**4. Research Design**

In order to answer the question of whether or not the exposure to conflict influences the number of Disability adjusted Life Years attributed to environmental risks this thesis assumes, that conflict increases the morbidity attributable to unsafe access to water, sanitation and hygiene within the excess morbidity measured through Disability adjusted Life Years (DALY). Using the Global Burden of Disease dataset – data that displays repeated observations of disease and disability over time using the same set of countries – the level of morbidity before and after conflict is measured. This work will investigate the effect over time, using the GBD DALY estimates attributable to unsafe access to WASH as dependent variables and the exposure, intensity and length of conflict as independent variables. A subset of countries from Eastern Sub-Saharan Africa will serve as the sample with the country being the unit of analysis, spanning from  1990 to 2019 to cover three decades of time-series. Focusing on a few selected causes of disease in this specific region will not only test the robustness of the findings but help to establish specific causal claims that can inform future research and policy. Research on the relevance of environmental factors for the relationship between conflict and public health is scarce and still lacking concrete and robust findings. This reflects the need for studying the long-term health impacts of conflicts associated with environmental risks. The following subchapters will specify on the theoretical argumentation for the model and the operationalization of both the independent and the outcome variable, while simultaneously considering possible limitations of the data and methods used in this thesis.

**4.1. The Global Burden of Disease Study**

One of the main challenges in quantifying the health impacts of conflicts is the availability of data, especially in post-conflict societies (Murray et.al. 2002). As mentioned in chapter 2.1, most measures rely on census data that can be difficult to obtain at times of conflict, disease outbreaks or natural disasters (Hernandez & Kim, 2022). Besides the random missingness, outcome measures of public health can be operationalized and estimated very differently depending on the institution that is reporting them. Furthermore, health data is very vulnerable to reporting biases and instances of missingness not at random (ibid). Those problems have been especially addressed by the Global Burden of Disease Study (IHME 2020) by producing a large panel of different health estimators helping to standardize the capture of negative health impacts. The Global burden of disease study reports several measures of morbidity and indirect mortality disaggregated into 265 different causes of disease and disability, structured into four levels of indicators (IHME, 2020). Spanning from 1990 to 2019, yearly estimates on the number/ rate/ percentage of deaths, years of life lost (YLL), years lived with disability (YLD) and Disability adjusted life years (DALY) are modeled, based on regional and national health statistics and surveys like the DHS. The number of YLL and YLD is obtained by multiplying the attributed population at risk for each sex-age-location-year (ibid.). The number of DALY is calculated by adding the years of life lost (YLL) and years lived with disability (YLD).  The estimates are available on a global, regional, subregional and country level. The structure of the dataset is very complex, covering not only 190 countries and additional aggregated regions, but also four different measures of morbidity  – YLD, YLL, DALY –  and mortality as in number of deaths. All of those measures can be disaggregated into causes of morbidity (communicable diseases, non communicable diseases like chronic high blood pressure and injuries), available on four different levels of aggregation. Since 2007, the Global Burden of disease committee has been releasing an additional sub-dataset including attributable risk factors, which will be used in this analysis. Similar to the causes, the risk factors can be disaggregated into three levels of specification. Figure 2 displays a simplified illustration of the structure.*Should I extend this?*

Figure 2: Structure of the Global Burden of Disease Dataset *I will redo this and make it prettier*

Graphical user interface, application, Word

Description automatically generated

**4.2. Scope & sample selection**

As suggested in chapter 3, the theory's scope condition is the presence of unsafe access to WASH that causes a certain level of disabilities and disease prevalence. This means that this papers’ findings can only be inferred to a certain universe of cases, displaying levels of unsafe access to WASH. Otherwise, the assumptions the hypothesis relies on do not hold and the results would be invalid. As the number of DALY attributable to unsafe access to water, sanitation and hygiene has been generally decreasing significantly over the past three decades (GBD, 2019), identifying a set of cases most likely to display the expected relationship and relevance for this research topic is not intuitive. However, while globally the unsafe access to WASH has been decreasing as a risk factors for public health over the last 20 years (see Table 1), the region of Eastern Sub-Saharan Africa still displays one of the highest numbers of DALY attributable to this specific risk factor (see figure 3).

Table 1: Global change rate of DALY attributable to unsafe access to WASH

|  |  |  |
| --- | --- | --- |
| **Risk factor** | **ARC 1990-2019** | **ARC 2010-2019** |
| WASH (all) | -0.56% | -0.59% |
| unsafe water source | -0.92% | -1.14% |
| unsafe sanitation | -2.29% | -3.09% |
| no access to handwashing facility | -0.46% | -0.63% |

Global burden of Disease study 2019; ARC = aggregated rate of change (IHME, 2022)

The rate of DALY attributable to unsafe access to WASH was highest within Sub-Saharan Africa in 2019 at 3919 years/ 100 000 people compared to a global rate of 1244 years (ibid.). The countries within that region therefore constitute a most-likely case and a good sample to study the suggested causal mechanism.

Figure 3: all-cause SEV to unsafe access to WASH, age-standardized for 2019

Map

Description automatically generated

Global Burden of Disease, Risk profile summary (the Lancet, 2020)

The motivation to study one region rather than the global variation between single countries is partly motivated by the spatial turn in geography and area studies that disregards culture and society as being constrained to the container of the westphalian concept of the nation state and instead focuses on the transbordering/ fluent character of societal phenomena. It furthermore realizes space as constructed, this meaning the existence of competing frameworks and understandings of space at the same time, while stressing the importance of actors in the creation of it (Middel & Naumann, 2010)*.* The concepts of “nation” and “state” are considered spaces within  human geography as well. Nation hereby refers to being transformed into *“[...] an abstraction into a living organism, with a personality defined by the cultures, languages, and historical memories embedded within the populations enclosed within state boundaries”* (Young, 2012: p. 41).When dealing with statehood in the context of SSA, it is imperative to stretch the constructedness and colonial legacy of the concept in order to move beyond the traditional accounts of Hobbes and Weber. This is particularly important when studying or researching epidemiology. Limiting the analysis to single, isolated containers as cases would be irresponsible, since the spread of diseases does not stop at the border as well as conflict impacts are known to affect not only the national population due to spill over of violence, migration, economic impacts and weapons delivery. Although there are good reasons to adopt a regional approach, it is important to mention that the region of Eastern Africa is generally overstudied in public health research, which will be discussed in an additional ethics chapter further below. While this one-sidedly centered research poses several ethical challenges to this thesis, replicating this regional focus helps to draw on theoretical knowledge and previous studies within the region, adding a clear causal argument and robustness to the findings.

With the preceding critique of statehood in mind, this thesis thus stresses the importance to analyze within country variation in the region of Eastern SSA. This is not only motivated by external validity, comparability to previous research (see chapters 2.2 and 2.3.)  and means of replicability; the nation state as a political entity is thought to have important influence on policy decisions regarding the distribution of health care as well as the preparedness for and risk-reduction of  disasters. Those factors will be introduced as control variables on a country-year level to account for between country variation.

**4.3. Operationalization**

**4.3.1. Dependent Variable – morbidity attributable to the risk of unsafe access to WASH**

The **dependent Variable** – **morbidity attributable to the unsafe access to water, sanitation and hygiene** will be operationalized using the measure of Disability Adjusted Life Years (DALY) by the Global Burden of Disease study (IHME, 2020) Within the GBD study, 560 different risk outcome pairs have been identified (IHME, 2022). Risk describes a certain risk factor like the unsafe access to WASH whereas the outcome is measured through the disability adjusted life years caused by a certain disease. The exact definition by the GBD study of the risk factor used to operationalize the DV is as follows: *“Unsafe water, sanitation, and handwashing is an aggregate risk including exposure to unsafe water sources, unsafe sanitation facilities, and lack of access to handwashing facilities”* ( The Lancet, 2020). But still, the actual causal relationship between the risk factor and an outcome has to be assumed with caution. Talhami and Zeitoun (2021) point towards the problem of uncertainty, especially surrounding the causality of the relationship between destruction of access to safe water and negative public health consequences. In other words, it is not clear, how sure one can be that certain diseases prevalent in the Global Burden of Disease study are actually caused by unsafe access to WASH, since the link between destruction of access to water, sanitation and hygiene and adverse health effects is pre-assumed. However, the relative risk of a population is estimated through measuring the exposure to that risk through a) 81 systematic reviews of scientific literature and b) meta-regression modeling (GBD 2019 Risk Factors Collaborators, Murray et.al.: 2020). Using spatio-temporal Gaussian processes and Bayesian meta regression, the level of risk exposure in each sex-age-locatin-year is obtained composing the attributed population at risk. The Global burden of disease study offers some criteria for the inclusion of risk-outcome pairs, most importantly the existence of convincing or probable evidence for the relationship. The relationship inherent in the measurement of the dependent variable is furthermore accounted for through a large body of literature linking – like Sommer et.al.(2015) – safe access to WASH to decreased maternal and infant mortality (ibid.). Talhami and Zeitoun summarize, that “*over a century of epidemiological study of transmission routes has developed a robust scientific body of knowledge that infectious diseases can spread through water and wastewater* (ibid.: 2021, p. 1305), especially through untreated wastewater and attacks on the services of distribution of clean drinking water.

To summarize, the **dependent variable** – **morbidity attributable to unsafe access to WASH** – will be measured using a sub-dataset from the GBD study that accounts for diseases and disability attributable to this specific risk factor. As the Global Burden of disease estimates are only available on a country-year level, the level of analysis will not be disaggregated any further and cover the entire thirty-year time-series available from 1990 to 2019. The variable will be age-standardized and aggregated into both sex resulting in 394 individual country-years and 11760 observations before disaggregation into causes and second level risks. The dependent variable will be filtered to represent only one region – Eastern Sub-Saharan Africa – and log-transformed to account for the interval scaled nature of the variable. Additionally, lags of the variable will be introduced to account for the lingering effect of some disabilities and diseases.

**4.3.2. Independent Variable – experience of and exposure to conflict**

The **independent variable exposure to conflict** is measured using the Uppsala Conflict Data Program Geo-located event dataset (UCDP GED), as it contains precise information on the location (country) of the conflict fatalities occurring and covers 40 years of conflict history that can be used to create conflict-lags informing the model. As the data is on an event level, the conflict events will be summed up to create an aggregated **yearly estimate of fatalities per country.** The temporal span of the data will cover the years 1980 to 2019 to account for previous conflict years through lagging the variable. The data can be disaggregated into the type of conflict – the three UCDP types of state-based, non-state conflict and one-sided violence. It is sensible to make use of this differentiation as the theory suggests different levels of destruction of water infrastructure and differing incentives to supply emergency health services and respond to this kind of crises depending both on the regime type and type of violence. Rebels or terrorist organizations might be more likely to attack water infrastructure to damage civilians than a state depending on legitimization, also one-sided violence targeting a specific group might aim at reducing the access to safe drinking water. Furthermore, the number of conflict fatalities can be used to measure conflict intensity which in turn is expected to influence the level of DALY. The thresholds for conflict intensity incorporated into the UCDP GED data frame will be used to differentiate between different levels of the former. A continuous variable differentiating between low (n < 100), medium (n < 1000) and high (n > 1000) numbers of fatalities will be created, indicating the intensity level. Lastly, as theoretically suggested, the exposure to conflict (at least 25 battle related deaths) in a neighboring country will also be accounted for as this will affect the country in question through possible spill-overs of conflict, contamination of water, displacement and possible spread of diseases. Like the outcome variable, conflict will be log-transformed since the latter describes the count of fatalities.

To summarize, the independent variable will be on a country-year level, measuring the number of fatalities. The **conflict intensity** will be measured by creating a categorical variable differentiating between low (n of fatalities per year per country < 100), medium (n < 1000) and high (n > 1000) conflict intensity. The **exposure to conflict** is coded as a binary for the neighboring country experiencing war – 0 for no war experience and 1 for war experience. The **type of conflict** is differentiated using the UCDP categories of non-state and state-based violence.

**4.3.3. Control variables**

Not only disaster response strategies and the intensity and duration of the conflict play an important role in determining the relationship between conflict impacts on public health. There are several economic, social as well as climatic factors that need to be accounted for. Since the level of government expenditure as well as general budget available for risk adaptation influence the level of disease incidence (hence morbidity), they should be accounted for in the model. Sommer et.al. (2015) propose additional structural barriers, like foreign investment, gross domestic product, domestic investment or public health expenditure. Garfield (1989) adds the general level of inflation and loss of livelihood sources during conflict that could affect civilians on an individual level to access health care or clean water services. To account for the economic factors, the **government expenditure on health** as well as **foreign development assistance distributed for health** will be introduced as control variables in the model. General government expenditure will be excluded, as the most important effect is captured by the health specific expenditure.

Pre-conflict **resilience** will be accounted for through measures of **previous exposure to unsafe WASH**. An increased resilience to certain diseases pre-conflict is thought to influence the level of disease incidence due to conflict. Although Eastern Africa displays similar levels of climate vulnerability, it is expedient to include variables that capture both climate variability and vulnerability, since the risk-factors in this thesis can be attributed to overall environmental risk factors. The **number of deaths (mortality) due to climate related hazards** will be used to account for a country's vulnerability (EMDAT, 2022). Furthermore, to separate the effect of conflict from other possible causes of unsafe access to WASH, the model will control for the **exposure to** events of **natural disasters** like earthquakes, cyclones or tsunamis (using the Geocoded disaster dataset aggregated on national level) that could lead to contaminated or unsafe access to water. Lastly, demographic measures  of **population density** and percentage of the **population living in urban areas** will be used, since more populated, urban areas pose a greater risk for disease spread due to more dense living situations. Furthermore, those measures can be used to indicate development, an important confounder of public health and conflict and hence “*necessary to account for [...] to avoid attributing development effects to factors that tend to cause conflicts in the first place.”* (Gates et.al., 2012). All control measures used are on the macro level, since the proposed causal mechanism is expected to work systemic and only country-years are observed. Figure 3 below lists all control variables included in the different models and their variable source as well as level of aggregation. See Appendix, plot 3 for a descriptive analysis of all the variables.

Figure 3: Control Variables

|  |  |  |
| --- | --- | --- |
| **control variable** | **level of aggregation** | **source** |
| Foreign developmental aid to health | total sum in US$, country-year | IHME |
| governance expenditure on health | % of GDP, country-year | WDI |
| Exposure to natural disasters | natural disaster event, aggregated to country-year | GDIS |
| Vulnerability | number of deaths due to climate related hazards | EM-DAT |
| access to improved sanitation facilities and reliable drinking water | proportion of population, country-year | ND-Gain, country indicators |
| population density | per sq-km of land, country-year | WDI |
| population living in urban areas | % of total population, country year | WDI |

**4.4. Method specification**

The analysis will be structured as follows: As a first step – after producing descriptive statistics for all the variables used in my models – an univariate analysis of the DALY estimates will be performed producing a time trend. As a second step, both the dependent as well as the independent variable will be log-transformed as both represent count data as the distance of the data points (difference between 10 deaths and 1000 deaths or 1 year of life lost versus 100 due to disability) cannot be considered linear. The heart of the statistical analysis will be the fixed effects model and triangulating this model with a small predictive model, testing the predictive power of the independent variables to confirm or disconfirm the theory. The analysis will finish with optional robustness tests.

**4.4.1. Fixed effects model**

Since this thesis constitutes the first time investigating the relationship between public health, conflict and environmental hazards using this novel set of estimators provided by the GBD, a simple statistical test of the significance of the relationship seems fitting. This will be done by applying a fixed effects model to both account for the temporal and spatial component of the dependent variable, introducing spatial as well as lags of previous conflict years.

Panel data is data that displays multiple hierarchies – meaning repeated observations of multiple groups over time. In simple terms, Panel data can be thought of as a combination of cross-sectional and time-series data; a common example being the UCDP conflict data or most health survey data as both can be divided into different groups (households, municipalities, countries, conflicts, age and sex) and are observed or reported repeatedly over a period of multiple years. Since being hierarchical and dealing with a temporal dimension, a generalized linear model is no longer applicable to this type of data structure. Both the dependent and independent variables display such characteristics, hence Panel data specific regression models have to be chosen. Generally speaking, three main options lie ahead: pooled regression, non-pooled regression (fixed effects) and partial-pooling (random effects). The main difference between the three models is the existence of group specific effects and whether or not they are isolated and time-invariant or informing each other. A fixed effects model allows for comparison of a unit (one country) with themselves and investigating the variation of the level of morbidity within one country over time dependent on conflict. As the variation of the effect of conflict on morbidity between countries is caused by something, several control  variables have been chosen that will be held constant to ensure to investigate the isolated effect of conflict (see 4.3.1). With the between country variation being fixed by introducing a dummy for every country in the sample, out-of-sample prediction, meaning the possibility of inference to a larger universe of cases, is not possible. *I will add more on the fixed effects model, I need a specific book that I did not have access to.*

The Nullhypothesis of this thesis is that conflict does not impact the level of DALY attributable to environmental risks. Through the fixed effects model the probability of the number of DALY increasing under the effect of conflict is tested. This method is part of Null-hypothesis significance tests within statistics. As mentioned above, it is reasonable to investigate the probability of the relationship as a first inquiry into this field. However, the sole reporting of significance tests within social sciences and economics has come under a lot of scrutiny the past decade. Researchers (mot prominently Ward et.al. 2010)  increasingly stress the limitations of Null-hypothesis significance testing, the biggest of all being that the significance levels against which the performance of the models is measured, are completely arbitrary and oftentimes suspect to bias (so called “p-hacking”). The rigorous limitation to p-values furthermore contributes to dismissing large, influential factors just because they don’t show a significant p-value (Ward et.al., 2010). This is due to significance tests only focusing on so-called type 1 errors – trying to diminish the false positive rate, while omitting type 2 errors – the false negatives. An overemphasis on type 1 errors  could lead to falsely accepting the null hypothesis and dismissing the relationship between conflict, health and environmental hazards on the basis of insignificant p-values. A predictive modeling is expected to address some of the problems mentioned, since it estimates the performance of the model itself rather than the significance of the relationship (ibid.), potentially reducing type 1 errors.

**4.4.2. Predictive modeling – beyond the traditional Null-hypothesis testing**

To test actual the predictive power of conflict on the level of DALYs, several additional measures are added to the analysis. Opposite to Null-hypothesis testing, a predictive model is calculating the probability of belonging to a positive or negative class (Voss, 2005).  The predictive power of a model can be assessed by investigating the Sensitivity and Specificity of the model. Sensitivity describes the proportion of true positives identified by the model, while Specificity describes the true negative rate (ibid.). Within Statistics, there are several measures to describe the predictive power. The Receiver Operator Characteristics (ROC) is a measure to see how good a model can distinguish between the true positives and negatives. In graphical terms, the sensitivity rate is plotted against the specificity rate, while the former is aimed to be high and the latter low (we want as many true positives as possible). The measure of the Area under the Receiver Operator Curve (AUROC) can assess how good the model including the predictor is, hence the effect of the deletion of the predictor is tested. Similar to the fixed effects model, this specific predictive model can only assess in-sample predictive power.

The additional analysis using measures of predictive power will serve first and foremost as a robustness test to the fixed effects model and will also add a further scrutiny test to the theoretical assumptions. As mentioned in the previous subchapter, predictive models differ from Null-hypothesis significance testing models in such a way, as they assess the predictive power and hence help identify a good predictor for the model. Because predictive models do not care about OLS assumptions, they can be used as robustness tests for NHST. One downside of the use of predictive models however is the missing standardization of this method, which can make it difficult to implement and very sensitive to overfitting and data leakage.

**4.4.3 Limitations of the data**

Besides the limitations of null-hypothesis significance testing, other potential sources of weakness for the following  analysis have to be addressed. While conceptual clarity is given for both the DV and IV, as the GBD and UCDP datasets are well established and the concepts are exclusive measures, their input uncertainty leads to problems of reliability. Reliability here means that the measure is repeatable or consistent over measurements. With the UCDP dataset, every coder is subject to their own scrutiny as well as language barriers and news reporting biases  that can lead to potential underreporting of cases. It is therefore not set, that  if repeated, every event would be measured the same way. Similar challenges occur with the GBD datasets, as their committee changed the weight and estimation process of mortality and  morbidity over the time. However, the recent dataset also used in this thesis, contains updated estimates for the entire time-series. However, the GBD estimates of Disability adjusted Life years are not comparable with other datasets using the same concept, like the WHO (WHO, 2020), since the latter use different estimation techniques. This fact makes it furthermore impossible to triangulate the data of the DV using other datasets.

* missingness of data ( not only health data, also EMDAT and GDIS)

The concept of validity describes to what extent the concept actually measures what it is supposed to  measure. Given the endogeneity within the dependent variable of this thesis, it could be argued that the data used captures more than the concept of the DV. Also, the validity of the risk factors could be questioned as they are set by a committee and not triangulated yet

While some of the problems laid out above will already be addressed by a predictive model, additional robustness tests simulating with a greater sample size and imputing missing data will be performed.

* threshold of 25 BRD

**5.Analysis**

**5.1. Descriptive Analysis & Vizualization**

* look at missingness
* Outliers?
* zero inflation?
* is the panel data balanced or unbalanced? and what does it mean for the analysis
* time trends of the data
* look at the distribution

**5.2. Fixed effects**

**5.3. Robustness tests**

5.3.1. testing for OLS assumptions of the model

5.3.2. assessing the predictive power

**5.4. Findings**

**6. Discussion**

***6.2. Limitations***