Analyzing the Sensitivity of Climate Impact Model Outputs to Ethical and Epistemic Uncertainties

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Analyzing the Sensitivity of Climate Impact Model Outputs to Ethical and Epistemic Uncertainties

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Abstract

To be prepared for future risks of climate change, policy makers need to decide on the most adequate climate adaptation strategy. Such decisions often depend on the results of climate risk models, which include various uncertainties. These uncertainties arise due to incomplete knowledge about the complex climatic and socio-economic systems. Scientific studies on the nature of uncertainties in climate modelling suggest a classification into three categories: aleatory, epistemic and ethical. In climate risk modelling, there is substantial scientific interest in further deepening the understanding of uncertainties, to increase the credibility of model results for decision-making. In this thesis, I therefore quantitatively assess the effects of ethical and epistemic uncertainties on model outputs. Specifically, I investigate how sensitive the outputs of climate impact models are to different assumptions regarding the inputs, whether these different outputs imply different climate adaptation decisions and how ethical and epistemic uncertainties in the model can be assessed. To do so, I execute assumption, uncertainty and sensitivity analyses with two case studies (flooding in San Salvador and tropical cyclones in Vietnam), within the climate risk model CLIMADA. My analyses show that the models' sensitivity towards different assumptions on the input parameters depends most on the modifications of these input parameters' variation-ranges and less on the specific output and case study. I further observe that the uncertainties that I selected do not impact the ranking of cost-benefit ratios of different climate adaptation options and that ethical uncertainties are more challenging to represent with these uncertainty and sensitivity analyses than epistemic uncertainties. The results of my thesis suggest that the output of the analysis is strongly connected with the specific design of the analysis. More research should be conducted on the robustness of sensitivity analysis, concerning modifications of the input variation-ranges.

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1. Introduction

Even with great effort to reduce greenhouse gas emissions in the future, not all impacts of climate change can be fully avoided. Although the governments that have ratified the Paris Agreement decided to limit warming to below 1.5° C above preindustrial levels, this temperature rise will still be associated with major global and regional climatic and meteorological changes, which have great impacts on natural systems and humanity (IPCC, 2018).
As climate change is ongoing, its global and regional impacts are noticeable. In Switzerland, for example, the temperature has increased by 2.1°C since the beginning of temperature records in 1864 (MeteoSwiss, 2021). The impacts on humans go far beyond warmer temperatures. The National Centre for Climate Services presented four climate scenarios on how Switzerland could be affected by climate change in the future: drier summers, stronger precipitation, more extended heat waves and less snow in winter (CH2018, 2018). Events such as drier summers or more extended heat waves affect the natural environment and society by increasing the risk of forest fires through lack of rain in summer or health damage due to more pronounced heat waves.

It is therefore essential to be able to estimate the future risks due to climate change to adapt appropriately (SwissRe, 2021). Probabilistic climate risk models are useful tools for this purpose and therefore very important for scientific research as well as in industry, for example for reinsurances (SwissRe, 2019). They assess the probability and impact of by climate change enhanced hazards on nature and society by considering a broad range of possible future scenarios (Aznar-Siguan and Bresch, 2019). Some climate risk models are further designed to compare different climate adaptation measures with each other, by calculating their respective cost-benefit ratios (Bresch and Aznar-Siguan, 2020).

Climate risk modelling is highly challenging and requires making a great number of assumptions since two complex systems, the climate system and the socio-economic system are coupled with one another and the interactions between these two systems themselves are manifold. As a consequence, many important components, such as the state of the climate, the social impacts and the variety of available adaptation measures and the magnitude of their consequences are not known perfectly (Bradley and Steele, 2015). Additionally, when modelling in science, assumptions must often be made due to missing data and computational limitations. The various assumptions that are included in the model calculations affect the output. As a consequence, the model outputs can be quite uncertain.

Uncertainties arise when more than one assumption seems equally plausible. Depending on their origin and character, a differentiation between ethical, epistemic and aleatory uncertainty can be made. Basing decisions on the model output without accounting for these uncertainties or underestimating the implications of these uncertainties in the modelling process can result in decisions that are not in the decision-maker's best interest and might be later regretted or judged to be unethical for different reasons (Weaver et al., 2013; Bradley and Steele, 2015; Hansson and Hirsch Hadorn, 2016). It is therefore essential that model developers and users are aware of the possible uncertainties and their potential to affect the model results and the decisions based on these results.

Different methods are known in science to improve the handling of climate model outputs under uncertainties: It is generally suggested that decisions that are made due to the potentially uncertain model outputs should be based on robustness considerations (Weaver et al., 2013). With an analytical framework called "robust decision making", robust strategies are found to make decisions under deep uncertainties (RAND Corporation, 2021). Uncertainties are considered as being deep when they have such a drastic influence on the models' output that they may even have consequences on the decision-making process itself (Marchau et al., 2019; DMDU Society, 2021). As a recommended practice to assess the robustness of the output and the final decision with respect to uncertain model inputs or assumptions, sensitivity and uncertainty analyses are very common tools (Pianosi et al., 2016). Sensitivity analyses give information about the relative influence of different drivers of uncertainties (in the model input) on the output. Its application in climate modelling is well documented by many studies (such as Sobol, 2001; Saltelli, 2005; Saltelli et al., 2008, 2010, 2019; Saltelli and D'Hombres, 2010; Norton, 2015; Pianosi et al., 2016). Despite the high level of interest in research about the consequences of uncertainties on climate models and resulting decision-making, the influence of different (ethical and epistemic) uncertainties on climate risk model outputs has not yet been fully explored.

In this Master's thesis, I address this issue, by analyzing the sensitivity of the probabilistic climate risk model CLIMADA to ethical and epistemic uncertainties. For this purpose, uncertainty and sensitivity analyses, based on the data of two case studies (flooding in San Salvador and tropical cyclones in Vietnam), are performed with previously selected model assumptions and justified variation-ranges of the respective input parameters. The model assumptions are selected based on an assumption justification scheme that was elaborated in a previous philosophical study (Rüegsegger, 2020).
I investigate the following three main questions:

- How sensitive are the outputs of climate risk models to different assumptions made in the modelling process?
- Do these different outputs imply different preferred climate adaptation decisions?
- What are possible ways that ethical and epistemic uncertainties in the model outputs can be presented?

The thesis starts with a section about the relevant conceptual background on climate modelling, climate risk assessment and model uncertainties. In the following section, the data with which the analyses were carried out as well as the precise procedure is outlined in detail. Thereafter the results are presented and discussed, from which answers to the research questions are then drawn. Finally, the significance of the findings and possibilities for future research based on them are addressed.

2. Scientific Background

2.1 Climate Impact Modelling

2.1.1 Modelling Climate Change

It is to date scientifically proven that greenhouse gases, which are emitted by humans into the atmosphere are causing an irreversible change of climatic conditions on Earth (Solomon et al., 2009). This leads to an increase of the global mean temperature as well as further, ongoing and far-reaching changes in the climate and earth's system that will severely affect humanity and the ecosystems inhabiting the Earth (IPCC, 2014).

Well-developed complex numerical climate models that reproject the dynamics and interactions of the different Earth system spheres, enable the simulation of the ongoing and upcoming effects of anthropogenic climate change on the earth with high accuracy (Lloyd and Winsberg, 2018). These impacts can be predicted on different temporal and regional scales (NOAA climate.gov, 2021), such as global as well as local effects, which can be very diverse. An example of such a climate change impact prediction is the increase in frequency and intensity of rainfalls in the coming 25-30 years in the region around El Salvador, Central America, which will lead to increased flooding events, especially in areas near rivers (Pohl et al., 2018). Other examples are coastal regions in the tropics such as Vietnam that experience an increased intensity of tropical cyclones due to the climatic changes (Takagi et al., 2014).

Moreover, climate models can be used to compare different potential future scenarios to evaluate how we need to act in the present to shape the future for the best. Such as the IPCC's RCP scenarios that project future climate warming under different levels of greenhouse gas emissions (IPCC, 2014). These insights can be the basis for important political and economic decisions regarding mitigating climate change. So, for example, the Paris Climate Convention, wherein various nations have agreed to minimize their emissions in such a way that the temperature limit of 1.5°C above pre-industrial levels will not be exceeded since otherwise, the major global and regional climatic and meteorological changes can have far-reaching impacts on nature and human systems (IPCC, 2018). Where the risks of climate change are predicted to be severe, despite any mitigation measures taken, models can provide information on what the most appropriate adaptation measures are.

2.1.2 Probabilistic Climate Risk Models

Climate risk models link climate models with the socio-economic and demographic aspects of a specific region. They combine the predictions about by changing climate triggered disasters such as extreme weather events with impacts on society and economy for instance through damage to people and infrastructure (Aznar-Siguan and Bresch, 2019). They are useful tools to assess the socio-economic risks of climate change, which is important both for scientific research (Aznar-Siguan and Bresch, 2019) and in industry, for example for reinsurances (SwissRe, 2019).

According to IPCC (2012), disaster risk is defined as the likelihood of the occurrence of an undesirable severe impact on an exposed entity over a specific period of time that leads to "(…) widespread adverse human, material, economic, or environmental effects that require immediate emergency response (…)"(IPCC, 2012, p. 3). It is quantitatively assessed by combining the probability and severity of an impact (Aznar-Siguan and Bresch, 2019). The probability of an impact can be evaluated by considering a broad range of past and possible future scenarios.

Figure 2.1 illustrates the concept of a climate risk model: Natural variability and anthropogenic climate change influence the magnitude and the frequency of different weather and climate events. The arising hazard in combination with the exposure and vulnerability of an object result in the disaster risk. Knowing the magnitude of the risk, the economic and societal impact can then be assessed (Aznar-Siguan and Bresch, 2019). This can help to develop different disaster risk management and climate change adaption measures.

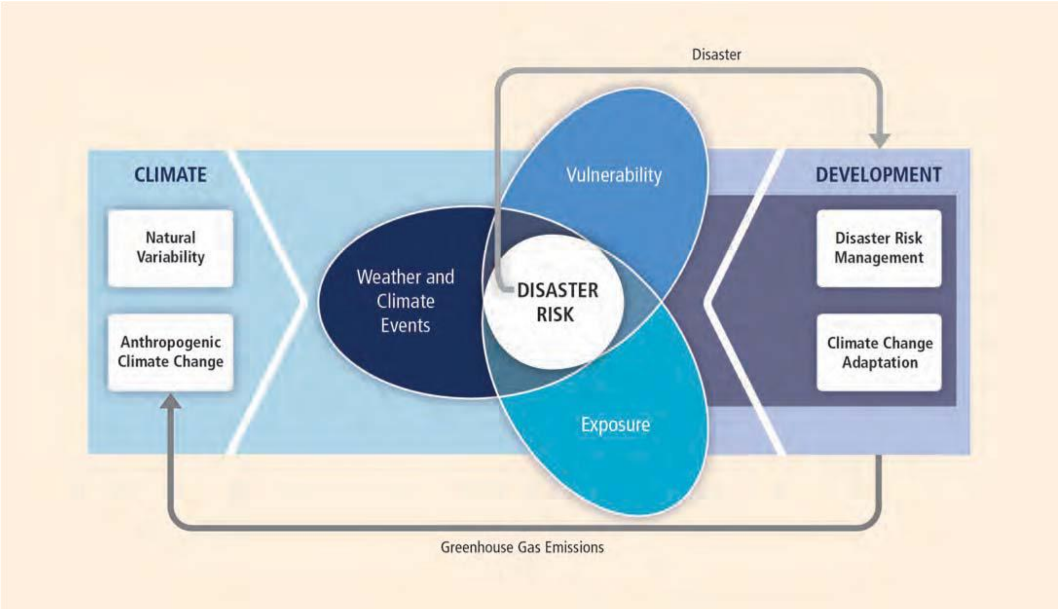

Figure 2.1: Concept of a climate risk model (IPCC, 2012, p. 2)

In this thesis, the analyses were carried out using the probabilistic climate risk model CLIMADA. This model was developed to support decision makers on climate adaptation, by giving information about the probability and the impact of occurring hazards in view of climate change (Aznar-Siguan and Bresch, 2019) as well as the costs and benefits of different climate adaptation options (Bresch and Aznar-Siguan, 2020).

2.2 Climate Risk Assessment and Adaptation Options Appraisal

Climate risk models are usually embedded within a bigger framework that aims to guide decision-makers from assessing the risk to adapting appropriately to climate change. The climate adaptation decision cycle from Willows and Connell (2003) in Figure 2.2 reflects the approach of such a climate risk assessment and adaptation options appraisal process. The process consists of eight steps, which are arranged in a cycle since continuous reviewing and adjustment regarding the latest findings cause repetitions of the different steps. Climate risk models serve as tools to assess the risk and identify and appraise the options (Steps 3 to 5 Figure 2.2).

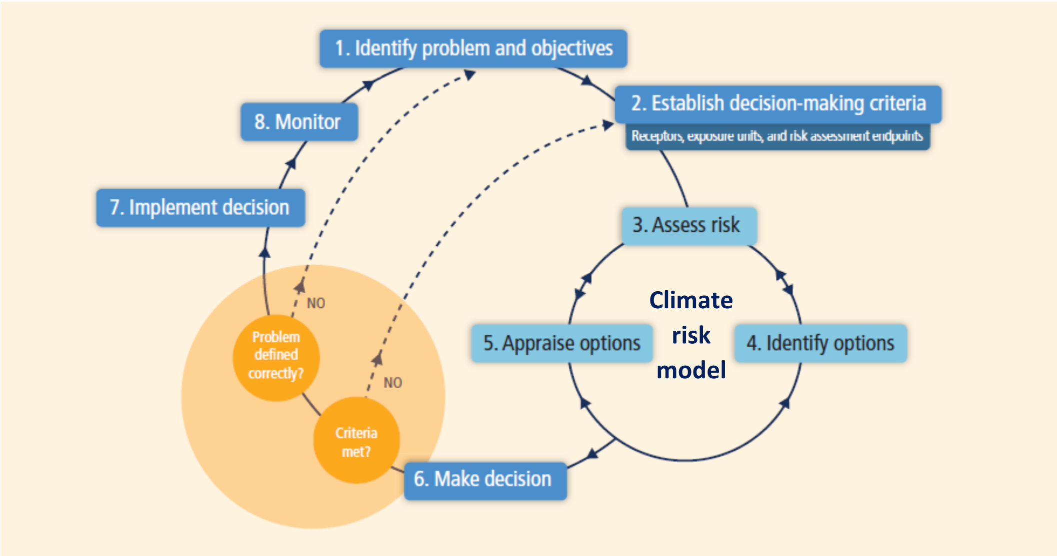

Figure 2.2: Climate adaptation decision cycle from Willows and Connell (2003) *adjusted with indicating the climate risk model as a tool to implement steps 3, 4 and 5*

Various economic methodologies exist to implement the climate adaptation decision process adequate to the risks of a certain region and the perspectives of the various stakeholders (Aznar-Siguan and Bresch, 2019). One such methodology, to which particular attention is paid in this thesis since CLIMADA forms an integral part of it, is the Economics of Climate Adaptation (ECA). This methodology is very useful to help decision-makers such as re-insurance companies or investors to work out the most suitable climate adaptation strategy regarding a specific risk that the area of interest is facing by providing them with the necessary background knowledge and comparing the effect of different adaptation measures (Wieneke and Bresch, 2016).

The ECA-Methodology is divided into three steps (Figure 2.3):

- In the first step the scope of the study is defined and the required data are gathered. The framing of the study involves several stakeholder workshops, to include all relevant aspects.
- The second step is to determine the extent of the expected loss. This includes the definition of different future scenarios based on climate change and socio-economic development, the consideration of the intensity and frequency of the particular hazard and the valuation of present assets. With the formulation of damage functions, the hazard and the assets are then brought into relation with each other. The impact can then be calculated within the climate impact model CLIMADA.
- In the third step, which is also conducted through CLIMADA, the risk will then be addressed by assessing and comparing different climate adaptation measures, through calculating their implementation and maintenance costs and their benefits by means of damage reduction. (Souvignet et al., 2016; Wieneke and Bresch, 2016)

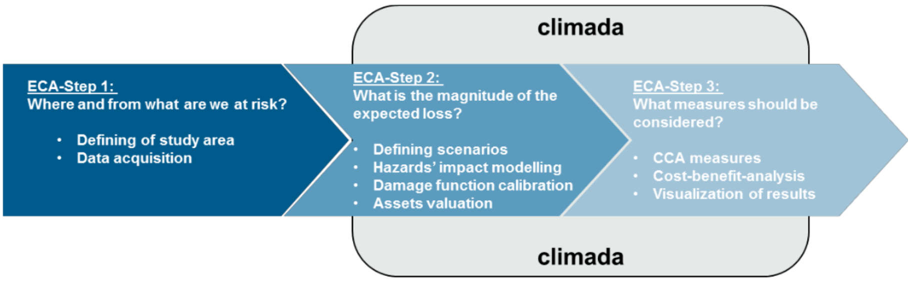

Figure 2.3: The three steps of the ECA-Methodology (Wieneke and Bresch, 2016, p. 4)

2.3 Uncertainties in Climate Impact Modelling

2.3.1 Model Assumptions

"All models are wrong, but some are useful"

George E. P. Box (2009)

In nature, myriad processes take place simultaneously and interact with each other in manifold ways. It is impossible to entirely reproduce all these natural processes. Therefore, scientific models are never an accurate reflection of reality (Box, Luceno and del Carmen Paniagua-Quiñones, 2009). They are used to simplify the complex nature, in order to make good analyses, predictions, scenario building and finally even economic and political decisions (Wieneke and Bresch, 2016). Its role is becoming increasingly important, as we learn more about our environment every day and our ability to collect, store and process data is improving. Therefore we need methods to break down the overload of information to the essential parts that are necessary for a specific purpose.

However, since reality is much more complex than a model, the model users themselves do not know everything about all the components and states that the model simulates. This leads to many assumptions being made about reality, which are then part of the model. Regarding climate risk assessment and adaptation option appraisal modelling, these assumptions regard the state of the climate, the social impacts of actions and the variety of available actions and the magnitude of their consequences (Bradley and Steele, 2015). Assumptions can also be made since some data are missing which would be needed for modelling or due to computational limitations. Also, assumptions are made unconsciously since the model-user is never aware of all his knowledge gaps.

2.3.2 Sources of Uncertainties

The fact that more than one assumption seems equally plausible leads to uncertainties. Uncertainty is generally defined as the deviation of the actual situation from the unachievable vision of having complete knowledge (Walker et al., 2003). Different fallacies exist when dealing with uncertainty, such as ignoring certain natural effects, misjudging scientific knowledge (Hansson and Hirsch Hadorn, 2016) and the supposition of being able to characterize uncertainty by a precise number and knowing all possible consequences and alternatives (Kandlikar, Risbey and Dessai, 2005).

The uncertainty cascade (Figure 2.4) describes how uncertainties arise in climate (impact) modelling: Uncertainties can emerge from alternations of current and future levels of emissions of greenhouse gases and aerosols, from natural perturbations such as volcanic eruptions and the variabilities of the solar radiation, as well as (climate-relevant) modifications of the land surface such as deforestation. Additionally, observations from nature that are used to calibrate the climate models may in general be uncertain due to the defectiveness of the measuring instruments. All these aspects serve as input data in the climate model, which itself contributes to various uncertainties, as different plausible functions and parameterizations exist. As a consequence, climate models produce different results despite having the same inputs. These modelling results can further be used for analyzing specific impacts on humanity and the environment. Since also the current and future socio-economic state and development and the natural environment are not known perfectly, further uncertainties regarding the vulnerability and exposure of a region to a specific climate hazard arise. All this information might then be used for decisions on adaptation and mitigation of climate change. These decisions have again consequences on different aspects that influence the climate modelling such as land use change or emissions (Mearns, 2010).

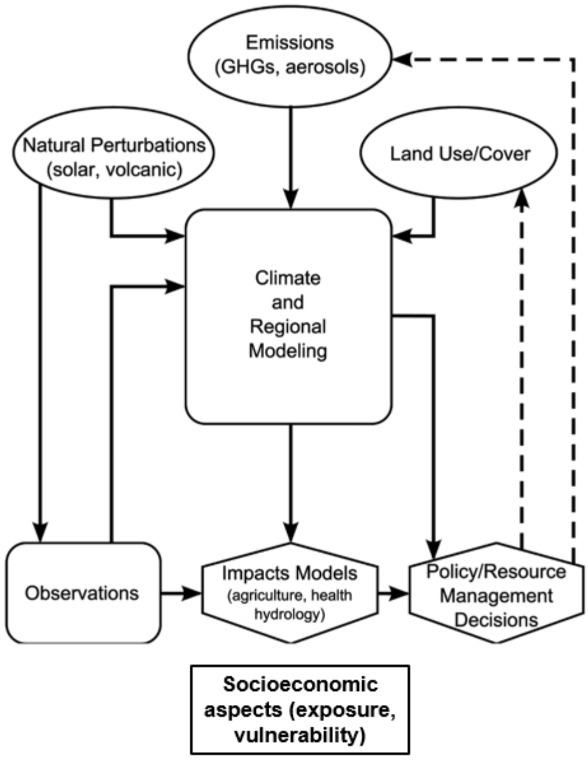

Figure 2.4: Uncertainty cascade (Mearns, 2010, p. 3) *extended with the socio-economic aspects*

For the specific case of the Economics of Climate Adaptation methodology, the potential for uncertainties can be relatively assigned to the different aspects of the modelling chain (Figure 2.5). In each phase of the previously described ECA-Methodology, assumptions are made. Big sources of uncertainty are the definition of (socio-economic and climate) scenarios and the modelling of the climate hazards, the latter especially because of the many uncertainties that occur in climate modelling, as explained through the uncertainty cascade above. Further uncertainties can occur considering the valuation of the assets and their vulnerabilities to the hazard (damage functions). Finally, also the costs and benefits of the different adaptation measures might not necessarily be perfectly known either (Souvignet et al., 2016).

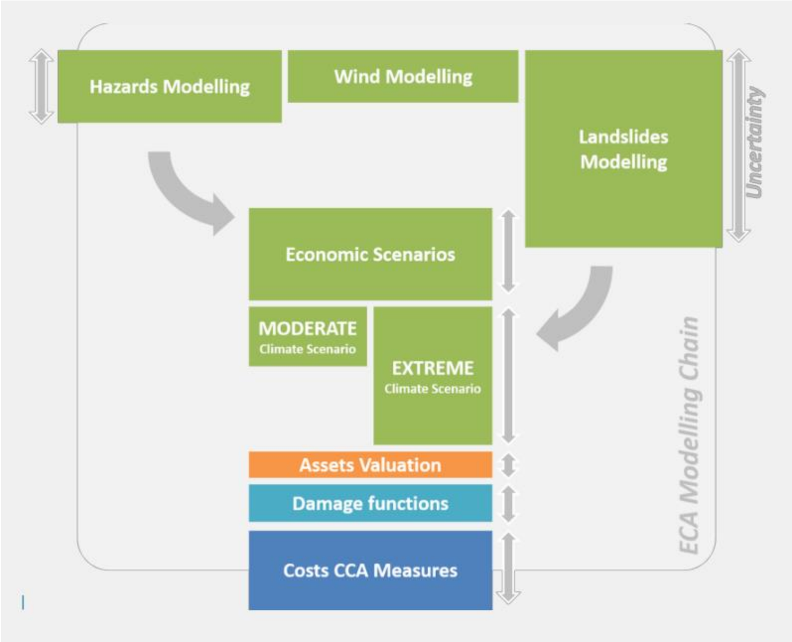

Figure 2.5: Uncertainties assigned to the different steps of the ECA-Methodology (Souvignet et al., 2016, p. 45). The *size of the arrows refers to the uncertainty potential of each step*

2.3.3 Types of Uncertainties

There are different ways how the model uncertainties can be characterized. There is a broad agreement in the literature on the characterization of uncertainty in terms of three dimensions: the location, the level and the nature of uncertainty (such as Walker et al., 2003 and Agusdinata, 2008).

Uncertainties can manifest themselves at different locations along the modelling process: at the boundaries of the modelled system, within the technical structure of the model, at the reference system, regarding the data and methods to calculate the model parameters or in the required outcome (Walker et al., 2003). The uncertainties can further be expressed on a spectrum of various knowledge levels "from the unachievable ideal of complete deterministic understanding at one end of the scale to total ignorance at the other" (Walker et al., 2003, p.11). The third dimension of uncertainty expression from Walker et al. (2003) corresponds to the most generally applied differentiation of uncertainties in science (Knüsel, 2020). It is the characterization of uncertainty in terms of its nature, meaning *why* something is uncertain. A generic distinction is made between two types: variability (or aleatory) and epistemic uncertainty.

- Variability (or aleatory) uncertainty occurs because of the intrinsic variability that the modelled systems have. These are for instance the random behavior of some weather phenomena, random errors in data collection (Agusdinata, 2008) or economic and technological variabilities (Walker et al., 2003). These uncertainties can never be fully reduced (Agusdinata, 2008) since they can't be directly identified due to their inherent randomness. But they can be taken into account when modelling, for example by regarding the climate impact as an average value over an entire year, to compensate for intra-annual variabilities.
- Epistemic uncertainty arises because of incomplete scientific knowledge (Knüsel, 2020), such as misrepresentation of processes (Curry and Webster, 2011) like the economic development of a region, the vulnerability of the assets to a specific hazard, and future states of the climate. Epistemic uncertainties can be reduced by more research and empirical efforts (Walker et al., 2003).

Some scientific sources also suggest a third type of model uncertainty in this category, which is the normative or ethical (also value) uncertainty (Bradley and Drechsler, 2014; Bradley and Steele, 2015; Mayer et al., 2017; Möller, 2016). Ethical uncertainty arises "in connection with evaluative judgements" (Bradley and Drechsler, 2014) when decision makers are unsure about how to value the various potential consequences (Bradley and Drechsler, 2014; Bradley and Steele, 2015). The main problem behind ethical uncertainty is that its impact is often underestimated since decision-makers are sometimes unconscious about their subjective preferences (Bradley and Drechsler, 2014). Examples of ethical uncertainties in climate impact modelling are the decision on the valuation unit (monetary valuation or valuation on human life) or the valuation of future generations (Mayer et al., 2017).

The clear differentiation between these categories is not always very straightforward (Walker et al., 2003). In this thesis, an attempt is made by focusing mainly on parametric uncertainties of ethical and epistemic nature.

2.3.4 Implications of Model Uncertainty on Decision-Making

Anticipating the possible future effects of climate change is highly complex and prone to many uncertainties. Therefore making decisions that tackle these possible future impacts is itself highly uncertain. When the uncertainties have such a drastic influence on the models' output that they may even have consequences to the decision-making process itself, they are referred to as "deep uncertainties" in science (Marchau et al., 2019). In climate decision-making policies, deep uncertainties occur when there is no comprehensive knowledge or agreement on the most appropriate model to connect the actions and consequences, the probability distribution of the uncertain variables and parameters that are put into the model and the prioritization and framing of different possible results (DMDU Society, 2021).

To make stable and responsible decisions based on the climate impact model outputs one has to understand the impact of uncertainties on the model (Saltelli et al., 2019). Weaver et al. propose that decisions should be made that perform well enough under many of the possible assumptions and are therefore robust to uncertainties (Weaver et al., 2013). Different procedures can be applied to assess a model and decisions based thereon in terms of its robustness to uncertainties. Very recommended methods in science are the sensitivity and uncertainty analyses (Saltelli et al., 2019). They are used to investigate how uncertain model inputs are then reflected in the output (Pianosi et al., 2016). This can be used to find out whether a model-based study is robust or sensitive to different uncertainties and to compare the sensitivity of the model under different uncertainties (Saltelli and D'Hombres, 2010; Saltelli et al., 2019).

These are also the methods applied in this thesis to analyze the sensitivity of climate impact models on ethical and epistemic uncertainties in order to assess the extent to which these affect decision-making on different climate adaptation options.

3. Methods and Data

3.1 CLIMADA

I conducted the analysis within CLIMADA, an open-source global probabilistic risk modelling platform and "multi-hazard decision support tool" (Aznar-Siguan and Bresch, 2019, p.1). It is embedded within the Economics of Climate Adaptation (ECA) methodology, an approach to help policy and decision-makers in choosing the best climate adaptation strategy (Souvignet et al., 2016). CLIMADA is an essential tool to implement the second and third step of the ECA-Methodology, namely assessing the impact that a hazard has on a region with regards to future economic and climatic developments and comparing the costs and benefits of different adaptation measures (see Figure 2.3).

Like other climate risk models, CLIMADA combines hazard, exposure and vulnerability to estimate the severity of an impact (see Figure 2.1). The risk can then be assessed by combining the severity with the probability of occurrence of such an event (Aznar-Siguan and Bresch, 2019). In CLIMADA, these different aspects are structured in three major classes (see Figure 3.1): hazard, entity and engine. In the hazard class different weather events like storms, droughts or heatwaves, are described in terms of their frequency, intensity and regional distribution. Historical data are collected and through stochastic methods, an ensemble of probabilistic events is produced. Centroids define the hazard's intensity at different geographic locations. All elements of a region, such as infrastructures, population or ecosystems, which will be exposed to a potential hazard (Aznar-Siguan and Bresch, 2019) as well as the information about different adaptation measures, discount rates and impact functions are gathered in the entity class (Bresch and Aznar-Siguan, 2020).
The engine stores the products when combining the information of the hazard and entity class. Therefore the centroids of the hazards have to be mapped to the exposures' coordinates. The impact function (f_{imp}) than translates the hazard's intensities (h_{ij}) to the respective exposure values (val_j) to calculate the impact (x_{ij}) for each event (i) at each location (j), by knowing the specific damage ratio (γ_j) (see Equation 3.1):

$$x_{ij} = val_j \, f_{imp}\left(h_{ij} \middle| \gamma_j\right)$$

Equation 3.1: Formula to calculate the impact per event and location (Aznar-Siguan and Bresch, 2019, p. 6)

The impact of each event at each location (x_{ij}) can then be combined with the respective frequencies to calculate different risk metrics:

- The Expected Annual Impact (EAI) is the impact of the expected event at a specific location when considering the annual frequency, and the Average Annual Impact (AAI) is the sum of all exposures' EAI.
- The Probable Maximum Impact (PMI) is the exceeded impact when looking at a low annual frequency. This way, for instance, the impact of a 100-year event, which has an annual frequency of $\frac{1}{100}$ and therefore a return period of 100 ($RP = \frac{1}{annual\ frequency}$) can be calculated. (Aznar-Siguan and Bresch, 2019)

The impact calculations can then be further used to assess and compare the potential of different adaptation measures to counteract the damage. The model calculates the benefit of the adaptation measures, namely the extent to which different adaptation measures will reduce the total climate risk. The total climate risk is defined as the total future impact up until a certain point in time with consideration of climatic and socio-economic changes and the respective discount rate. Knowing the costs of each of these adaptation measures, which are defined as the sum of the initial investment costs and the yearly maintenance costs, the cost-benefit ratios of all considered adaptation measures can be calculated. The comparison of these cost-benefit ratios of the different adaptation measures is a very useful tool to help decision-makers choosing the most cost-efficient adaptation strategy (Bresch and Aznar-Siguan, 2020). Therefore the main focus in this thesis was on the total climate risk calculations and the cost-benefit ratios of different adaptation measures.

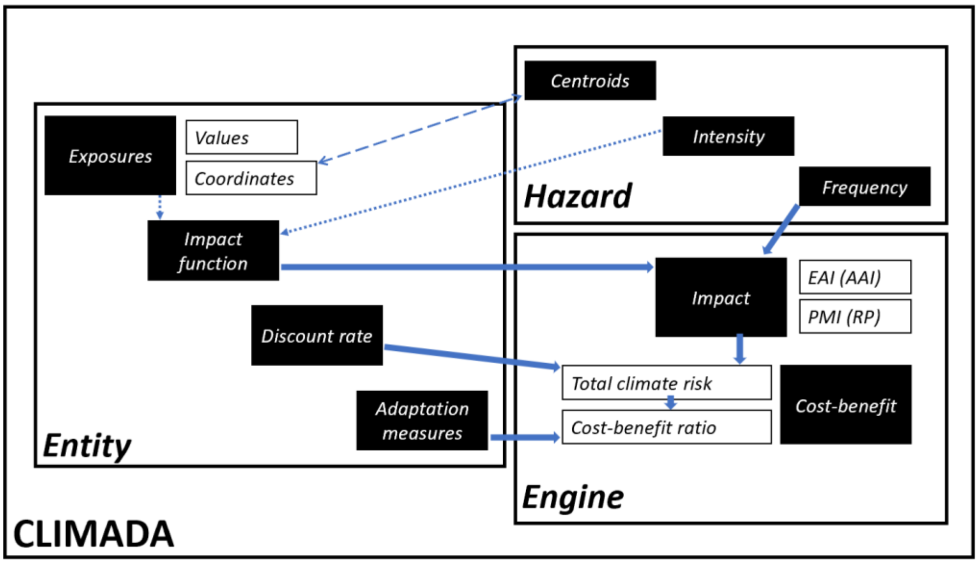

Figure 3.1: The three classes of the CLIMADA Model: Entity, Hazard and Engine with their sub-classes as black boxes and their interactions indicated with blue arrows (dashed= mutual influence, dotted = influence in one direction, filled = component for output calculations)

3.2 Case Studies

In this thesis, I performed the analyses within CLIMADA with the data of two different case studies. I conducted most analyses with the case study about flooding in San Salvador. To be able to check the validity and significance of the observed patterns in the results of the analyses, I then replicated the computational analyses with the data from another case study about tropical cyclones in Vietnam.

3.2.1 Flooding in San Salvador

The case study about flooding in San Salvador was conducted between March 2015 and April 2016. For its implementation, the ECA-Methodology was applied (Pohl et al., 2018). The study was commissioned by the Ministry of Public Works, Transport, Housing and Urban Development of El Salvador (MOPTVDU), financed by the German development bank KfW and coordinated by the Directorate for Adaptation to Climate Change and Strategic Management of Risk (DACGER) (Keilbach, 2016).

The focus was on the infrastructure risk of river floodings for the time from 2015 until 2040 in the metropolitan area of San Salvador (MASS), which is specifically sensitive to such hazards due to its poverty (Pohl et al., 2018). The aim was to assess the current and future risk due to climate change and collect and compare different adaptation measures to reduce these risks (Keilbach, 2016; Pohl et al., 2018). The value of the exposures was determined as the market value of the houses in the considered regions. The vulnerability of these houses towards river floodings was assessed by collecting data from past flood damage observations, wherefrom the impact function was then derived (Keilbach, 2016).

In this thesis, I have looked at a sub-branch of the whole case study, which encompassed a smaller area around the Acelhuate river that flows through the metropolitan area of San Salvador. In this sub-branch, only six adaptation measures were examined, which are all implementable on a household level: dual discharge toilets, water-saving devices, no toilet discharge during rain, reuse of rinse water, bridges without litter around foundations and collection of rainwater on properties (Keilbach, 2016). To simplify matters, I will refer to this sub-branch as the San Salvador case study in this thesis.

I have used this case study as the main focus of my analyses due to its extensive documentation (two open-source Jupyter Notebooks[1] and an ECA report from Keilbach 2016), because its execution already dates back some years and several post-analysis and other research work have been conducted on this case study since, such as the assumption justification scheme by Rüegsegger (2020).

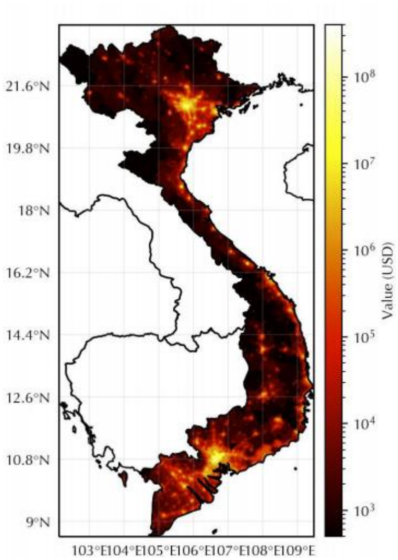

Figure 3.2 Left: Map of San Salvador with the red square framing the region in main focus: a residential area around the Acelhuate river (ETH Zurich, 2017)*; Right: Night Light Intensity in Vietnam* (Insuresilience Solutions Fund, 2021)

3.2.2 Tropical Cyclones in Vietnam

The case study about tropical cyclones in Vietnam has been conducted very recently, from June 2020 until September 2020 and some post-analysis is still ongoing. As with the San Salvador case study, this one also has been carried out with the ECA-Methodology. It was implemented by InsuResilience Solutions Fund, ETH Zurich, AXA and KfW Vietnam (Insuresilience Solutions Fund, 2021).

The focus was on risks from tropical cyclones, storm surges and sea-level rise on the agricultural production and residential housing throughout the whole country of Vietnam for the time 2020-2050 (Insuresilience Solutions Fund, 2021). The exposure data were assessed from the UN Global Assessment Report on Disaster Risk Reduction (UNISDR, 2015), where the geographical distribution was estimated based on night light intensity wherefrom then the regional distribution of asset values was derived with the country's Gross Domestic Product (De Bono and Chatenoux, 2014).

In this thesis, the data was extracted from the case study that referred only to the hazard of wind from tropical cyclones and their impact on residential housing. One adaptation option was examined: planting mangroves as protection. I will refer to this extracted part as the Vietnam case study in this thesis.

[1] Accessible at : https://nbviewer.jupyter.org/github/CLIMADA-project/climada_python/blob/main/script/applications/eca_san_salvador/San_Salvador_Adaptation.ipynb and https://nbviewer.jupyter.org/github/CLIMADA-project/climada_python/blob/main/script/applications/eca_san_salvador/San_Salvador_Risk.ipynb (accessed on March 10th, 2021)

3.3 Procedure

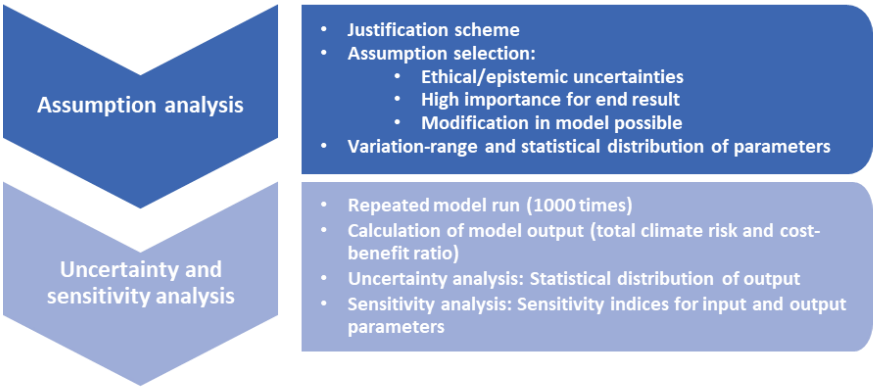

Figure 3.3: Procedure of the methods applied in this thesis

The general procedure that was applied in this thesis can be roughly divided into two parts.
The first part is a purely philosophical approach, where I conducted an assumption analysis of the San Salvador case study through thorough literature research and with the help of previous work (Rüegsegger, 2020). This analysis resulted in the selection of a few model parameters and variation-ranges of their input values that reflected these assumptions and their resulting uncertainty potential within the model.

The outcome of this philosophical assumption analysis was then the input of the subsequent quantitative methodology, the sensitivity and uncertainty analysis. With the help of a specific module constructed for this purpose within CLIMADA[2], I assessed the variance of the output distribution due to the variation of the corresponding input parameters. This was conducted for the San Salvador case study as well as for the Vietnam case study, to being able to get an understanding whether the patterns and conclusions identified in the first case study were data specific or if similar results could be found in the second case study, thus indicating a general pattern.

3.4 Assumption Analysis

The first part of the procedure was dedicated to the comprehensive preparation of the input parameters for the subsequent quantitative uncertainty and sensitivity analysis. I conducted the assumption analysis solely with the San Salvador case study, which is very well documented and has already been used as a background case study for a previous Master's thesis (Rüegsegger, 2020) where an assumption justification scheme was created. Since the current Master's thesis builds upon the findings of this previous thesis and to pursue the work seamlessly, I carried out the assumption analysis with the same case study.

The assumption justification scheme from Rüegsegger (2020) formed the starting point for the assumption analysis. The framework gives a comprehensive overview of which assumptions were made when performing the San Salvador case study that could lead to ethical and epistemic uncertainties. Building on that I made a selection of model parameters, which reflect a subset of different assumptions. Lastly, through literature research, with case study specific as well as more general scientific literature, I set plausible variation-ranges for each of the model parameters and statistical distributions reflecting how frequent the input parameters take on which of the values within these variation-ranges.

[2] The Uncertainty Module for CLIMADA is accessible via: https://github.com/CLIMADA-project/climada_python/tree/feature/uncertainty

3.4.1 Justification Scheme

The assumption justification scheme, which was elaborated by Rüegsegger (2020), analyzed the model assumptions on their justification since poorly justified model assumptions lead to considerable uncertainties (Rüegsegger, 2020). For the construction of this framework, a philosophical method called argument analysis has been applied, to extend the reasoning on uncertainties, which works only with argument-based tools and without making use of any kind of quantitative analysis (Hansson and Hirsch Hadorn, 2016). Therein different model assumptions that were made when the case study about flooding in San Salvador was conducted, have been compiled. The framework evaluated the assumptions by focusing on the strength of the justification of each assumption and the type of uncertainty this assumption leads to. Where an assumption was identified as being strongly justified if the relationship between "premises and conclusion is coherent" (Knüsel, 2020). Inconclusively justified assumptions were classified into the two categories ethical or epistemic uncertainty (Rüegsegger, 2020). The analysis found that assumptions relating to the adequacy-for-purpose of the model, the choice of options and the way these options are implemented in the model, the benefits and costs calculation and the discount rate when modelling future climate risks, lead to the most problematic uncertainties (Rüegsegger, 2020).

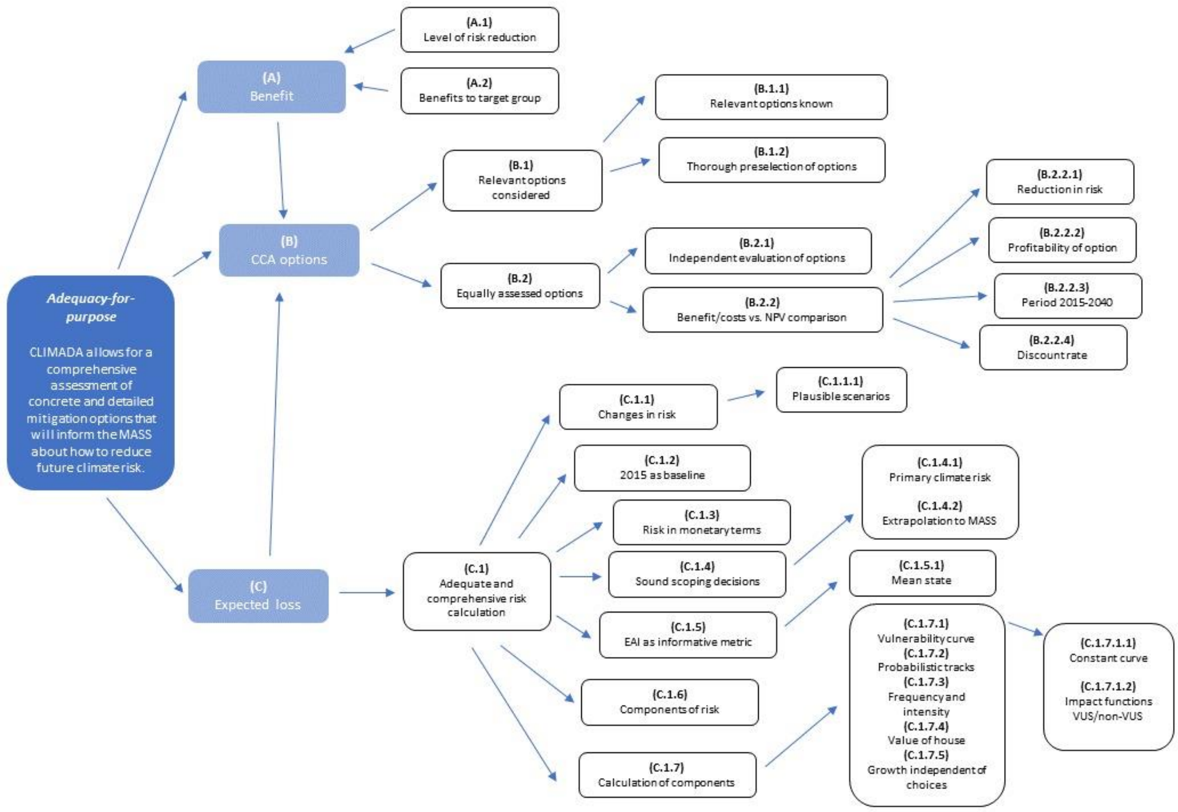

Figure 3.4: Justification scheme by Rüegsegger (2020) *that reflects and structures the numerous assumptions made in the San Salvador case study*

3.4.2 Assumption Selection

In decision-making situations, such as those when evaluating different climate adaptation measures for flooding risks in San Salvador, there is always a great number of assumptions and resulting uncertainties (Hansson and Hirsch Hadorn, 2016). This is also clearly noticeable when looking at the numerous assumptions identified in the justification scheme (Figure 3.4). To analyze the models' sensitivity it is therefore essential to filter out the most significant assumptions.

In this thesis, I selected those assumptions from the justification scheme which were most suitable for the analyses. They were filtered according to the following conditions:

- The assumption has to lead to an uncertainty of type ethical or epistemic
- The importance for the result is expected to be sufficiently high
- The assumption leading to uncertainty has to be modifiable in the model by varying the value of the input parameter

Based on these conditions a couple of input parameters were selected for further investigations.

3.4.3 Variation-Range and Statistical Distribution

After having decided which model input parameters are most suitable for further analyses, I set plausible variation-ranges for the values that each of these parameters can have. With the help of case study specific as well as general scientific literature, I found maximum and minimum bounds for the parameters. Then I chose statistical distributions describing how often a parameter takes on a certain value within the corresponding ranges. In this thesis, uniform distribution was assumed for all input parameters that is that each value occurs with the same probability within the variation-ranges. These distributions of input values were used to generate random input data for the quantitative analysis.

3.5 Uncertainty and Sensitivity Analysis

3.5.1 Statistical Analysis of the Output

A model is always applied for a specific purpose and the output of the model should provide information to respond to a certain question (Saltelli, 2005). In other words, we are interested in different kinds of outputs when we are running the model for different purposes. In this thesis, the purpose of running the climate impact model CLIMADA was to learn something about its sensitivity to different assumptions that may be sources for different ethical and epistemic uncertainties. The interest was therefore in the distribution of the output values due to variations in the input for the two outputs total climate risk and cost-benefit ratio of different adaptation measures. To analyze these output distributions, uncertainty and sensitivity analyses were applied. These are statistical methodologies used in science to investigate the uncertainty of scientific models (such as in Sobol, 2001; Saltelli, 2005; Saltelli et al., 2010, 2019; Norton, 2015; Pianosi et al., 2016). These two methodologies complement each other and are not always considered separately in practice. In the remainder of this thesis, these two methods will be treated separately from one another where this makes sense since this was also recommended by Saltelli et al., (2019).

For the uncertainty as well as for the sensitivity analysis, the first step is to identify those input parameters that are sources of uncertainties. There would have been also further sources of model uncertainties, such as different data, resolution levels or the model structure, which were not taken into account in this thesis. These model uncertainties, reflected in the thesis through varying the values of the input parameters, lead to differing model outputs. The uncertainty analysis reveals the empirical distribution of these model outputs, whereas the sensitivity analysis decomposes the uncertainties of the model output into the different sources (Saltelli et al., 2019), meaning the output of the model can be traced back to the different assumptions made when the values of the input parameters were determined (Saltelli, 2005) (Figure 3.5).

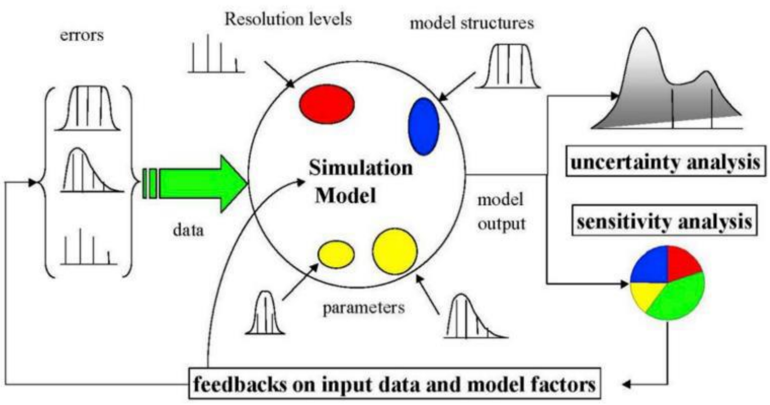

Figure 3.5: Functioning of the uncertainty and sensitivity analyses (Saltelli et al., 2019, p.30)

To conduct the sensitivity and uncertainty analyses in this thesis, sets with the values of the model parameters that reflect the uncertainty in the input had to be generated first. This was done with the Monte-Carlo Simulation, as it is recommended in the literature (Pianosi et al., 2016; Saltelli et al., 2019, Raychaudhuri, 2008). With this method, the sets of input values for the model parameters were constructed pseudo-randomly, where the variation-range of the parameters, their statistical distribution within this range and the size of the set were specified. After the sets of input parameters were generated, the model was run multiple times with all possible combinations of all the elements of the different sets.

3.5.2 Uncertainty Analysis

The uncertainty analysis elaborates the overall spread of the model's output due to the variability in the input parameters, without distinguishing how much each input parameter is responsible for this output distribution but just looking at all parameter variations together (Pianosi et al., 2016; Saltelli et al., 2019). In this thesis, I conducted the uncertainty analysis preceding the sensitivity analysis, to first get an overall impression about the magnitude of the uncertainty in the model output, as it was also recommended by Saltelli et al. (2019). The uncertainty in the output was analyzed statistically with box plots and frequency plots, which identified the characteristics of the output distribution by displaying the interquartile range, the median, the mean, the standard deviation, the minimum and maximum value. This gave already a lot of useful information about the behavior and trends of the sets of output values.

3.5.3 Sensitivity Analysis

After the uncertainty analysis, I carried out a sensitivity analysis, which revealed, in addition to the general characteristics of the distributions, how much each of the individual input variations contributed to the total output variation (Pianosi et al., 2016; Saltelli et al., 2019). From this, it could thus be deduced, how significant each of the assumptions and the respective uncertainties, represented by the varied input parameters, were for the model output (Saltelli et al., 2019). This information is helpful to improve the overall performance of and confidence in the model. It reveals for which input parameter the resulting uncertainty in the output is the highest and it is, therefore, most advisable to invest more time and effort in collecting background information to estimate its value. On the other hand, there are input parameters that have only a minor influence on the output uncertainty and therefore it is sufficient to keep this parameter constant at an approximate value (Saltelli et al., 2019).

I executed the sensitivity analysis by following a basic workflow that was suggested by Pianosi et al. (2016) since it applies to various approaches of sensitivity analyses. This workflow contains three main steps: input sampling, model evaluation and post-processing. The single steps will be further clarified in the following sections.

Input Sampling

Before the analysis can be carried out, the input parameters which will be analyzed must be prepared. This was conducted in this thesis through an assumption analysis, where the set of parameters for further analysis, their variation-ranges and statistical distributions were chosen. The selection of the variation-range has a major impact on the outcome of the sensitivity analysis since it directly influences the model and therefore the model's output.

Depending on how the variability space is selected, two types of sensitivity analyses are distinguished: the global and the local sensitivity analysis. In this thesis, a global sensitivity analysis was carried out, which means that the variation-ranges of the input parameters were selected to be within a wide range of possible values, which were all located within a defined parameter space (Saltelli, 2005; Pianosi et al., 2016). This contrasts with the local sensitivity analysis, where the variation-ranges are always centered around a certain reference point (Pianosi et al., 2016). Having the range and distribution of the input parameters, the input samples were then generated, with a size of 1000 elements for each parameter.

Model Evaluation

Various methods of sensitivity analyses exist. Due to the available computing source, the selected type (global) of the input sampling and the overall purpose of the analysis, which was to identify for each input factor their relative contribution to the output variability, I applied the variance-based Sobol' method. In this method, the model's sensitivity on different input parameters is determined with numeric values which represent the deviation from the model output when varying the input parameters. Three main categories of these sensitivity indices are distinguished:

- First-order indices (S1) provide information on how a single input parameter alone influences the output.
- Second-order indices (S2) provide information on how the interaction of two input parameters influence the output.
- Total-order indices (ST) provide information on how the model output is influenced by both, the input parameter alone and in interaction with all other input parameters.
  (Pianosi et al., 2016; Herman and Usher, 2019)

These sensitivity indices were calculated by dividing the output variance when fixing one or multiple input parameters through the total output variance (Norton, 2015; Pianosi et al., 2016):

$$SI = \frac{output\ variance\ with\ fixed\ input\ parameter(s)}{Total\ output\ variance}\ with\ 0 \leq SI \leq 1$$

Equation 3.2: Formula to calculate a variance-based sensitivity index

For each parameter **(p')** it was determined how strong it contributes to the total variability of the output **(y)**, both for each parameter individually and in combination with each other (Norton, 2015). The variability was calculated by the variance, the mean square deviation of a variable from its expected value **(E)** (Norton, 2015).

The formula to calculate the sensitivity of the model to a specific input parameter **($S_{p'}$)** looks as follows:

$$S_{\mathbf{p}'} = \frac{E_{\mathbf{p}'}\left[(\bar{y}_{\mathbf{p}'} - \bar{y})^2\right]}{E[(y - \bar{y})^2]} = \frac{E_{\mathbf{p}'}\left[(\bar{y}_{\mathbf{p}'} - \bar{y})^2\right]}{var(y)}$$

Equation 3.3: Formula to calculate the sensitivity of a model to a specific input parameter (Norton, 2015, p. 170)

In other words, the sensitivity to the input parameter or subset of input parameters p' **($S_{p'}$)** is the ratio between the mean square deviation from the mean output $(\overline{\boldsymbol{y}})$ when <u>fixing</u> the specific input parameter or a subset of input parameters p' $(\overline{\boldsymbol{y}}_{\boldsymbol{p}'})$ **($E_{p'}\left[(\overline{y}_{p'} - \overline{y})^2\right]$)** and the variance of the output **($E\left[(y - \overline{y})^2\right]$).**

$S_{p'}$ can be between 0 and 1. Where 0 means no effect of the (subset of) input parameter(s) **(p')** on the output **(y)** variability and 1 means the (subset of) input parameter(s) **(p')** accounts for all the variability in the output **(y).** (Norton, 2015)

Since I was looking at the uncertainty of multiple input factors, I analyzed the behavior of each of the input factors separately by always only varying one factor and keeping the others at a constant value and I also varied all (or several) input factors at-a-time. The first approach gave information about the direct effect of each input factor on the output variability separately, whereas the second approach also considered interactions among the different input factors themselves. The variability of one input factor could for example have a dampening or amplifying effect on the variability that another input factor has on the output. (Pianosi et al., 2016)

Therefore with the first approach, I calculated the sensitivity index (first order sensitivity index, **S1**), by fixing one input parameter $\boldsymbol{p}'(=\boldsymbol{p_j})$ alone whereas, with the second approach, I calculated the sensitivity index (total order sensitivity index, **ST**) by fixing all parameters except the observed input parameter $\boldsymbol{p}'(=\boldsymbol{p}_{\sim j})$ and then calculating the difference from this ratio from one (Norton, 2015):

$$S_{Tj} \triangleq 1 - \frac{var(\bar{y}_{p\sim j})}{var(y)}$$

Equation 3.4: Formula to calculate the sensitivity index of total order (Norton, 2015, p. 171)

The Sobol' method, which I applied in this thesis, enabled an in-depth investigation of the contribution of each input parameter separately and in interaction with one another, by decomposing the output into components which were distinguished by being influenced from different combinations of the varied input parameters (Norton, 2015).

$$y(\mathbf{p}) = y_0 + \sum_{j=1}^{m} y_j(p_j) + \sum_{j=1}^{m-1}\sum_{k=j+1}^{m} y_{jk}(p_j, p_k) + \cdots$$

Equation 3.5: The Sobol' decomposition (Norton, 2015, p. 171)

The formula above is called the Sobol' decomposition and is applicable under the assumption that all parameters are distributed uniformly. By combining this formula with the definition of sensitivity as variance ratio, the whole sensitivity, in the case here the variance ratio, can therefore be decomposed into the different contributions of combinations of multiple input parameters:

$$1 = \sum_{j=1}^{m} S_j + \sum_{j=1}^{m-1} \sum_{k=j+1}^{m} S_{jk} + \cdots + S_{123\ldots m}$$

Equation 3.6: Decomposition of the model sensitivity into subsensitivities (Norton, 2015, p. 171)

Post-Processing

After I calculated the sensitivity indices, I represented the results using appropriate visualizations to facilitate the interpretation. I created bar plots to display the sensitivity indices of first and total order of the varied input parameters for one output alone, matrices to reflect the sensitivity indices of second order for all combinations of each two input parameters and scatterplots to compare the sensitivities of different datasets and different outputs with one another.

In addition to a meaningful visualization of the results to facilitate their interpretation, comparison and communication, the credibility of the results must be verified (Pianosi et al., 2016). This is important to be able to know later on whether reliable conclusions can be drawn from the results of the model evaluation. I executed this verification by calculating and representing the confidence intervals of the sensitivity indices of first and total order (Pianosi et al., 2016). This gave information about how significantly the values of the indices were different from one another and how much each of the calculated values could be trusted.

The verification was further conducted by repeating the analysis with different variation-ranges of one input parameter as well as with repeating the analysis with the same input variations but with the data from the Vietnam case study instead of the data from the San Salvador case study. This revealed how strongly the results were influenced by the design of the analysis alone and whether there are patterns in the results which are recurring in the different analyses and from which therefore general interpretations could be drawn.

4. Results

4.1 Assumption Analysis of the San Salvador Case Study

The procedure for selecting suitable model assumptions and their respective variation-ranges has already been explained in the methods and data chapter (see Section 3.4). The table below summarizes the final product of the assumption analysis. The model assumptions about asset value, discount rate, impact function, cost of adaptation measures, climate change scenario, economic growth rate and risk metric were considered as being most suitable for further analyses, as they best fulfilled the three main filtering conditions:

- The assumptions that are represented in model parameters could potentially lead either to uncertainties of type ethical or epistemic since they are only weakly justified in the literature and multiple other values for the parameters would be equally plausible.
- They are expected to have sufficiently high importance for the result.
- They are modifiable within CLIMADA as their values are stored in one of the three classes.

Table 1: Outcome of the assumption analysis

Parameters	**Type of Uncertainty**	**Range**	**Justification**	**Literature**
Asset value	Epistemic	60 – 120%	Property valuation market	*Mallinson et al 2000, GPG 2021*
Discount rate	Ethical	0 – 10%	No discounting vs. Interest rate in developing countries	*Stern 2007, CIA 2021*
Impact function	Epistemic	Low – high vulnerability	Mdd for different vulnerabilities	*Huizinga et al. 2017*
Cost of adaptation measures	Epistemic	95 – 110%	Construction costs	*Rauzana 2018, Ökmen et al 2010*
Climate change scenario	Epistemic	90 – 110%	Hazard intensity deviation from RCP 8.5 scenario	*IPCC 2014*
Economic growth rate	Epistemic	-2 – +4%	Actual economic growth in developing countries	*World Bank Group 2020*
Risk metric	Ethical	RP5, RP100, EAI	Favoring the weakest vs. considering the average population	*Hallegatte et al., 2017*

In the following, each of the seven selected assumptions, their corresponding model parameters and their variation-ranges are outlined in more detail:

4.1.1 Asset Value

The assets considered in the San Salvador case study were the houses in the according region. Their monetary value was estimated with field surveys and value assessment of different residential buildings (Keilbach, 2016). This was assessed by determining the costs of constructions, repair and market price of the house or part of the house which could potentially be exposed to flooding events. The market price was determined by taking into consideration the neighborhood where the house is located, the age of the house and the items inside the house (Keilbach, 2016).

Even though the estimation of the value of the houses was very thorough, the true value can deviate substantially from this assumption. The reason for that is that the valuation of the market prices is always very complex (Mallinson and French, 2000) and the housing market in El Salvador is especially uncertain (Global Property Guide, 2021). Some neighborhoods are unpopular due to high criminality or high risk of natural disasters. As a consequence, houses can lose up to 40% of their initial value in only a few months (Global Property Guide, 2021). On the other hand, the market prices of houses in El Salvador can also be underestimated because they are located in a popular neighborhood such as a gated community.

Since the upper-end uncertainty is generally less than the lower-end uncertainty when estimating property market values (Mallinson and French, 2000), I selected a variation-range of 60-120% of the initially assumed asset values in this thesis. The variation of the real value is due to a lack of full knowledge about the market behavior and therefore an uncertainty of type epistemic.

I set the variation-range of the asset value in the model by multiplying the values of the exposures inside the entity class with values between 0.6 and 1.2 (AV, see Appendix 1).

4.1.2 Discount Rate

The discount rate is the rate at which a future value of an object is calculated back to the present (Flanigan, 2011). In the economics of climate adaptation, it is used to reflect the costs of future climate risk and the cost-benefit ratios of climate adaptation options with the present valuation (Souvignet et al., 2016). When looking at a longer time scale, such as the period from 2015 until 2040 in the San Salvador case study, one has to take into account that not only the natural but also the socio-economic conditions of a region change substantially over time, especially in developing countries. Therefore also the vulnerability of the region towards the climate risk and the potential to adapt appropriately change constantly (Souvignet et al., 2016).

The ECA-Methodology suggests that the discount rate for cost-benefit calculations is equal to the real rate of interest and should therefore correspond to the economic growth rate of the region. The justification for that is that this is the rate at which the future is traded in the present (Souvignet et al., 2016). So for the San Salvador case study the discount rate was originally set at 2%, since this is the assumed economic growth rate[3].

There is a lot of discussion going on in science about how and whether to discount the future in the economics of climate change[4]. A purely economic approach suggests a high discount rate, especially for developing countries, due to potentially high rates of return (Beckerman and Hepburn, 2007). On the other hand, discounting and thus giving more value to the present than to the distant future, can be considered unethical, as this means that the wellbeing of future generations is considered to be

[3] For further details about this assumption refer to Section 4.1.6 Economic Growth Rate
[4] See for example Frederick, Loewenstein and O'Donoghue, 2002; Beckerman and Hepburn, 2007; Nordhaus, 2007; Stern, 2007; Gardiner, 2010; Lloyd and Winsberg, 2018

less important than that of present-day generations (Nordhaus, 2007), which results, for instance, in regarding investments in a climate adaptation measure as less attractive whose benefits will arise in the far future in comparison to investments in a climate adaptation measure whose benefits arise immediately. Therefore zero or near-zero discounting is well justified from an ethical point of view.

Knowing that there is good justification for the choice of a high as well as of a low discount rate, I selected the variation-range in such a way that both extremes were taken into account. Therefore I set the lower-end of the variation-range at 0%, as it is suggested by Stern (2007). To select the upper-end I looked at the high economic discount rates in Nordhaus (2007) and compared them to the economic growth and inflation rates of developing countries of the Central Intelligence Agency (CIA, 2021). Consequently, I set the upper-end at 10%. The variation of the discount rate is a matter of perspective and a trade-off between the welfare of different generations, therefore it leads mainly to ethical uncertainties.

I set the variation-range of the discount rate in the model by simply changing the value of the discount rate, which is stored in the entity-class (DR, see Appendix 1).

4.1.3 Impact Function

The impact functions express to what extent an asset (e.g. house) is damaged at different intensities of a specific hazard such as flooding (Aznar-Siguan and Bresch, 2019). The corresponding variable is the mean damage degree (mdd) and is given as a percentag. In the San Salvador case study, the impact functions were derived by collecting data about historical damages on houses due to flooding events and comparing similar structures from different countries (Keilbach, 2016). These data sets were then applied to the HAZUS model to generate the corresponding functions (Keilbach, 2016). The HAZUS model is a worldwide used tool to evaluate risk information (FEMA, 2020). Two different impact functions were derived for houses in vulnerable and non-vulnerable settlements (Keilbach, 2016).

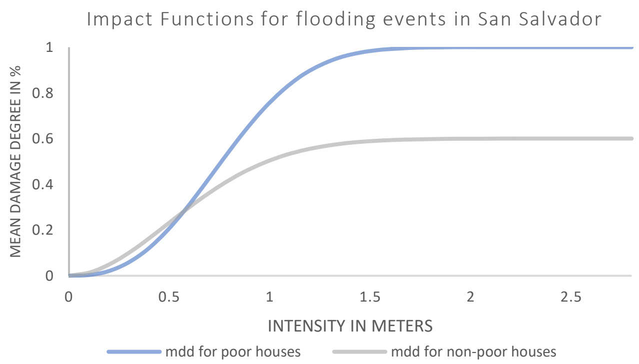

Figure 4.1: Original impact functions in the San Salvador case study

Since the collected data was limited and no systematic study on the vulnerability of the houses due to the flooding intensities inside the region of the case study itself was conducted (Keilbach, 2016), it is not conclusively justified that the derived impact functions are the most appropriate ones.

However, there is a large amount of data collected worldwide on the vulnerability of houses to flooding. To analyze the uncertainty of the impact functions set in the case study, I considered different flood depth damage functions from a global database. These functions were also generated with the HAZUS model (Huizinga, de Moel and Szewczyk, 2017). Different regions have different vulnerabilities to flooding hazards, because they have, for example, more solid houses or better protection strategies.

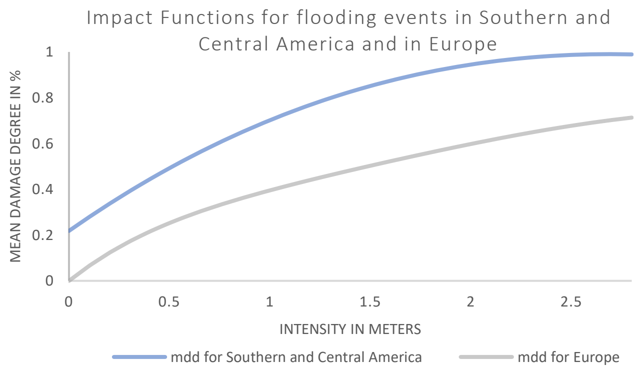

Figure 4.2: Alternative impact functions for upper and lower variation-range

I selected two alternative impact functions from this global database that differ as much as possible in their vulnerability: An impact function from data across Europe with a very small mdd as the lower limit of the variation-range and an impact function from data across South America with a very large mdd for the upper limit (Huizinga, de Moel and Szewczyk, 2017). No differentiation was made between poor and non-poor housing, but all houses were assessed with the same impact function.

I embedded this variation-range of the mdds of the impact functions in CLIMADA in such a way that the mdd, determined in the entity class, was defined to be the sum of the lower mdd limit (mdd_{Europe}) and a term that is the product of the difference between the lower and upper limit ($mdd_{SC\ America} - mdd_{Europe}$) and a variable that can take values between 0 and 1 (IF, see Appendix 1).

$$mdd = mdd_{Europe} + \left(IF \times \left(mdd_{SC\ America} - mdd_{Europe}\right)\right)$$

Equation 4.1: Formula to calculate the varied mean damage degree

4.1.4 Adaptation Cost

In the San Salvador case study, six different adaptation measures were examined, which are all implementable on a household level: The installation of more water-efficient toilet-flushes in households, the attachment of water-saving devices on the outlet of water pipes, an information campaign about not discharging water into the canalization when it rains, the installation of storage tanks to reuse rinse water, the removal of domestic litter at passages and conflicting sections and the collection of rainwater in storage tanks for reuse in homes, schools and commercial buildings[5]. The total cost of each adaptation measure was calculated as the sum of the initial investment costs and the yearly maintenance costs. The information on these costs was derived from the market prices of the materials required, the labour costs and the construction and repair costs. (Keilbach, 2016)

As already pointed out in the section about the asset values, determining the value of a property by reference to market prices is always based on uncertainties (Mallinson and French, 2000). Furthermore, there is uncertainty in the estimation of climate adaptation costs due to a general lack of data, especially in developing countries (IPCC, 2014). The costs of the adaptation measures include, besides the material, the cost of the implementation of the information campaigns and the costs of construction work. In the following, only the uncertainties with regards to the costs of construction work are

[5] In the remaining part of this thesis, these six measures are described as follows: Dual discharge toilets; Water saving devices; No toilet discharge during rain; Reuse of rinse water; Bridges without litter around foundations; Collection of rainwater on properties

considered, assuming that they are representative of the uncertainties of the total expenses of the adaptation measures.[6]

According to Rauzana (2018), the cost variations in a construction project arise particularly due to incomplete knowledge about the physical conditions, the scale and scope of the project, the project site and design and the current local financial and economic situation. Construction costs tend to be rather underestimated than overestimated, as unforeseen events can increase them (Rauzana, 2018).

I assessed the upper and lower level of the cost variation by looking at a study where the uncertainty range of a construction project was analyzed thoroughly. In this study, variations of approximately 4.5% to 6.5% around the initially estimated costs were found (Ökmen and Öztaş, 2010). Taking into account the observation that the upper limit of cost estimations tends to be rather higher, I chose a variation-range of -5% to +10% for the climate adaptation costs in the San Salvador case study. The uncertainties in the adaptation costs arise mainly due to knowledge gaps about the actual expenses of the implementation and are thus epistemic uncertainties.

I set the variation-range of the adaptation cost in the model by multiplying the values of the costs of the adaptation measures, which are stored within the entity class, with values between 0.95 and 1.1 (AC, see Appendix 1).

4.1.5 Climate Change Scenario

To incorporate the climatic changes in the model, the case study worked with the Representative Concentration Pathways (RCP) developed by the IPCC (IPCC, 2014). These pathways present different possible levels of greenhouse gas and air pollutant emissions and atmospheric concentrations as well as changes in land use during the 21st century. Based on the society's commitment to mitigate climate change, four scenarios are distinguished, from very strong mitigation and thus a small emission rate to weak mitigation and thus a strong emission rate: RCP2.6, RCP4.5, RCP6.0 and RCP8.5 (IPCC, 2014). Through climate models, the resulting global temperature increase and the multiple climatic and meteorological implications were further estimated for each of the emission pathways.

For the San Salvador case study, only the extreme climate change scenario RCP8.5 was considered. A consequence of this extreme climate change scenario is the shift in precipitation intensities and frequencies. For the studied area, it was estimated that the intensity of flooding events will increase by 10% and the frequency will decrease by 10% (Keilbach, 2016).

The prediction of (river) flood events with a changing climate is very uncertain, as it depends not only on changes in precipitation but also on various other parameters that are connected in a complex way (Zimmerli, 2006). Moreover, the predictions of precipitation changes due to climate warming are very variable themselves (Bindoff et al., 2013).

Therefore, I selected a variation-range of +/-10% of the flooding intensity from the assumed extreme scenario. The uncertainties considering the different changes in flooding intensities due to climate change are of epistemic kind since they occur due to incomplete scientific knowledge.

I set the variation-range of the flooding intensity in the model by multiplying the values of the flooding intensities, which are stored within the hazard class, with values from 0.9 to 1.1 (CC, see Appendix 1).

[6] For an accurate assessment of the uncertainties of the different adaptation measures' costs, each adaptation measure would need to be analyzed individually in more detail. This was not feasible within the scope of this thesis.

4.1.6 Economic Growth Rate

After the financial crisis in 2009 El Salvador experienced a relatively low but constant economic growth fluctuating around 2% (World Bank Group, 2021). At the time of the implementation of the San Salvador case study in 2015, it was assumed that future societal and natural changes will not have a strong impact on the overall annual economic growth rate and that it will accordingly remain at around 2% for the following 25 years (Keilbach, 2016).

A global crisis like the Covid-19 pandemic, even if it happens extremely rarely, is predicted to lead to a worldwide economic recession of enormous magnitude and will have a particularly severe and lasting impact on developing countries (World Bank Group, 2020). The consideration of such an event in the estimation of the future economic growth thus appears very sensible.

Based on past observations and future forecasts for the next 25 years concerning economic growth in El Salvador (World Bank Group, 2020), I assumed a fluctuation in the economic growth rate of +/-2% around the initially set 2% in the case study. Due to the potentially strong negative impact of unpredictable global catastrophes such as a pandemic, I further reduced the lower limit of the variation-range by 2%. Thus, the variation of the economic growth rate was set between -2% and +4%. This uncertainty can also be assumed to be mainly epistemic, as it is based on a lack of information.

I included the variation-range of the economic growth rate in CLIMADA by simply changing the value of the economic growth rate, which is stored in the entity-class (EcoG, see Appendix 1).

4.1.7 Risk Metric

When modelling climate risks in CLIMADA, the hazards' impact on the region of study can be calculated with different risk metrics[7] (Aznar-Siguan and Bresch, 2019). In the San Salvador case study, it was calculated by considering the expected average annual impact.

The assumption that the expected average annual impact is adequate to analyze the risk of a region facing a disaster, presupposes that the regions' impact through weaker but more frequent events averages out the impact through infrequent but very extreme events which cause a tremendous loss, meaning that the regions' vulnerability is proportional to the magnitude of an event. This approach is reasonable for the average population of a studied region, but if one looks only at the poorest areas this is not always true. Economically not developed and sensitive areas are especially vulnerable to severe damages, often suffer from secondary impacts and have more difficulties recovering from it (Hallegatte et al., 2017). This approach can therefore be too simplistic and lead to insufficient consideration of the most vulnerable in society.

The consideration of risk by means of the average annual impact over the whole population can thus lead to ethical uncertainties, as it is a trade-off between the small share of high impact for the poor and the large share of smaller impact for the average population.

In the Uncertainty and Sensitivity analyses, I investigated this by making the same calculations with not only using the expected annual impact (EAI) but also the impact of events occurring every 5 years and 100 years (RP5 and RP100) as risk metrics.

[7] See Section 3.1 CLIMADA for more detailed information about the calculation of the different risk metrics

4.2 Uncertainty Analysis

I conducted the uncertainty analysis by varying the input values of the six parameters: asset value, discount rate, impact function, adaptation cost, climate change scenario and economic growth rate within their set variation-ranges. I varied all parameters simultaneously and for each parameter, I assumed that they can take on any value in their particular variation-range with equal probability (uniform distribution, see Appendix 2). The calculations within the CLIMADA model were then repeated multiple times, each time with different values of the six input parameters. For the uncertainty analysis, the calculations were conducted using the expected annual impact as the risk metric for calculating the total climate risk and the cost-benefit ratios of the adaptation measures. I carried out the analysis for both case studies, whereas the same variation-ranges and probability distributions of the six input parameters were applied.

4.2.1 Uncertainty Analysis of the San Salvador Case Study

Total Climate Risk for the San Salvador Case Study

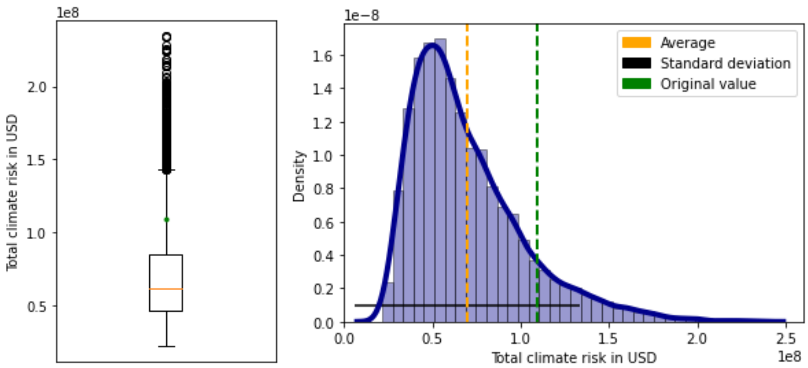

Figure 4.3: Total climate risk for the San Salvador case study; Left: Boxplot with output distribution of the total climate risk in USD; Right: Frequency density plot of the total climate risk; the orange line indicating the average value, the green dot/line the original case study value and the black horizontal line (right figure) the standard deviation

The total climate risk due to flooding events in San Salvador for the year 2040 was calculated to be 109 million USD with the original model assumptions (indicated in green in Figure 4.3). When the input parameters take on any values within the specified variation-ranges, the total climate risk varies between approximately 10 and 250 million USD. Whilst the distribution curve is positively skewed, with the highest density at around 60 million USD and some outliers in the upward direction. This results in an average of 69.6 million USD (orange line in Figure 4.3) with a standard deviation of 31.8 million USD (black line in Figure 4.3 right). The uneven distributions of the set variation-ranges of the input parameters around the originally assumed parameter values lead to a deviation of the average total climate risk from the original total climate risk. The original value is slightly bigger than the average value, however, this difference is smaller than the standard deviation.

Cost-Benefit Ratio for the San Salvador Case Study

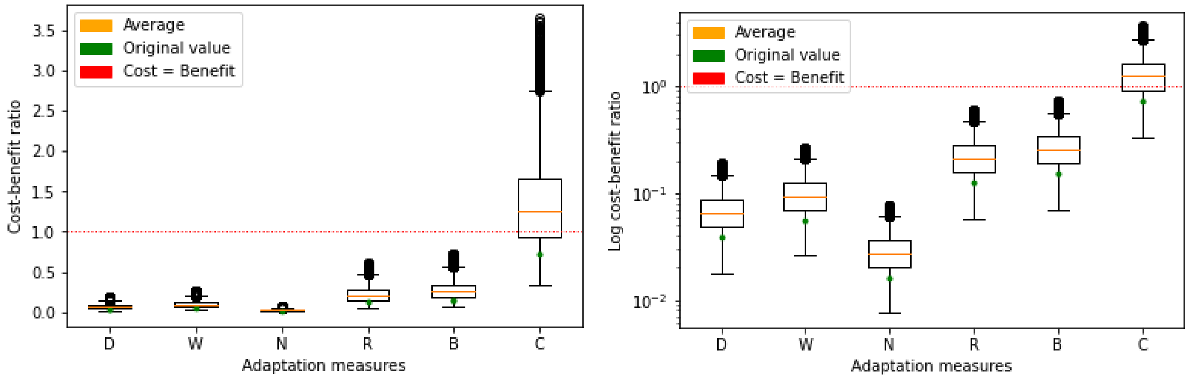

*Figure 4.4: Cost-benefit ratios of the six adaptation measures for the San Salvador case study: **D**ual discharge toilets, **W**ater saving devices, **N**o toilet discharge during rain, **R**euse of rinse water, **B**ridges without litter around foundations, **C**ollection of rainwater on properties; Left: Boxplot with output distribution of the cost-benefit ratios, Right: Boxplots with logarithmic y-axis; red line indicating the point where the costs equal the benefits, original values in green and average values in orange*

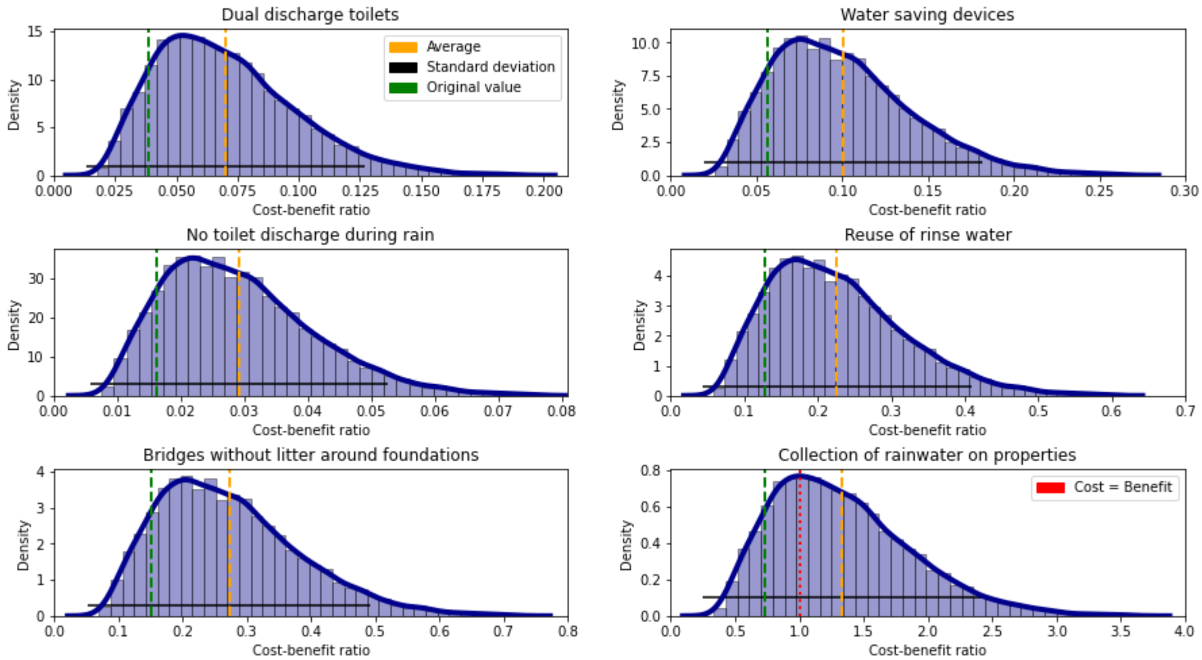

Figure 4.5: Frequency density plots with output distribution of cost-benefit ratios of the six adaptation measures for the San Salvador case study; red line in the bottom right indicating the point where the costs equal the benefits, the orange line the average value, the green dot/line the original case study value and the black horizontal line the standard deviation

The cost-benefit ratios of the different adaptation measures span from 0 to 3.5. Five adaptation measures have cost-benefit ratios distributed between 0 and 0.8 and only one adaptation measure, the one about the collection of rainwater on properties, has cost-benefit ratios exceeding 1.0 (red line in Figure 4.4 left and Figure 4.5 bottom right). This implies that for the five adaptation measures with all cost-benefit ratios below 1.0, even under uncertainty, the benefit is always higher than the cost. Therefore, only for the adaptation measures about the collection of rainwater on properties the uncertainty influences the profitability.

When looking at the distribution of the cost-benefit ratios on a logarithmic scale (Figure 4.4 right), it is noticeable that all six adaptation measures have similar distributions in proportion to the size of their cost-benefit ratios. In addition, the difference between the average cost-benefit ratio (orange lines in Figure 4.4 and Figure 4.5) and the original cost-benefit ratio (green dots in Figure 4.4 and Figure 4.5) is similar for all adaptation measures in proportion to their sizes. These similar distributions of the cost-benefit ratios of the six adaptation measures are also clearly visible when looking at the shapes of the frequency density curves in Figure 4.5. Consequently, the cost-benefit ratios of the six adaptation measures behave the same concerning the variations of the input parameters.

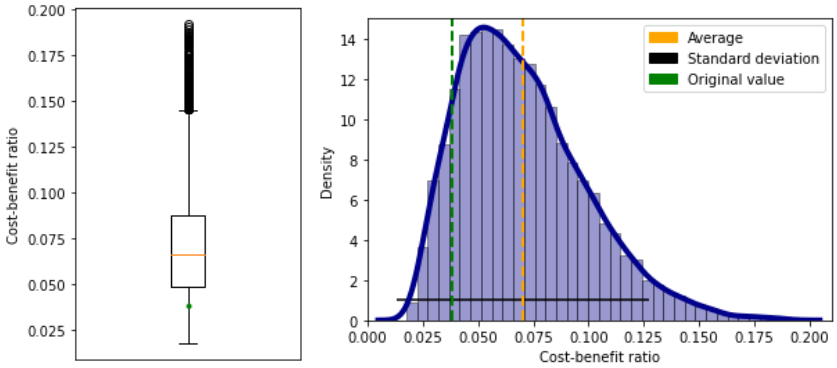

Figure 4.6: Cost-benefit ratio of the adaptation measure "Dual discharge toilets" for the San Salvador case study; Left: Boxplot with output distribution of the cost-benefit ratio; Right: Frequency density plot of the cost-benefit ratio; the green dot/line is indicating the original value, the orange line the average value, and the black horizontal line (right figure) the standard deviation

Since the sensitivities of all considered adaptation measures are similar, for the rest of the results chapter only one adaptation measure is further analyzed, which is the "Dual discharge toilets". The cost-benefit ratio of this adaptation measure in the San Salvador case study was 0.038 (indicated in green in Figure 4.6) before I made any variations in the input parameters. After input parameter variations and multiple model run, the output values are distributed between 0 and 0.2. The distribution curve is positively skewed, just as the distribution of the total climate risk, but with a shorter tail in the upward direction. Most data points lie between 0.05 and 0.08 with some outliers in the positive direction (Figure 4.6, left). The average cost-benefit ratio is 0.07 (indicated in orange in Figure 4.6) with a standard deviation of 0.02 (black line in Figure 4.6, right). The original cost-benefit ratio is smaller than the average cost-benefit ratio. This is opposite to the observations made for the uncertainty analysis of the total climate risk, where the original value was bigger than the average value. This is because the benefit of an adaptation measure is defined as the potential averted damage and consequently an increase in the total climate risk increases the benefit, which decreases the cost-benefit ratio.

4.2.2 Uncertainty Analysis of the Vietnam Case Study

Total Climate Risk for the Vietnam Case Study

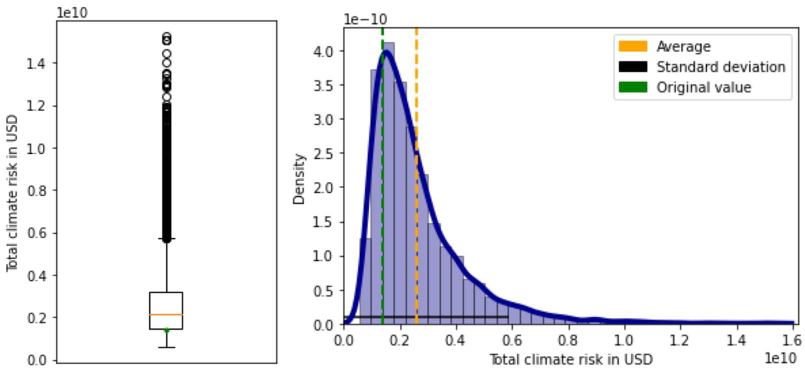

Figure 4.7: Total climate risk for the Vietnam case study; Left: Boxplot with output distribution of the total climate risk; Right: Frequency density plot of the total climate risk; the green dot/line indicating the original value, the orange line the average value and the black horizontal line (right figure) the standard deviation

The total climate risk of tropical cyclones in Vietnam is around 1.4 billion USD for the year 2050 (indicated in green in Figure 4.7), with the initial model assumptions. After applying the same variations, with the same ranges and probability distributions of the six input parameters as for the San Salvador case study (see Table 1), the total climate risk is distributed between 1 and 17.5 billion USD. The distribution curve is also positively skewed with a long tail in the upward direction and a very high density of values lying around 2 billion USD (see Figure 4.7 right). The average is at 2.61 billion USD (indicated in orange in Figure 4.7) and the standard deviation 1.65 billion USD (black line in Figure 4.7, right).

The original value of the total climate risk is smaller than the average value of the total climate risk, but the difference between those two is still smaller than the standard deviation. The reason for the original total climate risk being smaller than the average total climate risk in the Vietnam case study whereas it was the other way round in the San Salvador case study is that the originally assumed input parameter values were not the same in the two case studies. For example, in the San Salvador case study the discount rate was originally assumed to be 2%, whereas in the Vietnam case study it was originally assumed to be 6%. Consequently, the distribution of the output parameters in the uncertainty analysis is different for the two case studies.

Cost-Benefit Ratio for the Vietnam Case Study

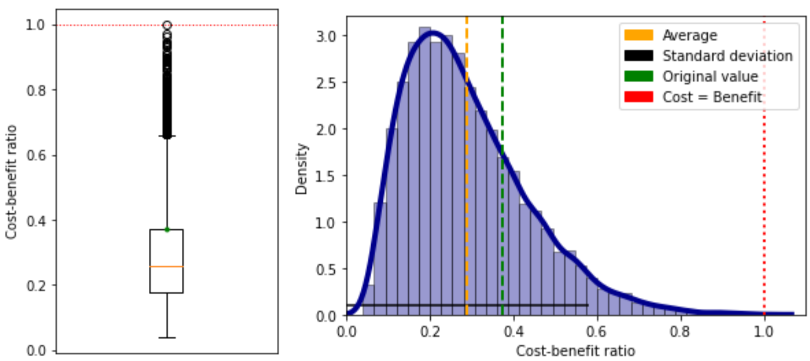

Figure 4.8: Cost-benefit ratio of the adaptation measure "Mangrove" for the Vietnam case study; Left: Boxplot with output distribution of the cost-benefit ratio; Right: Frequency density plot of the cost-benefit ratio; the green dot/line indicating the original value, the orange line the average value, and the black horizontal line (right figure) the standard deviation

The original value for the cost-benefit ratio of the climate adaptation measure about planting mangroves was 0.373 (indicated in green in Figure 4.8). With a variation of the input parameters, the cost-benefit ratios are distributed between 0 and 1, which means that even under uncertainty the benefit of this adaptation measure is bigger than the cost. The distribution curve is slightly right skewed (Figure 4.8 right), although less distinctive than the distribution curve of the total climate risk, and half of all data points lie between 0.1 and 0.3. The average cost-benefit ratio is with 0.288 slightly smaller than the original cost-benefit ratio (indicated in orange in Figure 4.8), but still within the standard deviation, which amounts to 0.146 (black line in Figure 4.8, right).

4.3 Sensitivity Analysis

To understand more precisely how the six input parameters (asset value, discount rate, impact function, adaptation cost, climate change scenario and economic growth rate) and their variations within the set ranges contribute to the spread in the output distribution and therefore to the uncertainty of the model results, sensitivity analyses were carried out. This was done by running the model multiple times, whilst some of the input parameters were varied and some were fixed at a specific value. The sensitivity was then assessed through indices that were calculated by dividing the output variance when fixing one or multiple input parameters through the total output variance (Norton, 2015; Pianosi, 2016). The sensitivity index of first order (S1) was assessed by fixing one input parameter, which represents how one parameter alone contributes to the output variation, the sensitivity index of second order (S2) was assessed by fixing two input parameters, which represents how their interaction contributes to the output variation and the sensitivity index of total order (ST) was assessed by fixing all input parameters except one, which represents how one input parameter contributes to the output variation alone and in interaction with all other parameters (see Section 3.5.3). ST is therefore the sum of S1 and S2 and any sensitivity indices that represent higher order interactions. ST is larger than S1 if the interactions among the different input parameters contribute to the model sensitivity. The value of the sensitivity indices decreases sharply with increasing order. S1 was observed to be up to ten times larger than S2 in previous studies (Sobol, 2001). Defining the sensitivity as variance ratio in combination with decomposing the total model sensitivity into subsensitivities, implies that the ST values (and therefore also S1, S2 and sensitivity indices of higher order) of all input parameters add up one. Therefore, the sensitivity index of one input parameter represents its share of the total model sensitivity (see Equation 3.6).

In the first part of this section, S1, S2 and ST were assessed for the total climate risk and the cost-benefit ratio of one adaptation measure for the San Salvador case study as well as for the Vietnam case study for all six input parameters. To get an understanding of how much the sensitivities rely on the spread of the variation-ranges of the input parameters, in the second part of this section, the sensitivity analysis was then repeated with different variation-ranges of the discount rate, from 0 to 2% and from 0 to 5%. The calculations were first conducted with the expected annual impact as risk metric, as was also done in the uncertainty analysis. To assess if the model sensitivity depends on the choice of the risk metric, in the third part of this section, the sensitivity analysis was also conducted with alternative risk metrics, which were the 5-year and the 100-year return period.

4.3.1 Sensitivity Analysis of the San Salvador Case Study

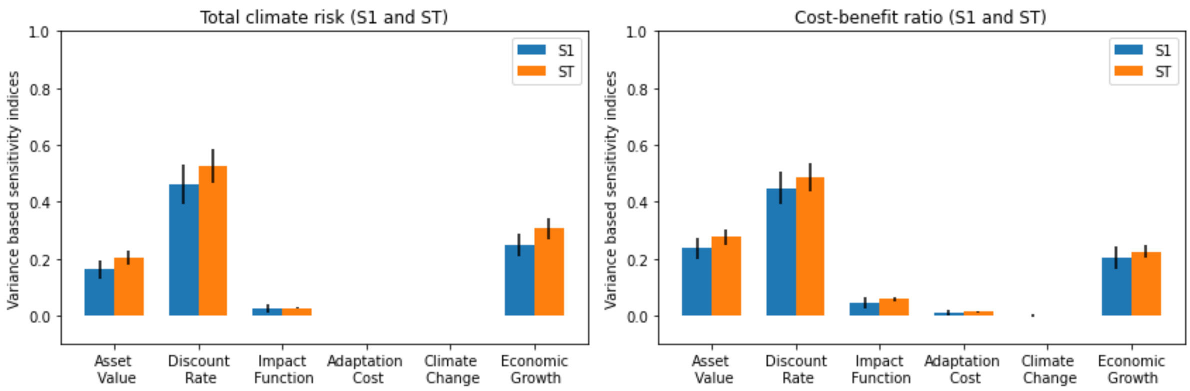

Figure 4.9: Sensitivity indices S1 (blue) and ST (orange) for the six input parameters for total climate risk (left) and cost-benefit ratio (right) with corresponding confidence intervals as black vertical lines for the San Salvador case study

In the San Salvador case study, the sensitivity indices for the total climate risk and the cost-benefit ratio look very similar. ST is for all input parameters and both outputs larger than S1. This indicates that additionally to the variation of the individual input parameters alone, also their interactions contribute to the model sensitivity. For both outputs S1 and ST for the climate change scenario are zero, indicating that the outputs are insensitive to the variations of the climate change scenario. Both outputs have the highest S1 and ST values for the discount rate, around 0.5, followed by the S1 and ST values for the economic growth rate and asset value around approximately 0.2 and the values for the impact function and adaptation cost between 0 and 0.1 (see Figure 4.9). The confidence intervals of the S1 and ST values represent the range where 95% of the results lie. These ranges are smaller than the differences of the sensitivity indices between the input parameters, meaning that the observed ranking of the sensitivity indices applies with a high degree of confidence.

The sensitivity indices of the two different outputs would be equal if it was expected that the uncertainties in the six input parameters have the same influence on the model sensitivity for both outputs. Arranging the S1 and ST values of both outputs on a scatterplot, it is, however, noticeable that they are not the same for the two outputs (see Figure 4.10). The diagonal indicates where in the plot the S1 and ST values of the two outputs would lie if they were equal. Only the S1 and ST values for the climate change scenario lie on this diagonal since they are zero for both outputs. The biggest deviations from the diagonal have the S1 and ST values for the parameters asset value and economic growth rate. This deviation is substantial since it impacts the ranking of the sensitivity indices. The model sensitivity towards variations in the economic growth rate is larger than towards variations in the asset values when looking at the total climate risk whereas it is the opposite when looking at the cost-benefit ratio. This is due to the different calculations of the two outputs and thus the different influences of the input parameters.

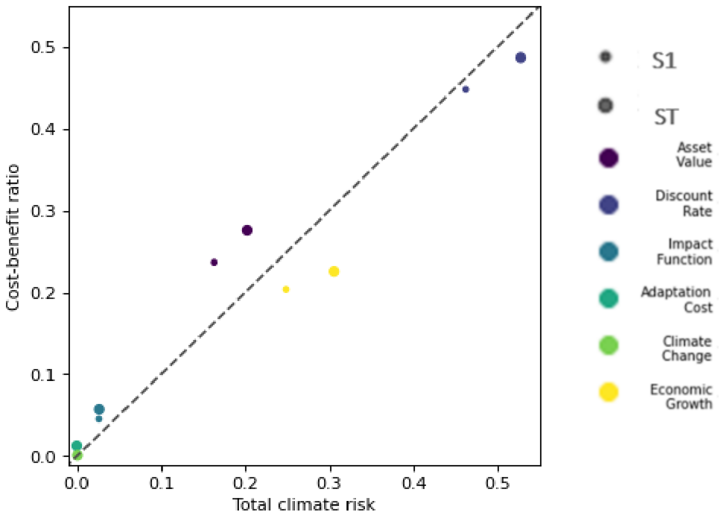

Figure 4.10: Scatterplot to compare the sensitivity indices of the total climate risk (x) to those of the cost-benefit ratio (y) for the San Salvador case study

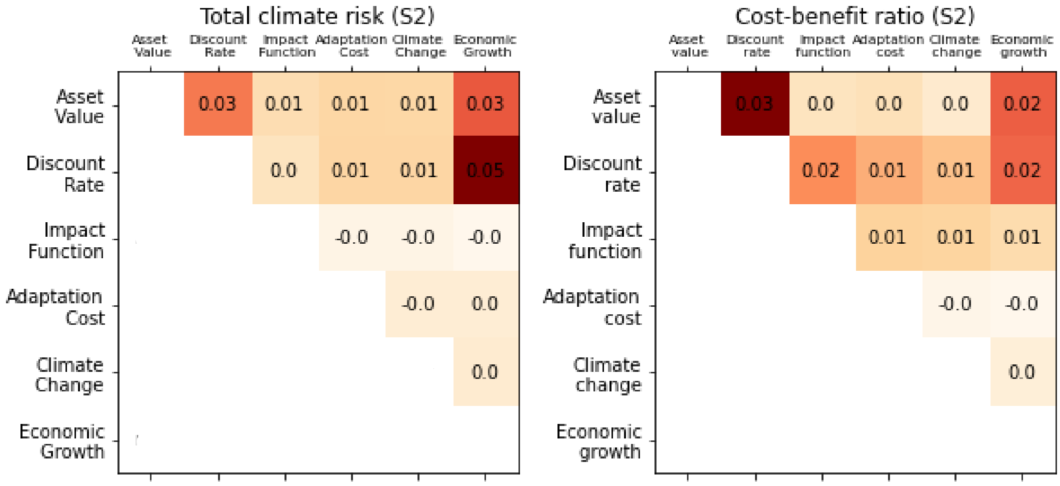

Figure 4.11: Sensitivity index of second order (S2) for the total climate risk (left) and cost-benefit ratio (right) for the San Salvador case study

The assumption that the interactions among the input parameters impact the model sensitivity, based on the observation that the ST values are larger than the S1 values for all input parameters (see Figure 4.9), is confirmed when looking at the S2 values (see Figure 4.11), which are around 10 times smaller than the S1 values of the corresponding input parameters. The S2 values further confirm the dominance of the sensitivities of the three input parameters discount rate, economic growth rate and asset value that was observed when looking at S1 and ST. For the total climate risk, the interactions among economic growth rate and discount rate lead to the highest S2 values, whereas the interactions of each of these two parameters with the asset value show smaller S2 values. All other interactions have much smaller or even no sensitivity at all. This is similar for the cost-benefit ratio, whereas here the interactions among the parameters of discount rate and asset value lead to the highest S2 values, and the interactions of these two parameters with the economic growth rate share second place. This fits well with the observations made when looking at S1 and ST, where the variation of the asset values had the second-highest sensitivity indices for the cost-benefit ratios and the third-highest for the total climate risk and vice versa for the economic growth rate. The interaction between the impact function and the discount rate seem to have a higher S2 for the cost-benefit ratio compared to the total climate risk.

4.3.2 Sensitivity Analysis of the Vietnam Case Study

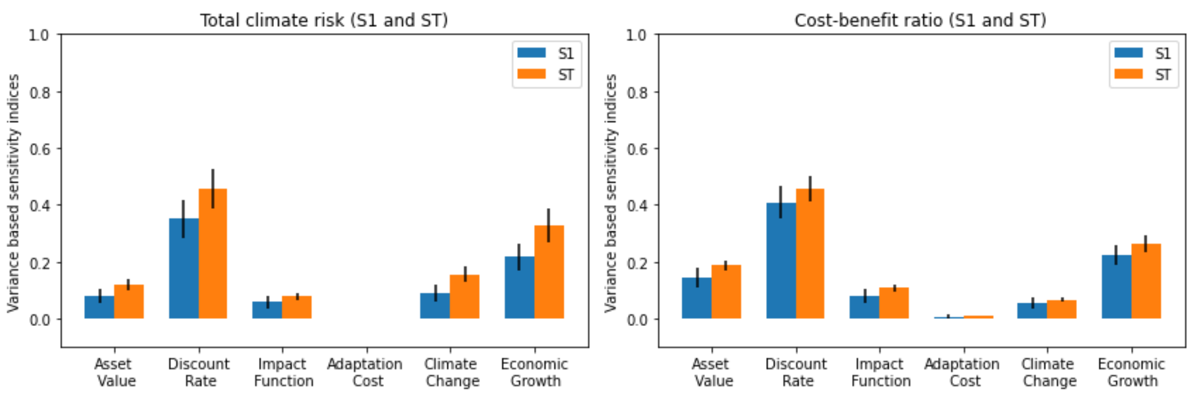

Figure 4.12: Sensitivity indices S1 (blue) and ST (orange) for the six input parameters for total climate risk (left) and cost-benefit ratio (right) with corresponding confidence intervals as black vertical lines for the Vietnam case study

For the Vietnam case study, a similar pattern for the S1 and ST values can be observed than for the San Salvador case study (Figure 4.12). The ST values are always higher than the S1 values, indicating that interactions among the input parameters influence the output sensitivity. The discount rate has the highest sensitivity indices at around 0.4, followed by the economic growth rate at around 0.2. For the total climate risk, the S1 and ST values for the climate change scenario have approximately the same size as those for the asset value at around 0.1. These are closely followed by the S1 and ST values for the impact function. For the cost-benefit ratio, the S1 and ST values for the climate change scenario are with values around 0.05 smaller than those for asset value around 0.15 and even smaller than those for variations of the impact function around 0.1. Also here the ranges of the confidence intervals do not exceed the differences of the sensitivity indices among the input parameters.

Comparing the values of the sensitivity indices for the two outputs on a scatterplot, it can be recognized that the indices of the asset value and those of the climate change scenario differ the most among the two outputs since their deviations from the diagonal are largest (Figure 4.13).

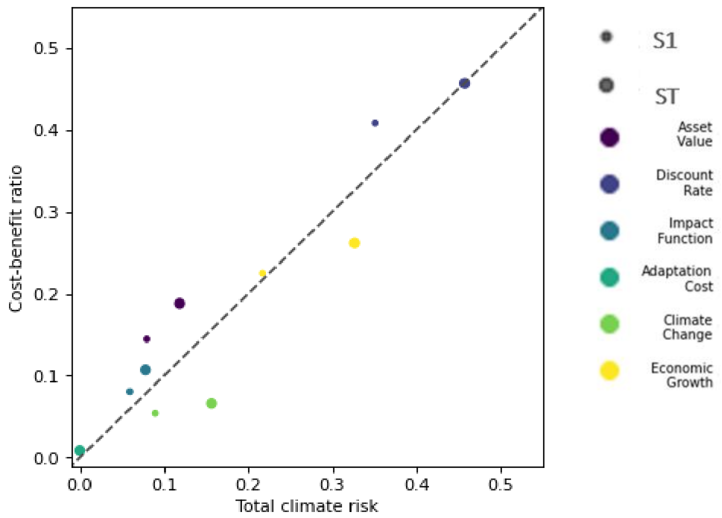

Figure 4.13: Scatterplot to compare the values of the sensitivity indices of the total climate risk (x) to the sensitivity indices of the cost-benefit ratio (y) for the Vietnam case study

The finding that the ST values are bigger than the S1 values indicates that the interactions among the input parameters impact the model sensitivity (see Figure 4.12). This is confirmed by the S2 values (see Figure 4.14) which are the largest for interactions among those input parameters that also have the largest S1 and ST values. For the total climate risk, the index indicating the model sensitivity due to interactions between the discount rate and the economic growth rate stands out, which fits the observation that these two input parameters had the highest S1 and ST values. This is followed by the S2 values for interactions between the discount rate and the climate change scenario that had the third-largest S1 and ST values. For the cost-benefit ratio, the highest S2 is the one indicating interactions among the asset value and the discount rate closely followed by the S2 values indicating interactions among the economic growth rate and the discount rate and the economic growth rate and the asset value.

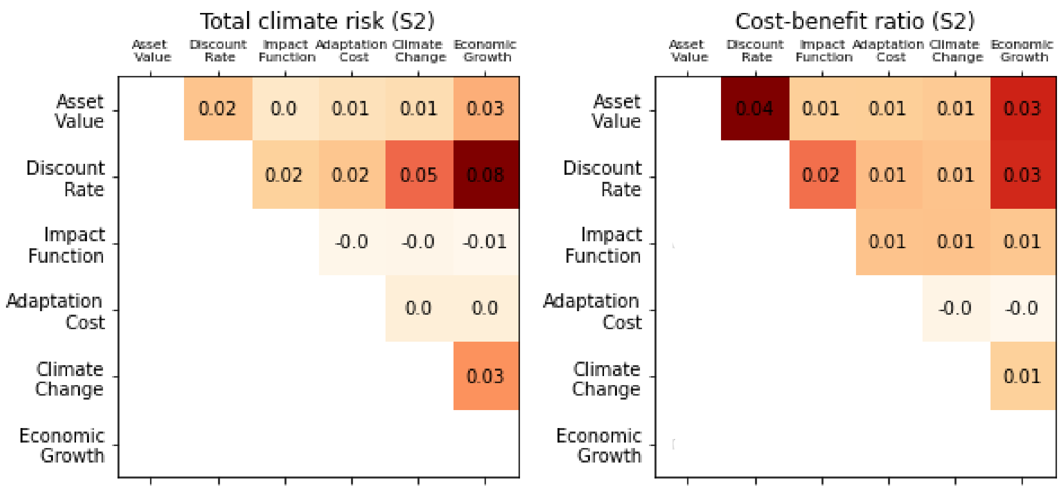

Figure 4.14: Sensitivity index of second order (S2) for the total climate risk (left) and cost-benefit ratio (right) for the Vietnam case study

4.3.3 Comparison of the Sensitivity Indices of the two Case Studies

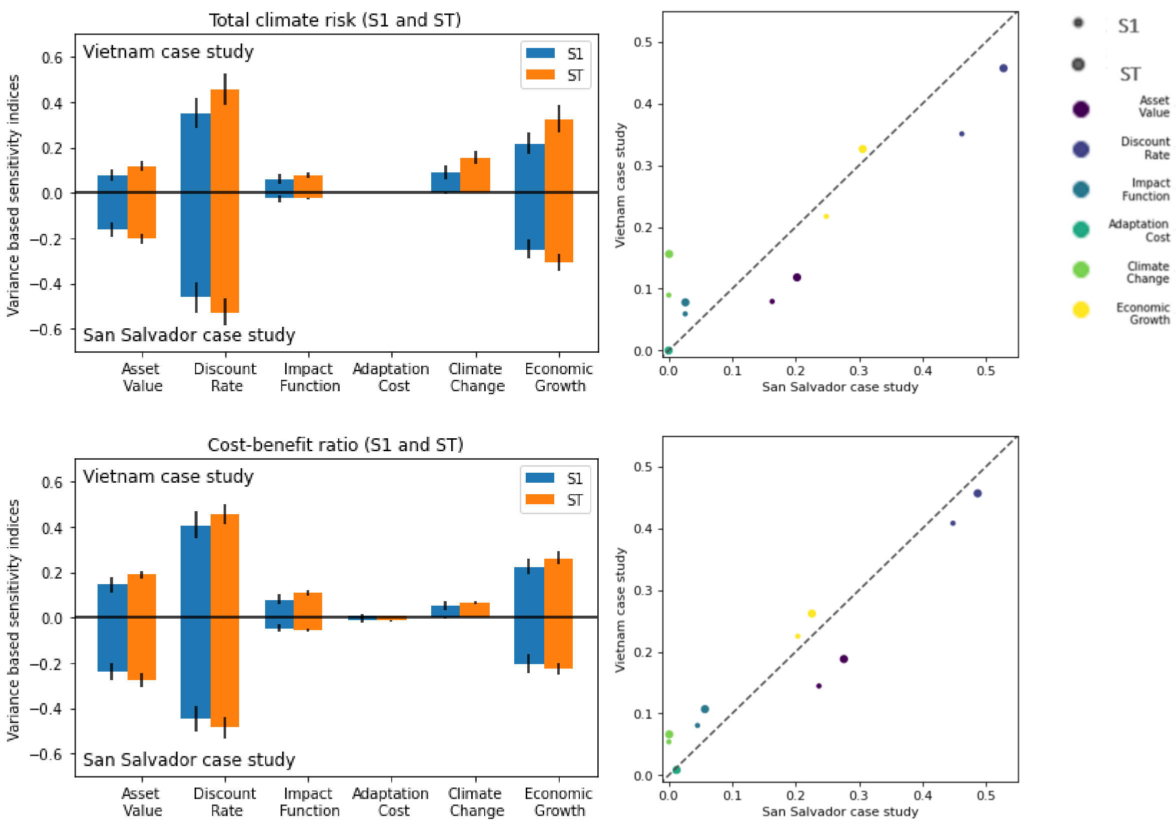

Figure 4.15: Comparison of the sensitivity indices of the San Salvador and the Vietnam case study; Left: Sensitivity indices S1 (blue) and ST (orange) for the six input parameters for total climate risk (upper row) and cost-benefit ratio (lower row) with corresponding confidence intervals as black vertical lines; Right: Scatterplots to compare S1 and ST of the two case studies for the total climate risk (upper row) and the cost-benefit ratio (lower row)

In both case studies and for both outputs, the S1 and ST values for the discount rate are the largest, followed by the values for the economic growth rate and the asset value. The S1 and ST values for the climate change scenario are larger in the Vietnam case study than in the San Salvador case study. Also the S1 and ST values for the impact function are slightly larger in the Vietnam case study whereas the S1 and ST values for the asset value are smaller in the Vietnam case study than in the San Salvador case study (Figure 4.15).

4.3.4 Alternation of Discount Rate Variation-Range

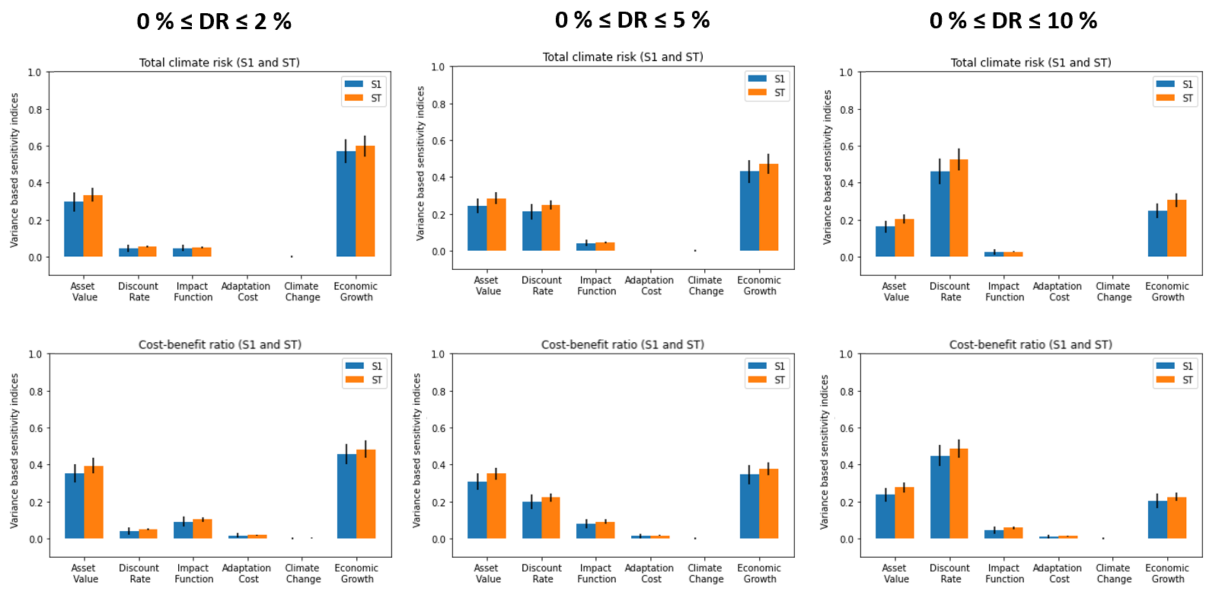

Figure 4.16: Sensitivity indices S1 (blue) and ST (orange) for both outputs with different variation-ranges of the discount rate with corresponding confidence intervals as black vertical lines for the San Salvador case study

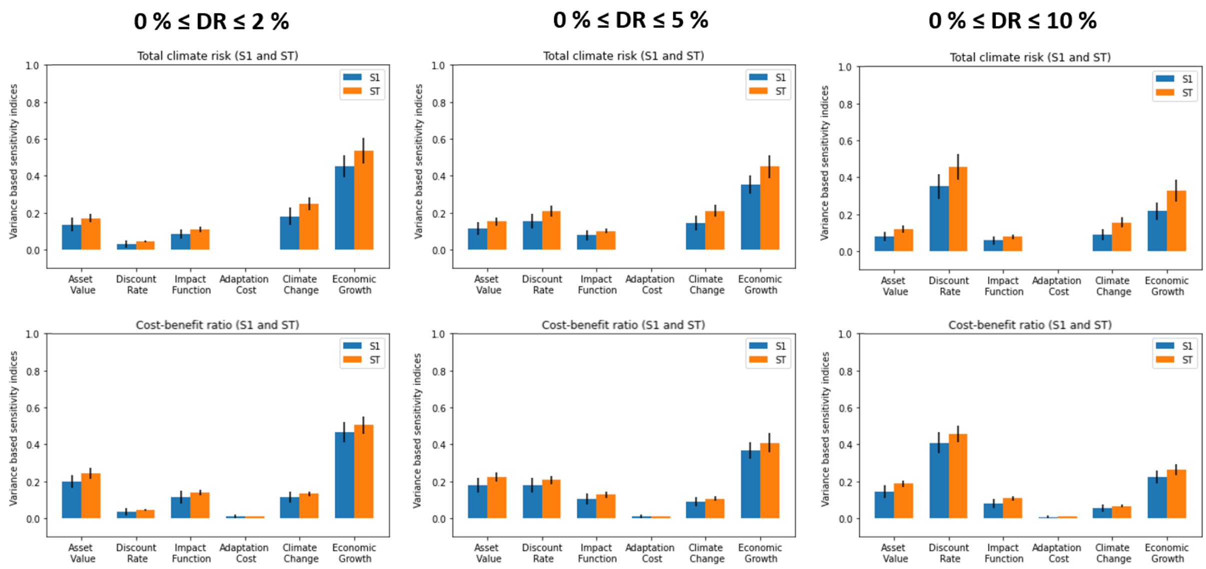

Figure 4.17: Sensitivity indices S1 (blue) and ST (orange) for both outputs with different variation-ranges of the discount rate, with corresponding confidence intervals as black vertical lines for the Vietnam case study

With different variation-ranges of the discount rate, also the S1 and ST values of the discount rate parameter for both outputs and in both case studies change (Figure 4.16 and Figure 4.17). A smaller variation-range of the discount rate parameter leads to smaller S1 and ST values of the discount rate. With a variation-range of the discount rate parameter of 0-2%, the corresponding S1 and ST values in the San Salvador case study are equally small as those of the impact function for the total climate risk and even smaller than those of the impact function for the cost-benefit ratio. In the Vietnam case study, the S1 and ST values of the discount rate become smaller than the S1 and ST values of the impact function for both outputs with the variation-range of 0-2%. With smaller S1 and ST values of the discount rate, the S1 and ST values of the economic growth rate and the asset value increase for total climate risk as well as for cost-benefit ratios in both case studies and also the S1 and ST values of the impact function increase. In the Vietnam case study also the S1 and ST values of the climate change scenario increase, but not in the San Salvador case study. The S1 and ST values for the adaptation cost parameter do not change for both outputs and in both case studies. The changes in the S1 and ST values due to the alternation of the variation-range of the discount rate parameter are larger than the changes of the S1 and ST values when comparing the two different outputs or the two different case studies. This implies that the sensitivity indices, and consequently the result of the sensitivity analysis, depend more on the setting of the variation-ranges of the input parameters than on the output or case study.

4.3.5 Alternation of Risk Metric

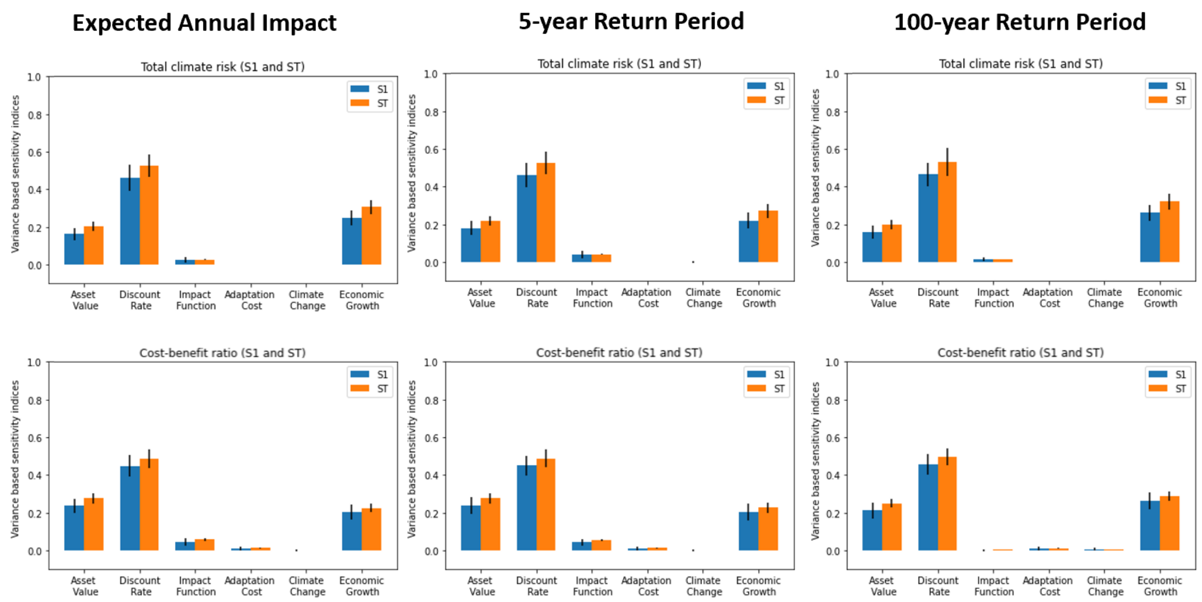

Figure 4.18: Sensitivity index S1 (blue) and ST (orange) for both outputs when calculating with different risk metrics, with corresponding confidence intervals as black vertical lines for the San Salvador case study

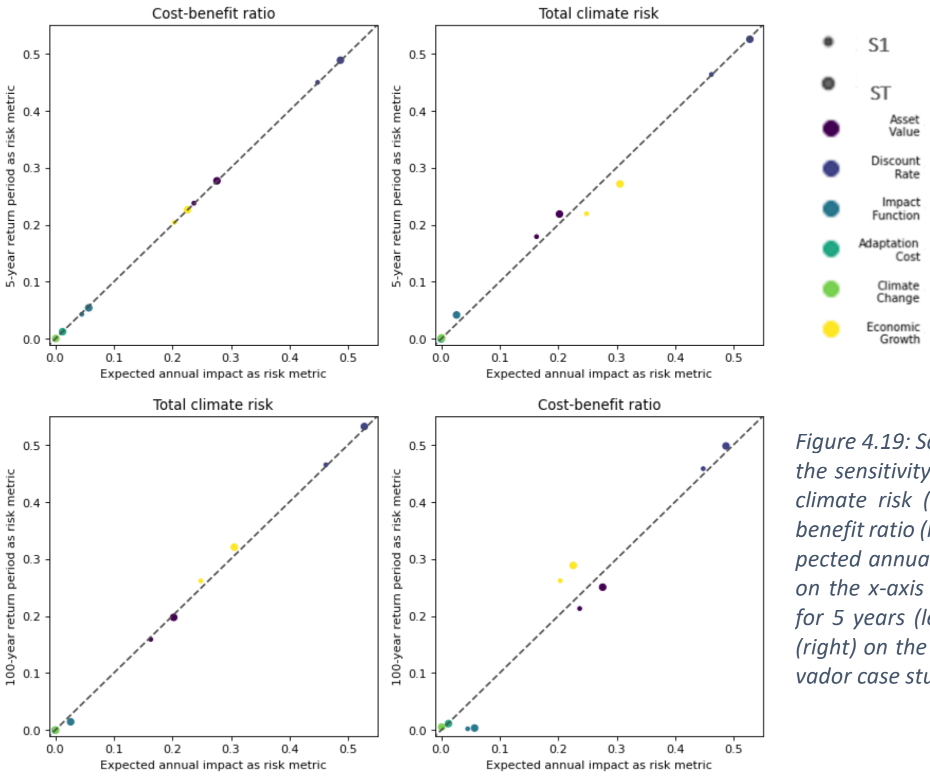

Figure 4.19: Scatterplots to compare the sensitivity indices with the total climate risk (upper row) and cost-benefit ratio (lower row) with the expected annual impact as risk metric on the x-axis and the return period for 5 years (left) and for 100 years (right) on the y-axis for the San Salvador case study

When making the same calculations but instead of the expected annual impact taking the return period of 5 years or the return period of 100 years as risk metrics, the S1 and ST values for the total climate risk and also for the cost-benefit ratio are very similar for variations of all six input parameters for the San Salvador case study (Figure 4.18). This is also visible when comparing the S1 and ST values on scatterplots (Figure 4.19). For the total climate risk as output, the S1 and ST values for the economic growth rate are slightly smaller with the 5-year return period as a risk metric and the S1 and ST values for the asset value are slightly bigger. These differences are, however, so small that they still lie within the confidence intervals and are therefore not significant. The differences in the S1 and ST values are even smaller when comparing the total climate risk with expected annual impact as risk metric with the total climate risk with the 100-year return period for the San Salvador case study. When looking at the cost-benefit ratio as output, there is no difference in the S1 and ST values when comparing the calculations with expected annual impact as risk metric and the calculations with the 5-year return period as risk metric. For the calculations with the 100-year return period, however, the S1 and ST values for impact function and asset values are smaller, and for the climate change scenario, it is slightly bigger than the ones for the calculations with the expected annual impact as a risk metric in the San Salvador case study (Figure 4.18 and Figure 4.19). In the Vietnam case study, the differences of the S1 and ST values when with different risk metrics are very small for both outputs. Only the climate change scenario has slightly higher S1 and ST values for both outputs (Figure 4.20 and Figure 4.21).

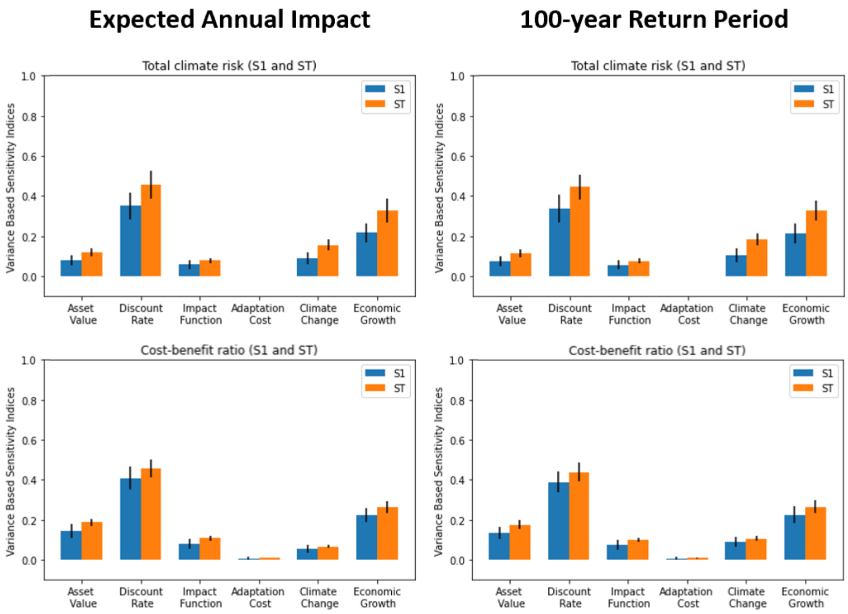

Figure 4.20: Sensitivity index S1 (blue) and ST (orange) for the total climate risk (upper row) and the cost-benefit ratio (lower row) when calculating with the expected annual impact (left) and the 100-year return period (right) as risk metrics, with corresponding confidence intervals as black vertical lines for the Vietnam case study

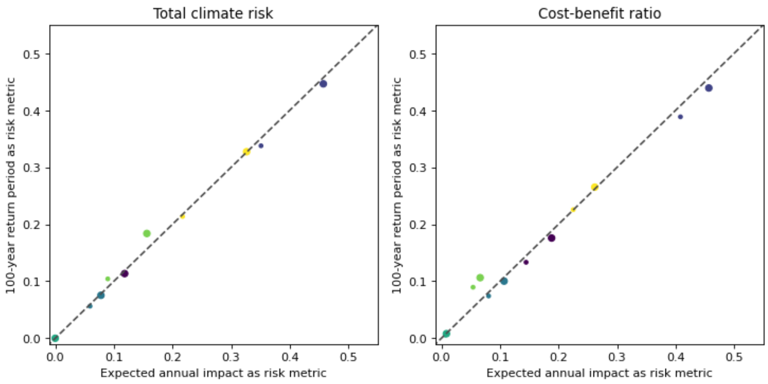

Figure 4.21: Scatterplots to compare the sensitivity indices with the total climate risk (left) and cost-benefit ratio (right) with the expected annual impact as risk metric on the x-axis and the 100-year return period as risk metric on the y-axis for the Vietnam case study

5. Discussion

Ethical and epistemic uncertainties affect the results of climate risk models and therefore also decisions of policy-makers that are made based on these results. The assumption, uncertainty and sensitivity analyses conducted in this thesis assessed these uncertainties within the model. Their influence on the model output was analyzed qualitatively and quantitatively. The focus was placed on epistemic rather than on ethical uncertainties because the latter are less often represented in input parameters that are comparable with one another. The output distributions of the uncertainty analysis conducted with the San Salvador case study revealed that different assumptions in the model input, reflected by varying the values of the respective parameters, did not affect the overall ranking of the adaptation measures on their cost-benefit ratios. For the San Salvador as well as for the Vietnam case study, the model results were most sensitive to uncertainties arising from assumptions about the discount rate and least sensitive to assumptions about the costs of adaptation measures. In comparison to the San Salvador case study, the Vietnam case study showed higher sensitivities for assumptions made about the climate change scenarios and smaller sensitivities for assumptions regarding the asset values. In both case studies, the sensitivity indices differed slightly for the two outputs, total climate risk and cost-benefit ratio. Further, the sensitivity indices of all six input parameters changed substantially when modifying the spread of the variation-range of the discount rate. In contrast, the sensitivity indices changed very little when calculating the model outputs with different risk metrics.

5.1 Interpretation of the Results

The assumption analysis of the San Salvador case study found seven assumptions as suitable for further analyses on their uncertainty potentials. Of these seven assumptions, five were characterized as leading to epistemic uncertainties. These were: the variation of the asset values, the impact function, the costs of adaptation measures, the climate change scenarios and the economic growth rate. Two were classified as leading to ethical uncertainties. These were the variation of the discount rate and the application of different risk metrics, whilst the latter was not analyzed by varying an input parameter but by adjusting calculations within the CLIMADA model itself. That more epistemic than ethical uncertainties have been analyzed should not be interpreted as meaning that ethical uncertainties are less relevant or less frequent in climate risk models. It rather means that ethical uncertainties arise less likely in a model in such a way that their influence on the output can be quantified by varying input parameters. This finding is not surprising, as Rüegsegger (2020) has already noted that the implications of ethical uncertainties are difficult to quantify. It further confirms the statement of Kandlikar et al. (2005) that many uncertainties in climate modelling cannot be characterized by a precise number as their consequences and alternatives are often not fully known.

The decisions as to which uncertainties and underlying assumptions are most suitable to analyze quantitatively are case study specific. For example, an assumption regarding the value of a certain input parameter could be well justified for one case study, if there exists enough case study specific literature upon which it may be based. The same assumption might be insufficiently justified for another case study for which there is hardly any background information on the matter. In the latter situation, the assumption might lead to a much higher degree of uncertainty and its quantitative assessment in the model output would therefore be of higher interest than in the first case study. However, there are also similarities among the justification of assumptions from different case studies when they followed the general workflow of a climate risk assessment methodology (see Section 2.2), such as the three steps of the ECA-Methodology. Model assumptions that are based on the recommendations of the ECA-Methodology, such as the San Salvador and the Vietnam case study analyzed in this thesis, are grounded upon the same justifications in different case studies. For example, the ECA-Methodology recommends setting the discount rate equal to the economic growth rate (Souvignet et al., 2016). As a consequence, analyzing the resulting uncertainty can be equally interesting for different case studies concerning assumptions that are based on recommendations of the ECA-Methodology.

These similarities and differences among the assumption analyses of different case studies also apply to the variation-ranges of the input parameters chosen to reflect the respective model uncertainties. There is no universally valid norm as to how these variation-ranges must be set. For this thesis, indications from various literature sources had to be interpreted and combined. For example, the variation-range for the costs of adaptation measures is not based on a direct recommendation of how much the costs of adaptation measures vary typically. Instead, the insight that most adaptation measures involve construction work resulted in the conclusion that uncertainties in construction costs provide a good and assessable basis for the variation-ranges. For another analysis with different aims and conditions, it might be meaningful to set the variation-ranges of the costs of each adaptation measure individually based on their different characteristics; but for this thesis, this more simplified approach was sufficient, because the aim was not to improve the performance of the San Salvador case study, but to understand the general behavior of different uncertain aspects of the model. The choice of variation-range is therefore always a trade-off between the aim of the analysis and the available resources.

The uncertainty analyses of the San Salvador as well as the Vietnam case studies showed that the variations of the six input parameters within the ranges that were set in the assumption analysis resulted in distribution curves of the calculated output values that were positively skewed. This was true for the total climate risks as well as for the cost-benefit ratios. The reason for this is that both the total climate risk and the cost-benefit ratio cannot, by definition, be smaller than zero, whereas they can take on any value above zero. Assuming that the variations in the input parameters have the same influence on the two outputs total climate risk and cost-benefit ratio for both case studies, one would expect that the output distribution curves would have exactly the same shape. This was, however, not the case. The reason for this is that the different calculations within the model (for the two outputs and the different datasets of the two case studies) resulted in the variation of the six input parameters, which had different influences on the output distributions. It was further observed that the original output and the average output values were not the same for both case studies and both outputs. However, the difference between the original and average output values was smaller than the respective standard deviations. The reason for this is that the variation-ranges of some input parameters were not set symmetrically around the originally assumed input values. For the discount rate, for example, a value of 2% was originally assumed, but the variation-range was set from 0-10%.

The uncertainty analysis for the cost-benefit ratios of the different adaptation measures of the San Salvador case study showed similar output distributions for all adaptation measures in proportion to their sizes. The input parameters and their variation-ranges consequently had the same influence on the calculation of the cost-benefit ratios for all adaptation measures. Thus, the ranking of the adaptation measures according to their cost-benefit ratios remained the same. It was further found that for five of the six adaptation measures of the San Salvador case study, as well as for the adaptation measure of the Vietnam case study, the cost-benefit ratios in the output distribution of the uncertainty analyses were always below 1, meaning that the benefit was larger than the cost. Only for one adaptation measure of the San Salvador case study were the cost-benefit ratios distributed around 1. Hence for most adaptation measures, the uncertainties reflected in the variations of the input parameters had no crucial influence on the question of whether the adaptation measure was financially beneficial or not. However, this does not necessarily mean that decisions about adaptation measures are not influenced by uncertainties, as they depend not only on the cost-benefit ratios but also on the total financial resources available, on the interests of the decision-maker and other political, social, regional and temporal aspects (see for example Palutikof et al., 2019). Moreover, the calculation of an adaptation measures' potential to avert damage, the benefit (Wieneke and Bresch, 2016), differs among case studies, and consequently, the influence of the model uncertainty on the cost-benefit ratios of adaptation measures may also differ likewise.

The sensitivity analysis revealed that the variations of the input parameters contribute in different magnitudes to the model uncertainty. In the San Salvador case study, the model outputs were most sensitive to variations in the discount rate and also very sensitive to variations in the asset values and the economic growth rate, while the model outputs were least sensitive to variations in climate change scenarios and adaptation costs. This was also very similar for the Vietnam case study, with the difference that the climate change scenarios and the impact functions had much higher sensitivity indices and that the variation in asset values had smaller sensitivity indices than in the San Salvador case study. This ranking of the sensitivity indices of the different input parameters was observed for sensitivity indices of first order as well as for sensitivity indices of second and total order. This suggests that the model was most sensitive to the interactions among those varied input parameters to which it was also most sensitive in reference to the single input parameter alone. For both case studies, there were differences in the models' sensitivity to the variation of the input parameters among the two outputs total climate risk and cost-benefit ratio, whilst the overall pattern remained similar. The implication was that in the San Salvador case study the total climate risk was more sensitive to the economic growth rate than to the adaptation cost, and vice versa for the cost-benefit ratio. In the Vietnam case study, the total climate risk was more sensitive to the climate change scenario than to the impact function, and vice versa for the cost-benefit ratio. When calculating the different outputs with the different risk metrics expected annual impact, the 100-year and 5-year return period, the pattern looked very similar, and the values of the different indices varied only very slightly in both case studies. It can therefore be concluded that the model was not very sensitive to different risk metric calculations.

That the sensitivity indices among the two case studies differed despite identical variations of the input parameters climate change scenarios, impact functions and asset values, suggests that these sensitivity indices are due to different characteristics of the case studies. Therefore, also the underlying assumptions and uncertainties might be case study specific and very much depending on the hazard, the exposed area and the vulnerability to the impacts. Other input parameters, such as the discount rate, the economic growth rate and the adaptation cost, seemed to influence the models' sensitivities in the same way, regardless of the specificities of the case studies. Furthermore, the observed difference between the different outputs total climate risk and cost-benefit ratio implies that the sensitivity of the model on some input parameters is not only determined by the characteristics and data of the case study, but also by what is calculated with the climate risk model. It follows that the models' sensitivities on different input parameter variations and therefore different uncertainties depend on the specific purpose of climate risk modelling and the interests of the model user. This is also consistent with Knüsels' (2020) statement that the evaluation of a model performance should always be related to the adequacy of the model for a specific purpose.

The adequacy-for-purpose condition for evaluating the model's sensitivity to different uncertainties is further emphasized concerning the determination of the variation-ranges. That the setting of the variation-ranges is substantially dependent on the model user and their concerns was already recognized in the assumption analysis. The influence of these individual settings on the output distribution was further implied when looking at the shape of the output distribution curves and the deviations between average and original values in the uncertainty analysis. It was further confirmed by repeating the sensitivity analysis for different variation-ranges of the discount rate: A very high variation-range from 0-10%, as it was set in the assumption analysis, resulted in the highest sensitivity index for the discount rate in comparison to the other input parameters. Smaller variation-ranges of the discount rate (0-5% and 0-2%) resulted in a substantially lower sensitivity index of the discount rate. This also impacted the sensitivities of the model towards the other input parameters, because the sensitivity index of an input parameter always depends on the total output distribution, which varies when changing the variation-range of one input parameter. The changes of the sensitivity pattern due to alternations of the variation-ranges of the discount rate was much higher than the observed differences of the sensitivity pattern due to the different case studies and types of output. In conclusion, the choice of variation-range has a substantially bigger impact on the sensitivity indices, and therefore on which input parameter contributes how much on the output sensitivity than the specific case study or type of output. It is thus very important to explore various plausible variation-ranges of the input parameters when assessing the model sensitivity towards different uncertainties.

5.2 Implications

There is a significant scientific interest in learning more about uncertainties in climate risk modelling to improve the reliability of the model results and the robustness of climate change mitigation and adaptation decisions. Model uncertainties are generally classified by different categories (Walker et al., 2003; Agusdinata, 2008). A common distinction is made between aleatory and epistemic uncertainties (Walker et al., 2003; Agusdinata, 2008; Curry and Webster, 2011; Knüsel, 2020). With regard to socio-economic decision-making, such as climate adaptation options appraisal, the classification by a third category, ethical uncertainty, is recommended (Bradley and Drechsler, 2014; Bradley and Steele, 2015). In a former scientific study, a framework has been elaborated that assessed possible sources of ethical and epistemic uncertainties of the San Salvador case study within the climate impact model CLIMADA by applying an argument-based method (Rüegsegger, 2020). The findings of the current Master's thesis complement the framework of Rüegsegger (2020) by deepening the understanding of how uncertainties, reflected in plausible variation-ranges of input parameters, affect the model output.

A recommended method to analyze the influence of uncertainties on a model are sensitivity and uncertainty analyses. Due to the method's property to apportion its total sensitivity towards the different uncertainties and their mutual interactions, it is widely applied in science and therefore also well researched (see for example Sobol, 2001; Saltelli et al., 2005, 2010, 2019; Saltelli and D'Hombres, 2010; Norton, 2015; Pianosi et al., 2016). However, its application for cost-benefit ratios of different climate adaptation options and total climate risk calculations through climate risk models is to date still limited. To facilitate the application of sensitivity and uncertainty analyses within the climate risk model CLIMADA, an uncertainty module was created by the weather and climate risk group of ETH Zurich.[8] This thesis is one of the first practical applications of this uncertainty module. The findings from this thesis may thus serve to further develop the module as well as to provide well-documented guidelines for subsequent applications. It is also a contribution to the application of uncertainty and sensitivity analyses for other climate risk models than CLIMADA that work similarly.

In addition, the in-depth examination of the various uncertainties within the CLIMADA model provides a deeper understanding of uncertainties in model outputs and thereby also of the application of the ECA-Methodology. The analyses conducted in this thesis showed how the uncertainty of different input parameters behave in the model and how they interact with each other. It suggests that some variations in input parameters may have a larger impact on the total output uncertainty than others and that this is closely connected to the set variation-ranges of the input parameters. By comparing two case studies that differ considerably in their characteristics, it was further found that some patterns concerning the model's sensitivity very much depend on the specific case study, whereas others

[8] The module is available open-source on GitHub: https://github.com/CLIMADA-project/climada_python/blob/feature/uncertainty/climada/engine/uncertainty/unc_cost_benefit.py

are similar across the case studies. This is very helpful for conducting case studies using the ECA-Methodology and applying CLIMADA, because it provides guidance to users about which uncertainties may have a big influence on the results and are therefore worth investing extra time in, to minimize them by thorough research.

This thesis provided indications of how model uncertainties may influence decision-making, for example by affecting the costs of total climate risk and consequently the decision about the urgency of taking climate action, or by influencing the cost-benefit ratios of different adaptation measures and therefore the decision about the best adaptation strategy. The finding that the model uncertainties did not influence the ranking of the cost-benefit ratios of climate adaptation measures was only based on the considered six adaptation measures from the San Salvador case study and could therefore be different for another case study. Nevertheless, this thesis contributes to the research of seeking ways to make more robust decisions under deep uncertainties in climate science (Marchau et al., 2019; DMDU Society, 2021).

5.3 Limitations

This thesis has limitations that future research should address. While there were similarities in the results across the two case studies examined here, the calculated model sensitivities and uncertainties are not necessarily generalizable. This is because the respective sensitivity indices of the individual input parameters depend on the selected parameters and their variation-ranges. These may deviate substantially in other case studies.

This thesis does not claim that the selection of assumptions and the chosen variation-ranges of input parameters fully cover all uncertainties of the San Salvador case study. There are many more ethical as well as epistemic uncertainties in this case study that would be interesting to explore in an uncertainty and sensitivity analysis. Also, the set variation-ranges are themselves driven by different uncertainties since literature could not always provide clear guidance and trade-offs had to be made that were not unbiased by personal preferences. More background knowledge on the case study, time, technical resources as well as more exchange with colleagues could have contributed to a more representative selection. The limitations are as follows:

- The uncertainties regarding the costs of the adaptation measures through the variation of construction costs are presented in a very simplified manner. With in-depth research, they could have been adjusted to the true uncertainties of the individual adaptation measures.
- The model sensitivities in this thesis are also affected by disregard of the relationship between the discount rate and the economic growth rate. By definition, it is not logical to have a much higher discount rate than the economic growth rate. In a practical application of the sensitivity and uncertainty analyses, the upper limit of the variation-ranges of these two rates should be better balanced, which would probably reduce the models' sensitivity towards the variations of these two input parameters.
- The assumption analysis was only conducted for the San Salvador case study, but not for the Vietnam case study. This was done because there is much more background information available on the San Salvador case study, whilst the case study about tropical cyclones in Vietnam is still ongoing. Nonetheless, the sensitivities in the Vietnam case study were useful for comparison, which helped to understand how the sensitivities of the same uncertainties differed due to the different datasets of the two case studies. However, this means that the sensitivities of the Vietnam case study do not reflect the real uncertainties inherent in that case study.

It was beyond the scope of this study to improve the performance of the two analyzed case studies as well as to provide a generally applicable and fully comprehensive list of model uncertainties and their respective influence on the output. The aim rather was to improve the overall understanding of the influence of uncertainties on the output of a model and of the methods used to quantify such uncertainties.

5.4 Recommendations

For future analyses about the implications of different uncertainties on the model results, the significance of a thorough assumption analysis preceding the uncertainty and sensitivity analysis is highly recommended. In addition to literature research, expert interviews might be helpful to gain a comprehensive picture of the different assumptions that were made when conducting the case study. Interviews might also help reveal how to best reflect the underlying uncertainties by setting plausible variation-ranges of the respective input parameters.

Since this thesis found that the setting of variation-ranges very much influences the overall model sensitivities, it is useful to understand, for each parameter, how much the sensitivity indices change when the variation-ranges are modified. For this purpose, a so-called robustness analysis module of the different model sensitivities is currently developed for the CLIMADA model. It will enable the model user to vary different variation-ranges of all the considered input parameters in order to assess how robust the model is towards different input variations, and thus how credible the results of the sensitivity analysis are.

Further investigations on how this uncertainty and sensitivity analyses could be included within the workflow of the ECA-Methodology will also be a necessary and important contribution since research of this kind has a high potential to improve decision-making based on model results. It makes much sense to apply sensitivity and uncertainty analysis because that way they may gain a thorough understanding of the input data of the model. To this end, however, more resources should be invested in researching how to make the application of the sensitivity and uncertainty analyses within CLIMADA and the ECA-Methodology more user-friendly.

6. Conclusion

This thesis aimed to deepen the understanding of how ethical and epistemic uncertainties, reflected in plausible variation-ranges of input parameters, affect the model output and how they influence risk assessment and climate adaptation options appraisal based on cost-benefit calculations. To do so, a qualitative analysis of the assumptions made in a case study about flooding events in San Salvador within the climate risk model CLIMADA was conducted. This resulted in a collection of model input parameters and variation-ranges of their values, which reflect the uncertainties underlying the assumptions made in the case study. It then was quantitatively assessed how the model output changes due to variations in the input parameter, by applying uncertainty and sensitivity analyses to the data from the San Salvador case study and the data from another case study about tropical cyclones in Vietnam. From the results of this assessment, it could then be derived how sensitive the CLIMADA model was towards the different uncertainties. The results showed that the different uncertainties, reflected by the variations in the input parameters, had different influences on the change of the model output and thus on the model sensitivity. The overall pattern of the model sensitivity was further found to be depending on the specific type of model output, the case study and the modifications in the variation-ranges of the input parameters. The latter had by far the greatest impact on the pattern of the model sensitivity. Additionally, it was observed that the ranking of different climate adaptation options according to their cost-benefit ratios was not influenced by these uncertainties. The method applied to analyze the model sensitivity towards different uncertainties showed to be very suitable for epistemic uncertainties but less suitable for ethical uncertainties since most ethical uncertainties are not representable by varying different input parameters.

These findings emphasize that the model sensitivity is strongly influenced by several factors which are very much depending on the design of the analysis itself, such as the choice of input parameters to be varied and their respective variation-ranges, or the output to be calculated. It is therefore strongly recommended that model users always perform an assumption analysis prior to the sensitivity and uncertainty analysis, as this impacts the outcome of the analysis. To further improve the validity of such a sensitivity analysis and consequently strengthen the confidence in the model outputs, more research should be conducted on the understanding of the robustness of the results of a sensitivity analysis towards modifications of the variation-ranges of the input parameters.

Even though the scientific interest in uncertainties of climate modelling is high, the quantitative assessment of the (ethical and epistemic) uncertainties in climate risk modelling, especially towards cost-benefit calculations of adaptation options and the implication of these on decision-making, is to date not well-researched. By addressing this issue by conducting sensitivity analyses within the climate risk model CLIMADA, this thesis has made a valuable contribution to research concerning more robust decision-making in climate research.

7. Bibliography

Agusdinata, D. B. (2008) *Exploratory modeling and analysis: a promising method to deal with deep uncertainty*, pp. 1-303. Available at: https://www.researchgate.net/publication/27346533_Exploratory_modeling_and_analysis_a_promising_method_to_deal_with_deep_uncertainty.

Aznar-Siguan, G. and Bresch, D. N. (2019) 'CLIMADA v1: A global weather and climate risk assessment platform', *Geoscientific Model Development*, pp. 3085–3097. doi: 10.5194/gmd-12-3085-2019.

Beckerman, W. and Hepburn, C. (2007) 'A review of the Stern Review on the economics of climate change', *Journal of Economic Literature*, 45(3), pp. 686–702. doi: 10.1257/jel.45.3.686.

Bindoff, N.L., P.A. Stott, K.M. AchutaRao, M.R. Allen, N. Gillett, D. Gutzler, K. Hansingo, G. Hegerl, Y. Hu, S. Jain, I.I. Mokhov, J. Overland, J. Perlwitz, R. Sebbari and X. Zhang (2013) 'Detection and Attribution of Climate Change: from Global to Regional', *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Edited by: Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley. *Cambridge University Press*, Cambridge, United Kingdom and New York, NY, USA, pp. 867–952.

De Bono, A. and Chatenoux, B. (2014) *A Global Exposure Model for GAR 2015: Input Paper prepared for the Global Assessment Report on Disaster Risk Reduction 2015*. Geneva, Switzerland, pp. 1-20.

Box, G. E., Luceno, A. and del Carmen Paniagua-Quiñones, M. (2009) *Statistical Control By Monitoring and Adjustment*. John Wiley & Sons, USA, pp. 1-333. ISBN: 978-0-470-14832-7.

Bradley, R. and Drechsler, M. (2014) 'Types of Uncertainty', *Erkenntnis*, 79(6), pp. 1225–1248. doi: 10.1007/s10670-013-9518-4.

Bradley, R. and Steele, K. (2015) 'Making Climate Decisions', *Philosophy Compass*, 11(10), pp. 799–810. doi: 10.1111/phc3.12259.

Bresch, D. and Aznar-Siguan, G. (2020) 'CLIMADA v1.4.1: Towards a globally consistent adaptation options appraisal tool', *Geoscientific Model Development Discussions*, pp. 1–20. doi: 10.5194/gmd-2020-151.

Central Intelligence Agency (CIA) (2021) *Real GDP growth rate - The World Factbook*. Available at: https://www.cia.gov/the-world-factbook/field/real-gdp-growth-rate/country-comparison (Accessed: 15 March 2021).

Curry, J. A. and Webster, P. J. (2011) 'Climate science and the uncertainty monster', *Bulletin of the American Meteorological Society*, 92(12), pp. 1667–1682. doi: 10.1175/2011BAMS3139.1.

CH2018 (2018) CH2018– Climate Scenarios for Switzerland, Technical Report, National Centre for Climate Services, Zurich, 271 pp. ISBN: 978-3-9525031-4-0.

DMDU Society (2021) DMDU Society – The Society for Decision Making Under Deep Uncertainty. Available at: https://www.deepuncertainty.org/ (Accessed: 11 March 2021).

ETH Zurich (2017) *Jupyter nbviewer: Assessing flood risk in San Salvador*. Available at: https://nbviewer.jupyter.org/github/CLIMADA-project/climada_python/blob/main/script/applications/eca_san_salvador/San_Salvador_Risk.ipynb (Accessed: 3 April 2021).

FEMA (2020) *What is Hazus? | FEMA.gov*. Available at: https://www.fema.gov/flood-maps/tools-resources/flood-map-products/hazus/about (Accessed: 15 March 2021).

Flanigan, T. E. (2011) 'On Discount Rates in the Cost-Benefit Analysis of Climate Change', (2007), pp. 1–22. Available at: http://scholar.harvard.edu/files/eflanigan/files/discounting.pdf.

Frederick, S., Loewenstein, G. and O'Donoghue, T. (2002) 'Time discounting and time preference: A critical review', *Time and Decision: Economic and Psychological Perspectives on Intertemporal Choice,* 40 (2), pp. 351-401. doi: 10.1257/002205102320161311.

Gardiner, S. M. (2010) 'Ethics and Global Climate Change'*. Oxford University Press.*

Global Property Guide (GPG) (2021) *Investment Analysis of Salvadoran Real Estate Market*. Available at: https://www.globalpropertyguide.com/Latin-America/El-Salvador/Price-History (Accessed: 11 March 2021).

Hallegatte, S., Vogt-Schilb, A., Bangalore, M., Rozenberg, J. (2017) *Unbreakable-Building the Resilience of the Poor in the Face of Natural Disasters*. World Bank Group, pp. 1-201, DOI: 10.1596/978-1-4648-1003-9.

Hansson, S. O. and Hirsch Hadorn, G. (2016) *The Argumentative Turn in Policy Analysis, Reasoning about Uncertainty.* Volume 10. Edited by S. O. Hansson and G. Hirsch Hadorn. Springer. doi: 10.1007/978-3-319-30549-3.

Herman, J. and Usher, W. (2019) *SALib Basics*. Available at: https://salib.readthedocs.io/en/latest/basics.html (Accessed: 10 March 2021).

Huizinga, J., de Moel, H. and Szewczyk, W. (2017) *Global flood depth-damage functions. Methodology and the database with guidelines*, Joint Research Centre (JRC). doi: 10.2760/16510.

Insuresilience Solutions Fund (2021) *Climate Risk Analysis*. Available at: https://www.insuresilience-solutions-fund.org/our-work/climate-risk-analysis (Accessed: 10 March 2021).

IPCC (2012) 'Summary for Policymakers', *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation.* Edited by Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 1-19. doi: 10.1017/cbo9781139177245.

IPCC (2014) *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Journal of Crystal Growth.* Edited by R. K. Pachauri and L. A. Meyer. Geneva, Switzerland: IPCC. pp- 1-151. doi: 10.1016/S0022-0248(00)00575-3.

IPCC (2018) 'Summary for Policymakers', *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development and efforts to eradicate poverty.* Edited by Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield.

Kandlikar, M., Risbey, J. and Dessai, S. (2005) 'Representing and communicating deep uncertainty in climate-change assessments', *Comptes Rendus - Geoscience*, 337(4), pp. 443–455. doi: 10.1016/j.crte.2004.10.010.

Keilbach, T. (2016) *Climate Change Adaptation in Urban Areas in Central America El Salvador Vulnerability Analysis + ECA Final Report*. Tech rep. Germany: GFA Consulting Group. pp. 1-725.

Knüsel, B. (2020) *Epistemological Issues in Data-Driven Modeling in Climate Research.* Diss. ETH No. 26626. Zurich: ETH Zurich.

Lloyd, E. A. and Winsberg, E. (2018) *Climate Modelling: Philosophical and Conceptual Issues*, Palgrave Macmillan, pp. 1-497, doi: 10.1007/978-3-319-65058-6.

Mallinson, M. and French, N. (2000) 'Uncertainty in property valuation – The nature and relevance of uncertainty and how it might be measured and reported', *Journal of Property Investment & Finance*, 18(1), pp. 13–32. doi: 10.1108/14635780010316636.

Marchau, V. , Walker, W. E., Bloemen, P. J. T. M., Popper, S. W. (2019) *Decision Making Under Deep Uncertainty. From Theory to Practice*, *Springer*, Switzerland, pp. 1-405, doi: 10.1007/978-3-030-05252-2_18.

Mayer, L. A., Loaa, K., Cwikb, B., Tuanac, N., Kellerd, K., Gonnermanf, C., Parkera, A. M., Lemperta, R. J. (2017) 'Understanding scientists' computational modeling decisions about climate risk management strategies using values-informed mental models', *Global Environmental Change*. Elsevier Ltd, 42, pp. 107–116. doi: 10.1016/j.gloenvcha.2016.12.007.

Mearns, L. O. (2010) 'Quantification of uncertainties of future climate change: Challenges and applications', *Philosophy of Science*, 77(5), pp. 998–1011. doi: 10.1086/656817.

MeteoSwiss (2021) *Climate Change in Switzerland - MeteoSwiss*. Available at: https://www.meteoswiss.admin.ch/home/climate/climate-change-in-switzerland.html (Accessed: 11 March 2021).

Möller, N. (2016). 'Value Uncertainty', *The Argumentative Turn in Policy Analysis*. Edited by S. O. Hansson and G. Hirsch Hadorn. Vol. 10. Logic, Argumentation & Reasoning. Springer, pp. 105–133. DOI: 10.1007/978-3-319-30549-3_5.

NOAA climate.gov (2021) *Climate Models | NOAA Climate.gov.* Available at: https://www.climate.gov/maps-data/primer/climate-models (Accessed: 12 March 2021).

Nordhaus, W. D. (2007) 'A Review of the Stern Review in Climate Change', *Journal of Economic Literature*, 45, pp. 686–702. Available at: http://piketty.pse.ens.fr/files/Nordhaus2007b.pdf.

Norton, J. (2015) 'An introduction to sensitivity assessment of simulation models', *Environmental Modelling and Software*. Elsevier Ltd, 69, pp. 166–174. doi: 10.1016/j.envsoft.2015.03.020.

Ökmen, Ö. and Öztaş, A. (2010) 'Construction cost analysis under uncertainty with correlated cost risk analysis model', Construction Management and Economics, 28(2), pp. 203-212. doi: 10.1080/01446190903468923.

Palutikof, J. P., Street, R. B. and Gardiner, E. P. (2019) 'Decision support platforms for climate change adaptation: an overview and introduction', Springer, pp. 1-459. doi: 10.1007/s10584-019-02445-2.

Pianosi, F., Beven, K., Freer, J., Hall, J.W., Rougier, J., Stephenson, D. B., Wagener, T. (2016) 'Sensitivity analysis of environmental models: A systematic review with practical workflow', *Environmental Modelling and Software*. Elsevier Ltd, 79, pp. 214–232. doi: 10.1016/j.envsoft.2016.02.008.

Pohl, M., Juarez, C., Cisneros, A., Varela, E., Amaya, E. (2018) *Flood Risk Modeling Using the ECA-CLIMADA Methodology in Urban Rivers of the Metropolitan Area of San Salvador Modelling of Impact Climate Scenarios,* Lleida, pp. 23-26.

RAND Corporation (2021) *Robust Decision Making | RAND*. Available at: https://www.rand.org/topics/robust-decision-making.html (Accessed: 11 March 2021).

Rauzana, A. (2018) 'Uncertainty Variables on Cost Estimation in Project Construction'*, IOSR Journal of Business and Management*, 20(1), pp. 80–87. doi: 10.9790/487X-2001018086.

Raychaudhuri, S. (2008) 'Introduction to Monte Carlo simulation, Proceedings of the 2008 Winter Simulation Conference', *AIP Conference Proceedings,* pp. 17–21. doi: 978-1-4244-2708-6/08.

Rüegsegger, C. (2020) *Assumptions and Uncertainty in Climate Impact Modeling.*

Saltelli, A. (2005) 'Global Sensitivity Analysis : An Introduction', *Sensitivity Analysis of Model Output,* pp. 27–43. Available at: https://www.lanl.gov/library/.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S. (2008) *Global Sensitivity Analysis: The Primer, John Wiley & Sons Ltd*, pp. 1-305. doi: 10.1111/j.1751-5823.2008.00062_17.x.

Saltelli, A., Annoni, P., Azzini, I., Camoplongo, F., Ratto, M., Tarantola, S. (2010) 'Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index', *Computer Physics Communications.* Elsevier B.V., 181(2), pp. 259–270. doi: 10.1016/j.cpc.2009.09.018.

Saltelli, A. and D'Hombres, B. (2010) 'Sensitivity analysis didn't help. A practitioner's critique of the Stern review', *Global Environmental Change*. Elsevier, 20(2), pp. 298–302. doi: 10.1016/j.gloenvcha.2009.12.003.

Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., Li, S., Wu, Q. (2019) 'Why so many published sensitivity analyses are false : A systematic review of sensitivity analysis practices', *Environmental Modelling and Software*. Elsevier, 114(1), pp. 29–39. doi: 10.1016/j.envsoft.2019.01.012.

Sobol, I. M. (2001) 'Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates', *Mathematics and Computers in Simulation*. Elsevier, 55, pp. 271–280. doi: 10.1016/S0378-4754(00)00270-6.

Solomon, S., Plattner, G. K., Knutti, R., Friedlingstein, P. (2009) 'Irreversible climate change due to carbon dioxide emissions', *Proceedings of the National Academy of Sciences of the United States of America,* 106(6), pp. 1704–1709. doi: 10.1073/pnas.0812721106.

Souvignet, M., F. Wieneke, L. Müller, and D. N. Bresch (2016). 'Economics of Climate Adaptation (ECA) - Guidebook for Practitioners', *Materials on Development Financing,* 6(6).

Stern, N. (2007). Economics, Ethics and Climate Change. In The Economics of Climate Change: The Stern Review (pp. 25-45). Cambridge: Cambridge University Press. doi:10.1017/CBO9780511817434.006

SwissRe (2019) *Natural catastrophes and climate change - Swiss Re Corporate Responsibility Report.* Available at: https://reports.swissre.com/corporate-responsibility-report/2018/cr-report/solutions/natural-catastrophes-and-climate-change.html (Accessed: 11 March 2021).

SwissRe (2021) *Mitigating climate risk | Swiss Re.* Available at: https://www.swissre.com/risk-knowledge/mitigating-climate-risk.html (Accessed: 11 March 2021).

Takagi, H., Thao, N. D. and Esteban, M. (2014) *Tropical Cyclones and Storm Surges in Southern Vietnam, Coastal Disasters and Climate Change in Vietnam: Engineering and Planning Perspectives*. Elsevier Inc. doi: 10.1016/B978-0-12-800007-6.00001-0.

UNISDR (2015). *Making Development Sustainable: The Future of Disaster Risk Management. Global Assessment Report on Disaster Risk Reduction.* Geneva, Switzerland: United Nations Office for Disaster Risk Reduction (UNISDR).

Walker, W. E, Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P., Krayer von Krauss, M.P. (2003) 'Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support', *Integrated Assessment*, 4(1), pp. 5–17. doi: 10.1076/iaij.4.1.5.16466.

Weaver, C. P., Lempert, R. J., Brown, C., Hall, J. A., Revell, D., Sarewitz, D. (2013) 'Improving the contribution of climate model information to decision making: The value and demands of robust decision frameworks', *Wiley Interdisciplinary Reviews: Climate Change*, 4(1), pp. 39–60. doi: 10.1002/wcc.202.

Wieneke, F. and Bresch, D. N. (2016) 'Economics of Climate Adaptation (ECA) in Development Cooperation: A Climate Risk Assessment Approach Supporting decision making on climate change adaptation measures', *Materials on Development Financing*, (5), p. 19.

Willows, R.I. and Connell, R.K. (Eds.) (2003) '*Climate adaptation: Risk, uncertainty and decision-making', UKCIP Technical Report.* UKCIP, Oxford.

World Bank Group (2020) *Global Economic Prospects, The Financial Crisis and the Global South,* Washington, DC: World Bank. doi: 10.1596/978-1-4648-1553-9, License: Creative Commons Attribution CC BY 3.0 IGO.

World Bank Group (2021) *Country Profile El Salvador | World Development Indicators.* Available at: https://databank.worldbank.org/views/reports/reportwidget.aspx?Report_Name=CountryProfile&Id=b450fd57&tbar=y&dd=y&inf=n&zm=n&country=SLV (Accessed: 16 March 2021).

Zimmerli, P. (2006) 'Natural Catastrophes and reinsurance', SwissRe, Available at: https://media.swissre.com/documents/Nat_Cat_reins_en.pdf.

8. Appendix

Appendix 1: Python Code for Varying the Input Parameters within CLIMADA

In the following, the code for writing the functions that define the hazard and entity classes with the varied input parameters for the uncertainty and sensitivity analysis are shown:

San Salvador Case Study

```
#Function to define hazard 2040
# CC = Varied input parameter
def haz40_SanSal (CC=1,haz40=haz40, haz40_or=haz40_or):
   haz40.intensity=haz40_or.intensity*CC
   return haz40
#---------------------------------------------------------------------------------------------------------------------------------
#Function to define entity 2040
# AV, EcoG, DR, IF, AC = varied input parameters
def ent40_SanSal (AV=1, EcoG=0.02, ent40=ent40, exp15=exp15, ent15_or=ent15_or, discount=discount,
DR=1, IF=1, if_diff1=if_diff1, if_diff2=if_diff2, impf_set=impf_set, AC=1, meas_set=meas_set):#if_set= if_set;
if_set=if_acel, meas_set=meas_acel, discount=discount, DR=1):
   exp15['value'] = ent15_or.exposures.value.values*AV
   ent40.exposures['value'] = exp15.value.values*(1 + EcoG)**(2040 - 2015)
   ent40.impact_funcs.get_func('FL')[0].mdd = impf_set.get_func('FL')[0].mdd + IF * if_diff1
   ent40.impact_funcs.get_func('FL')[1].mdd = impf_set.get_func('FL')[1].mdd + IF * if_diff2
   for i in (0,5):
      ent40.measures.get_measure('FL')[i].cost=meas_set.get_measure('FL')[i].cost*AC
   discount.fill(DR)
   ent40.disc_rates.rates=discount
  return ent40
#---------------------------------------------------------------------------------------------------------------------------------
#Function to define entity 2015
# AV, DR, IF, AC = varied input parameters
def ent15_SanSal (AV=1, ent15=ent15, ent15_or=ent15_or, discount=discount, DR=1, IF=1, if_diff1=if_diff1,
if_diff2=if_diff2, impf_set=impf_set, AC=1, meas_set=meas_set):#if_set= if_set; if_set=if_acel,
meas_set=meas_acel, discount=discount, DR=1):
   ent15.exposures['value']=ent15_or.exposures.value.values*AV
   ent15.impact_funcs.get_func('FL')[0].mdd = impf_set.get_func('FL')[0].mdd + IF * if_diff1
   ent15.impact_funcs.get_func('FL')[1].mdd = impf_set.get_func('FL')[1].mdd + IF * if_diff2
   for i in (0,5):
      ent15.measures.get_measure('FL')[i].cost=meas_set.get_measure('FL')[i].cost*AC
   discount.fill(DR)
   ent15.disc_rates.rates=discount
   return ent15
```

Vietnam Case Study

```
#Function to define hazard 2050
# CC = Varied input parameter
def haz50_Viet (CC=1,haz50=haz50, haz50_or=haz50_or):
   haz50.intensity=haz50_or.intensity*CC
   return haz50
#---------------------------------------------------------------------------------------------------------------------------------
```

```
#Function to define entity 2050
# AV, EcoG, DR, IF, AC = varied input parameters
def ent50_Viet (AV=1, EcoG=0.02, ent50=ent50, exp20=exp20, ent20_or=ent20_or, IF=1, if_or=if_or, AC=1,
meas_set=meas_set, discount=discount, DR=1):
   exp20['value'] = ent20_or.exposures.value.values*AV
   ent50.exposures['value'] = exp20.value.values*(1 + EcoG)**(2050 - 2020)
   ent50.impact_funcs.get_func('TC')[0].mdd = if_or*IF
   ent50.measures.get_measure('TC')[0].cost=meas_set.get_measure('TC')[0].cost*AC
   discount.fill(DR)
   ent50.disc_rates.rates=discount
   return ent50
#-----------------------------------------------------------------------------------------------------------------------------------
#Function to define entity 2020
# AV, DR, IF, AC = varied input parameters
def ent20_Viet (AV=1, ent20=ent20, ent20_or=ent20_or, IF=1, if_or=if_or, AC=1, meas_set=meas_set, dis-
count=discount, DR=1): #, IF=1, if_or=if_or, AC=1, meas_set=meas_set):
   ent20.exposures['value']=ent20_or.exposures.value.values*AV
   ent20.impact_funcs.get_func('TC')[0].mdd = if_or*IF
   ent20.measures.get_measure('TC')[0].cost=meas_set.get_measure('TC')[0].cost*AC
   discount.fill(DR)
   ent20.disc_rates.rates=discount
  return ent20
```

Uncertainty and Sensitivity Analysis for Cost-Benefit Calculations[9]

Here for the San Salvador case study, identical but with customized terms for the Vietnam case study

```
#Prepare Container for later analyses
haz40 = haz40_SanSal
ent40 = ent40_SanSal
ent15 = ent15_SanSal

distr_dict_haz40= {"CC": sp.stats.uniform(0.9,0.2)}

distr_dict_ent15 = {"AV": sp.stats.uniform(0.6, 0.6), "DR": sp.stats.uniform(0, 0.1), "IF": sp.stats.uniform(0, 1),
"AC": sp.stats.uniform(0.95,0.15)}

distr_dict_ent40=dict(distr_dict_ent15,**{"EcoG":sp.stats.uniform(-0.02,0.06)})

ent40_unc = UncVar(ent40, distr_dict_ent40)
haz40_unc = UncVar(haz40, distr_dict_haz40)
ent15_unc = UncVar(ent15, distr_dict_ent15)
#-----------------------------------------------------------------------------------------------------------------------------------
#Uncertainty analysis
pool = Pool()

unc_cb = UncCostBenefit(haz_unc=haz15, ent_unc=ent15_unc, haz_fut_unc=haz40_unc,
ent_fut_unc=ent40_unc, pool=pool)
unc_cb.make_sample(N=1000)
unc_cb.calc_cost_benefit_distribution() #(risk_func=risk_rp_100) #(risk_func=risk_rp_5)
```

[9] For a complete documentation on the conduction of Uncertainty and Sensitivity analysis see the Uncertainty Module in CLIMADA: https://github.com/CLIMADA-project/climada_python/blob/feature/uncertainty/climada/engine/uncertainty/unc_cost_benefit.py

```
pool.close()
pool.join()
pool.clear()
#------------------------------------------------------------------------------------------------------------------------------------------
#Sensitivity analysis
pool = Pool()
unc_cb.pool = pool
cb_sobol_dict=unc_cb.calc_cost_benefit_sensitivity()
pool.close()
pool.join()
pool.clear()
```

Appendix 2: Input Distribution for Sensitivity and Uncertainty Analysis

For the six varied input parameters asset value, discount rate, impact function, adaptation cost, climate change and economic growth rate, sets of values were generated with random sampling within their respective variation-ranges. The values of these sets were all expected to be uniformly distributed and each set contained 1000 elements. The following plots show the density distribution of the values of the six sets of model input parameters for the San Salvador case study.

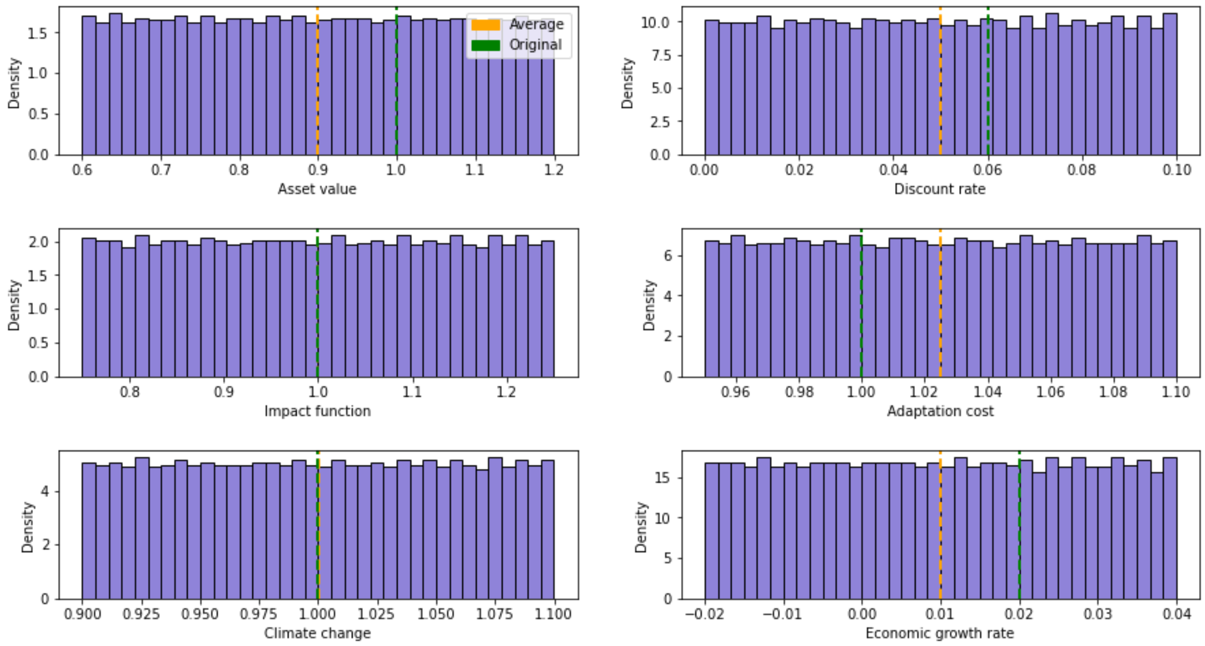

Figure 8.1: Input distribution of the six varied model parameters for the San Salvador case study

Appendix 3: Sensitivity Analysis of the Benefit

The results of the sensitivity analysis showed that the sensitivity indices are slightly different for the two outputs total climate risk and cost-benefit ratio (see Figure 8.2). The explanation for that is that the two outputs are calculated differently and thus the input parameters have different functionalities and different effects on the output.

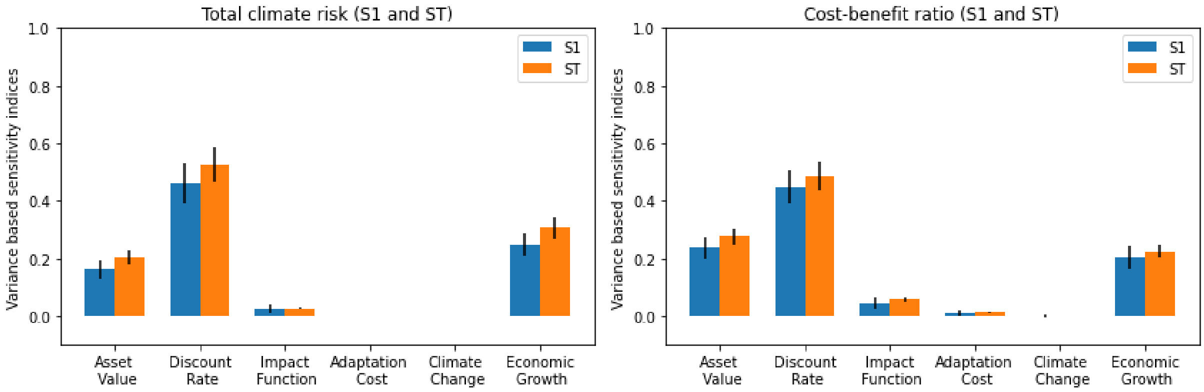

Figure 8.2: Sensitivity indices S1 (blue) and ST (orange) for the six input parameters for total climate risk (left) and cost-benefit ratio (right) with corresponding confidence intervals as black vertical lines for the San Salvador case study

To better understand these differences in the calculations of the output, the sensitivity of one additional output, the benefit, was therefore analyzed (Figure 8.3). It was observed that the sensitivity indices of the benefit are more similar to the sensitivity indices of the total climate risk (Figure 8.3, bottom right) than to the sensitivity indices of the cost-benefit ratio (Figure 8.3, bottom left).

Since the calculations of the cost-benefit ratios are influenced by the calculations of the costs of the adaptation measures, the calculations of the benefits of the adaptation measure, and the division between those two, it can consequently be concluded that the calculations of the cost of the adaptation measures and the division between cost and benefit have a substantial effect on the output sensitivity of the cost-benefit ratio that is responsible for these different sensitivity indices. The sensitivity of the output towards the adaptation costs are also responsible for the observed differences in the sensitivity indices of the outputs, as they are only incorporated in the calculation of the cost-benefit ratio, but not in the calculation of the total climate risk and the benefits. Equal observations were made for the Vietnam case study.

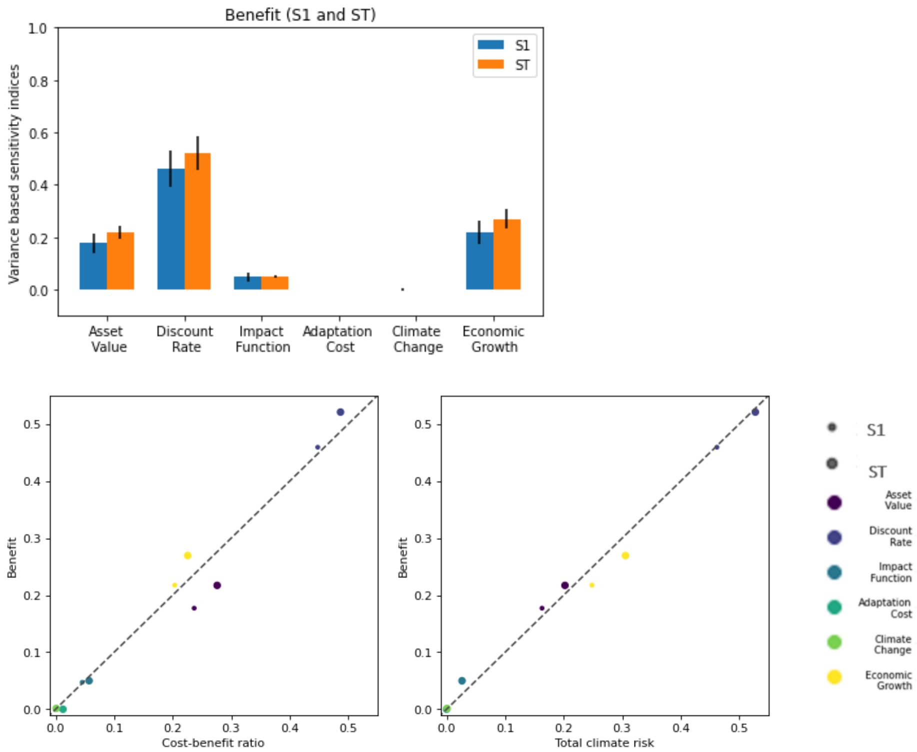

Figure 8.3: Up: Sensitivity indices S1 (blue) and ST (orange) for the six input parameters for the benefit with corresponding confidence intervals as black vertical lines; Bottom, left: Scatterplots to compare sensitivity indices of the cost-benefit ratio (x) with the benefit (y); Bottom, right: Scatterplots to compare sensitivity indices of the total climate risk (x) with the benefit (y) for the San Salvador case study

Appendix 4: Assumption on Risk Expression

For the assumption analysis in the San Salvador case study, only two assumptions that were selected for further analysis were found to lead to ethical uncertainties. These were the assumption on the discount rate and the assumption on the risk metric to calculate the impact of a hazard for a region. Another assumption that can lead to substantial ethical uncertainties, is the assumption that the future climate risk can be expressed in monetary terms. This assumption is often made in climate risk modelling because it enables consistency of the risks assessment through different hazards and at different locations (Rüegsegger, 2020). Nevertheless, it is a simplification and it is equally plausible to define climate risk in terms of the health and life threats to the population living in the studied region.

The effect of the ethical uncertainty about different approaches to risk valuation on the model output is difficult to assess in sensitivity and uncertainty analyses. Therefore, despite its significance, it was not included in the analyses of this thesis. However, the uncertainty was considered through literature research for the San Salvador case study. In this case study, different adaptation measures in response to flood damages were evaluated towards their potential to minimize the risk of people being harmed. This was then compared with the risk in terms of financial losses. A clear pattern was observed, suggesting that the reduction of financial risks is closely linked to the reduction of people being harmed (Figure 8.4). Consequently, the adaptation measure that is most beneficial to minimize financial risks is also most beneficial to minimize risks of people being harmed (Keilbach, 2016).

For the San Salvador case study, this suggests that the approach of defining risks in monetary terms does not conflict with the approach of defining risks in terms of human safety. Therefore this assumption does very likely not lead to substantial ethical uncertainties in the output of the San Salvador case study.

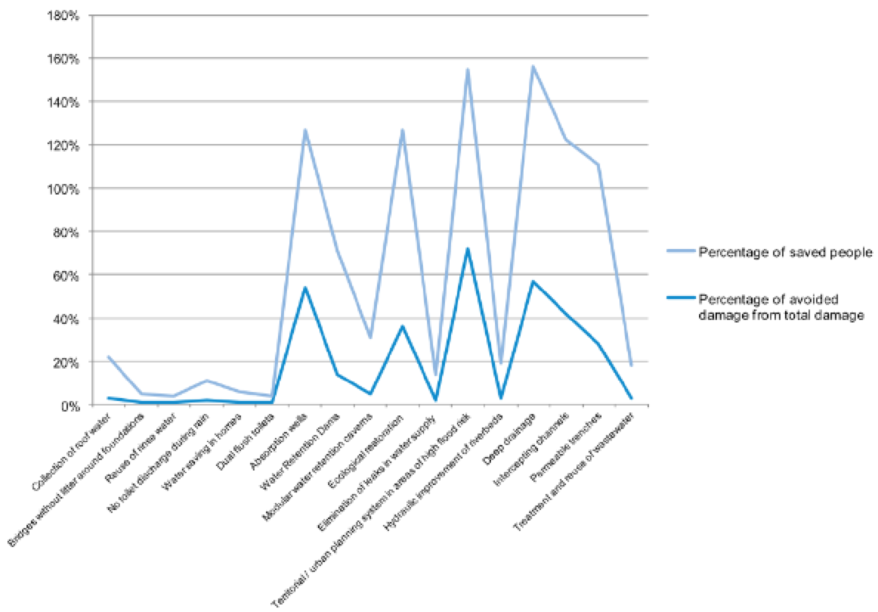

Figure 8.4: Benefit of adaptation measures towards risk of flooding in San Salvador indicated as percentage of avoided (financial) damage (dark blue) and percentage of saved people (light blue). Note that more adaptation measures were considered here than the six in the thesis. (Keilbach, 2016)

Appendix 5: Declaration of Originality

ETH

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Declaration of originality

The signed declaration of originality is a component of every semester paper, Bachelor's thesis, Master's thesis and any other degree paper undertaken during the course of studies, including the respective electronic versions.

Lecturers may also require a declaration of originality for other written papers compiled for their courses.

I hereby confirm that I am the sole author of the written work here enclosed and that I have compiled it in my own words. Parts excepted are corrections of form and content by the supervisor.

Title of work (in block letters):

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Authored by (in block letters):
For papers written by groups the names of all authors are required.

Name(s):	First name(s):
Otth	Laura

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