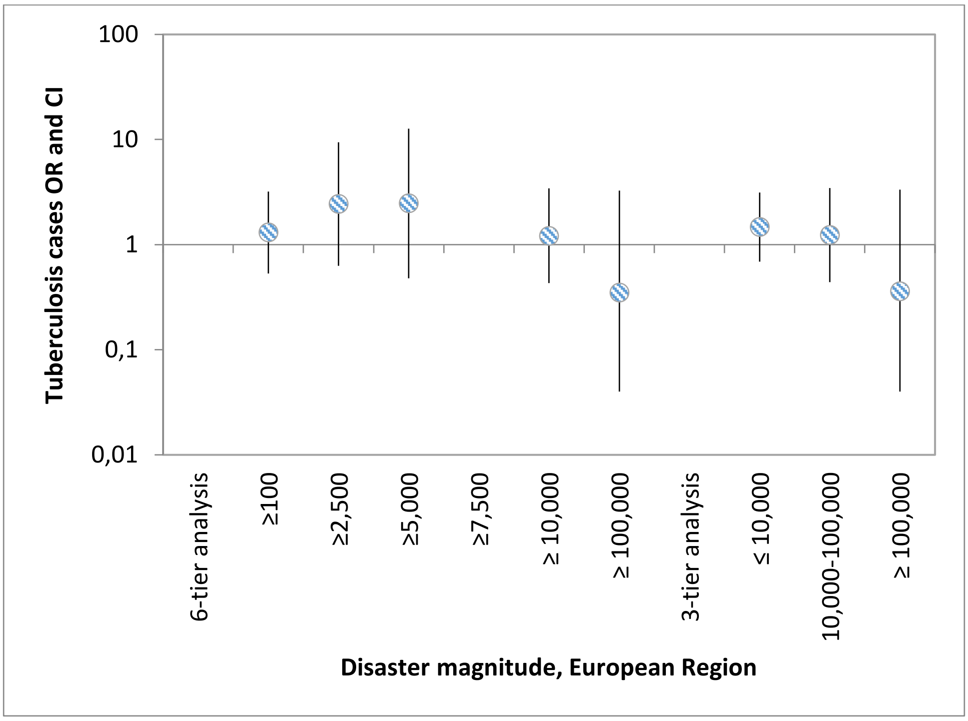


Figure 7.9a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases in the European Region, between 2000 and 2013.

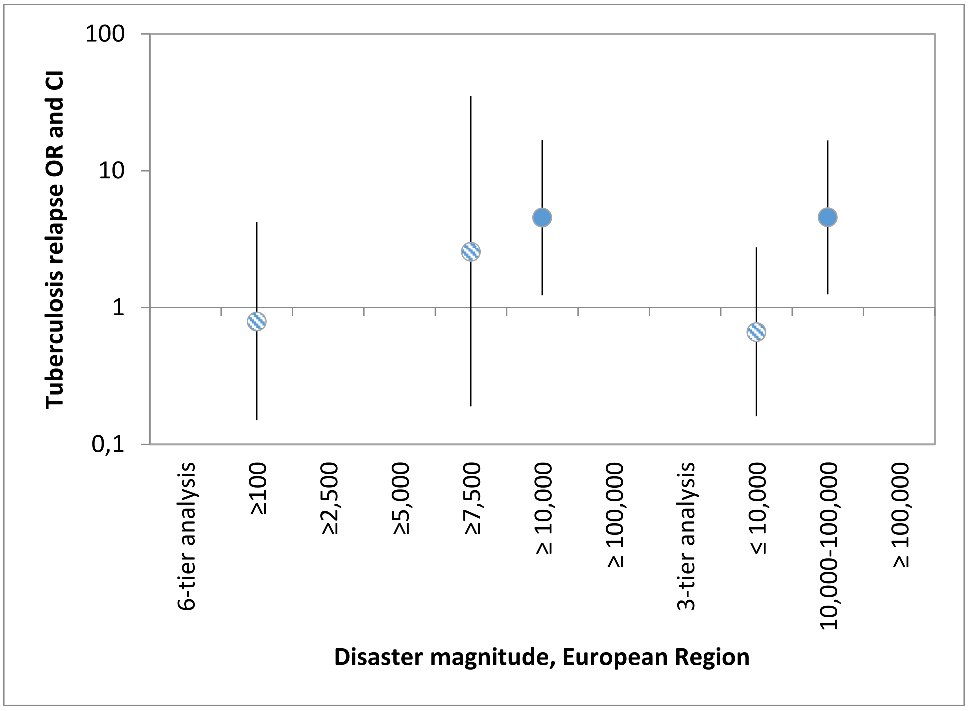


Figure 7.9b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse in the European Region, between 2000 and 2013.

Western Pacific

For tuberculosis relapses in the Western Pacific Region (Figure 7.10b), significant results were found for years with between 10,000 and 100,000 people affected by disasters (OR=7.85; 95%CI=1.33-46.48; *P*=0.02). There were no significant results for tuberculosis cases (Figure 7.10a).

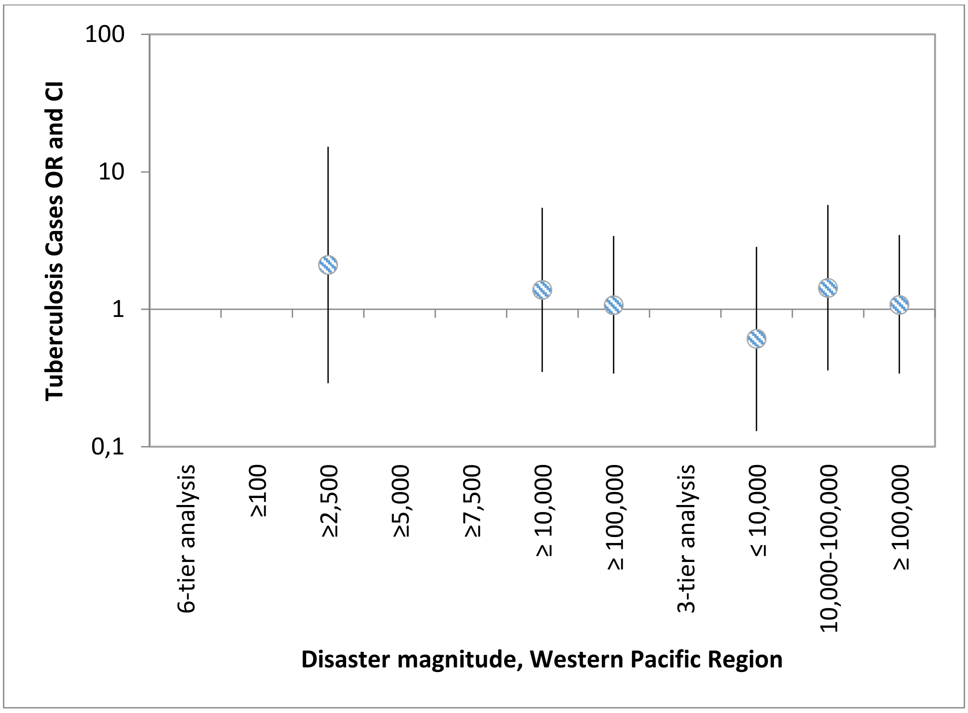


Figure 7.10a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases in the Western Pacific Region, between 2000 and 2013.

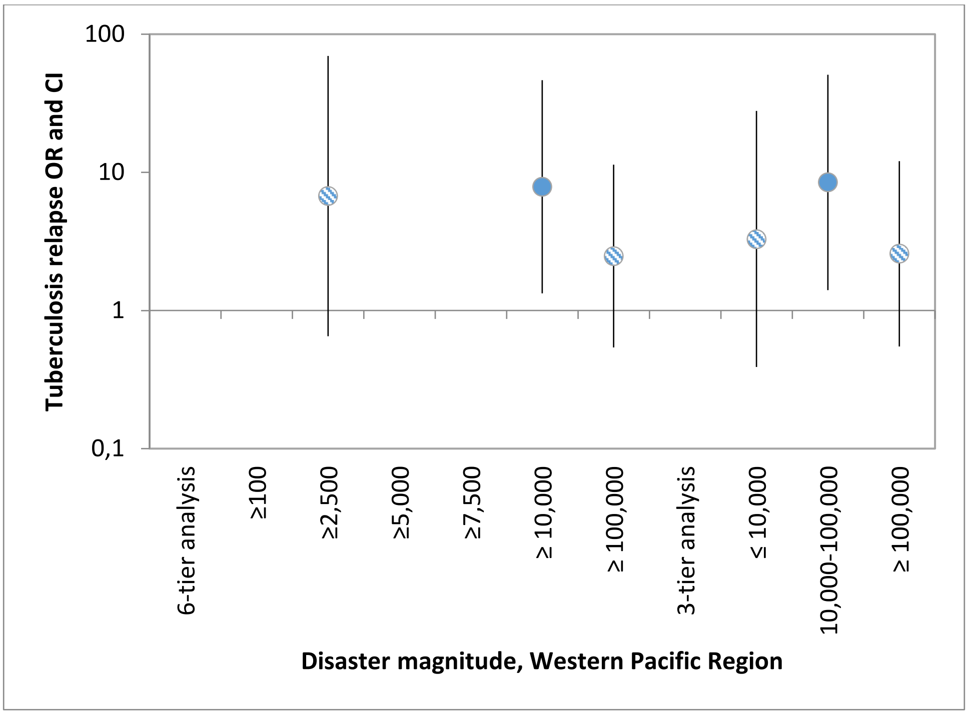


Figure 7.10b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse in the Western Pacific Region, between 2000 and 2013.

Other regions

While no significant results were found for the South-East Asian Region (Figure 7.11 a and b) and Eastern Mediterranean Region (Figure 7.12 a and b), the results are still presented in this section.

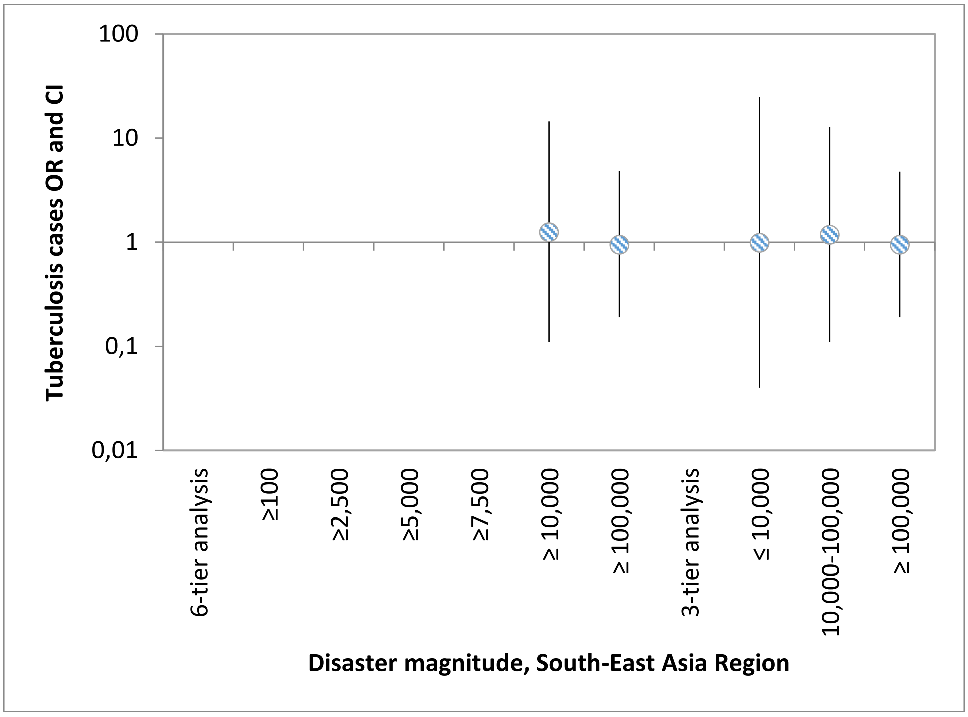


Figure 7.11a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases in the South-East Asian Region, between 2000 and 2013.

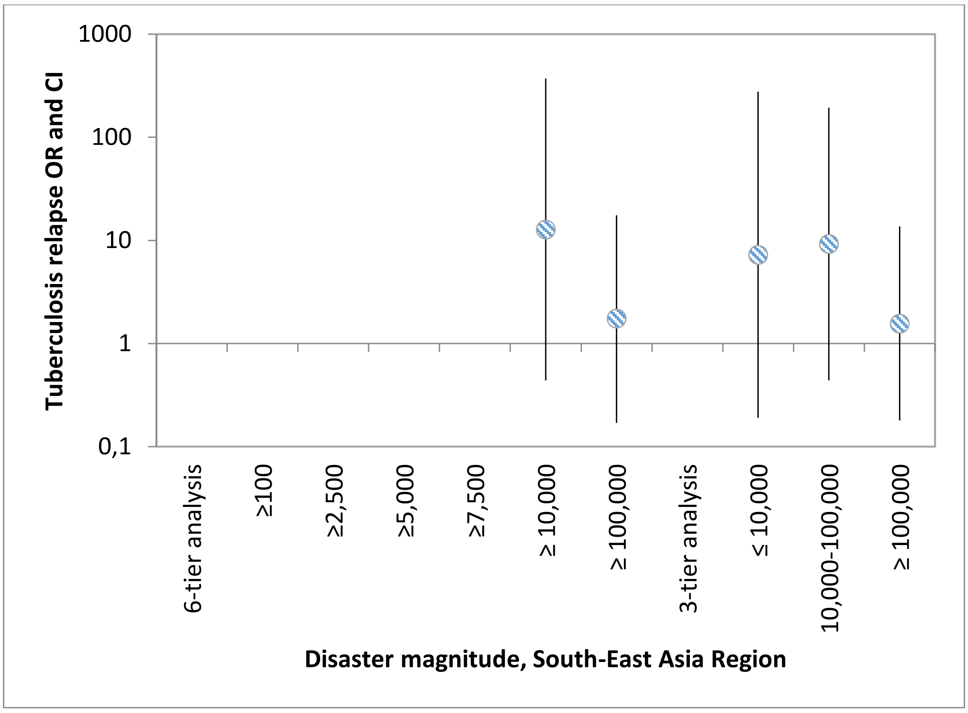


Figure 7.11b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse in the South-East Asian Region, between 2000 and 2013.

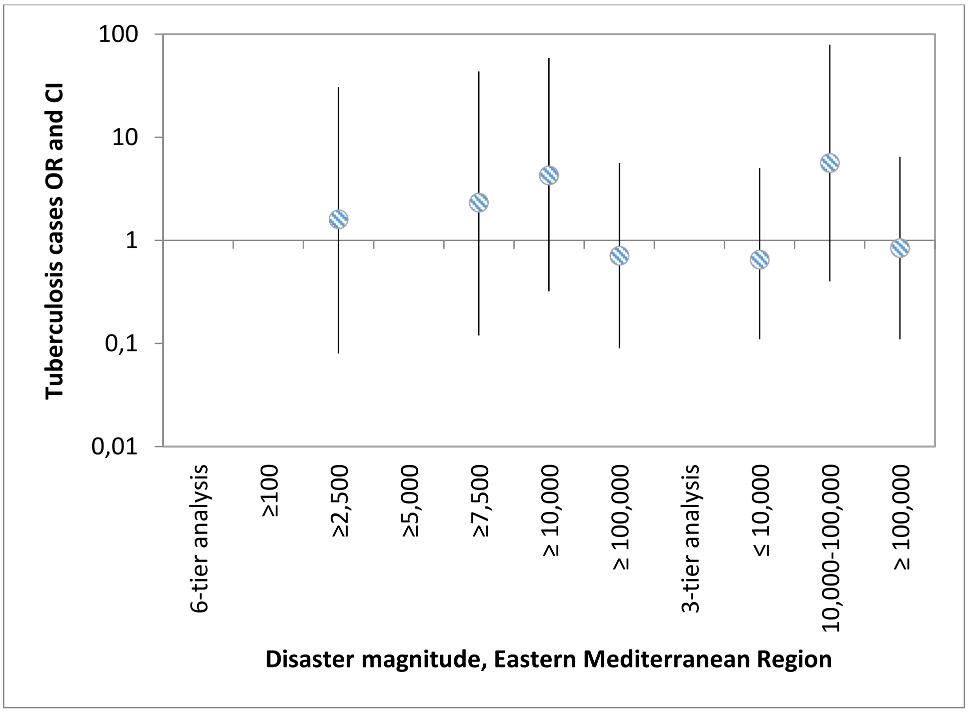


Figure 7.12a: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases in the Eastern Mediterranean Region, between 2000 and 2013.

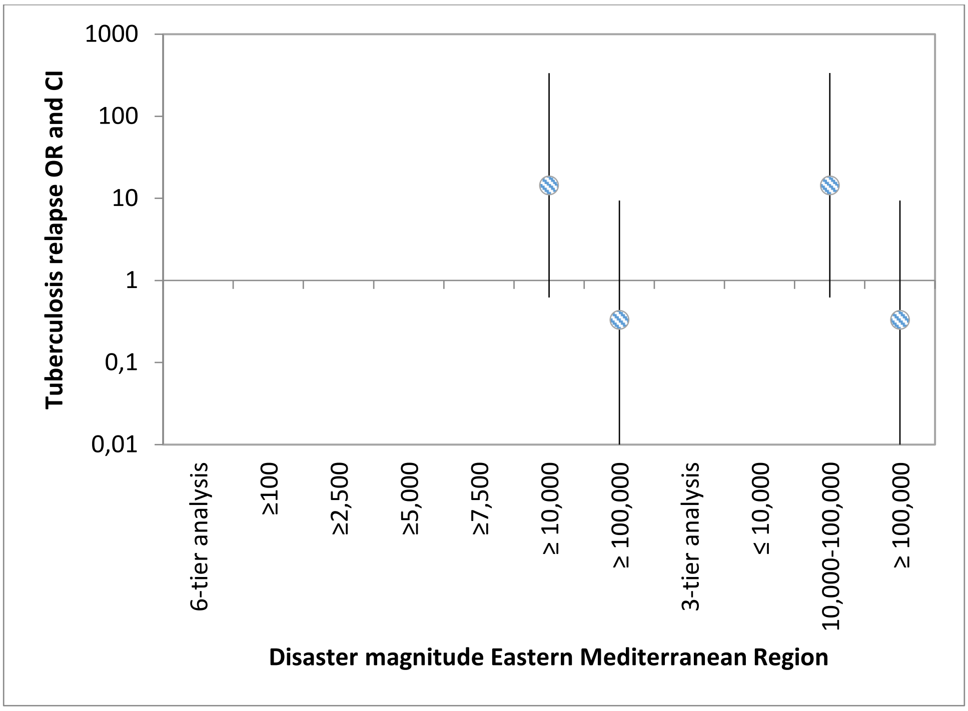


Figure 7.12b: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse in the Eastern Mediterranean Region, between 2000 and 2013.

7.3.3 1-year lag and 2-year lag analysis for tuberculosis cases and relapse

This section summarises results of the time lag analysis. Figures 7.13 presents the overview of total disasters, figures 7.14 and 7.15 show graphic representation of disaster types with significant results. The results are for both tuberculosis cases and relapses across the disaster types, and for a 1-year and 2-year lag. As with previous figures, these are plotted on a logarithmic scale, and represent odds ratios (circle) and confidence intervals (whiskers). Significant results are represented by a solid coloured circle. For the purposes of brevity, only analysis with significant results will be displayed in this section. The complete results of the lag analyses can be found in appendix 11 for tuberculosis cases and 12 for tuberculosis relapse.

Total disasters

A significant increase in average tuberculosis relapse cases was noted with a 1-year lag after natural disasters (Figure 7.13), at above 100,000 affected people (OR=2.16, 95%CI= 1.15-4.03, P= 0.02). For the magnitude tier between 5,000 and 7,499 people affected and the tier between 7,500 and 9,999 people affected, not enough data was available for analysis. After 2 years, there is an amelioration of the effect, with numbers returning to average.

No significant results were found for overall tuberculosis cases, as can be seen in appendix 11.

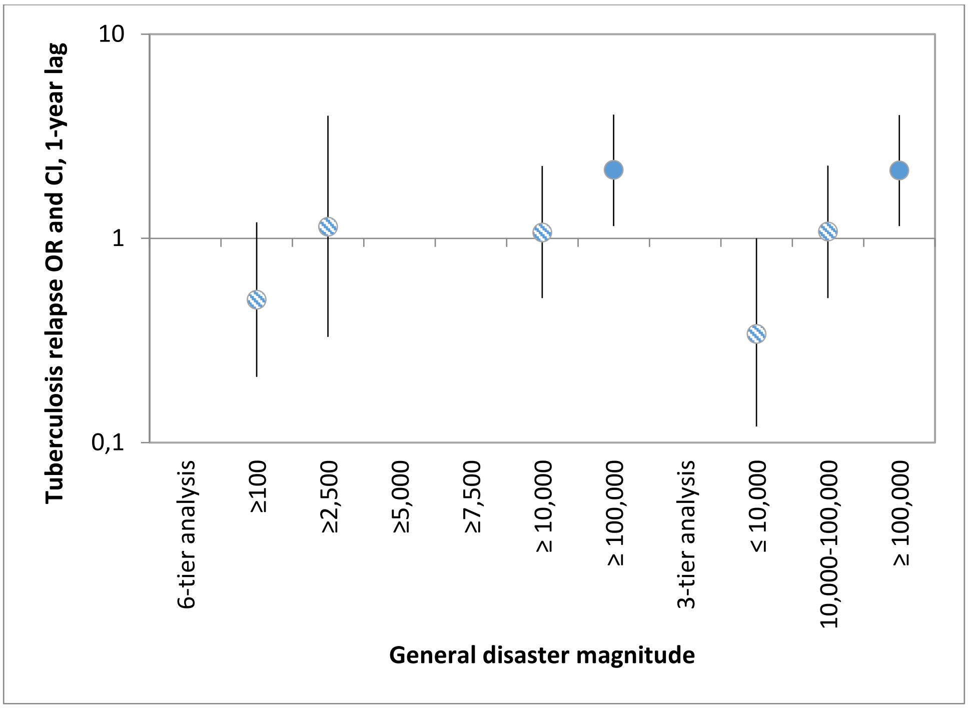


Figure 7.13: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse at 1-year lag for total disasters, between 2000 and 2013.

Hydrological disasters

For hydrological disasters, significant increases were found for tuberculosis relapse at 1-year lag (Figure 7.14). These were found for both 6-tier and 3-tier analysis, at above 100,000 population (OR: 3.14, 95%CI: 1.59-6.20, *P*= 0.001). As was the case for total disasters, there was an amelioration in the effect after a 2 year lag.

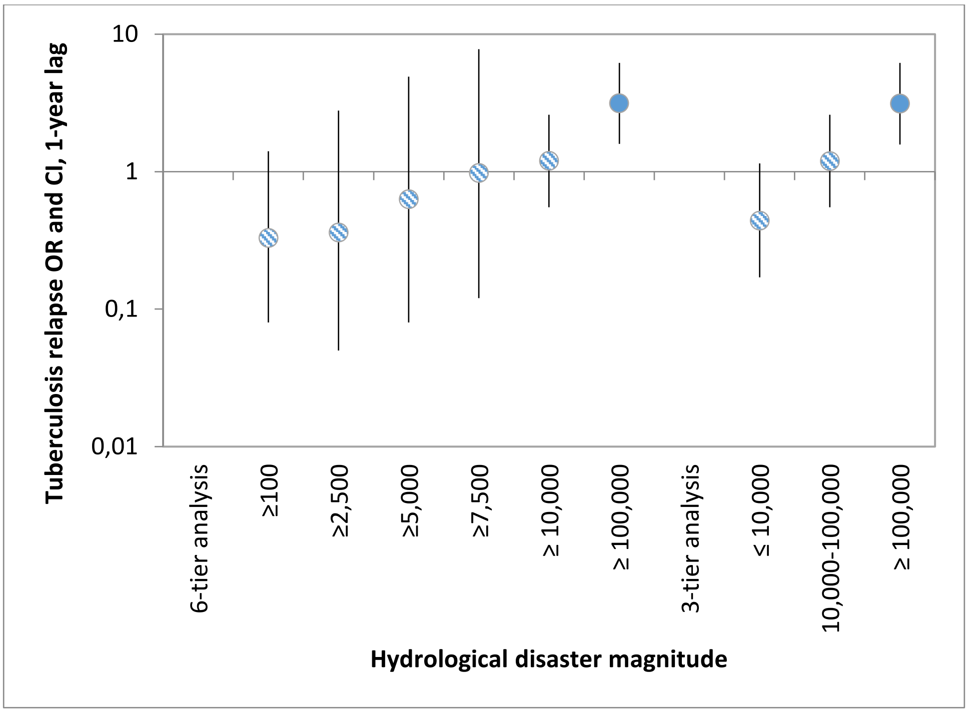


Figure 7.14: Graphic representation of odds ratios and confidence intervals for average tuberculosis relapse at 1-year lag for hydrological disasters, between 2000 and 2013.

Other disasters

For Meteorological disasters, a significant increase in odds was found for tuberculosis cases after 1 year (Figure 7.15) – the only significant result for overall tuberculosis cases – at above 100,000 population affected (OR: 2.42, 95%CI: 1.23-4.87, P:0.01). No significant results were found at 2-year lag.

For relapse cases, no results were found for meteorological disaster, either at 1 year or 2 year lag.

Furthermore, no significant results were found for any of the other disaster types.

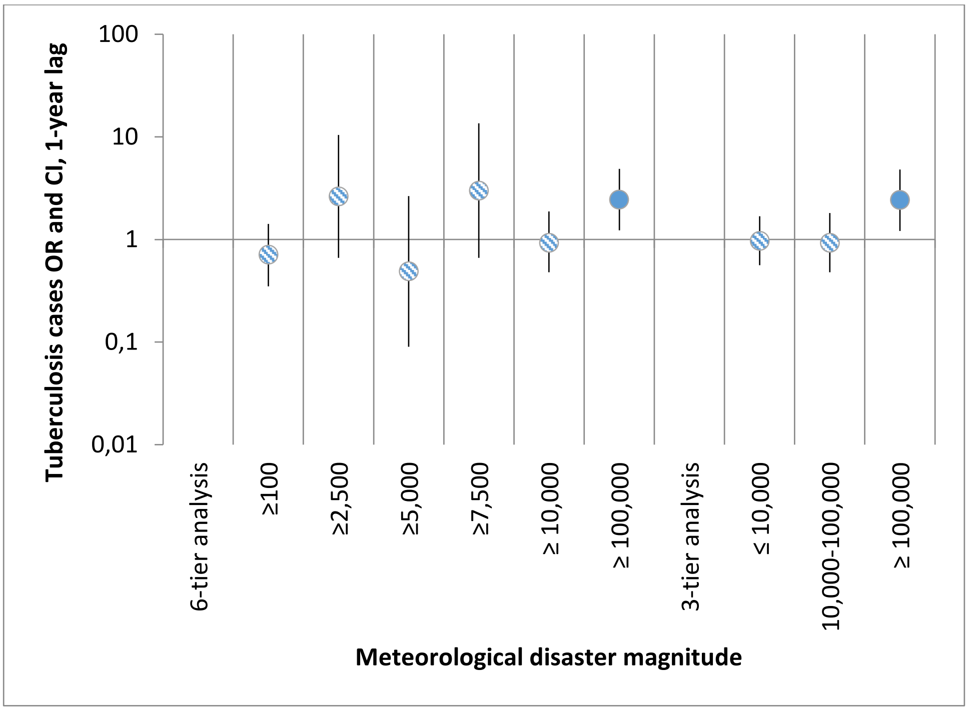


Figure 7.15: Graphic representation of odds ratios and confidence intervals for average tuberculosis cases at 1-year lag for meteorological disasters, between 2000 and 2013.

Meteorological disasters

For relapse cases at 1-year lag, there was a significant increase (OR: 2.36 CI: 1.09-5.14, *P*=0.03) at above 100,000 affected. A significant decrease (OR: 0.22 CI: 0.06-0.78, *P*=0.02) was found for small scale disasters affecting between 100 and 2,500 people.

Parts of the results presented in this section were previously presented at the 28th Annual Conference of the International Society of Environmental Epidemiology (ISEE), 2016 (Fairley, 2016a).

7.4 Discussion

7.4.1 Tuberculosis cases vs. tuberculosis relapse

As noted in Section 7.1, no significant relationship between tuberculosis and natural disasters has been identified in previous research. This respiratory infection is considered a minor concern during disaster situations (Heymann, 2015), and some studies even found tuberculosis numbers to reduce in the aftermath of disasters (Myint et al., 2011).

Investigating the results across disaster types and geographic regions, there are more significant results relating to tuberculosis relapse than there are to overall tuberculosis cases. When looking only at the classic 6-tier analysis, there are only four instances where average tuberculosis cases show significant increases in relation to natural disaster. These are for total disasters at between 2,500 and 5,000 affected people in the Americas Region (OR 12.48, 95%CI: 1.17-132.89, *P*=0.04), at above 100,000 affected people in the Africa Region (OR: 3.24, 95%CI: 1.34-7.84, *P*=0.01), and at over 100,000 affected people for meteorological disasters (OR: 2.12 95%CI: 1.04-4.27, *P*=0.04). The final significant result is for hydrological disasters affecting between 2,500 and 5,000 people in the European Region (OR: 5.65, 95%CI: 1.48-21.44, *P*=0.01) – this result is not visible in the result section, but can be found in the regional breakdown of disasters types in the appendix. In the first of these three results, the confidence interval is very wide (1.17-132.89), and the result needs to be interpreted with caution.

On the other hand, there are a total of twelve significant results for tuberculosis relapse. The results are across the categories, with the exception of geophysical disasters, suggesting a notably stronger association of relapse with disasters as opposed to tuberculosis cases. This may be an indication for a larger issue: tuberculosis relapse may occur when treatment is interrupted – an obvious problem given the lengthy treatment course of DOTS, leaving it vulnerable to interruption by various events. Access to treatment facilities is one of the major reasons for treatment interruption (Nour El-Din, Elhosseeny, & Mohsen, 2013). It is a logical conclusion that, in the event of a natural disaster, where disruption of health infrastructure has been shown to be a concern (Connolly et al., 2004), patient's access to treatment may be impaired for a prolonged period of time, if the transition from emergency relief to routine health care does not progress smoothly (Leaning & Guha-Sapir, 2013). It was thus theorised at the outset of this chapter that tuberculosis relapse may be a previously unnoticed consequence of natural disasters, and the findings of Section 7.3 are consistent with that hypothesis.

Of course, it may also be considered that in the aftermath of a natural disaster, the affected people may have more pressing concerns than going to receive tuberculosis treatment. As stated by Burkholder and Toole (1995), in the early stages after an emergency, people mostly try to escape physical and emotional trauma. While this specifically applies to complex emergencies, it has been shown that survivors of natural disasters also may suffer from depression, anxiety, and post-traumatic stress (Goldmann & Galea, 2014). Additionally, large disasters may cause severe destruction, leaving people in shelters for a period of time (Leaning & Guha-Sapir, 2013). All of this contributes to keeping people from seeking continued tuberculosis treatment – potentially leading to relapse of the disease.

7.4.2 Disaster types

If tuberculosis relapse is considered a proxy indicator for the collapse of health infrastructure – and potentially the inability for the affected community to re-establish a fully functional health infrastructure (Leaning & Guha-Sapir, 2013) – it follows that natural disasters causing greater levels of destruction should have a more significant impact on tuberculosis cases and relapse.

Although geophysical disasters – mainly earthquakes – could be arguably the most severe in terms of destruction, not a single significant result was found for them, neither for tuberculosis cases nor for relapse. No results were found for climatological disasters, although it becomes evident when looking back at Chapter 2 (section 2.4.5) that climatological disasters do not typically cause internal displacement, hence no collapse of health infrastructure occurred.

In contrast, meteorological disasters and hydrological disasters appeared to be related to more significant associations with tuberculosis, especially with relapse. Hydrological disasters such as tsunamis, and meteorological disasters such as storms, may go hand in hand with severe destruction. The discrepancy between these two types of disaster and geophysical disasters suggests that the way in which they affect infrastructure may have different effects on the levels of tuberculosis. This may be related to the fact that meteorological and hydrological disasters often are associated with water (i.e. storms and floods), and disasters where flooding occurs leads to internal displacement in temporary, overcrowded shelters – ideal conditions for the spread of pulmonary infections. Alternatively, it may relate to the location where these disasters are likely to strike geographically.

It was noticed that there were a few instances of significantly increased TB cases and relapses for disasters affecting relatively few people (Figure 7.8a for TB cases in the WHO of the Americas, figure 7.16 for TB relapse after 1 year for geophysical disasters). Why these, by comparison, years of small scale disasters expressed relatively high average number of TB cases and relapse remains unclear with the data available in this chapter, but may be a subject for further research.

7.4.3 Geographical differences

In the regional comparison, there were relatively few findings for overall TB cases across regions. High-magnitude disasters (affecting over 100,000 people in a year) have been shown to trigger significant increases in TB cases (OR=3.13; 95%CI=1.31-7.84; *P*=0.01) in the African Region. Disasters affecting relatively small numbers of the population affect the numbers of TB in the Americas (total disasters affecting between 2,500 and 4,999 people, OR=12.48; 95%CI=1.17-132.89); *P*=0.04) and in Europe (hydrological disasters affecting between 2,500 and 4,999 people, OR=5.64; 95%CI=1.48-21.44; *P*=0.01).

For relapse cases, by contrast, a number of significant results were found across regions. In the European Region at above 100,000 people affected (OR=4.56; 95%CI=1.25-1665; *P*=0.02) as well as the Western Pacific Region at between 10,000 and 99,999 people affected (OR=8.45; 95%CI=1.40-50.91; *P*=0.02), general high impact disasters lead to increased risk of tuberculosis relapse. In the African Region, high impact meteorological disasters (OR=17.33; 95%CI=1.27-191.62; *P*=0.02) and hydrological disasters (OR=2.90; 95%CI=1.04-8.07; *P*=0.04) were shown to have significantly affected the numbers of TB relapse. Hydrological disasters affecting up to 100,000 people were also shown to increase TB relapse risk significantly in the Region of the Americas (OR=3.98; 95%CI=1.16-13.62; *P*=0.03). Additionally, there was a significant change in TB relapse risk for climatological disasters in the Americas Region at above 100,000 people affected (OR=4.54; 95%CI=0.10-20.77; *P*=0.05).

The regional differences presented above suggest a higher vulnerability in the African region to TB relapse after hydrological and meteorological disasters, which may inform the result of meteorological disasters having an overall higher risk of increased TB (both for cases and relapse). A higher vulnerability to meteorological disasters than to geophysical disasters in the investigated regions with a significant increase in TB risk could explain this. The present data however does not serve to provide a reason as to why these regions are more vulnerable to one type of disease and not the other. As was suggested in section 7.4.2 above, the types of disaster may have different effects on the health infrastructure required to control tuberculosis spread and treatment. A possible explanation when looking at the affected regions may be that after natural disasters, other diseases such as malaria and cholera (both especially problematic after disasters involving flooding) take acute priority after disasters, allowing TB to go undetected until the later stages of disaster management.

7.4.4 Lag-analysis

A 1-year and 2-year lag analysis was chosen in order to estimate the effect of time on tuberculosis, as the disease has a relatively long incubation period and may appear in surveillance data with considerable delay (Vynnycky & Fine, 2000). It has been recorded in previous research that tuberculosis cases decrease after natural disasters (Myint et al., 2011). This may be due to successful tuberculosis control measures being in place before the disasters, but it may also be due to case detection being hindered in the post-disaster phase, causing cases to go undetected. This observation is not supported by the present analysis, as for those few instances where significant results were found, they all suggested a positive association. At 1-year lag, there was an increase for meteorological disasters at the above 100,000 magnitude tier – the same as the in-phase analysis. This suggests the effect persists into the following year, before returning to average numbers in the 2nd year after the disaster. This was the only significant result found for tuberculosis cases, which is in line with assumptions that disasters have no effect on tuberculosis. The reason meteorological disasters may be the only cause of such an effect may be that these disasters more commonly lead to internal displacement. Shelter conditions (especially overcrowding) are a risk factor for transmission of respiratory infections (Bellos et al., 2010; Wisner & Adams, 2002). To be certain of what caused the increase in TB cases in meteorological disasters, further research is necessary.

Interestingly, a number of significant results were found in the 1-year lag analysis for tuberculosis relapse. This makes sense, as the recurrence would occur some time after the disrupted treatment. At 1 year lag, there was an increase in tuberculosis relapse at the above 100,000 magnitude tier for general disasters (OR: 2.16; 95% CI: 1.15-4.03; *P*=0.02), and a similar effect was found for this highest magnitude tier for hydrological disasters (OR: 3.14; 95% CI: 1.59-6.20; *P*=0.001). Both of these are in line with the findings of the in-phase analysis, and both have returned to average levels by the 2nd year after the disaster. There is one more significant result in the 3-tier analysis, at the magnitude tier of below 10,000 people affected (OR: 0.34; 85% CI: 0.12-1.00); *P*=0.05). The result is only narrowly significant, and the odds ratio suggests that after lower magnitude disasters, there is a probability of lower than average tuberculosis relapse. This result, compared to the remaining findings of this Chapter, appears counter-intuitive. It may be a reflection of inconsistent reporting in the aftermath of disasters, or it may be an outlier. Either way, the results warrant that further attention is paid to tuberculosis relapse in the context of natural disasters, a field that has been largely neglected in previous research.

7.4.5 Future research implications

The results reported in this chapter highlight the potentially meaningful impact of TB relapse in the aftermath of disasters. Evidence of the relapse of TB after disasters has not been reported in existing literature thus far, indicating a lack of research coverage in that area. In recent years, especially with the refugee crisis, the resurgence of Tuberculosis has posed significant threats to human health and has given rise to concern among health professionals, prompting large numbers of studies into the occurrence of drug-resistant TB (Cousins, 2014; WHO, 2014). The implications of TB relapse on the latter is known, but thus far no evidence has been shown to indicate natural disasters as a potential risk factor for TB relapse. This is a research gap that needs to be further explored, as it may provide new – or changed – priorities in post-disaster management.

7.5 Conclusion

In conclusion, tuberculosis has been a neglected disease when it comes to assessing the risk of infectious disease after disaster. Research into the subject is limited, and guidelines generally do not prioritise tuberculosis in the post-disaster phases. It may have no implications in the acute disaster phase, but that may be exactly the reason why there is an increase in recurrence after disasters. By not including tuberculosis as a priority for disaster response, ongoing treatment may be more likely to be interrupted in the aftermath of a disaster. Health care professionals focus on the priorities set out for them as guidelines, and the patients themselves have vastly different concerns when faced with cleaning up after a natural disaster (Noji, 2005a; Leaning & Guha-Sapir, 2013). Regular administration of tuberculosis medication may move to the background of people's mind, or access to the necessary treatment may be disrupted. This exacerbates the risk of treatment failure, of recurring TB, and by extension the risk of drug resistance in tuberculosis bacteria.

This Chapter has shown that there is an increase in tuberculosis relapse after natural disasters, compared to a much smaller effect of disasters on overall tuberculosis cases. Further research should be encouraged, and a potential re-evaluation of tuberculosis guidelines for natural disasters may be necessary.

Chapter 8: Co-infection with HIV and Tuberculosis after Natural Disasters

Chapter Contents

8.1 Background

The human immunodeficiency virus (HIV), the aetiological agent of the Acquired Immuno-deficiency Syndrome (AIDS), was first isolated in 1983. To this day, the disease remains a rampant threat in developing countries, with HIV control efforts encountering harmful misconceptions and lack of education on sexual health and safety that have hindered efforts to bring the transmission of HIV under control (Kallings, 2008). By 2016, an estimated 36.7 million people were living with HIV/AIDS (UNAIDS, 2016). The virus is most commonly transmitted via sexual intercourse (despite the initial stigma of homosexual intercourse being the main route of transmission, unprotected heterosexual intercourse is just as likely to transmit HIV as any other form of unprotected intercourse), from mother to child, or by contaminated drug injecting paraphernalia (e.g. syringes and needles) (Heymann, 2015). While available data indicates that Africa is the continent most severely affected by HIV, accounting for over one million deaths due to AIDS in 2016 (UNAIDS, 2016), HIV/AIDS remains a priority across the globe, with high prevalence in the population across regions (Figure 8.1).

The spread of HIV/AIDS has been shown to be affected by complex, humanitarian disasters that force populations into long-term displacement (Connolly et al., 2004). This is attributable to unsafe blood transfusions, lack of available protection from sexually transmitted infections (STIs), lack of available treatment in emergency facilities and an increase in unsafe sexual behaviour. It has been previously acknowledged that the direct effect of natural disasters on people living with HIV is near impossible to measure, and there has been no conclusive evidence that temporary shelters and camps after natural disasters influence risk behaviour related to HIV transmission (Wilson, 2008). However, similar to disruptions in tuberculosis therapy, it can be assumed that natural disasters disrupt routine measure of HIV prevention, as well as routine care setups for people with HIV (Wilson, 2008). This can result in a deterioration of people's health, and can lead to severe co-infections with pneumonia or tuberculosis. Furthermore, due to the long incubation period, it is difficult to establish correlations between new infections of HIV/AIDS and natural disasters, as there may be years between initial infection and symptomatic AIDS (Heymann, 2015).

As HIV/AIDS is characterised by a compromised immune system, HIV-infected patients are more vulnerable to disease in extreme risk conditions – such as after natural disasters (Heymann, 2015). In particular, immunocompromised patients are at heightened risk of morbidity and mortality due to diseases such as influenza, pneumonia, or tuberculosis. Co-infection with tuberculosis (TB) has been shown to be a major risk in HIV-infected patients, with an 8-fold increase in the risk of developing symptomatic tuberculosis (Heymann, 2015) In the year 2013, WHO data showed over 50% HIV prevalence in new tuberculosis cases in countries in southern Africa, and up to 20% across countries of the world, including North America, Russia, and parts of Europe (Figure 8.2). Drug interactions between antiretroviral therapies administered to HIV-infected patients and anti-bacterial chemotherapy for tuberculosis has been shown to increase drug resistance in tuberculosis patients, setting back TB eradication efforts (Heymann, 2015). Having shown the importance of tuberculosis control in the context of natural disasters and disease relapse in chapter 7, the present chapter will approach tuberculosis in the context of HIV/AIDS.

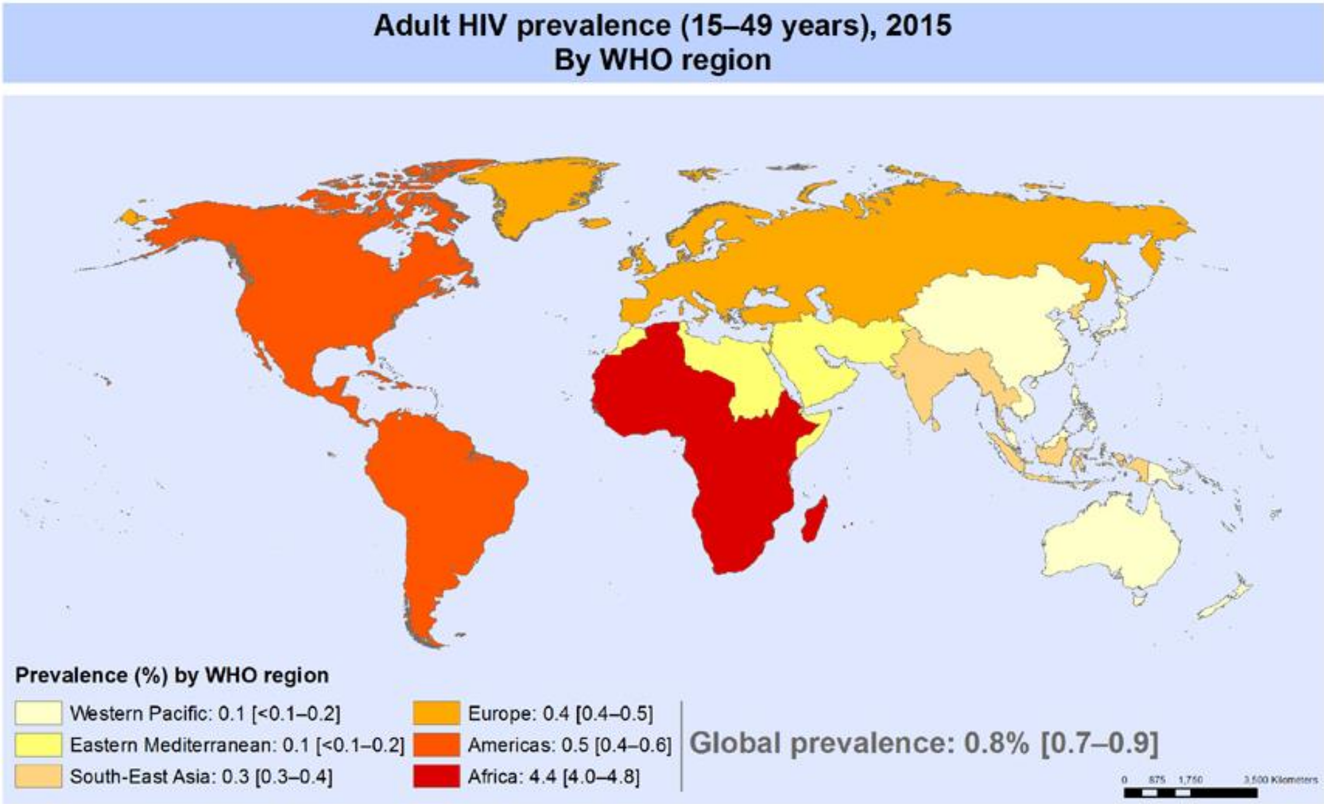


Figure 8.1: Prevalence of HIV in adults (aged 15-49) by WHO region, 2015 (source: http://www.who.int/gho/hiv/hiv_013.jpg?ua=1, accessed 30/01/17).

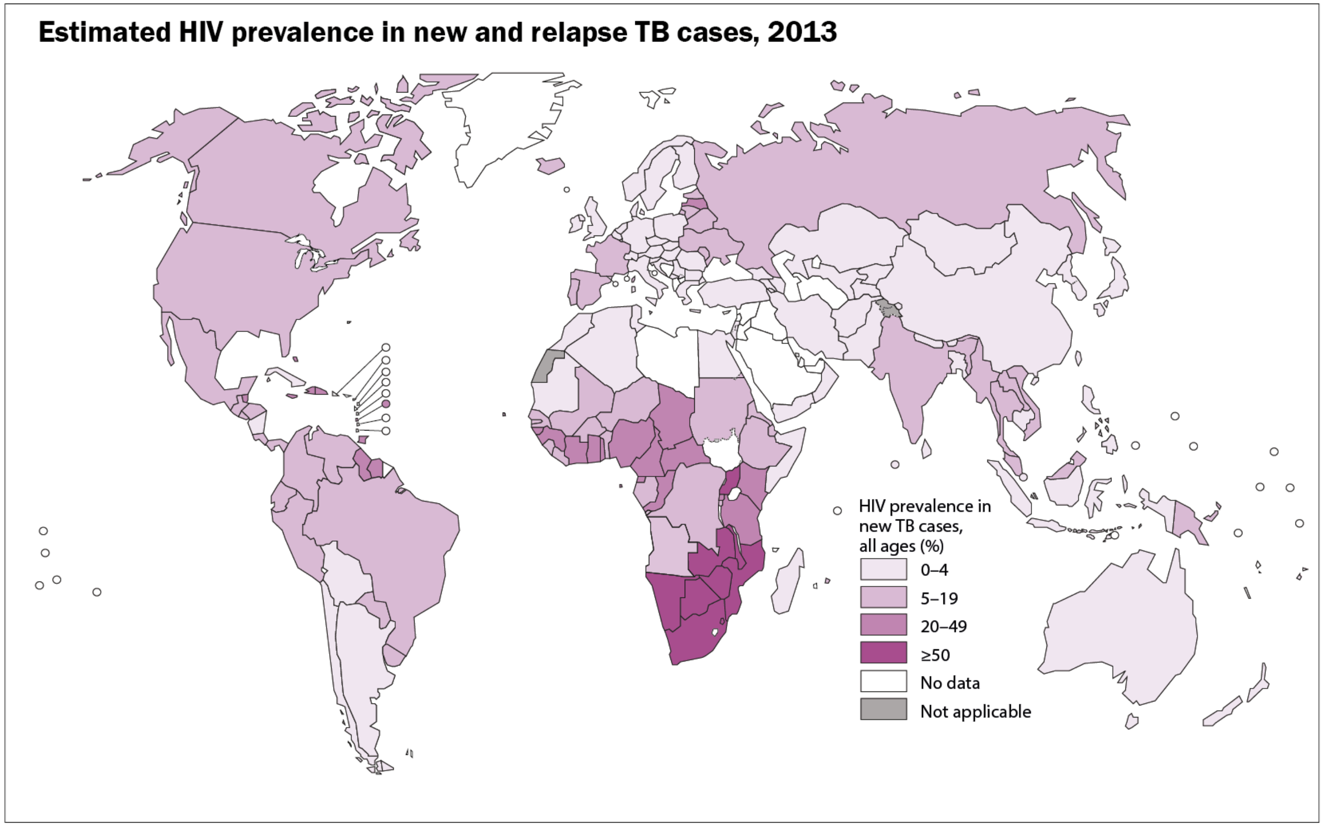


Figure 8.2: Estimated HIV prevalence in new tuberculosis cases, 2013 (source: http://gamapserver.who.int/mapLibrary/Files/Maps/Global_HIVprevalence_TBcases_2013.png, accessed: 30/01/17).

8.2 Methodology

8.2.1 Data sources

Data on the global occurrence of HIV and TB coinfections were retrieved from the Global Health Observatory of the World Health Organisation (WHO, 2016a). The relevant indicator was 'Tested TB patients HIV-positive' – providing information on the percentage proportion of HIV-positive patients with new TB infections. It is important to indicate here that this indicator includes only patients with known infection status for HIV. For example, in 2013 a total 113,603 new TB patients were reported in the Democratic Republic of the Congo, of which 44% had information on their HIV infection status recorded in the TB register. Of these 44% tested patients, 14% were known to be infected with HIV, accounting for an estimated 7,000 HIV infected TB patients (WHO, 2016a). Data was available in this format from 2003 onwards, and thus the years 2000-2002 will be excluded from the present analysis in this chapter, as was outlined in the Methodology chapter. In accordance with the Methodology outlined in Chapter 4, disaster data were gathered via the EM-DAT database (see Section 4.3).

8.2.2 Data analysis

Disease data were dichotomised by determining above and below average percentage of TB-HIV co-infection. In order to arrive at the above and below average co-infection numbers, the national average r for country i was calculated for each country. The annual percentage proportion of co-infection t was then compared to the 10 year average r_i. If t was larger than r_i, the year was coded as above average (1), if t was below or equal to r_i it was coded as below or equal to average (0).

This accounted for a total of 561 country-years with an above average percentage of TB co-infection in HIV patients, compared to 1,287 country-years for average or below average co-infection rates.

To determine the association between HIV/TB co-infection and natural disaster magnitude, logistic regression analyses were performed for the different tiers of disaster magnitude described in detail in Chapter 5. In accordance with the methodology in Chapter 3, logistic regression analysis was performed for different magnitude tiers of disasters. One set of analyses was performed using 6 tiers of magnitude and a separate set of analysis for 3 tiers of magnitude (Section 4.3.2).

Consistent with the analysis in Chapter 5–7, analysis in this chapter was performed for each of the six WHO regions and for four types of disasters (geophysical, meteorological, hydrological, and climatological). Following the methodology outlined in Chapter 7, in phase analysis was supplemented by a lag analysis that was performed at 1 and 2 lag years. Both AIDS and TB are characterised by long incubation periods that would reasonably mean new TB cases in HIV patients may only present significantly after the acute disaster phase. Lag analysis will allow insight into HIV/TB co-infections over time and offer a better understanding of the impact of disaster on the diseases. In this lag analysis, the country year of disasters (t) was compared with TB/HIV data from t+1 year and t+2 years.

8.3 Results

The principal results of the logistic regression analysis are summarised in Sections 8.3.1 to 8.3.3. An overall summary of the results is presented in section 8.3.1, while subsequent sections present a summary of the regional analysis (Section 8.3.2) and the lag analysis (Section 8.3.3). The tables present odds ratios, 95% confidence intervals, and associated *P*-values. Values of $P < 0.05$ are highlighted in green, values of $P < 0.10$ are highlighted in yellow.

8.3.1 Global HIV and TB co-infection by disaster magnitude

Table 8.1 displays the results of the logistic regression for TB/HIV coinfection in relation to the global set of disasters (all disaster types) in the period under consideration. The data revealed no statistically significant associations in either the 6-tier or 3-tier analysis.

Table 8.1: Odds ratio and confidence interval of average TB/HIV co-infection for all disasters, between 2003 and 2013.

All disasters 6-tier	**OR (95%CI); *P***
≥100	0.97 (0.40-2.35); 0.95
≥2,500	1.91 (0.75-4.87);0.18
≥5,000	1.53 (0.41-5.66);0.52
≥7,500	1.44 (0.40-5.22); 0.58
≥ 10,000	1.29 (0.74-2.25); 0.37
≥ 100,000	1.03 (0.59-1.78); 0.93
All disasters 3-tier	
≤ 10,000	1.36 (0.76-2.45); 0.30
10,000-100,000	1.28 (0.74-2.25); 0.37
≥ 100,000	1.02 (0.59-1.77); 0.94

Disaster types

When examined by disaster type, a significant association is identified for meteorological disasters affecting between 5,000 and 7,499 people (OR=5.21; 95% CI=1.00-27.55; *P*=0.05) (Table 8.2). None of the other levels of disaster magnitude showed significant results in either the 6-tier and 3-tier analysis. For geophysical, hydrological, and climatological disasters, no significant results were obtained (Table 8.3). Note that, in Table 8.3, insufficient data were available to perform logistic regression for geophysical disasters affecting between 5,000 and 7,499 people and climatological disasters affecting between 2,500 and 4,999 people and between 7,500 and 9,999 people.

Table 8.2: Odds ratio and 95% confidence interval of average TB/HIV co-infection for meteorological disasters, between 2003 and 2013.

Meteorological disasters 6-tier	**OR (95%CI); P**
≥100	0.70 (0.25-1.98); 0.50
≥2,500	1.60 (0.35-7.32); 0.54
≥5,000	5.21 (1.00-27.55); 0.05
≥7,500	2.91 (0.63-13.40); 0.17
≥ 10,000	1.34 (0.61-2.93); 0.47
≥ 100,000	0.53 (0.19-1.47); 0.22
Meteorological disasters 3-tier	
≤ 10,000	1.49 (0.76-2.92); 0.24
10,000-100,000	1.34 (0.61-2.93); 0.47
≥ 100,000	0.53 (0.19-1.45); 0.22

Table 8.3: Odds ratio and 95% confidence interval of average TB/HIV co-infection for geophysical, hydrological, and climatological disasters, between 2003 and 2013.

	Geophysical disasters OR (95%CI); P	**Hydrological disasters OR (95%CI); P**	**Climatological disasters OR (95%CI); P**
6-tier			
≥100	0.56 (0.12-2.72); 0.48	0.84 (0.37-1.91); 0.68	4.30 (0.77-24.01); 0.10
≥2,500	0.68 (0.13-3.43); 0.64	1.91 (0.74-4.93); 0.18	/
≥5,000	/	0.65 (0.13-3.23); 0.60	2.10 (0.13-34.10); 0.60
≥7,500	5.30 (0.45-61.85); 0.18	2.38 (0.73-7.75); 0.15	/
≥ 10,000	0.88 (0.22-3.52); 0.86	1.04 (0.58-1.85); 0.90	3.54 (0.58-21.78); 0.17
≥ 100,000	0.36 (0.08-1.65); 0.19	0.94 (0.47-1.85); 0.86	0.75 (0.33-1.79); 0.53
3-tier			
≤ 10,000	1.03 (0.41-2.62); 0.95	1.24 (0.71-2.16); 0.45	2.16 (0.61-7.65); 0.24
10,000-100,000	0.88 (0.22-3.51); 0.86	1.04 (0.58-1.85); 0.90	3.54 (0.58-21.80); 0.17
≥ 100,000	0.36 (0.08-1.67); 0.19	0.94 (0.48-1.84); 0.85	0.77 (0.33-1.79); 0.54

8.3.2 Regional HIV and TB co-infection by disaster magnitude

The regional breakdown presented in Table 8.4 produced very few results, owing to limited data availability. Of the results that were obtained, none reached statistical significance at a P=0.05 significant level. In two instances, the analysis for all disaster types yielded results that approached near significant level, namely disasters affecting above 100,000 of the population in the Region of the Americas and the European Region.

A complete breakdown of regional results by disaster type can be found in appendix 13.

Table 8.4: Regional breakdown of odds ratio and 95% confidence interval of average TB/HIV co-infection for overall disasters, between 2003 and 2013.

	Africa	**Americas**	**South-East Asia**
disasters 6-tier	**OR (95%CI); *P***	**OR (95%CI); *P***	**OR (95%CI); *P***
≥100	0.43 (0.04-4.35); 0.48	/	/
≥2,500	2.42 (0.46-12.75); 0.30	1.11 (0.15-8.42); 0.92	/
≥5,000	1.02 (0.08-12.66); 0.99	2.27 (0.17-30.03); 0.54	/
≥7,500	0.99 (0.08-13.00); 0.99	/	/
≥ 10,000	0.44 (0.12-1.55); 0.20	0.71 (0.20-2.60); 0.61	/
≥ 100,000	1.01 (0.38-2.67); 0.99	0.32 (0.09-1.13); 0.08	1.66 (.016-16.85); 0.67
disasters 3-tier			
≤ 10,000	1.17 (0.37-3.69); 0.79	0.38 (0.10-1.45); 0.16	/
10,000-100,000	0.43 (0.12-1.54); 0.20	0.71 (0.20-2.54); 0.60	/
≥ 100,000	1.01 (0.38-2.66); 0.99	0.32 (0.09-1.12); 0.08	1.66 (0.16-16.85); 0.67
	Europe	**Eastern Mediterranean**	**Western Pacific**
disasters 6-tier	**OR (95%CI); P**	**OR (95%CI); P**	**OR (95%CI); P**
≥100	2.62 (0.75-9.08); 0.13	/	/
≥2,500	/	4.33 (0.21-90.53); 0.35	/
≥5,000	0.92 (0.06-13.03); 0.95	/	/
≥7,500	2.68 (0.26-28.11); 0.41	/	/
≥ 10,000	2.12 (0.64-7.06); 0.22	2.43 (0.13-45.79); 0.55	2.01 (0.24-17.27); 0.52
≥ 100,000	10.13 (0.91-112.96); 0.06	4.97 (0.17-148.75); 0.36	0.45 (0.04-5.53); 0.53
disasters 3-tier			
≤ 10,000	1.57 (0.55-4.51); 0.40	5.05 (0.48-52.83); 0.18	/
10,000-100,000	2.00 (0.62-6.42); 0.24	2.48 (0.13-47.35); 0.55	2.01 (0.24-17.27); 0.52
≥ 100,000	10.01 (0.91-110.69); 0.06	4.49 (0.15-135.46); 0.39	0.45 (0.04-5.53); 0.53

8.3.3 Global HIV and TB co-infection for 1-year lag and 2-year lag

In the lag analysis, disaster data from year t was associated with disease data from the following year (y+1) and two years later (t+2) to allow for any potential delays in disease manifestation. As with the analysis in Sections 8.3.1 and 8.3.2, no statistically significant results were found in this time-lagged analysis (Tables 8.5a and 8.5b).

There are near-significant results for all disasters affecting between 100 and 2,499 people after 2 years, and hydrological disasters after 1 year (≥100 magnitude tier) and after 2 years (≥10,000 magnitude tier). The latter is closest to statistical significance (OR=1.77; 95%CI=0.98-3.21; P=0.06).

Table 8.5a: Odds ratio and 95% confidence interval of average TB/HIV co-infection between 2003 and 2013, accounting for 1-year lag.

	All disasters	**Geophysical disasters**	**Meteorological disasters**	**Hydrological disasters**	**Climatological disasters**
	OR (CI); p	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**
6-tier analysis					
≥100	0.78 (0.31-1.96); 0.60	/	1.21 (0.46-3.15); 0.70	0.38 (0.14-1.03); 0.06	2.62 (0.52-13.37); 0.25
≥2,500	5.28 (0.17-1.62); 0.26	0.31 (0.04-2.55); 0.27	1.54 (0.34-7.13); 0.58	0.94 (0.34-2.60); 0.91	/
≥5,000	1.40 (0.38-5.18); 0.61	/	2.86 (0.62-13.19); 0.18	0.55 (0.11-2.77); 0.47	2.21 (0.14-35.88); 0.58
≥7,500	4.94 (0.10-2.39); 0.38	4.68 (0.41-53.95); 0.22	1.74 (0.38-8.00); 0.48	1.07 (0.31-3.72); 0.91	/
≥ 10,000	0.98 (0.56-1.72); 0.94	0.54 (0.11-2.62); 0.44	1.21 (0.54-2.69); 0.65	0.96 (0.54-1.70); 0.88	3.79 (0.62-23.30); 0.15
≥ 100,000	1.27 (0.75-2.16); 0.37	1.11 (0.35-3.53); 0.86	0.85 (0.34-2.12); 0.73	1.34 (0.71-2.54); 0.37	1.45 (0.68-3.12); 0.34
3-tier analysis					
≤ 10,000	0.72 (0.38-1.36); 0.31	0.47 (0.15-1.42); 0.18	1.56 (0.80-3.06); 0.20	0.63 (0.34-1.17); 0.14	1.68 (0.46-6.15); 0.43
10,000-100,000	0.98 (0.56-1.73); 0.95	0.54 (0.11-2.59); 0.44	1.21 (0.54-2.69); 0.65	0.96 (0.54-1.70); 0.88	3.79 (0.62-23.32); 0.15
≥ 100,000	1.28 (0.76-2.17); 0.36	1.13 (0.36-3.58); 0.84	0.85 (0.34-2.11); 0.73	1.34 (0.71-2.53); 0.37	1.46 (0.68-3.13); 0.33

Table 8.5b: Odds ratio and 95% confidence interval of average TB/HIV co-infection between 2003 and 2013, accounting for 2-year lag.

	All disasters	**Geophysical disasters**	**Meteorological disasters**	**Hydrological disasters**	**Climatological disasters**
	OR (CI); p	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**
6-tier analysis					
≥100	2.15 (0.90-5.15); 0.08	0.30 (0.04-2.42); 0.26	2.08 (0.81-5.35); 0.13	1.31 (0.56-3.04); 0.53	4.23 (0.62-21.05); 0.09
≥2,500	0.87 (0.27-2.79); 0.82	/	/	1.44 (0.51-4.02); 0.49	/
≥5,000	2.30 (0.61-8.69); 0.22	/	1.30 (0.24-6.95); 0.76	0.31 (0.04-2.61); 0.28	/
≥7,500	0.77 (0.16-3.84); 0.75	1.18 (0.10-14.46); 0.90	1.23 (0.23-6.52); 0.81	0.63 (0.13-3.05); 0.56	/
≥ 10,000	1.58 (0.87-2.88); 0.14	0.33 (0.04-2.63); 0.29	0.68 (0.25-1.86); 0.46	1.77 (0.98-3.21); 0.06	1.02 (0.11-9.34); 0.99
≥ 100,000	0.91 (0.49-1.69); 0.75	0.92 (0.24-3.55); 0.91	0.64 (0.21-1.95); 0.43	0.63 (0.27-1.46); 0.28	1.12 (0.48-2.60); 0.80
3-tier analysis					
≤ 10,000	1.48 (0.78-2.80); 0.23	0.42 (0.12-1.48); 0.18	1.29 (0.62-2.69); 0.49	1.05 (0.56-1.97); 0.87	1.81 (0.45-7.31); 0.40
10,000-100,000	1.59 (0.87-2.90); 0.13	0.33 (0.04-2.65); 0.30	0.68 (0.25-1.86); 0.45	1.78 (0.99-3.24); 0.06	1.02 (0.11-9.35); 0.99
≥ 100,000	0.92 (0.49-1.72); 0.79	0.93 (0.24-3.56); 0.92	0.64 (0.21-1.94); 0.43	0.64 (0.28-1.47); 0.29	1.12 (0.48-2.61); 0.79

8.4 Discussion

8.4.1 Discussion of findings

This chapter has examined the association between natural disasters and numbers of HIV/TB coinfection. The above results have shown very few significant results, indicating a weak link between disaster and HIV/TB coinfection. Only in one instance were the results found to be significant – namely for meteorological disasters affecting populations between 5,000 and 7,499 (OR=5.21; 95% CI=1.00-27.55; *P*=0.05). There is no obvious explanation from the data, suggesting other factors may be responsible for this result, or it may be due to chance, signifying a type I error. However, when looking back at the results for tuberculosis cases and relapse in Chapter 7, meteorological disasters were showing significant increases in both categories (Section 7.3.1) so there might be more factors to investigate in relation to meteorological disasters that influence the epidemiology of TB.

In a few instances, results were reaching near-significant levels, namely for high impact disasters (affecting more than 100,000 of the population) in the Americas Region (OR=0.32; 95% CI=0.09-1.13; *P*=0.08) and Europe (OR=10.13; 95% CO=0.91-112.96; *P*=0.06). While statistical significance is of course desirable, near-significance also provides potential for future research priorities. The findings suggest that more significant results may have emerged if more data was available for analysis and other potential confounders may play a significant role. Especially the near significant result in the Americas Region, with a small confidence interval, may be an indication for data limitations that can be addressed by improved surveillance data.

In the time lagged analysis, no statistically significant results were found to suggest a change over time. Near significant results were found for 1-year lags and 2-year lags in relation to hydrological disasters. This is despite the long incubation period of the two diseases, which would suggest a change might become visible with a time lag. However, there were a rather large number of results reaching near significant levels at *P*<0.10 in the 2-year lag – more results of the kind than for the in-phase analysis, or the 1-year lag analysis. With a significance level set at 0.05, hydrological disasters affecting between 10,000 and 99,999 people came closest to statistical significant (OR= 1.77; 95% CI= 0.98-3.21; *P*=0.06). Perhaps this points towards the possibility that significance could be found after 2 years, if more data were available, or data of a different nature to fully explain this potential association. As such, the 2-year lag analysis provides a useful starting point for further research.

There were instances in which the logistic regression yielded no results at all, due to insufficient data. For geophysical disasters affecting between 5,000 and 7,499 people, as well as climatological disasters affecting between 2,500 and 4,999 people and between 7,500 and 9,999 people, not enough data were available to perform a logistic regression. In detail, this was because of the 2717 total country years in the overall dataset, there were only 11 country-years with geophysical disasters in the ≥5,000 magnitude tier, 7 country-years and 1 country-year in the ≥2,500 and ≥7,500 magnitude tiers for climatological disasters respectively.

This problem extends to several of the analyses presented in section 8.3. For the South-East Asian Region, not enough data was available to perform the analysis for disasters affecting less than 100,000 people. Of South East Asia's 155 total country–years, disasters affecting over 100,000 people were recorded in 84 country-years, while for the remaining magnitude tiers there were only 20 country-years with disasters affecting between 10,000 and 99,999 people, and no more than 5 country years in the remaining tiers respectively, rendering a logistic regression unfeasible. Similarly, in the Western Pacific Region with a total of 379 country-years, the magnitude tiers only barely counted over 40 country-years per tier. For the ≥100, ≥5,000, and ≥7,500 magnitude tiers of the 295 country-years in the Eastern Mediterranean Region, there were 22, 5, and 6 country-years with recorded disasters respectively. In the Americas Region, there were 49 country-years in the ≥100 magnitude tier and 7 in the ≥7,500 tier, of 491 total country-years, in the European region there were only 20 country-years with disasters in the ≥2,500 magnitude tier.

Not enough data to complete the analysis was available for geophysical disasters in the ≥100 and ≥5,000 magnitude tier and the climatological disasters for the ≥2,500 and ≥7,500 magnitude tiers at 1-year lag. For the 2-year lag analysis, data was insufficient for geophysical disasters at ≥2,500 and ≥5,000 magnitude tiers, for meteorological disasters ≥2,500 magnitude tier, and for all climatological disaster's magnitudes between 2,500 and 9,999 people affected.

A look at Chapter 7 and the results of tuberculosis cases and relapse affected by natural disaster reveals that, despite published evidence, tuberculosis has implications in the aftermath of disasters. While these results are not reflected in this chapter, the matter should not be dismissed. HIV numbers have been shown to be affected by events of long-term displacement, such as camps for refugees from political conflict (Connolly et al., 2004), but not by natural disasters – as is consistent with the present analyses. The effect of disasters on tuberculosis numbers can therefore be considered stronger and independent of HIV status and the increased risk of TB infection that is associated with immunodeficiency. This chapter, when compared to Chapter 7, shows that natural disasters appear to have a stronger, measurable effect on the risk of TB cases and relapse, irrespective of HIV status. The effect of natural disasters on HIV appears negligible.

8.4.2 Natural disaster and risk of HIV

Evidence for the occurrence of HIV/AIDS being affected by natural disasters is limited, and the findings on co-infection in this chapter support this. HIV has been shown as a major concern in complex emergencies (Connolly et al., 2004), but natural disasters do not seem to affect sexually transmitted diseases to the same extent.

Despite the lack of empirical evidence for HIV being a priority issue after natural disasters, there is a phenomenon of 'theoretical HIV vulnerability' (Wilson, 2008). This phenomenon assumes populations affected by disaster are disproportionally more vulnerable to HIV infection for various reasons – collapsed primary healthcare and therefore distribution of condoms as well as testing for STIs, disrupted education on safe sexual practices, and complications for HIV infected mothers giving birth in post-disasters conditions leading to infection of infants. This theoretical HIV vulnerability results in overestimation of the HIV risk after disasters, as well as pushing preconceptions in the media, and in the end only fosters prejudice and more stigma for HIV patients (Wilson, 2008).

Gathering empirical evidence of HIV after natural disasters to gain more understanding of the true vulnerability in post-disaster conditions must be a priority to counter harmful assumptions and misdistribution of resources.

8.4.2 Limitations

There are limitations to what the present analyses show and what they cannot show. First, all results are based on the 'known HIV status' which may be problematic in and of itself. According to data published by UNAIDS in November 2016, potentially 40% of people with HIV may not have access to testing facilities and would therefore fall within the 'HIV status unknown' category (UNAIDS, 2016). Such cases would not appear in the presented analyses. In order to account for this, estimates would need to be made to add numbers where relevant. It was decided against that estimation, as for this analyses, only recorded and fully documented data was utilised.

Inconsistent surveillance reporting was a second limitation to the analyses. Not all data was available for every country-year, with large gaps in reporting, sometimes missing full years (for example 2003-2005 were missing for several countries). In total for the years 2003 to 2005, one third to half of the data was missing, as opposed to more recent years like 2013, where only 13 country-years' worth of data on co-infection were missing. This, paired with the small numbers of natural disasters in various instances (noted in Section 8.4.1) affected the ability to perform a meaningful logistic regression, and has not –

to this extent – occurred in the other diseases investigated in Chapter 5 through 7.

8.5 Conclusion

HIV is an issue prominent in people's mind as one of the biggest health challenges of our time. The virus in its active stages leaves patients vulnerable to co-infection with other diseases such as tuberculosis, with potentially lethal outcome. In the aftermath of natural disasters, it is assumed that because of disruptions in routine care, HIV patients might be obstructed from seeking treatment and may be more at risk of contracting a co-infection.

This Chapter has attempted to find a quantitative association between natural disasters and an increase in HIV and TB co-infections. Significant results were limited, partly due to constraints of the data, but it cannot be said for certain how strong the association is with the data available for this chapter. Further research is necessary to remove some of the data noise that might interfere with the calculations. It was impossible to arrive at solid conclusions with the same methodology that was used for the previous three chapters, but the findings do provide a starting point for future research.

Chapter 9 - Discussion

Chapter Contents

9.1 Introduction

Interpreting the nexus between natural disasters and infectious diseases requires an understanding of risk, its measures and implications in an epidemiological setting. Risk, according to the Merriam Webster dictionary, describes 'a possibility of loss or injury'. In the context of epidemiology, risk is usually referred to as the probability of an event (i.e. an illness or death) occurring (Irwig, Irwig, Trevena, & Sweet, 2008). Risk is usually presented in probabilities, rather than absolutes. In the context of natural disasters, one important consideration of risk are the factors involved in altering the risk of disease. As described in Section 2.1, these factors include:

- Factors related to population displacement
    - Overcrowding
    - Temporary shelters
    - Poor water supply and sanitation facilities
    - Food shortage
- Socio-economic factors
    - Vaccination coverage
    - Access to healthcare
    - Access to clean water
    - Financial stability
- Environmental and geographical factors
    - Climate
    - Vector breeding grounds
    - Extreme weather conditions
    - Frequency of natural disasters
    - Accessibility of healthcare facilities

Risk has been a pivotal concept in the analytical sections of this thesis. It has been measured in different ways to provide insight into the occurrence of infectious diseases after natural disasters: relative risk (RR) and odds ratio (OR). While these terms are often used interchangeably, they approach risk from differing perspectives. Relative risk is usually considered to be the more straight forward approach to assessing risk. It assesses the probability of an event occurring in a group exposed to a certain condition compared to the risk of the same event occurring in a group without the exposure. The odds ratio by contrast, used in logistic regression analysis, looks at the odds of being exposed to a condition in a case and a control group. Because of this difference, relative risk is typically used in randomized controlled trials (RCT) and cohort studies, and the odds ratio is the measurement of choice for case-control studies.

Both relative risk (Chapter 3) and odds ratio (Chapters 5–8) have been examined in the present study, and the ways in which these results intersect and complement each other is a key point for discussion in this chapter.

9.2 Discussion of meta-analysis

9.2.1 Discussion of Methodology

Literature

In past studies, an understanding of the links between natural disasters and infectious diseases has proceeded on the assumption that natural disasters are the direct cause of disease outbreaks. As has been noted in Chapter 2, much of the currently available research has focused on the short term effects of natural disasters, and only in rare instances (such as the ongoing cholera epidemic in Haiti) has research into the long term consequences appeared in the literature. However, it has been noted that many of the diseases of interest after natural disasters will have a natural delay in potential outbreaks – such as malaria, affected by mosquito breeding cycles (Kouadio et al., 2012). Such time-lag effects have become more widely recognised and addressed in research, with recent publications acknowledging that a different approach is required to understand the dynamics of disasters and communicable diseases (Kouadio et al., 2012; Leaning & Guha-Sapir, 2013). This shift in awareness of the shortcomings of disaster response to infectious diseases has evolved over the last 40 years, beginning with Lechat's criticism of disaster response efforts in 1976 (Lechat, 1976). Such developments have been slow, and the examination of the existing literature in Chapter 2 has resulted in an identification of gaps in research coverage of disasters and disease. These include:

- The lack of data on the long-term consequences of natural disasters on infectious disease morbidity and mortality. This goes hand in hand with the problematic transition from acute emergency care to lasting routine care, and has been noted as an issue with research on disasters and disease in previous publications (Barzilay et al., 2013; Kouadio et al., 2012; Myint et al., 2011; Noji, 2005a).
- The imbalance in reporting on certain types of disasters and certain types of diseases. There is an evident research bias in favour of disasters that have received a wide global attention – such as the 2010 earthquake in Haiti or the 2005 South-East Asia tsunami – while disasters that may have affected large numbers of people but have had little media attention go by with relatively limited coverage in the epidemiological literature. Table 2.4 and Section 2.3 have highlighted this discrepancy.
- The slow progress in adapting to challenges in the aftermath of natural disasters (Section 2.4). This issue emerged from reviewing the literature and identifying the same issues (coordination of relief work, inappropriate donation, and the transition to routine services) brought up by publications from the 1970s (Lechat, 1976), 1990s (Logue, 1996), and as recently as 2013 (Leaning & Guha-Sapir, 2013). It is most surprising that our means of preparedness and response to natural disasters in general, and infectious diseases after natural disasters in particular, have received so little attention from researchers over this extended timeframe.

This thesis has examined the literature using two complementary methods. Chapter 2 provided a conventional literature review to identify the above-mentioned shortcomings in research on natural disasters and infectious diseases. It provided a map of disaster epidemiology over the past 40 years, identified the most common risk factors that influence the outbreak of diseases after disasters, and created a framework for the remaining chapters to start filling potential gaps. Chapter 3, on the other hand, used the literature in a quantitative approach, to put interpretable numbers on the risk of disease after disasters, and to identify the risk factors related to this dynamic. While Chapter 2 approached the literature in a very explorative, narrative way, Chapter 3 approached the literature in a more systematic way that was more restrictive in terms of its inclusion and exclusion of publications. Though the same publications formed the basis of both chapters, the approaches to the literature were very different and permitted a distilling of different information that has provided a more comprehensive picture for future analysis.

Meta-Analysis Methodology

What sets the quasi meta-analysis of Chapter 3 apart from previously conducted literature reviews is the methodological approach, the use of a new 'checklist' to narrow down inclusion criteria for analysis. The PICOS approach described in detail in section 4.2.2 and 4.2.3 was originally a tool for the development of strong, standardised, informative research questions for clinical research (O'Connor et al., 2011). The tool is typically used for research questions of Randomized Controlled Trials and to identify them for literature reviews. The decision to modify this tool to identify publications with relevant data for this analysis was made in order to keep the included data as standardised as possible. The pitfalls in standardisation (as discussed in section 3.4.2) are a result in and of themselves. More standardised presentation formats for research findings would facilitate data pooling in research on natural disasters and infectious diseases, and would allow for a more comprehensive picture to base disaster response efforts on and avoid inadequate resource management and donations (Leaning & Guha-Sapir, 2013).

9.2.3 Summary of meta-analysis results

The modified selection procedure of Chapter 3, described in section 3.2.2 and 3.2.3, identified a total of 55 publications from a sample of 393. It is by no means assumed this is a complete sample, but greatest care was taken to minimize this risk of missing publications during the literature search. Accepting this limitation, it may be assumed that the literature sample is valid and it is suggested that the PICOS search strategy may become a useful tool beyond randomized controlled trials.

The publications covered 29 disaster events between 1982 and 2014, and the four major categories of infectious diseases identified in the literature review (diarrhoeal diseases, acute respiratory infections, vector borne diseases, wound infections; see Chapter 2). The analysis found increased relative risks of disease after disasters (section 3.3.3). For all disasters, formed to include all 55 publications in the sample, the relative risk of disease after disasters was estimated at 3.45 (P<0.0001). For earthquakes there was a much higher relative risk of 6.04 (P<0.0001); for tsunamis the relative risk was 2.94 (P<0.0001); and for storms the relative risk was only slightly elevated 1.24 (P=0.0012). Extreme weather conditions showed no significant change in relative risk at 0.94 (P=0.09).

9.3 Discussion of chapters 5-8: associations of natural disaster and infectious disease

9.3.1 Discussion of Methodology

The statistical methodology for Chapters 5 through 8 aimed to develop the 2013 longitudinal study of cholera in the aftermath of earthquakes, conducted by Sumner et al. (2013). The aim was to take the approach employed by that study a step further, not restricting the analysis to a single subcategory of geophysical disasters (earthquakes), but instead widening the pool of data by including all disasters that occurred in a set period of time. This was done in order to overcome some limitations identified in Sumner and colleagues' original methodology. No statistically significant results were found in the original study, suggesting outbreaks of cholera after earthquakes may be due to random chance, due to limited data availability, or caused by complex interactions that may not have been fully captured by the methodology.

While developing the adapted methodology in Chapter 4, a number of observations were made that should be taken into consideration. Because no significant results were found in the original study by Sumner and colleagues, the decision was made to add a new, higher magnitude tier to the analysis, to account for disasters on a larger scale. Sumner and colleagues only focused on earthquakes, hence their smaller tiers were reasonable. The inclusion of different disaster types, many of which affect millions of people at once, called for a new tier to acknowledge the higher number of large magnitude disasters. Adding the ≥100,000 magnitude tier added another layer of data, and as was displayed in Chapters 5-8, this allowed for new insights that had previously gone undetected. Furthermore, it was decided to remove the restriction of only investigating earthquakes. This added a critical amount of data to the analysis. While Sumner's analysis was more focused, it was attempted to include as much data as possible in this present research. Logistic regression works best with large quantities of data, making the results more reliable. Hence, more data was necessary to allow proper calculations and even reach significance in some instances. To return some of the focus, it was decided to undertake separate analyses for the four main disaster types (Section 4.3).

Naturally, adding significant amounts of data to an already complex analysis comes with a major limitation. Data noise is inevitable, and may lead to bias in the data. This noise may exaggerate or misattribute an effect, or may render it impossible to isolate a given effect of natural disasters on disease at all. With several confounding variables to account for (GDP, average life expectancy, under 5 years child mortality, access to clean water, and access to sanitation, and geographic region) there is a considerable amount of noise already, yet there are still factors that could not be accounted for in this analysis. Seasonal climate, and political situation, for example, may have a significant influence on a population’s capability of responding and coping with the aftermath of a natural disaster. (The issue of noise as a source of bias is examined in more detail in Section 9.4.5)

Logistic regression analyses were performed to determine odds ratios as measures of disease risk after disasters (Chapter 4). This was performed for four different diseases, that will be discussed in the following section. Data was dichotomised for analysis. While the reduction of complex data into the equivalent of a ‘yes’/’no’ response appears to imply a loss of data, it was deemed an informative way of dealing with the present data by this researcher. It has the effect of reducing the noise in the data, and simplifies the complexity of a disease outbreak to ‘were numbers in this year above national average, or not’.

In addition to the in-phase analysis that looked at numbers of diseases in the same year as the disasters, a time-lagged analysis was performed. In order to account for the possible delay in disease outbreaks, numbers of infectious diseases were related to disasters from a year before, and in the case of HIV and tuberculosis 2 years before, as both diseases have longer latency periods. The lag analysis has not been done to this extent in previous research, as most findings of diseases after natural disasters are restricted to the immediate weeks after the disaster, and may miss the delay that has been shown in such cases as the cholera epidemic in Haiti.

When multiple tests are conducted on the same data, it can be assumed that statistically significant results are found purely based on chance. This would be a type 1 error, in which the null hypothesis (no effect of disaster on disease) would be rejected based on a chance finding (Lindenmayer & Burgman, 2005). Typically, the significance level determines how certain one is about the findings (i.e., a 0.05 significance level indicates that a false positive will be accepted in 5% of cases), and thus the significance level would have to effectively be much smaller than the typical 0.05. Table 9.1 indicates the total number of tests performed and the total number of significant results. At a 5% significance level, the null hypothesis would have been falsely rejected in cases where less than 5% of results are significant (meaning these significant findings could be due to chance or factors not accounted for in the models). Further examination of all significant findings will be necessary in the future, to explore the underlying mechanisms that may have gone undetected in this research. This is especially obvious for HIV/tuberculosis co-infection and for tuberculosis.

Table 9.1: Total number of tests performed vs. total number of statistically significant results per data set.

	total tests / significant tests (%)
cholera morbidity	135/15 (11.1)
cholera mortality	45/3 (6.7)
malaria morbidity	360/15 (4.2)
malaria mortality	90/10 (11.1)
tuberculosis cases	405/8 (2.0)
tuberculosis relapse	405/26 (6.4)
HIV/tuberculosis cases	405/1 (0.2)

9.3.2 Summary results of disease profiles

Chapters 5 to 8 investigated the dynamic between natural disasters and four selected diseases from the categories identified in Section 2.6. These diseases were cholera, as an example of water borne diseases, malaria as a vector borne disease, tuberculosis as an acute respiratory infection and, to supplement the analysis of tuberculosis, co-infections with HIV and tuberculosis

Cholera (Chapter 5)

When investigating the association of cholera morbidity and mortality based on the example of Sumner and colleagues (Sumner et al., 2013), a number of observations were made. Most significant results occurred for cholera morbidity in disasters affecting more than 100,000 people, the magnitude tier added to the base methodology proposed by Sumner et al. – this was true for overall disasters as well as for specific disaster types, namely geophysical and meteorological disasters (Section 5.3.1). The regional examination limited the available data for analysis, but still revealed some insightful results. There was a significant change in risk for overall disasters in the Americas (5.3.2), as well as for geophysical and hydrological disasters.

At 1-year lag, there were significant results for geophysical and meteorological disasters affecting between 10,000 and 100,000 of the population, supporting the statement made in Chapter 2 on the long term effects of natural disasters on populations and infectious diseases.

Malaria (Chapter 6)

Similar to cholera, natural disasters affecting over 100,000 people showed a significant change in the average number of malaria cases. However, there were no significant results for the breakdown by disaster type, with the exception of malaria mortality in hydrological disasters. A significant change in average malaria deaths was associated with hydrological disasters affecting over 100,000 of the population. This is relevant, considering the transmission of malaria through mosquito bites and given mosquito breeding grounds (bodies of standing water as small as puddles) will likely be affected by disasters involving water (Krishnamoorthy et al., 2005; Kumari et al., 2009).

For the regional analysis, there was only one significant result found for the American region with disasters affecting up to 10,000 people.

The lag analysis rendered some interesting results: hydrological disasters affecting between 10,000 and 100,000 of the population showed a significant and negative association after 1 year, suggesting malaria numbers might decrease in consequence of an environmental lag-response. This may be due to standing water sources that might exist in the aftermath of a disaster disappearing after a year, returning mosquito populations to normal levels (Gunasekaran et al., 2005; Morgan et al., 2005). Malaria deaths on the other hand are still at above average numbers after a year. In hydrological disasters, on the other hand, a significant increase in average malaria cases was noted after a year.

Tuberculosis (Chapter 7)

In view of an alarming increase in tuberculosis in recent years (Cousins, 2014; WHO, 2014) – especially in refugee populations – new insights into the dynamic of tuberculosis are invaluable. In Chapter 7, a number of highly interesting observations have been made on tuberculosis cases and relapse after natural disasters (Sections 7.3.1 – 7.3.3).

There was a significant change in tuberculosis cases for meteorological disasters affecting over 100,000 people, and a number of significant results for relapse cases, namely in meteorological and hydrological disasters, as well as for all disasters, irrespective of type. This is an interesting observation, as tuberculosis relapse (a potential indicator for collapsing health infrastructure) has not been investigated in the aftermath of natural disasters in previous research. Similarly, there were more statistically significant results for relapse cases in the regional breakdown (mostly in the African region and the Region of the Americas) than in the incident tuberculosis cases.

In the lag analysis, new tuberculosis cases were significantly higher only for meteorological disaster affecting more than 100,000 of the population after 1 year, the same magnitude tier as the in-phase analysis, and no significant changes in the 2-year lag. A similar pattern occurred for relapse cases, with numbers returning to average after 2 years.

HIV and tuberculosis co-infection (chapter 8)

In addition to tuberculosis, TB/HIV co-infection was investigated to learn about the unique dynamic of the two diseases. However, with the available data, results were limited and possibly due to random chance. This is testimony to the complexity of co-infection, and the many variables that contribute to changes in the numbers. No convincing conclusions could be drawn from the present research. Previous research found no evidence to suggest an effect of natural disasters in HIV to the same extent as with complex emergencies, and the findings of Chapter 8 support that rather weak association.

However, the analysis did yield some results that were approaching conventional levels of statistical significance. With additional data, or a different approach to the data, a stronger association might be found, so further research is advised. However, so far no findings suggest an association that warrant the status of HIV as a priority issue in disaster response and management.

9.4 Discussion of findings

9.4.1 Discussion of overall disasters impact

In Chapters 3 through 8, different measures of disaster impact on infectious disease were employed to achieve an indication of risk. The analyses used different methods to investigate the association, as described in the above sections.

In Chapter 3, relative risk was calculated to broadly determine which disasters had an effect on infectious disease, and the nature of that effect. The relative risk for disease for the entire set of natural disasters in the literature sample was 3.45 (95%CI=3.13-3.82; $P<0.001$), indicating a 3-fold increase in the probability of infectious disease after disasters. Furthermore, the chapter identified two factors (average life expectancy and WHO region) as significant factors influencing disease mortality after disasters. These results were used as a source of information for the remaining analytical chapters; they helped determine the relevant confounders to be included in Chapters 5–8, and they provided a first insight into what could be expected from the analyses described there.

In Chapters 5–8, disaster and disease associations were calculated using yearly averages of pre-determined diseases and disaster magnitudes. The most immediate observation to be made when looking at the results of Chapters 5–8 for total disasters on a global scale is that, for disasters that affected more than 100,000 people, there is an increase of cases compared to the national averages calculated for the years under study. This is true for cholera, malaria, and tuberculosis relapse cases (Table 9.1). The strongest association was found for tuberculosis relapse, at a 2-fold increase in odds. No significant results were found for overall tuberculosis cases and for co-infection with HIV and TB. The results can be considered robust with narrow confidence intervals, likely due to large numbers of observations. Once the data is compartmentalised into different disaster types and different regions, confidence naturally decreases, as will be discussed in the following sections.

Table 9.2: Summary results of total disasters at 100,000 population affected for cholera, malaria, tuberculosis, and HIV and TB co-infection. Highlighted results are statistically significant at $P \leq 0.05$.

	≥100,000 population affected **OR (95%CI); *P*-value**
Cholera cases	1.89 (1.01-3.55); 0.05
Cholera deaths	1.47 (0.73-2.98); 0.28
Malaria cases	1.80 (1.05-3.09); 0.03
Malaria deaths	1.58 (0.88-2.83); 0.13
Tuberculosis cases	1.41 (0.90-2.20); 0.14
Tuberculosis relapse	2.03 (1.20-3.43); 0.01

HIV and TB co-infection	1.03 (0.59-1.78); 0.93

It was stated in the literature that the magnitude of a disaster was not necessarily the determining factor of disease occurrence, but the conditions resulting from the disaster (Leaning & Guha-Sapir, 2013). However, as is evident from the results of this research, there is a greater risk of infectious disease after high magnitude disasters. This, of course, is likely because disasters of high magnitude affect large numbers of people and will ultimately have a stronger effect on physical and health infrastructure. The survivors will have to manage life in the aftermath with altered surrounding conditions in favour of infectious disease spread, in accordance with risk factors identified in Chapter 2 and Section 9.1. This may serve as an explanation for significant results in disasters that affect fewer people, as low as the magnitude tier between 7,500 and 9.999 population affected (for cholera morbidity OR=4.69; 95% CI=1.26-17.01; *P*=0.02 in section 5.3.1 and for tuberculosis relapse at between 10,000 and 99,999 population affected with OR=2.06; 95% CI= 1.19-3-55; *P*=0.01 in section 7.3.1). Even natural disasters that affect lower numbers of people can have a significant effect on the surrounding conditions and thus increase disease risk.

9.4.2 Discussion of results by disaster types

The effect of disasters on infectious diseases varies by disaster type. As summarised by Linscott (2007), different types of diseases will potentially become problematic after different types of disasters (Linscott, 2007). Thus, an analysis the different types of disasters offers interesting insights into the dynamics of disasters and disease.

In Chapter 3, four disaster types were drawn from the literature for analysis: earthquakes, tsunamis, storms, and extreme weather conditions. In Chapters 5–8, it was elected to use broader disaster categories in accordance with the EM-DAT database (Table 2.1). These disaster categories include the four types identified for Chapter 3 (geophysical disasters include earthquakes, hydrological disasters include tsunamis, meteorological disasters include storms, and climatologically disasters include extreme weather conditions). Therefore, the results can still be compared and have relevant implications for each other and for the discussion of the association between disaster and disease, even if they do not use the same vocabulary.

Geophysical disasters

The analysis in Chapter 3 yielded a relative risk of 6.04 (95%CI=5.51-6.64; *P*<0.0001) for infectious disease after earthquakes. This is a staggeringly high RR, also compared to the overall relative risk of 3.45 (95%CI=3.13-3.82; *P*<0.001). However, upon critical examination, these findings have likely been biased by the repeated inclusion of the Haiti earthquake and severe cholera epidemic in several of the reviewed publications. The same bias may also have influenced the results in Chapters 5–8 (Table 9.3).

Table 9.3: summary results of geophysical disaster at 100,000 population affected for cholera, malaria, tuberculosis, and HIV and TB co-infection. Highlighted results are statistically significant at P≤0.05.

	≥100,000 population affected **OR (95%CI); *P*-value**
cholera cases	5.98 (1.99-17.99); 0.001
cholera deaths	8.97 (2.83-28.44); 0.001
malaria cases	1.24 (0.41-3.79); 0.71
malaria deaths	0.84 (0.25-2.84); 0.78
tuberculosis cases	0.53 (0.16-1.72); 0.29

tuberculosis relapse	0.54 (0.12-2.51); 0.43
HIV and TB co-infection	0.36 (0.08-1.65); 0.19

Looking at the results of the remaining chapters (5 through 8), cholera is identified as the only disease in which geophysical disasters have a significant impact on yearly disease averages. Specifically, geophysical disasters affecting >100,000 people resulted in significantly increased odds for cholera cases (OR=5.98; 95% CI= 1.99-17.99; *P*=0.001) and for cholera mortality (OR=8.97; 2.83-28.44; *P*=0.001). Again, it is probable that the inclusion of the Haiti earthquake and cholera epidemic may have significantly influenced these results, especially so when it is recognised that Sumner and colleagues found no significant associations between earthquakes and cholera in their analysis performed without the Haiti earthquake. They chose to not include it in their analysis focused specifically on cholera after earthquakes, because it could strongly bias the results (Sumner et al., 2013). This is in line with what was observed in Chapter 3, with the much larger RR of disease after earthquakes than the other disaster types.

Interestingly, there is a significant result for cholera after geophysical disasters affecting up to 2,499 people. Such small-scale disasters having an impact is unusual, and it cannot reliably be explained with the data in this research. Further investigation will be necessary to fully understand the reasons behind this result.

None of the other diseases showed a significant probability of increased average cases after geophysical disasters. This may be due to a number of reasons. Malaria is largely dependent on vector breeding, so if geophysical disasters do not have as strong an effect on the mosquito breeding grounds – or perhaps even decrease these – there is no reason for malaria figures to rise. For tuberculosis, a respiratory infection, one might expect the numbers to rise given that geophysical disasters are destructive and often send the affected population into shelters. Crowded emergency shelters are a main risk factor for transmission of respiratory infection after disasters (Bellos et al., 2010). Still, no result was found for tuberculosis. This suggests the surrounding conditions may be different in emergency shelters for geophysical disasters as compared to, for example, meteorological disasters.

Meteorological disasters

In Chapter 3, storms were associated with a relative risk for infectious diseases of 1.24 (95%CI=1.09-1.41; *P*=0.001). This is not a substantially inflated risk, as an RR of 1 indicated no change in risk between exposure and non-exposure. However, a few interesting results could be observed in Chapters 5-8 (Table 9.4).

Table 9.4: summary results of meteorological disaster at 100,000 population affected for cholera, malaria, tuberculosis, and HIV and TB co-infection. Highlighted results are statistically significant at P≤0.05.

	≥100,000 population affected **OR (95%CI); *P*-value**
cholera cases	3.48 (1.48-8.08); 0.004
cholera deaths	2.52 (0.91-6.93); 0.07
malaria cases	1.00 (0.42-2.38); 1.00
malaria deaths	1.31 (0.53-3.22); 0.56
tuberculosis cases	2.12 (1.04-4.27); 0.04
tuberculosis relapse	1.58 (0.68-3.66); 0.29
HIV and TB co-infection	0.53 (0.19-1.47); 0.22

At over 100,000 people affected, significant results were found for cholera cases (OR=3.48; 95% CI=1.48-8.08; *P*=0.004) and tuberculosis cases (OR=2.12; 95% CI= 1.04-4.27; *P*=0.04). The odds ratios hint at stronger associations than the relative risk estimate from Chapter 3, which may reflect on the effect of disaster magnitudes. Additionally, for tuberculosis relapse a significant result was found at between 10,000 and 99,999 people affected (OR=2.20; 95% CI=1.05-4.53; *P*=0.03).

For meteorological disasters, no results were found for small scale disasters, suggesting smaller storms have no significant effect on infectious diseases.

For meteorological disasters at between 5,000 and 7,499 people affected, there was a significant increase in the probability for HIV and TB co-infection (OR=5.21; 95% CI=1.00-27.55; *P*=0.05). It is the only significant result for this analysis, likely due to data limitations, and possibly relevant factors that may have gone unmeasured in this research. There have been studies on the challenges of HIV after Hurricane Katrina, where access to HIV care was severely disrupted early on (Clark et al., 2006), but there is no explanation for why these effects occur after meteorological disasters but not geophysical disasters.

Hydrological disaster

In Chapter 3, a relative risk of 2.94 (95%CI=2.66-3.27; *P*=0.0012) was estimated for infectious diseases after tsunamis, because the South-east Asia tsunami of 2004 was a major event repeatedly studied in the literature. There might be a case of reporting bias similar to that which occurred with the Haiti earthquake and cholera. It has to be noted that a tsunami is sometimes classified as a geophysical event (as it follows an earthquake), and sometimes as a hydrological disaster. Table 9.5 summarises the results of logistic regression for the ≥100,000 magnitude tier.

Table 9.5: summary results of hydrological disaster at 100,000 population affected for cholera, malaria, tuberculosis, and HIV and TB co-infection. Highlighted results are statistically significant at P≤0.05.

	>100,000 population affected **OR (95%CI); *P*-value**
cholera cases	1.86 (0.90-3.85); 0.10
cholera deaths	1.62 (0.74-3.56); 0.23
malaria cases	1.46 (0.81-2.65); 0.21
malaria deaths	2.01 (1.07-3.77); 0.03
tuberculosis cases	1.51 (0.89-2.59); 0.13
tuberculosis relapse	1.93 (1.06-3.53); 0.03
HIV and TB co-infection	0.94 (0.47-1.85); 0.86

As Table 9.5 shows, elevated levels of malaria deaths and tuberculosis relapse were associated with significant increases in probability after hydrological disasters. It is interesting that, for malaria, no similar increase was found for cases. This suggests that disasters may not necessarily affect the numbers of vectors leading to larger numbers of cases but, rather, the vulnerability of people and their ability to survive the illness. Similarly, it may indicate that a health system's capacity to provide the necessary treatment is affected by a disaster. It has been argued in the literature that hydrological disasters affect vector breeding grounds (Krishnamoorthy et al., 2005; Kumari et al., 2009; Morgan et al., 2005), but it has also been noted that malaria control remains strong even after disasters, as it is a well-established measure of post-disaster management.

Climatological disasters

No significant results were found for any of the diseases under investigation for climatological disasters. Furthermore, in many instances, there was too little data available for the logistic regression analysis to be performed. To be more precise, when looking at country-years with climatological disasters by magnitude tier, the following data was available:

Of 2751 country-years in total, there were 42 country-years with climatological disasters affecting between 100 and 2,499 people; 7 country-years with disasters affecting between 2,500 and 4,999; another 7 country-years with disasters affecting between 5,000 and 7,499; only 1 country-year with disasters affecting between 7,500 and 9,999; 26 country-years with disasters affecting between 10,000 and 99,999 people; and 146 country-years with disasters affecting over 100,000 people. These are too small numbers to conduct a logistic regression, so analysis could not be performed in these instances and no results were found. It has to be considered that a different approach will be necessary to analyse the impact of climatological disasters on infectious disease.

9.4.3 Discussion of results across geographic regions

The data for analysis in Chapter 5–8 were split into the six WHO regions (African Regions, Region of the Americas, South-East Asian Region, European Region, Eastern Mediterranean Region, and Western Pacific Region; see Figure 4.1) for analysis. A number of interesting results could be found and have potential to inform future research areas. One such result is that splitting the data down into six separate clusters reduced the numbers available for logistic regression analysis. The fact that the American Region consistently had results may suggest at first glance that more disasters strike there than in other regions. This is a questionable assumption. It is more likely that surveillance coverage is stronger in that region than is other regions, leading to a reporting bias of data on disasters and disease, and hence more available data for the American Region. The statistically significant findings for each region and for total disasters are summarised in table 9.6.

Table 9.6: Summary of statistically significant results of logistic regression for diseases in WHO regions.

	Africa (OR; 95%CI; P)	**America (OR; 95%CI; P)**	**South-East Asia (OR; 95%CI; P)**
Cholera	/	*≥100,000* (7.81; 1.31-46.7; 0.02)	/
Malaria	*≥100,000* (2.70; 1.17-6.22; 0.02	/	/
Tuberculosis	*≥100,000* (3.24; 1.34-7.84; 0.01)	*≥2,500* (12.48; 1.17-132.89; 0.04)	/
TB+HIV	/	/	/

Table 9.6 (cont.): Summary of statistically significant results of logistic regression for diseases in WHO regions.

	Europe (OR; 95%CI; P)	**Eastern Mediterranean (OR; 95%CI; P)**	**Western Pacific (OR; 95%CI; P)**
Cholera	/	/	/
Malaria	/	/	/

Tuberculosis	/	/	/
TB-HIV	/	/	/

For cholera and tuberculosis, significant results were found for the Region of the Americas – for cholera this was found at the ≥100,000 population affected tier and for tuberculosis cases at between 2,500 and 4,999 population affected. There were results approaching conventional levels of significance for HIV and TB co-infection at the ≥100,000 magnitude tier (OR: 0.32; 95% CI: 0.09-1.13; *P*= 0.08), suggesting the possibility that if other factors had been controlled for or more data had been available for analysis, an effect could have been shown. Availability of data for malaria was additionally limited by the endemicity of vectors.

In other regions, results were limited and non-significant. This may be due to a variety of reasons, likely related to data availability. For tuberculosis and malaria, significant results could be found at ≥100,000 of the population affected in the African region. Other regions were largely subject to a severe lack of data, making it impossible to perform a logistic regression.

9.4.4 Discussion of lag-analysis results

Among the most interesting findings of chapters 5 through 8 were the results of the lag analysis. Taking account of time lags in the effect of a natural disaster on infectious disease numbers is an important consideration, and one done only to a limited extent in previous research on the matter.

The relevance for a time-lagged analysis for the four diseases was described in Section 4.4, and in their respective chapters. Cholera outbreaks may be delayed for up to a year, as was observed in the Haiti earthquake in 2010, where the devastating cholera epidemic struck between several months and a year after the initial earthquake event (Barzilay et al., 2013; Tappero & Tauxe, 2011). Malaria outbreaks are subject to seasonality and breeding grounds, and the changes a natural disaster causes in the environment. Some disasters are more favourable for vector breeding (i.e. hydrological disasters that lead to pools of standing water) than others, and the effect may be delayed by the timing in the vector breeding cycles (Floret et al., 2006; Reiner, Geary, Atkinson, Smith, & Gething, 2015). As has become evident in chapter 7, relapse of tuberculosis was affected by natural disasters more dramatically than new infections. This is considered an effect of natural disasters disturbing health infrastructure and interrupting the intensive treatment course required for tuberculosis, leading to above average numbers of relapse within the first year after the disaster (Gadoev et al., 2015). An effect on HIV numbers may be assumed in circumstances where shelter conditions persist for an extended period of time, as happens for refugees of complex emergencies, but no results were found in chapter 8. The potential reasons for this will be further discussed in section 9.4.5.

Table 9.7 summarises the statistically significant findings of the 1-year lag analysis throughout the 4 chapters.

Table 9.7: Summary results of 1-year lag analysis from chapters 5-8.

	1-year lag, total disasters **(type) tier: OR (95%CI); *P*-value**
Cholera cases	(geophysical) ≥10,000: 4.74 (1.10-20.37); 0.04
	(meteorological) ≥10,000: 3.44 (1.15-10.32); 0.03
	(hydrological) ≥100: 3.35 (1.33-8.43); 0.01
	(hydrological) ≤10,000: 2.75 (1.27-5.97); 0.01
	(climatological) ≥2,500: 17.03 (1.03-282.40); 0.04
Malaria cases	(meteorological) ≥100: 5.22 (1.43-19.00);0.01
	(meteorological) ≥100,000: 2.84 (1.07-7.55); 0.04
	(hydrological) ≥10,000: 0.47 (0.23-0.98); 0.04
Malaria deaths	(total) ≥10,000: 2.01 (1.05-3.85); 0.04
	(hydrological) ≥10,000: 2.43 (1.32-4.48); 0.001
Tuberculosis cases	(meteorological) ≥100,000: 2.44 (1.23-4.87); 0.01
Tuberculosis relapse	(total) ≥100,000: 2.16 (1.15-4.03); 0.02
	(total) ≤10,000: 0.34 (0.12-1.00); 0.05

	(hydrological) ≥100,000: 3.14 (1.59-6.20); 0.001
HIV+TB co-infection	/

The disaster types most commonly associated with an increased odds of above average disease one year after the acute disaster are meteorological disasters and hydrological disasters. The finding for geophysical disasters and cholera cases is likely due to the Haiti earthquake in 2010 and the cholera epidemic that followed it 10 months later. The link with hydrological disasters and cholera as well as malaria is in line with assumptions about flood events affecting these diseases in particular (Linscott, 2007). Of course, the 2004 South-East Asia tsunami may also play a strong role in affecting these figures, even though the dramatic epidemic effect that occurred in Haiti after the 2010 earthquake did not happen to the same extent in the tsunami affected regions.

There are cases of significant results for low magnitude disasters – for cholera cases at the 100-2,499 magnitude tier for hydrological disasters, as well as for climatological disasters in the 2,500-4,999 tier; and for malaria cases as the 100-2,499 tier. This seems counter intuitive, as with previous instances, given that it is more likely for a large scale disaster to affect numbers of infectious diseases. While the result for cholera at the lowest tier has a relatively narrow confidence interval (OR=3.35, 95%CI=1.33-8.43; *P*=0.01), suggesting a level of confidence in the result, the other two have very wide 95% CI's. This suggests the significant results are most likely due to chance. The remaining results of disasters affecting vastly more than 10,000 of the population are consistent with findings of the in-phase analysis throughout the chapters, confirming the hypothesis that disasters affecting a large amount of people also have an effect on infectious disease numbers.

9.4.5 Data availability and noise

Analysis across chapters was subject to limitations of data availability and data noise, the two main problems restricting analysis.

Limits to data availability were an issue discovered throughout the chapters when data was disaggregated, especially by region, leading to small numbers per region per magnitude tier. This reduction in data for analysis by region can be seen in Table 4.4. With numbers as low as 110 country-years for a South-East Asia available for analysis – before breaking it down into magnitude tiers, it is difficult to arrive at any results with a logistic regression, and occasionally this resulted in the inability to run the analysis for certain regions and magnitude tiers altogether. A similar problem manifested when disaggregating the data by disaster type. For this reason, near significant results are of potential relevance to an understanding of the intersection between disasters and disease. More robust results could be achieved with larger quantities of data, shifting the findings into either a clearly significant or clearly insignificant direction. In some instances, examination of wide 95% confidence intervals reveals the limitations of the data, suggesting low confidence in the results. Despite these, the results are far from meaningless, but suggest that further research is necessary to arrive at reliable measures of the association between disasters and infectious diseases.

An additional problem to small numbers for analysis was the issue of data noise. An attempt was made to adjust the analysis for certain factors (mortality of under five year olds, national GDP, access to clean water, access to improved sanitation, and geographic region) that were factors considered relevant for influencing infectious diseases. However, this cannot be considered an exhaustive list of factors that may play a role in the nexus of disaster and disease. Additional factors that were not corrected for in the analyses presented in the previous chapters are considered 'noise'. There are countless possible factors effecting disease numbers – including political, cultural, and social factors that may be impossible to measure reliably – and these noise factors reduce the ability of logistic regression models to reliably predict the odds of above average disease levels after natural disaster.

Some of these noise-factors that lie outside the data available in the analyses of the previous chapters may also be present in the baseline of the national average of disease. In that case, some of them may be accounted for intrinsically in the data, while other noise may occur because of the natural disaster and not be accounted for.

While it can be assumed that a natural disaster becomes a priority factor in affecting health, it is difficult in retrospect to take apart the data and determine exactly which cases of infectious disease were directly linked to the disaster and which were caused by other circumstances that also play into the dynamic after disasters. The nexus of disaster and disease is complex, and even with the greatest care taken, the results of the previous chapters may only scratch the surface of finding the true effect. Some of the elements that affect risk of infectious disease can be discussed, others may not have been quantified yet, and more work will be needed to fill in pieces of the big picture.

9.5 Linkages between infectious diseases

In Chapter 2, risk factors that may affect a population's vulnerability to infectious disease after natural disasters have been identified through the literature. These risk factors, to some extent, affect each disease studied in the previous chapters, at all possible levels from disease prevention to disease detection and treatment. Natural disasters, and the changes they bring in their wake, affect the capability of a population to adequately respond to the challenges a disease poses to the population.

9.5.1 Factors of displacement

It has been shown that the health of a population is not directly affected by natural disasters, but by the conditions that arise in the aftermath thereof (Leaning & Guha-Sapir, 2013). Only a fraction of the cases of infectious disease – mostly wound infections – can directly be linked to injury sustained in the acute disaster (Linscott, 2007; Porter, 2012), whereas other diseases occur with a delay that has been empirically demonstrated in the lag-analyses of the previous chapters. In the aftermath of disasters, displacement, socio-economic factors, and factors related to the geography of the affected area (most of which exist before the disaster even strikes) are what affects the population's health, more so than the direct effects of the disaster (Leaning & Guha-Sapir, 2013).

Factors of population displacement – overcrowding, food shortage, and poor water and sanitation facilities – have been shown in the literature to exacerbate risk of acute respiratory infections and water related diseases such as diarrhoeal diseases and malaria (Linscott, 2007; Kouadio et al. 2012). Therefore it is likely that natural disasters in which displacement occurred will have a greater likelihood of experiencing increases in these diseases. Geophysical disasters, especially earthquakes, are prone to result in internal displacement with the destruction of homes and infrastructure. Geophysical disasters showed a large effect on cholera figures in the present analysis, which is in line with assumptions made about geophysical disasters affecting diarrhoeal diseases (Connolly et al., 2004). Meteorological disasters may have similarly destructive effects – as evidence by events such as Hurricane Katrina or cyclone AILA – and have shown a significant increase in odds of cholera and tuberculosis averages (Chapter 5 and Chapter 7).

Hydrological disasters have been shown to have a strong effect on water related diseases (Linscott, 2007; Schwartz et al., 2006), but the effect shown in the previous chapters was stronger on malaria than on cholera. This is perhaps an unexpected finding, as one would expect diarrhoeal diseases in flood related disasters, where water quality may be most affected. An assumption could be made that hydrological disasters do not lead to severe displacement in the same way geophysical disasters do. In the most general of terms, floods may allow people to return to their homes much quicker than an earthquake or severe storm might. However, living conditions and infrastructure upon returning home may be negatively affected, leading to a decreased ability to cope with a higher incidence of disease – leading to increased malaria deaths (Chapter 6), and to higher numbers of TB relapse after interrupted or unsuccessful initial treatment (Chapter 7).

Disasters that do not result in displacement show little to no evidence of increased disease risk (Watson et al., 2007). These are most often the climatological disasters, the most commonly being droughts – disasters with a slow onset, sometimes stretching over weeks or months, rather than an immediate onset and immediate destruction, like earthquakes or floods.

Malnutrition can occur within a few weeks of inadequate nutritional intake, and is a major risk factor for numerous diseases (Coulter, 1999). Poor nutrition leaves people vulnerable to disease, and reduces the bodies' capability of combatting an infection, increasing risk of death from disease as well (Spiegel, 2005). While it was not strongly featured in the previous chapters, the nutritional status of a population has been shown to be a major issue in complex humanitarian emergencies and populations displaced by such events (Watson et al., 2007). There has been only limited research conducted on the effects of natural disasters on agriculture and food security by extension, which suggests that there are health effects of natural disasters unaccounted for (FAO, 2015). These can be described as data noise, as mentioned in Section 9.4.5, which could not be accounted for in this research.

9.5.2 Socio-economic factors

The socio-economic factors were the easiest to control for in the analysis, as most of the data was available through the Global Health Observatory (WHO, 2016a). Data on vaccination status was left out of this research for now for several reasons. No specific data on cholera vaccination coverage was available in the Global Health Observatory, and the malaria vaccination is relatively new and still undergoing testing in the field. The effectiveness of the BCG vaccine for tuberculosis has been often contested in the past decades, resulting in no policy guidelines for TB vaccination programs, and therefore also no surveillance to that effect (Luca & Mihaescu, 2013). However, it might be that the overall status of vaccination in a population, or the implementation and surveillance of vaccination programs, may be a proxy indication for a functional primary health care infrastructure. However, this was beyond the scope of the present research.

A natural disaster disrupts the health infrastructure of an affected region, altering the ability to respond to an increased influx in patients, and making routine and emergency treatment more difficult. Hospitals may become overwhelmed, the necessary resources may run short, and the transition from emergency care to standard care in an affected region is often problematic (Berggren & Curiel, 2006; Leaning & Guha-Sapir, 2013).

Access to routine health care was a relevant factor for the dynamic of tuberculosis after natural disasters – and to some extent also for the HIV-TB co-infection (Section 4.2). The assumption was made that in the aftermath of a disaster, an increase in tuberculosis relapse would be possible due to collapses in health care infrastructure, leading to already treated patients being unable to complete their DOTS therapy, and therefore experiencing a relapse of disease. Relapse, or recurrence, as defined by the World Health Organization, may occur because of treatment interruption or treatment failure (WHO, 2016a). It was shown in Chapter 7 that, in line with existing research, no increase in tuberculosis cases was recorded in the aftermath of disasters. However, there was a significant change in TB relapse for high magnitude disasters, suggesting higher odds of above average numbers of relapse after natural disasters. This could specifically be observed for hydrological disasters. A striking finding however, as noted in Chapter 7, was that for disasters affecting between 10,000 and 99,999 of the population, there was a narrowly significant result that suggested a decrease in tuberculosis relapse one year after the disasters, whereas at above 100,000 of the population affected, there was a significant increase in relapse in the same time period. It was assumed the negative association could be an anomaly that needs to be further investigated with these new findings in mind. Research of tuberculosis after disasters must more thoroughly look into recurring cases - which carry an increased risk of drug resistance (Gadoev et al., 2015) - an area that has been often neglected thus far. It would be of further relevance to determine numbers of treatment failure specifically, and exiting drug resistance, to determine the effect natural disasters have on these numbers.

Another indicator for health care infrastructure collapses could be observed in the analysis of malaria in Chapter 6. In that case, not so much the new cases, but malaria mortality that showed a significant increase in high magnitude hydrological disasters and to a somewhat lesser extent for total disasters. Vector control has been shown to be functional even in the aftermath of disasters, a well-established measure in endemic areas, that contributes to keeping numbers of new infections in line with the national average (Kumari et al., 2009). An increase in average mortality, without a significant increase in average cases to reflect such a rise, may indicate that the ability of the population to adequately treat patients was affected by the disaster (Berggren & Curiel, 2006).

Access to clean water is a crucial measure to prevent diarrhoeal and water-borne diseases after natural disasters. The standard of water and sanitation quality and financial stability of the country are strong indicators of a population's health and coping ability. They were corrected for in the analyses of Chapters 5 through 8, but it was impossible to assess whether there were collapses in access to clean water and sanitation after disasters. The comparison of the effect of the earthquake and cholera in Haiti and the Dominican Republic illuminates the difference socio-economic stability can make (Tappero & Tauxe, 2011), but there was no means to get enough data on whether or not response measures to insure access to clean water and sanitation were successful, and only in selected publications were assessments of post disaster water quality available (Bhunia & Ghosh, 2011; Gupta et al., 2007).

9.5.3 Geographical factors

The geographical location of the disaster, as well as features in the environment of where the disaster strikes, can adversely affect the coping capacity of populations after natural disasters. It was attempted in the Chapter 5 through

8 to separate results by geographical region. The regions chosen were in accordance with the World Health Organization regions (Figure 4.1). Results were limited by data availability, with significant results occurring in the American region more commonly than in others, as was discussed in Section 9.4.3.

Factors of the physical environment in which natural disasters strike include predominantly vector breeding grounds that affect numbers of malaria and other vector borne diseases, weather and climate conditions, and the vulnerability of a region to natural disasters. For example, coastal regions or regions near rivers are more likely to experience flooding events than landlocked locations; cities located along fault lines such as San Francisco are more likely to experience earthquakes than others. Settling in these regions is part of human culture (Lechat, 1976). And we tend to return to the very regions we have repeatedly seen struck by disaster, to rebuild, instead of resettling in areas less prone to destruction (Steinberg, 2000). Recently, there has been an effort to understand disaster culture, and disaster's effect on culture, as such understanding is necessary to develop effective disaster response and to reduce the risk of disasters (Bankoff, Cannon, Krueger, & Schipper, 2015; IFRC, 2014; Kelman et al., 2015).

The effect of natural disasters on vector breeding grounds has been previously discussed, and differing opinions exist. Some disaster types may negatively affect vector breeding grounds (Floret et al., 2006), while others may facilitate breeding by increasing standing water pools (Krishnamoorthy et al., 2005). But geographical factors also include clean drinking water sources, and how they might be affected by natural disasters – contaminated wells, or river water for instance hold risk of water borne diseases.

With the data available, it was not feasible to make assumptions on geographical factors, other than the breakdown by region. But with the insights into risk factors that may have played into the data noise discussed in Section 9.4.5, and an understanding of the role of individual culture on risk, preparedness, and response to natural disasters, future research may become more sensitive to these factors and add to the understanding of the nexus between disaster and disease.

9.5.4 Drug resistance

An issue that has come up repeatedly while researching the nexus between disaster and disease was the risk of drug resistance. A challenge of the 21st century, drug resistance threatens the re-emergence of diseases that had been considered under control, and may damage efforts to eradicate such diseases as malaria and tuberculosis (Cousins, 2014; WHO, 2014). It has been noted that the large scale, standard vector control measures implemented after natural disasters may lead to increased insecticide resistance among vectors (Weinstein et al., 2010). It is advised to target such concerns now, with increased research into resistance developments, as natural disasters are likely to grow more frequent (Weinstein et al., 2010).

The risk of drug-resistant tuberculosis becomes exacerbated by treatment failure or interruptions, and may hinder efforts of TB control and eradication (Gadoev et al., 2015; WHO, 2015b). Globally, it is assumed that about 3% of TB cases are cases of multi-drug resistant TB (WHO, 2015a). In patients previously treated, that number is as high as 20% (WHO, 2015a). Furthermore, there are countries with epidemic levels of drug resistant TB. Successful treatment and recovery rates for drug resistant TB are below 50% (WHO, 2014b). All of this points towards a need for improved TB control efforts, yet it has remained almost completely neglected as a priority in disaster response (Heymann, 2015). There has been some recent attention on the Syrian refugee crisis and the increases in tuberculosis that have been seen in consequence (Cousins, 2014), but for natural disasters there is no equivalent reaction thus far.

Drug resistant cholera is not explicitly mentioned as a concern in the natural disaster literature thus far. In the severe epidemic after the earthquake in Haiti, a number of instances of resistance were discovered in the epidemic strain (Tappero & Tauxe, 2011).

Given the concerns arising with malaria and the risk of drug-resistant tuberculosis in the context of natural disasters, it might be worth taking a closer look at cholera and other diseases as well. Drug resistance is a primary challenge of infection medicine in this century, where the drugs that have been relied on for the past decades begin to fail and the need arises to find new means of treating such infections (Arias & Murray, 2009; Nolte, 2014). Preventing an increase in drug resistance is a priority for research in this decade.

Chapter 10: Conclusion

Chapter Contents

10.1 Addressing persisting challenges of infectious disease after natural disasters

10.1.1 Introduction

This final chapter aims to summarise the new insights found in this thesis, and provide an outlook on future research to expand on these findings. The association between natural disasters and infectious diseases is a complex network of factors, some can barely be quantified, others have not been identified yet, and their roles in this nexus are based on assumptions. There are claims that no link between natural disasters and infectious diseases exists, but the chapters of this thesis have attempted to show that there is at least some evidence to suggest that the opposite must be acknowledged. Natural disasters may not be the direct cause of disease – it cannot, from the presented evidence, be assumed that a flood itself makes people sick. It is the surrounding circumstances that emerge after a natural disaster which influence the infectious disease risk, filtering the direct effect of a disaster through a lens of infrastructure, access, resources, and culture.

Time is an essential factor in this dynamic. Many of the findings that claimed no link between disaster and disease were taken from the acute disaster phase, investigating the short term effect. In this phase, the most direct consequences of natural disasters are wounds from blunt force trauma, and the related risk of wound infections. It takes weeks, sometimes months, for other infectious diseases to appear in surveillance systems. This thesis, by including a time lag in the analysis, has attempted to show that there is valid reason to keep observing diseases for a longer period after natural disasters, as the true effects will not appear within the first few weeks or even months of the disaster.

At the outset of this thesis, the striking observation was that issues with natural disaster response have persisted for nearly half a century (Leaning; Lechat; etc). Our capabilities for research have grown, disease surveillance is more efficient than ever before in this century thanks to modern technology, with the possibility to have near real-time records of disease cases available. Of course, after a natural disaster there is a level of chaos that has to be considered, but the issues are known, and still they persist. This thesis reiterates these issues, especially that of the transition between emergency care to routine care and the capacity of the affected population to cope with the situation once the humanitarian aid has departed the area (Leaning & Guha-Sapir, 2013). This feeds back into the results of the lag analysis, suggesting the main burden of disease after disasters may only manifest several months after the disaster itself. Capacity building in order to improve the affected populations' ability to step in when relief organizations leave needs to be prioritised to be able to cope with delayed surges of infectious disease.

10.1.2 Insights from the present research

The present research has allowed new insights into the nexus of natural disasters and infectious diseases, and has provided some potential new approaches to target the challenges summarised in the previous section.

In reviewing the existing literature on this subject (Chapters 2 and 3), it was discovered that research on infectious diseases after natural disasters is irregular and unstandardized, with publications from various scientific disciplines (such as microbiology, epidemiology, general medicine) and differences in the information they provide. This was shown to make comparison difficult, if not impossible, and thus complicates the use of the existing data to inform future actions in disease and disaster management. In Chapter 3, PICO (Patient-Intervention-Confounders-Outcome) was used as a tool to identify studies for systematic, quantitative analysis, but this tool can and should be taken a step further. It can be argued that PICO (or a variation thereof) can be used as a guideline to standardise the reporting format of research on this subject. By standardizing the way results are presented, and the type of data that should be reported (in the abstract) as a minimum requirement, future identification and pooling of relevant data will be facilitated. By providing clear guidelines on what information will be relevant for the later pooling of data, researchers – even from different disciplines – will be able to integrate data from previous research to reach informed conclusions. This is not intended to limit what results should be reported, but rather to provide a minimum standard. How many cases of disease were recorded? How large was the total population from which this sample of patients was taken? What is the baseline prevalence of the disease in the population unaffected by disaster? This may seem like a straight forward, simple method, but it would significantly facilitate future efforts to pool data on infectious diseases after natural disasters and thus help improve preparedness and response efforts.

Chapters 5–8 investigated four different disease profiles that were previously identified in the literature review (Chapter 2). It became apparent that not every disease is a significant issue after every type of disaster (Linscott, 2007). It should therefore be possible to prepare for certain types of diseases that are more likely to become a problem after one type of disaster than after other types. Data was disaggregated by disaster type for that purpose, and the results can inform future response efforts. It was shown that after geophysical disasters, cholera was more frequent than other diseases. After meteorological disasters – particularly interesting in light of recent events such as Hurricanes Harvey, Irma and Maria in September 2017 – cholera and tuberculosis saw significant increases. And after hydrological disasters, malaria and tuberculosis were more frequent.

The results presented in this thesis are by no means exhaustive, but with information like this – and future research into the dynamics of disaster and disease – responses to disasters can be improved and disease control measures can be tailored to the type of disaster.

10.2 Drug Resistance: the challenge of disease control in the 21st century

Drug resistance has emerged as a major issue in efforts to eradicate diseases, and many measures shown as routine for natural disaster response may increase the threat of antimicrobial resistance. Especially striking were the findings on the role of tuberculosis in natural disasters, a disease that is given no priority in current disaster response guidelines (Heymann, 2015) while diseases such as HIV receive attention despite a lack of evidence for their role after disasters (Wilson, 2008).

The role of drug resistance in diseases after natural disasters must be more thoroughly examined. It could lead to complications for affected patients, as well as eventually becoming an issue for the entire population, as resistant strains of bacteria or resistant vectors become more widespread. Failed tuberculosis treatment and tuberculosis recurrence are risk factors for drug resistant TB (Gadoev et al., 2015; WHO, 2014b). The ongoing refugee crisis has seen a sharp increase in new tuberculosis infections, and the disease is on the rise. Tuberculosis is prone to developing drug resistance and could grow into a more serious problem in the future, not only within refugee situations. The current standard practices for vector control have also been linked to potential increases in insecticide resistant malaria vectors (Londono et al., 2009; Weinstein et al., 2010).

10.3 Future research direction

Guided by the findings of this research, future directions of research into the dynamic of natural disasters and infectious diseases can be identified. It has become obvious in Chapters 5–8, that there are complex interactions at work in the nexus of disaster and disease. A number of influencing factors have been identified through the literature reviews and analysis. Still, it has become evident especially in Chapter 8 on HIV and TB co-infection that stronger efforts will have to be made to control for surrounding data noise. As data of the surrounding conditions is difficult to come by when using third party sources instead of real time data, the most reasonable next step for this research will be collecting data from surveillance systems in real time. This can, of course, not be done at the same large scale as this research. Instead of using data from the national level, it would make more sense to use data from specific locations struck by a disaster. This will help reduce the effect of the ecological fallacy and make a more accurate statement on the effect of a disaster on the specifically affected location. The main drawback with this is the availability of baseline surveillance data that would have to be collected for specific locations as well, and access would therefore be needed to raw surveillance data where it is available. The implementation of reliable disease surveillance systems is therefore a priority. With modern technology, the WHO has already established highly useful tools for disease surveillance in numerous countries across their regions, and if disease data is to be effectively used to create predictive models of disease after disasters, such systems will need to be in place in as many countries as possible.

An ambitious but useful tool would be an ongoing database, mapping in real time the occurrence of natural disasters and new cases of certain infections – similar to what EM-DAT is already doing with disasters, but with the inclusion of infectious diseases. Such a tool would not only facilitate future research on the subject, but also – once enough data is gathered – allow for better modelling and informed disaster relief efforts and disease response. Using real time data would allow for more reliable modelling in the future.

Studying specifically insecticide resistant malaria vectors and drug resistant tuberculosis would be another feasible next direction to take. It has become evident in the literature that drug resistance is a major health concern. This has been primarily studied for drug resistant bacteria in infected wounds (Hiransuthikul et al., 2005; Uckay et al., 2008), but the issue will only get bigger if it is not targeted.

10.4 Concluding remarks

The challenges faced in disaster response found by this research are not new. However, the evidence of this research challenges the existing notion which dismisses the role of infectious diseases after natural disasters. By bringing these issues to the forefront, there may be potential to change the way disaster response approaches the management of infectious diseases, so that preparedness for the consequences of natural disasters may be improved. Disaster culture, and an increased frequency and magnitude of natural disasters due to climate change, will strongly determine future directions of research. The role of infectious diseases in this dynamic must be better understood in the future, through a combination of improved disease surveillance and systematic research. Now more than ever will societies need to be adequately prepared for disasters and their consequences.

Appendix

Appendix 1: Number of PubMed results per search term.

Natural disaster	***number of articles***
AND communicable diseases	284
AND infectious diseases	558
AND cholera	81
AND E.coli	53
AND shigellosis	6
AND leptospirosis	32
AND pneumonia	244
AND tuberculosis	92
AND acute respiratory infection	243
AND tetanus	46
AND wound infection	218
AND malaria	110
AND dengue	22
AND rabies	9

Appendix 2: Specific disasters mentioned in publications.

disaster specifics	# of publications
Cyclone in Odisha 1999	1
Cyclone Aila 2009	3
Cyclone Nargis	1
Flood in Sri Lanka 2011	1
flooding 1996	1
Flooding in Oahu 2006	1
Great East Japan Earthquake 2011	5
Haiti Earthquake 2010	8
Hurricane Georges 1998	1
Hurricane Hortense 1996	1
Hurricane Jeanne 2004	1
Hurricane Katrina 2005	2
Italy Earthquake 1980	1
Joplin Tornado 2011	1
Kashmir Earthquake 2005	3
Kocaeli Earthquake 1999	1
L'Aquila Earthquake 2009	1
Marmara Earthquake 1999	2
mild winter Sweden 2007	1
Mozambique flood 2000	2
Nimes Floods 1988	1
Pakistan Flood 2010	1
Philippines Typhoon 2009	1
Sichuan Earthquake 2008	4
Solomon Islands Earthquake 2007	1
Solomon Islands Tsunami 2013	1
Tsunami 2004	6
Typhoon Haitang 2005	1
Yogykarta Earthquake 2006	1

Appendix 3: Frequency of publications by country.

WHO region/country		**# of mentions**
Africa		*2*
	Mozambique	1
	Mozambique	1
Americas		*16*
	Brazil	1
	Haiti	9
	Puerto Rico	2
	United States (Hawaii)	1
	United States (Louisiana)	2
	United States (Missouri)	1
Eastern Mediterranean		*3*
	Pakistan	3
Europe		*7*
	France	1
	Italy	2
	Sweden	1
	Turkey	3
South-East Asia		*15*
	India	7
	Indonesia	2
	Myanmar	1
	Philippines	1
	Sri Lanka	2
	Thailand	2
Western Pacific		*12*
	China	4
	Japan	5
	Solomon Islands	2
	Taiwan	1

Appendix 4: 194 countries included in analysis of chapters 5-8. *countries excluded from malaria analysis.

Afghanistan	Bhutan	Comoros	Estonia *	Iceland *	Lesotho *
Albania	Bolivia	Congo	Ethiopia	India	Liberia
Algeria *	Bosnia and Herzegovina *	Cook Islands *	Fiji *	Indonesia	Libya *
Andorra *	Botswana	Costa Rica	Finland *	Iran (Islamic Republic of)	Lithuania *
Angola	Brazil	Croatia *	France *	Iraq	Luxembourg *
Antigua and Barbuda *	Brunei Darussalam *	Cuba *	Gabon	Ireland *	Madagascar
Argentina *	Bulgaria *	Cyprus *	Gambia	Israel *	Malawi
Armenia	Burkina Faso	Czech Republic *	Georgia	Italy *	Malaysia
Australia *	Burundi	Democratic People's Republic of Korea	Germany *	Jamaica	Maldives *
Austria *	Côte d'Ivoire	Democratic Republic of the Congo	Ghana	Japan *	Mali
Azerbaijan	Cabo Verde	Denmark *	Greece *	Jordan *	Malta *
Bahamas	Cambodia	Djibouti	Grenada *	Kazakhstan *	Marshall Islands *
Bahrain	Cameroon	Dominica *	Guatemala	Kenya	Mauritania
Bangladesh	Canada *	Dominican Republic	Guinea	Kiribati *	Mauritius *
Barbados *	Central African Republic	Ecuador	Guinea-Bissau	Kuwait *	Mexico
Belarus *	Chad	Egypt	Guyana	Kyrgyszstan	Micronesia (Federated States of) *
Belgium *	Chile *	El Salvador	Haiti	Lao People's Democratic Republic	Monaco *
Belize	China	Equatorial Guinea	Honduras	Latvia *	Mongolia *
Benin	Colombia	Eritrea	Hungary *	Lebanon *	Montenegro *

Appendix 4 (cont.): 194 countries included in analysis of chapters 5-8. *countries excluded from malaria analysis.

Morocco	Russian Federation	Syrian Arab Republic
Mozambique	Rwanda	Tajikistan
Myanmar	Saint Kitts and Nevis *	Thailand
Namibia	Saint Lucia *	Macedonia *
Nauru *	Saint Vincent and the Grenadines *	Timor Leste
Nepal	Samoa *	Togo
Netherlands *	San Marino *	Tonga *
New Zealand *	Sao Tome and Principe	Trinidad and Tobago *
Nicaragua	Saudi Arabia	Tunisia *
Niger	Senegal	Turkey
Nigeria	Serbia *	Turkmenistan
Niue *	Seychelles *	Tuvalu *
Norway *	Sierra Leone	Uganda
Oman	Singapore *	Ukraine *
Pakistan	Slovakia *	United Arab Emirates *
Palau *	Slovenia *	United Kingdom*
Panama	Solomon Islands	United Republic of Tanzania
Papua New Guinea	Somalia	United States of America *
Paraguay	South Africa	Uruguay *
Peru	South Sudan	Uzbekistan
Philippines	Spain *	Vanuatu
Poland *	Sri Lanka	Venezuela
Portugal *	Sudan	Viet Nam
Qatar *	Suriname	Yemen
Republic of Korea	Swaziland	Zambia
Republic of Moldova *	Sweden *	Zimbabwe
Romania *	Switzerland *	

Appendix 5: Results of Regional binary regression of total disasters and average cholera cases.

	Global			Africa		
6-tier analysis	**OR**	**95% CI**	***P*-value**	**OR**	**95% CI**	***P*-value**
≥100	1.32	0.51-3.40	0.57	3.14	0.7-14.15	1.34
≥2,500	1.31	0.41-4.11	0.65	0.34	0.04-3.09	0.34
≥5,000	0.62	0.08-4.91	0.61	1.2	0.12-12.28	0.88
≥7,500	4.64	1.26-17.01	0.02	4.89	0.4-59.61	0.21
≥ 10,000	1.05	0.49-2.25	0.90	0.39	0.1-1.54	0.18
≥ 100,000	1.89	1.01-3,55	0.05	0.85	0.32-2.3	0.75
3-tier analysis						
≤ 10,000	1.48	0.75-2.92	0.26	1.49	0.52-4.26	0.46
10,000-100,000	1.05	0.49-2.24	0.91	0.39	0.10-1.55	0.18
≥ 100,000	1.88	1.0-3.52	0.05	0.86	0.32-2.32	0.77
	Americas			**Europe**		
6-tier analysis	**OR**	**95% CI**	***P*-value**	**OR**	**95% CI**	***P*-value**
≥100	3.63	0.41-31.99	0.25	/	/	/
≥2,500	4.8	0.29-78.51	0.27	10.68	0.67-170.91	0.94
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	2.23	0.31-15.84	0.42	22.68	0.83-622.41	0.07
≥ 100,000	7.81	1.31-46.7	0.02	/	/	/
3-tier analysis						
≤ 10,000	2.87	0.41-19.99	0.29	2.19	0.15-31.49	0.56
10,000-100,000	2.2	0.31-15.67	0.43	24.79	0.91-674.92	0.06
≥ 100,000	7.97	1.32-48.27	0.02	/	/	/
	Eastern Mediterranean			**Western Pacific**		
6-tier analysis	**OR**	**95% CI**	***P*-value**	**OR**	**95% CI**	***P*-value**
≥100	/	/	/	/	/	/
≥2,500	/	/	/	1.26	0.11-13.85	0.85
≥5,000	/	/	/	/	/	/
≥7,500	24.01	0.84-689.79	0.06	/	/	/
≥ 10,000	2.47	0.07-83.62	0.61	0.29	0.02-3.50	0.33
≥ 100,000	1.64	0.07-39.23	0.76	0.85	0.17-4.25	0.85
3-tier analysis						
≤ 10,000	2.27	0.17-30.96	0.54	0.56	0.06-5.48	0.62
10,000-100,000	3.44	0.14-85.62	0.45	0.28	0.02-3.47	0.32
≥ 100,000	2.02	0.10-41.16	0.65	0.86	0.17-4.31	0.85

Appendix 6: Results of regional binary regression of disasters and average malaria cases.

	Africa	Americas
	OR (CI); p	OR (CI); p
General 6-tier analysis		
≥100	0.61 (0.12-3.20); 0.56	4.82 (0.63-37.16); 0.13
≥2,500	0.28 (0.03-2.33); 0.24	5.43 (0.66-44.83); 0.12
≥5,000	0.60 (0.06-5.79); 0.66	/
≥7,500	6.50 (0.54-78.67); 0.14	/
≥ 10,000	1.13 (0.42-3.06); 0.82	2.77 (0.63-12.19); 0.18
≥ 100,000	2.70 (1.17-6.22); 0.02	1.28 (0.27-6.00); 0.76
General 3-tier analysis		
≤ 10,000	0.68 (0.24-1.95); 0.47	4.58 (0.95-22.24); 0.06
10,000-100,000	1.12 (0.41-3.02); 0.83	2.73 (0.63-11.90); 0.18
≥ 100,000	2.63 (1.15-6.04); 0.02	1.23 (0.26-5.75); 0.79
	South-East Asia	**Europe**
General 6-tier analysis		
≥100	/	4.15 (0.11-159.83); 0.45
≥2,500	/	240.53 (0.03-1944813.93); 0.23
≥5,000	/	/
≥7,500	/	/
≥ 10,000	50.82 (0.85-3025.30); 0.06	8.43 (0.36-197.78); 0.19
≥ 100,000	19.53 (0.42-903.99); 0.13	29.76 (1.25-708.90); 0.04
General 3-tier analysis		
≤ 10,000	28.31 (0.19-4216.56); 0.19	3.52 (0.24-51.98); 0.36
10,000-100,000	52.11 (0.86-3173.78); 0.06	8.90 (0.36-221.78); 0.18
≥ 100,000	20.14 (0.42-956.48); 0.13	33.11 (1.31-840.12); 0.03
	Eastern Mediterranean	**Western Pacific**
General 6-tier analysis		
≥100	/	/
≥2,500	/	/
≥5,000	/	1.29 (0.05-31.50); 0.88
≥7,500	4.93 (0.22-111.61); 0.32	/
≥ 10,000	1.39 (0.09-21.63); 0.82	/
≥ 100,000	7.91 (0.50-124.59); 0.14	1.22 (0.18-8.36); 0.84
General 3-tier analysis		
≤ 10,000	0.66 (0.06-7.86); 0.74	0.98 (0.10-9.31); 0.99
10,000-100,000	1.39 (0.09-20.97); 0.81	/
≥ 100,000	7.06 (0.49-101.43); 0.15	0.92 (0.16-5.17); 0.92

Appendix 6 (cont.): Results of regional binary regression of disasters and average malaria cases.

	Africa	Americas
	OR (CI); p	**OR (CI); p**
Geophysical 6-tier analysis		
≥100	/	0.56 (0.04-8.25); 0.67
≥2,500	/	0.74 (0.06-9.71); 0.82
≥5,000	/	/
≥7,500	/	/
≥ 10,000	/	3.31 (0.20-53.55); 0.40
≥ 100,000	/	1.17 (0.06-21.45); 0.92
Geophysical 3-tier analysis		
≤ 10,000	0.53 (0.06-4.97); 0.57	0.98 (0.18-5.34); 0.98
10,000-100,000	/	3.46 (0.21-56.04); 0.38
≥ 100,000	/	1.11 (0.06-20.09); 0.95
	South-East Asia	**Europe**
Geophysical 6-tier analysis		
≥100	/	/
≥2,500	/	/
≥5,000	/	/
≥7,500	/	/
≥ 10,000	/	/
≥ 100,000	8.82 (0.60-130.39); 0.11	/
Geophysical 3-tier analysis		
≤ 10,000	/	269.16 (0.06-1214857.39); 0.19
10,000-100,000	/	/
≥ 100,000	8.82 (0.60-130-39); 0.11	/
	Eastern Mediterranean	**Western Pacific**
Geophysical 6-tier analysis		
≥100	0.97 (0.08-12.41); 0.98	/
≥2,500	/	/
≥5,000	/	1.40 (0.07-27.04); 0.83
≥7,500	/	/
≥ 10,000	/	/
≥ 100,000	2.08 (0.10-44.50); 0.64	0.43 (0.04-5.06); 0.50
Geophysical 3-tier analysis		
≤ 10,000	0.68 (0.06-7.39); 0.75	0.63 (0.05-8.58); 0.73
10,000-100,000	/	/
≥ 100,000	2.13 (0.09-46.08); 0.63	0.46 (0.04-5.37); 0.53

Appendix 6 (cont.): Results of regional binary regression of disasters and average malaria cases.

	Africa	Americas
	OR (CI); p	**OR (CI); p**
Meteorological 6-tier analysis		
≥100	0.41 (0.05-3.71); 0.43	547.62 (0.07-4269869.62); 0.17
≥2,500	/	0.79 (0.06-9.94); 0.86
≥5,000	1.96 (0.11-34.40); 0.64	/
≥7,500	/	/
≥ 10,000	/	2.56 (0.62-10.60); 0.20
≥ 100,000	7.26 (0.70-75.43); 0.10	1.64 (0.26-10.46); 0.60
Meteorological 3-tier analysis		
≤ 10,000	0.47 (0.10-2.31); 0.35	6.19 (1.05-36.35); 0.04
10,000-100,000	/	2.51 (0.62-10.20); 0.20
≥ 100,000	7.53 (0.72-78.20); 0.09	1.64 (0.27-10.13); 0.60
	South-East Asia	**Europe**
Meteorological 6-tier analysis		
≥100	/	/
≥2,500	/	/
≥5,000	/	/
≥7,500	/	/
≥ 10,000	3.86 (0.57-26.06); 0.17	/
≥ 100,000	2.87 (0.31-26.46); 0.35	/
Meteorological 3-tier analysis		
≤ 10,000	/	446.15 (0.48-413656.84); 0.08
10,000-100,000	3.86 (0.57-26.06); 0.17	/
≥ 100,000	2.87 (0.31-26.46); 0.35	/
	Eastern Mediterranean	**Western Pacific**
Meteorological 6-tier analysis		
≥100	/	1.61 (0.07-36.37); 0.77
≥2,500	/	/
≥5,000	/	/
≥7,500	5.01 (0.25-101.30);0.29	/
≥ 10,000	/	2.07 (0.09-49.82); 0.66
≥ 100,000	/	0.17 (0.01-2.50); 0.20
Meteorological 3-tier analysis		
≤ 10,000	4.31 (0.54-34.38);0.17	1.61 (0.07-36.37); 0.77
10,000-100,000	/	2.07 (0.09-49.82); 0.66
≥ 100,000	/	0.17 (0.01-2.50); 0.20

Appendix 6 (cont.): Results of regional binary regression of disasters and average malaria cases.

	Africa	Americas
	OR (CI); p	**OR (CI); p**
Hydrological 6-tier analysis		
≥100	1.09 (0.33-3.58); 0.89	3.69 (0.54-25.08); 0.18
≥2,500	/	4.31 (0.35-52.64); 0.25
≥5,000	0.49 (0.05-4.68); 0.54	2.21 (0.29-16.65); 0.44
≥7,500	8.67 (0.83-90.17); 0.07	/
≥ 10,000	1.07 (0.44-2.63); 0.88	1.09 (0.30-4.01); 0.89
≥ 100,000	2.39 (0.88-6.48); 0.09	0.78 (0.11-5.63); 0.81
Hydrological 3-tier analysis		
≤ 10,000	1.02 (0.40-2.57); 0.97	2.91 (0.77-10.97); 0.12
10,000-100,000	1.07 (0.44 (2.62); 0.89	1.15 (0.31-4.24); 0.84
≥ 100,000	2.30 (0.85-6.21); 0.10	0.82 (0.11-6.06); 0.85
	South-East Asia	**Europe**
Hydrological 6-tier analysis		
≥100	/	6.28 (0.23-173.96); 0.28
≥2,500	/	25.88 (0.06-12138.86); 0.30
≥5,000	/	/
≥7,500	/	/
≥ 10,000	57.64 (1.52-2186.77); 0.03	0.68 (0.02-22.06); 0.83
≥ 100,000	7.77 (0.21-291.80); 0.27	/
Hydrological 3-tier analysis		
≤ 10,000	14.97 (0.14-1629.55); 0.26	1.13 (0.16-7.90); 0.90
10,000-100,000	58.32 (1.51-2259.31); 0.03	0.54 (0.02-16.63); 0.72
≥ 100,000	8.07 (0.21-311.95); 0.26	/
	Eastern Mediterranean	**Western Pacific**
Hydrological 6-tier analysis		
≥100	1.99 (0.15-27.50); 0.61	/
≥2,500	4.75 (0.21-108.69); 0.33	/
≥5,000	/	/
≥7,500	/	/
≥ 10,000	6.25 (0.21-186.97); 0.29	/
≥ 100,000	61.49 (1.08-3506.26); 0.05	2.80 (0.42-18.80); 0.29
Hydrological 3-tier analysis		
≤ 10,000	2.77 (0.33-23.22); 0.35	1.07 (0.07-16.35); 0.96
10,000-100,000	7.14 (0.24-212.25); 0.26	/
≥ 100,000	71.85 (1.22-4230.33); 0.04	1.66 (0.31-8.82); 0.55

Appendix 6 (cont.): Results of regional binary regression of disasters and average malaria cases.

	Africa	Americas
	OR (CI); p	**OR (CI); p**
Climatological 6-tier analysis		
≥100	/	0.55 (0.04-7.40); 0.65
≥2,500	/	/
≥5,000	/	/
≥7,500	/	/
≥ 10,000	/	0.47 (0.03-6.69); 0.58
≥ 100,000	1.20 (0.43-3.31); 0.73	/
Hydrological 3-tier analysis		
≤ 10,000	/	1.19 (0.14-9.96); 0.88
10,000-100,000	/	0.41 (0.03-5.50); 0.50
≥ 100,000	1.20 (0.43-3.31); 0.73	/
	South-East Asia	**Europe**
Climatological 6-tier analysis		
≥100	/	/
≥2,500	/	/
≥5,000	/	/
≥7,500	/	/
≥ 10,000	/	/
≥ 100,000	1.19 (0.08-18.37); 0.90	/
Climatological 3-tier analysis		
≤ 10,000	/	/
10,000-100,000	/	/
≥ 100,000	1.19 (0.08-18.37); 0.90	/
	Eastern Mediterranean	**Western Pacific**
Climatological 6-tier analysis		
≥100	/	/
≥2,500	/	/
≥5,000	/	/
≥7,500	/	/
≥ 10,000	/	/
≥ 100,000	/	0.34 (0.03-3.46); 0.36
Climatological 3-tier analysis		
≤ 10,000	/	/
10,000-100,000	/	/
≥ 100,000	/	0.34 (0.03-3.46); 0.36

Appendix 7: 1-year lag analysis for malaria cases and disaster types, compared to in-phase analysis.

	malaria cases in phase			malaria cases 1-year lag		
Total affected	*odds ratio*	*95% CI*	*P-value*	odds ratio	95% CI	P-value
6-tier analysis						
≥100	*1.31*	*0.53-3.28*	*0.56*	1.03	0.28-3.73	0.97
≥2,500	*1.19*	*0.45-3.17*	*0.73*	1.13	0.36-3.57	0.84
≥5,000	*1.06*	*0.25-4.46*	*0.94*	3.66	0.73-18.20	0.11
≥7,500	*1.05*	*0.29-3.77*	*0.94*	0.53	0.10-2.75	0.45
≥ 10,000	*1.29*	*0.69-2.43*	*0.42*	0.60	0.27-1.34	0.21
≥ 100,000	*1.80*	*1.05-3.09*	*0.03*	1.1	0.58-2.07	0.78
3-tier analysis						
≤10,000	*1.19*	*0.63-2.25*	*0.60*	1.16	0.53-2.50	0.72
10,000-100,000	*1.30*	*0.70-2.43*	*0.42*	0.61	0.28-1.35	0.22
≥ 100,000	*1.80*	*1.05-3.09*	*0.03*	1.1	0.59-2.08	0.76
Geophysical disaster						
6-tier analysis						
≥100	*0.80*	*0.24-2.68*	*0.71*	0.57	0.11-2.89	0.50
≥2,500	*0.69*	*0.13-3.56*	*0.65*	1.30	0.23-7.29	0.77
≥5,000	*5.34*	*0.57-50.01*	*0.14*	/	/	/
≥7,500	*0.76*	*0.07-8.64*	*0.83*	0.84	0.07-9.93	0.89
≥ 10,000	*0.85*	*0.21-3.48*	*0.82*	/	/	/
≥ 100,000	*1.24*	*0.41-3.79*	*0.71*	0.87	0.22-3.37	0.84
3-tier analysis						
≤10,000	*1.05*	*0.47-2.35*	*0.90*	0.82	0.42-2.97	0.82
10,000-100,000	*0.85*	*0.21-3.51*	*0.82*	/	/	/
≥ 100,000	*1.25*	*0.41-3.82*	*0.70*	0.86	0.22-3.35	0.83
Meteorological disaster						
6-tier analysis						
≥100	*2.43*	*0.92-6.41*	*0.07*	5.22	1.43 - 19.00	0.01
≥2,500	*0.88*	*0.16-4.81*	*0.88*	0.76	0.08-6.82	0.81
≥5,000	*2.14*	*0.28-16.53*	*0.46*	/	/	/
≥7,500	*0.66*	*0.06-7.08*	*0.73*	/	/	/
≥ 10,000	*1.95*	*0.85-4.46*	*0.12*	2.09	0.80-5.51	0.13
≥ 100,000	*1.00*	*0.42-2.38*	*1.00*	2.84	1.07-7.55	0.04
3-tier analysis						
≤10,000	*1.70*	*0.80-3.64*	*0.17*	1.55	0.59-4.10	0.37
10,000-100,000	*1.95*	*0.85-4.46*	*0.12*	2.07	0.79-5.44	0.14
≥ 100,000	*1.01*	*0.42-2.40*	*1.00*	2.86	1.08-7.57	0.03

Appendix 7(cont.): 1-year lag analysis for malaria cases and disaster types, compared to in-phase analysis.

	malaria cases in phase			malaria cases 1-year lag		
Hydrological disaster	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	1.61	0.74-3.47	0.23	0.59	0.19-1.80	0.35
≥2,500	1.34	0.42-4.32	0.62	1.29	0.35-4.78	0.71
≥5,000	1.03	0.29-3.63	0.97	0.70	0.11-3.22	0.55
≥7,500	1.13	0.31-4.13	0.85	0.43	0.09-2.23	0.32
≥ 10,000	1.02	0.58-1.93	0.86	0.47	0.23-0.97	0.04
≥ 100,000	1.46	0.81-2.65	0.21	0.94	0.46-1.90	0.86
3-tier analysis						
≤10,000	1.36	0.76-2.35	0.30	0.68	0.32-1.45	0.32
10,000-100,000	1.06	0.58-1.93	0.86	0.47	0.23-0.98	0.04
≥ 100,000	1.47	0.81-2.65	0.21	0.94	0.47-1.90	0.87
Climatological disaster						
6-tier analysis						
≥100	1.13	0.19-6.60	0.89	/	/	/
≥2,500	/	/	/	/	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	0.36	0.04-3.45	0.38	/	/	/
≥ 100,000	0.83	0.40-1.69	0.60	0.54	0.22-1.33	0.18
3-tier analysis						
≤10,000	1.37	0.30-6.15	0.68	0.97	0.10-9.62	0.98
10,000-100,000	0.37	0.04-3.45	0.38	/	/	/
≥ 100,000	0.82	0.40-1.69	0.60	0.53	0.22-1.32	0.17

Appendix 8: 1-year lag analysis for malaria death and disaster types, compared to in-phase analysis.

	malaria deaths in-phase			malaria deaths 1-year lag		
Total affected	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	1.05	0.37-2.95	0.93	0.55	0.15-1.98	0.36
≥2,500	1.68	0.61-4.65	0.32	1.10	0.37-3.27	0.85
≥5,000	1.47	0.33-6.49	0.62	0.98	0.19-4.96	0.98
≥7,500	2.57	0.71-9.28	0.15	1.37	0.34-5.62	0.66
≥ 10,000	2.22	1.15-4.31	0.02	2.01	1.05-3.85	0.04
≥ 100,000	1.58	0.88-2.83	0.13	1.03	0.55-1.91	0.93
3-tier analysis						
≤10,000	1.51	0.77-3.00	0.23	0.91	0.44-1.91	0.81
10,000-100,000	2.21	1.14-4.29	0.02	2.00	1.05-3.84	0.04
≥ 100,000	1.57	0.88-2.82	0.13	1.02	0.55-1.91	0.94
Geophysical disaster						
6-tier analysis						
≥100	0.82	0.24-2.80	0.75	1.39	0.41-4.73	0.60
≥2,500	/	/	/	0.64	0.08-5.44	0.69
≥5,000	5.33	0.55-42.04	0.15	0.69	0.07-6.60	0.74
≥7,500	/	/	/	1.82	0.15-22.00	0.64
≥ 10,000	0.79	0.15-4.26	0.78	0.43	0.05-3.50	0.43
≥ 100,000	0.84	0.25-2.84	0.78	0.83	0.22-3.09	0.78
3-tier analysis						
≤10,000	0.74	0.31-1.83	0.53	1.09	0.44-2.70	0.86
10,000-100,000	0.81	0.15-4.39	0.80	0.43	0.05-3.53	0.43
≥ 100,000	0.84	0.25-2.85	0.78	0.83	0.22-3.10	0.78
Meteorological disaster						
6-tier analysis						
≥100	1.49	0.49-4.56	0.47	1.36	0.46-4.01	0.57
≥2,500	2.51	0.51-12.26	0.26	2.48	0.53-11.57	0.25
≥5,000	0.97	0.08-11.20	0.98	1.05	0.10-11.21	0.97
≥7,500	0.88	0.07-11.53	0.92	1.14	0.12-11.90	0.91
≥ 10,000	1.43	0.59-3.47	0.44	0.59	0.19-1.79	0.35
≥ 100,000	1.31	0.53-3.22	0.56	0.38	0.11-1.34	0.13
3-tier analysis						
≤10,000	1.52	0.65-3.54	0.33	1.49	0.66-3.36	0.33
10,000-100,000	1.43	0.59-3.46	0.44	0.59	0.19-1.79	0.35
≥ 100,000	1.31	0.53-3.23	0.56	0.38	0.11-1.34	0.13

Appendix 8 (cont.): 1-year lag analysis for malaria death and disaster types, compared to in-phase analysis.

	malaria deaths in-phase			malaria deaths 1-year lag		
Hydrological disaster	**odds ratio**	**95% CI**	***P*-value**	**odds ratio**	**95% CI**	***P*-value**
6-tier analysis						
≥100	2.03	0.89-4.63	0.09	0.82	0.29-2.29	0.70
≥2,500	3.72	1.15-12.01	0.03	1.46	0.38-5.64	0.58
≥5,000	1.72	0.48-6.17	0.40	1.61	0.40-6.42	0.50
≥7,500	3.13	0.82-11.99	0.10	2.59	0.69-9.69	0.16
≥ 10,000	1.68	0.89-3.15	0.11	2.43	1.32-4.49	0.001
≥ 100,000	2.01	1.07-3.77	0.03	1.20	0.60-2.40	0.61
3-tier analysis						
≤10,000	2.37	1.27-4.43	0.01	1.29	0.65-2.59	0.47
10,000-100,000	1.68	0.89-3.15	0.11	2.43	1.32-2.48	0.001
≥ 100,000	2.00	1.07-3.77	0.03	1.20	0.60-2.40	0.61
Climatological disaster						
6-tier analysis						
≥100	0.86	0.09-8.19	0.90	0.82	0.09-7.25	0.86
≥2,500	/	/	/	/	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	1.22	0.17-8.59	0.85	0.70	0.08-6.47	0.75
≥ 100,000	0.90	0.43-1.88	0.79	1.08	0.50-2.35	0.84
3-tier analysis						
≤10,000	0.54	0.06-4.80	0.58	1.25	0.24-6.50	0.79
10,000-100,000	1.22	0.17-8.59	0.84	0.7	0.08-6.49	0.75
≥ 100,000	0.90	0.43-1.88	0.79	1.08	0.50-2.34	0.85

Appendix 9: Regional results of logistic regression by disaster type, for total tuberculosis cases between 2000 and 2013.

	Africa	**Americas**	**South-East Asia**	**Europe**	**Eastern Mediterranean**	**Western Pacific**
Geophysical disasters 6-tier	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***
≥100	0.79 (0.07-9.22); 0.85	1.14 (0.09-14.09); 0.92	0.58 (0.02-19.92); 0.76	/	0.87 (0.08-9.60); 0.91	/
≥2,500	/	1.22 (0.10-14.40); 0.88	/	0.84 (0.08-9.35); 0.89	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	0.46 (0.02-9.09); 0.61	2.40 (0.31-18.75); 0.41	/	0.66 (0.07-6.51); 0.73	/	0.43 (0.04-4.46); 0.48
≥ 100,000	/	0.78 (0.14-4.48); 0.78	0.46 (0.04-5.71); 0.55	/	/	/
Geophysical disasters 3-tier						
≤ 10,000	1.14 (0.18-7.33); 0.89	0.93 (0.17-5.15); 0.93	1.84 (0.12-27.37); 0.67	0.64 (0.11-3.59); 0.61	1.96 (0.26-14.93); 0.52	0.46 (0.05-4.59); 0.51
10,000-100,000	0.47 (0.02-9.39); 0.47	2.67 (0.30-18.47); 0.41	/	0.65 (0.07-6.38); 0.71	/	0.43 (0.04-4.44); 0.48
≥ 100,000	/	0.79 (0.14-4.55); 0.80	0.40 (0.03-4.76); 0.46	/	/	/
Meteorological disasters 6-tier						
≥100	0.63 (0.15-2.63); 0.53	2.45 (0.55-10.99); 0.24	/	1.09 (0.30-3.89); 0.90	/	0.48 (0.05-4.81); 0.53
≥2,500	/	6.05 (0.47-77.78); 0.17	/	/	/	/
≥5,000	0.80 (0.05-13.83); 0.88	/	/	/	/	/
≥7,500	/	/	/	/	1.95 (0.11-34.25); 0.65	/
≥ 10,000	/	0.27 (0.05-1.50); 0.14	0.28 (0.04-1.88); 0.19	0.67 (0.05-4.07); 0.49	/	1.08 (0.21-5.56); 0.92
≥ 100,000	7.75 (0.73-82.23); 0.09	2.44 (0.75-7.92); 0.14	1.00 (0.09-11.73); 0.99	1.57 (0.13-18.96); 0.72	/	1.16 (0.26-5.19); 0.85
Meteorological disasters 3-tier						
≤ 10,000	0.73 (0.22-2.41); 0.60	2.99 (0.89-10.05); 0.08	/	1.43 (0.51-4.00); 0.50	0.39 (0.05-2.92); 0.36	0.66 (0.11-3.89); 0.65
10,000-100,000	/	0.27 (0.05-1.50); 0.14	0.28 (0.04-1.88); 0.19	0.46 (0.05-4.00); 0.48	/	1.08 (0.21-5.55); 0.92
≥ 100,000	7.94 (0.75-84.18); 7.94	2.43 (0.75-7.87); 0.14	1.00 (0.09-11.73); 0.99	1.67 (0.14-20.08); 0.69	/	1.16 (0.26-5.18); 0.85

Appendix 9 (cont.): Regional results of logistic regression by disaster type, for total tuberculosis cases between 2000 and 2013.

	Africa	Americas	South-East Asia	Europe	Eastern Mediterranean	Western Pacific
Hydrological disasters 6-tier	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***
≥100	1.71 (0.55-5.31); 0.35	1.23 (0.25-5.94); 0.80	/	1.29 (0.52-3.19); 0.58	0.68 (0,06-7.38); 0,75	0.52 (0.05-5.51); 0.50
≥2,500	0.38 (0.04-3.81); 0.41	0.79 (0.08-8.19); 0.84	/	5.64 (1.48-21.44); 0.01	/	2.25 (0.31-16.11); 0.42
≥5,000	0.38 (0.03-3.33); 0.35	0.89 (0.16-5.12); 0.90	/	1.74 (0.28 (11.03); 0.56	/	/
≥7,500	2.22 (0.28-17.49); 0.45	/	/	0.84 (0.08-8.32); 0.88	/	/
≥ 10,000	1.95 (0.80-4.76); 0.14	1.84 (0.61-5.55); 0.28	1.51 (0.17-13.36); 0.71	1.24 (0.31-4.94); 0.76	7.33 (0.38-140.57); 0.19	1.36 (0.31-5.94); 0.69
≥ 100,000	2.67 (0.97-7.37); 0.06	0.50 (0.10-2.58); 0.40	0.82 (0.15-4.58); 0.82	/	4.62 (0.34-62.66); 0.25	1.23 (0.33-4.51); 0.76
Hydrological disasters 3-tier						
≤ 10,000	1.12 (0.46-2.74); 0.80	0.92 (0.30-2.82); 0.88	0.98 (0.04-24.72); 0.99	1.80 (0.87-3.70); 0.11	0.35 (0.04-3.30); 0.36	0.92 (0.22-3.82); 0.91
10,000-100,000	1.95 (0.80-4.75); 0.14	1.81 (0.60-5.44); 0.29	1.33 (0.16-10.78); 0.79	1.21 (0.31-4.79); 0.78	6.66 (0.35-123.79); 0.21	1.36 (0.31-6.00); 0.69
≥ 100,000	2.70 (0.98-7.42); 0.06	0.50 (0.10-2.60); 0.41	0.87 (0.16-4.69); 0.87	/	4.12 (0.32-52.70); 0.28	1.24 (0.34-4.56); 0.75
Climatological disasters 6-tier						
≥100	/	5.70 (0.44-74.54); 0.19	/	1.59 (0.06-5.71); 0.65	/	0.61 (0.05-7.47); 0.70
≥2,500	/	2.30 (0.09-59.27); 0.62	/	/	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	/	/	/	/	/	/
≥ 100,000	1.05 (0.38-2.88); 0.92	1.17 (0.26-5.28); 0.84	0.36 (0.03-4.67); 0.43	/	0.12 (0.01-1.62); 0.11	/
Climatological disasters 3-tier						
≤ 10,000	/	4.16 (0.49-35.08); 0.19	/	0.39 (0.04-3.66); 0.41	/	0.61 (0.05-7.47); 0.70
10,000-100,000	/	/	/	/	/	/
≥ 100,000	1.05 (0.38-2.88); 0.92	1.17 (0.26-5.29); 0.84	0.36 (0.03-4.67); 0.43	/	0.12 (0.01-1.62); 0.11	/

Appendix 10: Regional results of logistic regression by disaster type, for total tuberculosis relapse between 2000 and 2013.

	Africa	Americas	South-East Asia	Europe	Eastern Mediterranean	Western Pacific
Geophysical disasters 6-tier	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***	**OR (CI); *P***
≥100	/	2.09 (0.16-27.81); 0.59	5.32 (0.12-265.05); 0.40	5.55 (0.45-68.83); 0.18	4.64 (0.16-134.52); 0.37	/
≥2,500	/	/	/	2.27 (0.19-27.85); 0.52	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	/	1.73 (0.16-18.78); 0.65	/	5.40 (0.66-44.05); 0.12	/	/
≥ 100,000	/	0.54 (0.06-5.15); 0.60	/	/	/	/
Geophysical disasters 3-tier						
≤ 10,000	/	0.71 (0.08-6.38); 0.76	9.70 (0.38-247.26); 0.17	3.75 (0.72-19.62); 0.12	2.91 (0.15 -57.60); 0.48	/
10,000-100,000	/	1.69 (0.16-18.39); 0.67	/	5.85 (0.73-46.77); 0.10	/	/
≥ 100,000	/	0.54 (0.06-5.19); 0.60	/	/	/	/
Meteorological disasters 6-tier						
≥100	0.73 (0.13-4.10); 0.72	/	/	0.74 (0.08-6.81); 0.79	/	/
≥2,500	/	3.02 (0.22-41.28); 0.41	3.02 (0.22-41.28); 0.41	/	/	/
≥5,000	/		/	6.17 (0.70-54.13); 0.10	/	/
≥7,500	/		/	/	/	/
≥ 10,000	/	2.06 (0.53-7.92); 0.30	2.06 (0.53-7.92); 0.30	5.37 (0.90-32.18); 0.07	/	2.15 (0.33-13.90); 0.42
≥ 100,000	17.20 (1.56-190.35); 0.02	0.76 (0.15-3.88); 0.74	0.73 (0.15-3.88); 0.74	/	/	1.42 (0.24-8.26); 0.70
Meteorological disasters 3-tier						
≤ 10,000	0.46 (0.09-2.34); 0.35	0.86 (0.17-4.38); 0.85	/	1.51 (0.36-6.43); 0.58	0.18 (0.01-3.70); 0.27	1.09 (0.12-11.05); 0.94
10,000-100,000	/	1.98 (0.52-7.58); 0.32	1.00 (0.13-7.64); 0.99	5.57 (0.93-33.42); 0.06	/	2.18 (0.34-14.14); 0.41
≥ 100,000	17.33 (1.27-191.62); 0.02	0.75 (0.15-7.58); 0.73	0.45 (0.02-8.44); 0.59	/	/	1.42 (0.24-8.33); 0.70

Appendix 10 (cont.): Regional results of logistic regression by disaster type, for total tuberculosis relapse between 2000 and 2013.

	Africa	**Americas**	**South-East Asia**	**Europe**	**E. Mediterranean**	**Western Pacific**
Hydrological disasters 6-tier	**OR (CI);** ***P***	**OR (CI);** ***P***	**OR (CI);** ***P***	**OR (CI);** ***P***	**OR (CI);** ***P***	**OR (CI);** ***P***
≥100	1.17 (0.32-4.27); 0.81	0.92 (0.09-9.15); 0.95	/	0.27 (0.03-2.26); 0.23	9.49 (0.47-192.94); 0.14	/
≥2,500	/	/	/	0.81 (0.09-7.03); 0.85	/	4.63 (0.52-41.25);0.17
≥5,000	0.82 (0.08-8.29); 0.87	2.38 (0.39-14.64); 0.35	/	1.71 (0.16-17.89); 0.65	/	/
≥7,500	/	/	/	3.70 (0.50-27.19); 0.20	/	/
≥ 10,000	0.94 (0.34-2.58); 0.90	3.81 (.12-13.03); 0.03	6.26 (0.30-132.35); 0.24	1.28 (0.25-6.47); 0.76	10.00 (0.24-421.77); 0.22	4.41 (0.77-25.12); 0.10
≥ 100,000	2.85 (1.02-7.91); 0.05	1.34 (0.24-7.49); 0.74	1.83 (0.18-18.47); 0.61	/	1.41 (0.04-40.26); 0.85	1.81 (0.37-8.79); 0.46
Hydrological disasters 3-tier						
≤ 10,000	0.66 (0.21-2.02); 0.46	1.61 (0.42-6.17); 0.49	6.83 (0.18-263.67); 0.30	0.82 (0.27-2.53); 0.73	1.69 (0.13-21.42); 0.69	1.83 (0.27-12.64); 0.54
10,000-100,000	0.94 (0.34-2.62); 0.91	3.98 (1.16-13.62); 0.03	4.47 (0.28-72.70); 0.29	1.26 (0.25-6.30); 0.78	6.06 (0.16-232.22); 0.33	4.65 (0.81-26.93); 0.09
≥ 100,000	2.90 (1.04-8.07); 0.04	1.29 (0.23-7.25); 0.77	1.67 (0.19-14.63); 0.64	/	1.33 (0.05-34.53); 0.86	1.85 (0.38-9.08); 0.45
Climatological disasters 6-tier						
≥100	/	/	/	/	/	1.92 (0.15-25.04); 0.62
≥2,500	/	/	/	/	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	/	0.63 (0.05-7.47); 0.72	/	/	/	/
≥ 100,000	0.86 (0.29-2.58); 0.79	4.54 (0.10-20.77); 0.05	527 (0.36-76.97); 0.22	/	0.29 (0.01-6.45); 0.43	/
Climatological disasters 3-tier						
≤ 10,000	/	/	/	2.87 (0.43-19.11); 0.28	/	1.92 (0.15-25.04); 0.62
10,000-100,000	/	0.63 (0.05-7.47); 0.72	/	/	/	/
≥ 100,000	0.86 (0.29-2.58); 0.79	4.54 (0.10-20.77); 0.05	5.27 (0.36-76.97); 0.22	/	0.29 (0.01-6.45); 0.43	/

Appendix 11: Time lag results for total tuberculosis cases, by disaster type between 2000 and 2013.

	Tuberculosis Cases 1-year lag	**Tuberculosis cases 2-year lag**
General disasters 6-tier	**OR (CI); *P***	**OR (CI); *P***
≥100	0.65 (0.34-1.22); 0.18	1.04 (0.56-1.93); 0.92
≥2,500	1.15 (0.54-2.44); 0.72	1.32 (0.60-2.90); 0.49
≥5,000	1.17 (0.47-3.44); 0.63	1.95 (0.73-5.21); 0.18
≥7,500	1.47 (0.49-4.41); 0.49	1.19 (0.36-3.92); 0.78
≥ 10,000	1.38 (0.88-2.16); 0.16	0.79 (0.47-1.32); 0.37
≥ 100,000	1.05 (0.68-1.65); 0.82	1.03 (0.64-1.67); 0.89
General disasters 3-tier		
≤ 10,000	0.93 (0.59-1.44); 0.73	1.22 (0.78-1.95); 0.37
10,000-100,000	1.37 (0.87-2.15); 0.17	0.79 (0.47-1.32); 0.36
≥ 100,000	1.05 (0.67-1.63); 0.85	1.03 (0.64-1.66); 0.90
Geophysical disasters 6-tier		
≥100	0.97 (0.35-2.68); 0.95	0.88 (0.28-2.76); 0.82
≥2,500	1.55 (0.43-5.57); 0.51	3.33 (0.95-11.68); 0.06
≥5,000	0.63 (0.07-5.82); 0.68	0.80 (0.09-7.36); 0.84
≥7,500	3.89 (0.34-44.23); 0.27	/
≥ 10,000	1.04 (0.35-3.06); 0.95	0.67 (0.19-2.41); 0.53
≥ 100,000	1.52 (0.52-4.45); 0.44	1.43 (0.48-4.31); 0.52
Geophysical disasters 3-tier		
≤ 10,000	1.20 (0.58-2.45); 0.62	1.22 (0.57-2.62); 0.60
10,000-100,000	1.03 (0.35-3.05); 0.96	0.66 (0.18-2.40); 0.53
≥ 100,000	1.53 (0.52-4.47); 0.44	1.43 (0.47-4.30); 0.53
Meteorological disasters 6-tier		
≥100	0.71 (0.35-1.42); 0.33	1.31 (0.67-2.56); 0.43
≥2,500	2.63 (0.66-10.43); 0.17	2.45 (0.64-9.36); 0.19
≥5,000	0.49 (0.09-2.64); 0.41	0.40 (0.05-3.31); 0.39
≥7,500	2.99 (0.66-13.55); 0.16	1.29 (0.25-6.73); 0.76
≥ 10,000	0.93 (0.48-1.87); 0.83	0.78 (0.36-1.66); 0.51
≥ 100,000	2.44 (1.23-4.87); 0.01	1.03 (0.47-2.26); 0.93
Meteorological disasters 3-tier		
≤ 10,000	0.97 (0.56-1.68); 0.92	1.29 (0.74-2.25); 0.37
10,000-100,000	0.93 (0.48-1.81); 0.83	0.78 (0.36-1.66); 0.51
≥ 100,000	2.42 (1.21-4.81); 0.01	1.03 (0.47-2.25); 0.94
Hydrological disasters 6-tier		
≥100	0.54 (0.29-1.02); 0.06	0.60 (0.30-1.19); 0.15
≥2,500	1.17 (0.52-2.61); 0.70	1.41 (0.62- 3.23); 0.42
≥5,000	0.49 (0.15-1.55); 0.22	1.12 (0.39-3.23); 0.84
≥7,500	1.83 (0.62-5.39); 0.28	1.15 (0.35-3.79); 0.81
≥ 10,000	1.50 (0.93-2.42); 0.10	1.03 (0.61-1.74); 0.92
≥ 100,000	0.97 (0.59-1.67); 0.90	1.15 (0.65-2.03); 0.63
Hydrological disasters 3-tier		
≤ 10,000	0.76 (0.49-1.18); 0.22	0.89 (0.55-1.42); 0.62
10,000-100,000	1.50 (0.92-2.41); 0.10	1.03 (0.61-1.73); 0.93
≥ 100,000	0.96 (0.56-1.67); 0.89	1.15 (0.65-2.03); 0.64
Climatological disasters 6-tier		
≥100	0.82 (0.25-2.68); 0.75	0.52 (0.11-2.34); 0.39
≥2,500	1.81 (0.11-29.66); 0.68	/
≥5,000	/	/
≥7,500	/	/
≥ 10,000	0.72 (0.14-3.82); 0.70	0.47 (0.06-3.97); 0.49
≥ 100,000	0.55 (0.27-1.10); 0.09	0.63 (0.30-1.35); 0.24
Climatological disasters 3-tier		
≤ 10,000	0.77 (0.27-2.20); 0.62	0.38 (0.09-1.68); 0.20
10,000-100,000	0.72 (0.14-3.82); 0.70	0.47 (0.06-3.97); 0.49
≥ 100,000	0.55 (0.27-1.10); 0.09	0.63 (0.30-1.35); 0.24

Appendix 12: Time lag results for tuberculosis relapse, by disaster type between 2000 and 2013.

	Tuberculosis relapse 1-year lag	Tuberculosis relapse 2-year lag
General disasters 6-tier	**OR (CI); *P***	**OR (CI); *P***
≥100	0.50 (0.21-1.20); 0.08	1.12 (0.56-2.23); 0.75
≥2,500	1.14 (0.33-3.99); 0.84	1.59 (0.68-3.71); 0.28
≥5,000	/	0.99 (0.28-3.52); 0.98
≥7,500	/	1.37 (0.37-5.12); 0.64
≥ 10,000	1.07 (0.51-2.26); 0.85	1.20 (0.69-2.07); 0.53
≥ 100,000	2.16 (1.15-4.03); 0.02	1.58 (0.95-2.64); 0.08
General disasters 3-tier		
≤ 10,000	0.34 (0.12-1.00); 0.05	1.24 (0.74-2.08); 0.41
10,000-100,000	1.08 (0.51-2.27); 0.85	1.19 (0.69-2.07); 0.53
≥ 100,000	2.15 (1.15-4.02); 0.02	1.58 (0.95-2.63); 0.08
Geophysical disasters 6-tier		
≥100	0.68 (0.09-5.29); 0.72	0.26 (0.03-1.99); 0.20
≥2,500	1.52 (0.19-12.36); 0.70	2.93 (0.81-10.59); 0.10
≥5,000	/	1.15 (0.12-10.62); 0.90
≥7,500	7.94 (0.66-95.02); 0.10	2.13 (0.19-24.13); 0.54
≥ 10,000	2.06 (0.52-8.10); 0.30	0.58 (0.13-2.60); 0.48
≥ 100,000	3.11 (0.91-10.63); 0.07	1.50 (0.47-4.85); 0.50
Geophysical disasters 3-tier		
≤ 10,000	1.19 (0.35-4.07); 0.78	1.07 (0.46-2.53); 0.87
10,000-100,000	2.05 (0.52-8.07); 0.31	0.58 (0.13-2.59); 0.47
≥ 100,000	3.14 (0.92-10.72); 0.07	1.52 (0.47-4.89); 0.49
Meteorological disasters 6-tier		
≥100	0.51 (0.14-1.82); 0.30	0.87 (0.39-1.95); 0.74
≥2,500	2.66 (0.50-14.24); 0.85	1.22 (0.25-6.00); 0.81
≥5,000	/	0.57 (0.07-4.75); 0.61
≥7,500	/	1.75 (0.33-9.15); 0.51
≥ 10,000	1.34 (0.50-3.59); 0.56	1.23 (0.59-2.57); 0.58
≥ 100,000	2.31 (0.90-5.93); 0.08	1.05 (0.45-2.48); 0.91
Meteorological disasters 3-tier		
≤ 10,000	0.60 (0.22- 1.62); 0.31	0.96 (0.50-1.83); 0.89
10,000-100,000	1.33 (0.50-3.58); 0.57	1.22 (0.59-2.57); 0.58
≥ 100,000	2.30 (0.90-5.89); 0.08	1.05 (0.45-2.47); 0.91
Hydrological disasters 6-tier		
≥100	0.33 (0.08-1.41); 0.13	1.25 (0.66-2.38); 0.49
≥2,500	0.36 (0.05-2.78); 0.33	1.83 (0.78-4.33); 0.17
≥5,000	0.63 (0.08-4.92); 0.66	0.58 (0.13-2.56); 0.47
≥7,500	0.98 (0.12-7.78); 0.98	1.87 (0.57-6.19); 0.30
≥ 10,000	1.20 (0.55-2.60); 0.65	1.04 (0.57-1.90); 0.89
≥ 100,000	3.14 (1.59-6.20); 0.001	1.50 (0.81-2.75); 0.20
Hydrological disasters 3-tier		
≤ 10,000	0.44 (0.17-1.15); 0.09	1.32 (0.81-2.16); 0.26
10,000-100,000	1.19 (0.55-2.59); 0.66	1.04 (0.58-1.90); 0.89
≥ 100,000	3.13 (1.58-6.18); 0.001	1.50 (0.81-2.76); 0.20
Climatological disasters 6-tier		
≥100	/	0.71 (0.16-3.22); 0.65
≥2,500	/	4.17 (0.26-67.32); 0.31
≥5,000	8.77 (0.54-142.95); 0.13	/
≥7,500	/	/
≥ 10,000	1.67 (0.19-14.42); 0.64	1.68 (0.32-8.78); 0.54
≥ 100,000	0.92 (0.33-2.57); 0.87	0.81 (0.36-1.83); 0.61
Climatological disasters 3-tier		
≤ 10,000	0.61 (0.08-4.74); 0.64	0.85 (0.24-2.98); 0.80
10,000-100,000	1.66 (0.19-14.41); 0.64	1.68 (0.32-8.77); 0.54
≥ 100,000	0.92 (0.33-2.58); 0.88	0.81 (0.36-1.83); 0.61

Appendix 13: Regional results for HIV + tuberculosis coinfection, by disaster type between 2003 and 2013.

	Africa	Americas	South-East Asia	Europe	Eastern Mediterranean	Western Pacific
Geophysical disasters 6-tier	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**
≥100	2.32 (0.13-40.21); 0.56	0.68 (0.06-8.39); 0.77	/	/	/	/
≥2,500	/	0.41 (0.03-5.28); 0.49	/	/	/	/
≥5,000	/	/	/	/	/	/
≥7,500	/	/	/	/	/	/
≥ 10,000	/	/	/	/	/	/
≥ 100,000	/	/	46.51 (0.50-4348.17); 0.10	/	/	/
Geophysical disasters 3-tier						
≤ 10,000	7.95 (0.74-85.96); 0.09	0.53 (0.09-3.21); 0.49	/	0.26 (0.02-3.84); 0.33	1.79 (0.10-30.69); 0.69	/
10,000-100,000	/	/	/	/	/	/
≥ 100,000	/	/	46.51 (0.50-4348.17); 0.10	/	/	/
Meteorological disasters 6-tier						
≥100	1.27 (0.11-15.37); 0.85	0.26 (0.05-1.41); 0.12	/	0.58 (0.05-6.44); 0.66	/	/
≥2,500	/	/	/	/	/	/
≥5,000	1.95 (0.11-33.42); 0.65	/	/	6.24 (0.58-66.64); 0.13	/	/
≥7,500	/	/	/	1.76 (0.10-31.09); 0.70	2.32 (0.12-45.84); 0.58	/
≥ 10,000	/	0.94 (0.23-3.87); 0.93	1.09 (0.09-13.95); 0.95	1.72 (0.22-13.38); 0.61	/	1.21 (0.09-15.58); 0.89
≥ 100,000	/	0.64 (0.15-2.74); 0.55	/	2.42 (0.13-43.35); 0.55	/	/
Meteorological disasters 3-tier						
≤ 10,000	3.60 (0.79-16.30); 0.10	0.29 (0.07-1.19); 0.09	/	1.55 (0.41-5.89); 0.52	2.75 (0.24-30.97); 0.41	/
10,000-100,000	/	0.96 (0.23-3.94); 0.96	1.09 (0.09-13.95); 0.95	1.68 (0.22-13.13); 0.62	/	1.21 (0.09-15.58); 0.89
≥ 100,000	/	0.66 (0.15-2.78); 0.57	/	2.39 (0.13-42.64); 0.55	/	/

Appendix 13 (cont.): Regional results for HIV + TB coinfection, by disaster type between 2003 and 2013.

	Africa	Americas	South-East Asia	Europe	Eastern Mediterranean	Western Pacific
Hydrological disasters 6-tier	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**	**OR (CI); p**
≥100	0.97 (0.21-4.44); 0.97	0.31 (0.03-3.45); 0.34	/	1.42 (0.40-5.07); 0.59	/	/
≥2,500	1.20 (0.10-14.83); 0.89	5.55 (0.56-55.01); 0.14	/	1.16 (0.24-5.52); 0.86	/	/
≥5,000	/	0.53 (0.04-6.80); 0.63	/	0.30 (0.01-9.61); 0.50	/	/
≥7,500	0.74 (0.07-8.20); 0.80	1.67 (0.10-28.88); 0.73	/	6.11 (0.54-69.180); 0.14	/	/
≥ 10,000	0.84 (0.31-2.32); 0.74	0.92 (0.26-3.24); 0.90	0.75 (0.03-19.55); 0.86	0.36 (0.06-2.04); 0.25	3.10 (0.09-107.73); 0.53	5.63 (0.63-50.38); 0.12
≥ 100,000	1.35 (0.43-4.25); 0.61	1.25 (0.24-5.55); 0.79	1.18 (0.90-16.31); 0.90	/	1.49 (0.03-73.65); 0.84	/
Hydrological disasters 3-tier						
≤ 10,000	0.76 (0.23-2.47); 0.64	1.23 (0.36-4.12); 0.74	/	1.49 (0.57-3.90); 0.42	/	2.75 (0.14-54.74); 0.51
10,000-100,000	0.84 (0.31-2.32); 0.74	1.04 (0.30-3.62); 0.95	0.75 (0.03-19.55); 0.86	0.36 (0.06-2.00); 0.24	3.10 (0.09-107.73); 0.53	4.88 (0.59-40.44); 0.14
≥ 100,000	1.33 (0.42-4.17); 0.63	1.25 (0.24-6.51); 0.79	1.18 (0.09-16.31); 0.90	/	1.49 (0.03-73.65); 0.84	/
Climatological disasters 6-tier						
≥100	4.30 (0.77-24.01); 0.10	/	2.88 (0.22-38.44); 0.43	/	2.66 (0.12-60.21); 0.54	/
≥2,500	/	/	/	/	/	/
≥5,000	2.10 (0.13-34.10); 0.60	/	/	/	3.75 (0.17-84.56); 0.41	/
≥7,500	/	/	/	/	/	/
≥ 10,000	3.54 (0.58-21.78); 0.17	/	2.95 (0.23-38.08); 0.41	/	/	/
≥ 100,000	0.75 (0.33-1.79); 0.53	1.70 (0.58-5.09); 0.34	/	/	/	1.99 (0.12-33.40); 0.63
Climatological disasters 3-tier						
≤ 10,000	2.16 (0.61-7.65); 0.24	/	1.18 (0.16-8.78); 0.87	/	3.16 (0.30-33.20); 0.34	/
10,000-100,000	3.54 (0.58-21.80); 0.17	/	3.22 (0.25-42.35); 0.37	/	/	/
≥ 100,000	0.77 (0.33-1.79); 0.54	1.70 (0.57-5.09); 0.34	/	/	/	1.99 (0.12-33.39); 0.63

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