Applying the Dynamic Adaptation Policy Pathways (DAPP) approach to select future flood risk reduction strategies

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by

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Preface

This report serves as thesis to conclude my Master of Science studies in Hydraulic Engineering at the Delft University of Technology. The thesis is about applying the Dynamic Adaptation Policy Pathways approach to create and select effective flood risk strategies under uncertain conditions. A framework has for this purpose been developed. An additional probabilistic assessment is conducted to evaluate the effectiveness under all conditions. I have been working on this thesis from February 2022 to November 2022 with the help of my supervisors of the university and Royal HaskoningDHV.

The interest within this topic originates from the courses of Probabilistic Design and Risk Management and Flood Defences. Whereas Probabilistic Design and Risk Management provided me with methods to quantify risks, Flood Defences allowed me to apply these methods to the context of Hydraulic Engineering. When I applied for a graduation internship at Royal HaskoningDHV, the climate adaptation project of the City-East Coast turned out to fit these interests. Together with my daily supervisor, we decided to set up a general approach for such projects and with that, we arrived at my graduation topic.

I am grateful for the opportunity given by Royal HaskoningDHV to be able to graduate for the company and especially, for being able to visit the project Area in Singapore. In particular, I would like to genuinely thank Matthijs Bos for the support during my thesis and the good care during my stay in Singapore. Always finding time for me to discuss new ideas or problems I ran into, encouraged me to get to an end product of which I can be proud. I also would like to thank my supervisors at TU Delft for the support during this process. The progress meetings were fruitful sessions that provided me with new insights. Finally, I would like to express my sincere gratitude to my family and friends. They unconditionally supported me along this journey. I am looking forward to the privilege to call myself an engineer and to contribute to society via challenging projects!

Joost Trommelen
Dongen, November 2022

Summary

Sea level variations and storm surges are expected to increase as a result of climate change. 570 cities and some 800 million people are by 2050 estimated to be exposed to these phenomena when emissions do not decrease (UCCRN, 2018). It is, however, deeply uncertain if and to what extent emissions will decrease. Additionally, the effects of climate change are not fully understood due to its complexity, resulting in a wide range of uncertainty. Flood risk measures can be implemented to reduce flood risk. The economic evaluation of such measures is affected by other factors of uncertain nature such as economic growth. The Dynamic Adaptive Policy Pathways (DAPP) approach has been identified as an approach capable of identifying and implementing effective flood risk strategies under uncertain conditions (Haasnoot et al., 2013). This approach aims to provide decision-makers with insight into what action to take when. Simultaneously, the approach focuses on ensuring flexibility which facilitates adjustments to unforeseen conditions. Within this approach, so-called adaptation pathways need to be developed. These pathways describe a sequence of actions over time required to ensure a minimum level of flood safety. The DAPP approach has been applied to simplified cases in previous research, but not yet to more detailed master-planning for which the creation and economic evaluation of pathways is a not straightforward process. This results in the main research question of this thesis:

How can the Dynamic Adaptive Policy Pathways (DAPP) approach be used to create and select effective flood risk strategies under highly uncertain conditions?

This research question has been addressed by developing a framework capable of creating adaptation pathways and evaluating them with an incorporated scenario-based economic evaluation. This framework is supplemented with a probabilistic assessment that evaluates the performance of pathways in the full range of possible but uncertain futures. The use of these tools has afterwards been validated by applying them to a fictive case and a case study along the South East Coast of Singapore. The framework can be used to assess the sensitivity of uncertainties. Additionally, it can be used to obtain the conditions for which a different pathway turns out to be more effective. Damages corresponding to certain water levels are required as input and are used to build the damage function of a specific project area. These damages can be modelled with damage modules like the Global Flood Risk Tool (GFRT). The damage function and other basic information like dimensions and characteristics of the project area are used to perform an economic optimisation of individual measures. A selection of adaptation pathways (consisting of combinations of measures over time) is made based on prerequisites and a scenario-based evaluation. The scenario-based evaluation is supplemented with a probabilistic assessment as the use of scenarios might lead to cognitive biases and does not cover the full range of future possibilities (Hoffmann, 2017). This probabilistic assessment is conducted by means of a Monte Carlo simulation and can be used to evaluate the robustness of pathways in the full range of possible futures. A pathway can afterwards be selected and trigger values that should initiate the implementation of subsequent measures can be obtained via the framework.

The developed method has first been applied to a fictive case. A small area with a standard damage function was assumed for this. After the framework had been validated, the input-conditions were altered to assess the individual influence of each uncertain input value. The outcome turned out to be dependent on the characteristics of the project area and the assumed conditions. An increased area resulted in a pathway with a flood wall instead of a landfill as first measure being most effective. Out of the uncertainties, the discount rate and socio-economic growth rate turned out to most significantly affect the Net Present Value (NPV) and Cost-Benefit Ratio (CBR) of flood risk strategies. Especially, low discount rates and high socio-economic growth rates resulted in pathways built up of individual measures with lifetimes exceeding the technical lifetime of measures. To prevent this, and to ensure a flexible approach, the lifetimes of individual measures were restricted. A flexible approach enables one to adjust to conditions other than those that have been assumed. Measures with a long lifetime ahead lead to bigger investment costs and these are irreversible when the conditions turn out to be

less severe than anticipated. The contrary also turned out to be possible. These short lifetimes corresponding to measures with practically infeasible low heights were prevented by setting a minimum height at which the linear relationship between the height and costs of measures starts. The probabilistic assessment was conducted after a pathway was selected. Increasing the range of uncertainty for this pathway logically led to a wider range of possible outcomes. This wider range of outcomes can be a reason not to select a certain pathway as the probability of a low NPV is higher. The fact that this difference could not be observed in the outcome of the framework underlines the need for this probabilistic assessment. Finally, trigger values were set for the selected pathway of the fictive case. The trigger values were initially set for the planned subsequent measures. However, it could be observed that the obtained trigger value for the planned subsequent flood wall increment did not result in sufficient time to implement a storm surge barrier without dropping below the required minimum level of flood safety. Therefore, trigger values corresponding to the next planned subsequent measure could potentially lead to the exclusion of other possible subsequent measures. Instead of setting trigger values for the planned subsequent measures, trigger values should provide enough time for all possible subsequent measures to forestall the exclusion of possible measures and ensure flexibility.

The findings from the fictive case led to adjustments of the framework to ensure practical feasibility and flexibility. The adjusted framework was afterwards applied to a real-life case along the South East Coast of Singapore characterised by a narrow water level distribution, i.e. a relatively small difference ($\sim$15 centimeters) between water levels that differ a factor of 10 in return period. A storm surge barrier turned out to be a factor of 10 more costly than alternative solutions, irrespective of the assumed sea level rise scenario. Therefore, it was concluded that the storm surge barrier was not the desired flood risk reduction measure for the project area and the area was subdivided into smaller areas to further optimise the flood risk reduction strategy. The framework was used to create flood risk reduction strategies. No measures turned out to be required until 2092 for the assumed conditions. The sensitivity analysis of this case study showed that assuming a more severe sea level rise scenario (an additional 58 centimeters in 2100) and accounting for additional storm surge caused by climate change, could result in measures being required over 50 years earlier. Without taking this into account, two pathways turned out to satisfy the safety standards until 2200 for the assumed conditions as can be seen in Figure 1. One pathway solely consists of a flood wall and subsequently flood wall increments (AP10) while dryproofing is the first measure of the other pathway and subsequently a flood wall and a flood wall increment are implemented (AP33). The costs of AP10 turned out to be slightly higher in the full range of futures than that of AP33 but the probability of obtaining a higher NPV than obtained from the framework was also higher (58% vs. 51% of the outcomes higher than the NPV of AP10 obtained in the framework). As the differences between the probabilistic assessments of the pathways are not substantial, the preferences of local stakeholders are even more important. Dryproofing can lead to inundation of the land for high water events with a return period lower than the safety standard while Singapore has set the goal to protect its coastlines and prevent inundation of the land. Therefore, the pathway consisting of a flood wall and flood wall increments turns out to be the most suitable solution for the project area.

This research contributes to the existing knowledge related to the DAPP approach as it smooths the not straightforward process of creating and evaluating adaptation pathways under uncertain conditions. It showed how to economically optimise individual flood risk reduction measures and build adaptation pathways out of those measures. A framework has been developed to automate this process and instantly evaluate the effectiveness of such pathways for set conditions. This study also showed how a probabilistic assessment of these adaptation pathways could be used to select a robust flood risk strategy. This developed method can further be fine-tuned by including transfer costs that reflect the costs of maintaining flexibility in the face of deep uncertainty. Additionally, flexibility can be incorporated within the probabilistic assessment to enable alteration of type and/or height of subsequent measures for conditions different than assumed. This would result in a more accurate assessment. Automating the integration of the probabilistic assessment within the framework can eventually lead to one complete tool which enhances the applicability and allows for the probabilistic assessment of all pathways instead of just a selection of pathways.

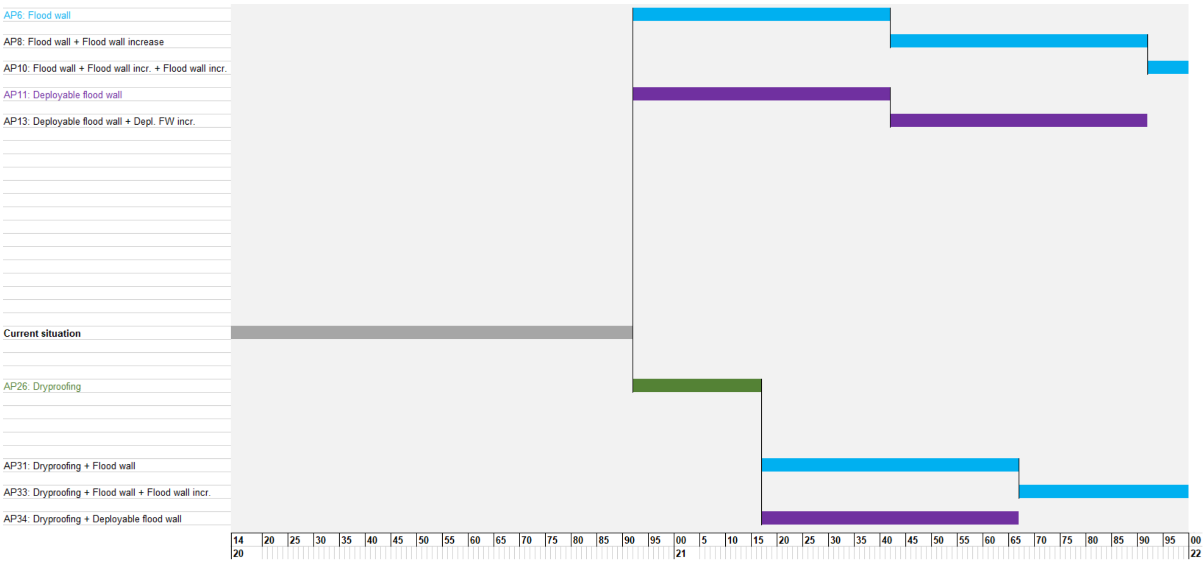


Figure 1: The possible Adaptation pathways for the case study

Contents

Glossary

Term	Definition
Adaptation Pathways	A sequence of policy actions or investments in infrastructure over time to achieve a set of pre-specified objectives under uncertain changing conditions
Adaptation Tipping Points	Points in time the current measures are no longer satisfactory to reach the objectives
Adaptive Policy	A step-wise approach for developing a basic plan which can be adapted to changing circumstances
Benefit-Cost Ratio (BCR)	All discounted benefits divided by all discounted costs
Dynamic Adaptive Policy Pathways	An approach that combines the concepts of Adaptation Pathways and Adaptive Policy-making to support the development of an adaptive plan while dealing with conditions of deep uncertainties
Investment costs	The costs required to implement measures
Net Present Value (NPV)	All discounted costs subtracted from the discounted benefits
Operation & Maintenance costs (O&M)	The costs required to keep measures maintained and in operation during their lifetime
Residual risk	The flood risk that is still present after implementation of flood risk measures
Safety level	The highest return period for which no inundation takes place
Total costs	The investment costs, O&M costs and residual risk combined
Trigger value	A value of sea level rise to initiate actions to prepare subsequent measures

List of Abbreviations

Abbreviation	Meaning
ATP	Adaptation Tipping Points
AP	Adaptation Pathways
BCR	Benefit Cost-ratio
CBA	Cost-Benefit Analysis
CDF	Cumulative Distribution Function
CD	Chart Datum
CPI	Consumer Price Index
DAPP	Dynamic Adaptive Policy Pathways
EAC	Equivalent Annual Costs
GEV	Generalised Extreme Value
GFRT	Global Flood Risk Tool
GDP	Gross Domestic Product
GSW	Greater Southern Waterfront
IPCC	Intergovernmental Panel on Climate Change
IR	Individual Risk
IRR	Internal Rate of Return
MCDA	Multi Criteria Decision Analysis
NPV	Net Present Value
PDF	Probability Density Function
PDI	Power Dissipation Index
PV	Present Value
ROA	Real Options Analysis
SGD	Singapore Dollar
SHD	Singapore Height Datum
SSS	Site-Specific Study
SST	Sea Surface Temperature

1 Introduction

1.1. General context

Flooding can form a risk to the value present in an area and the economic activities that take place in that area. This risk can be reduced by applying flood risk reduction measures. It is economically desired to implement such measures when the risk reduction as a result of these measures outweighs the costs. Another reason to implement measures can be to reduce the risk of dying due to a flood for people living in vulnerable areas. In the Netherlands, multiple casualties at once are considered to be less acceptable than the same number of casualties in multiple events. This can make it necessary to reduce the maximum probability of flooding per area. The maximum probability of flooding is often referred to as safety standard and is usually expressed as annual probability of occurrence. It can also be expressed as return period corresponding to a water level. This means that when an area has a maximum probability of flooding of 1/1,000 per year, no inundation takes place for water levels corresponding to return periods until 1,000 years. The actual safety level can differ from the safety standard. The actual safety level is in this thesis defined as the highest return period for which no inundation takes place. In this thesis, the actual safety level will be referred to as ”safety level”. The safety standard will be referred to as ”required safety level” and expressed as return period.

Flood risk assessments aim to give insight into the current and future flood risk and simultaneously provide possible, socially-desired and cost-efficient strategies to deal with these risks. The outcomes of the assessments have to be understandable to decision-makers and society. As society is dynamic and methods providing insights are continuously being developed, flood risk assessments can always be improved and made more understandable. An example of such an improvement is automation which makes it possible to evaluate a wider variety of strategies under changing circumstances.

These assessments are likely to become increasingly important as global emissions lead to an increase in temperature, resulting in melting ice caps and local sea level variations worldwide. The latter can form a threat to cities and populations worldwide. UCCRN (2018) even estimates that at least 570 cities and some 800 million people will be exposed to rising seas and storm surges by 2050, when emissions do not decrease. The rising sea level results in reduced actual safety levels and therefore, increased risk of flooding. Simultaneously, the population in coastal areas, as well as the value at risk, is globally increasing due to new developments. Risk is in the context of flood risk management often defined as the probability of a flood event multiplied by the consequences (Jonkman, Jorissen, et al., 2021) and as both are increasing, the global flood risk is increasing as well.

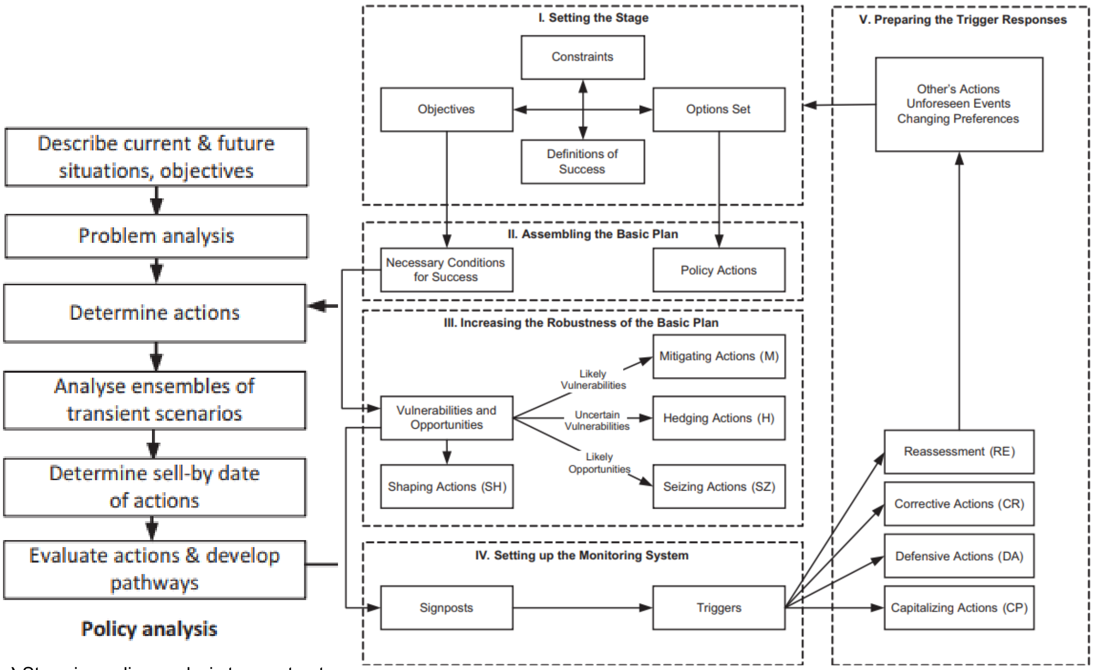
Both processes take place over a longer period of time and therefore, a long-term approach is required. Uncertainties are inherent to long-term approaches. Sea level rise is an example of such an uncertainty as it is dependent on the choices humanity makes now. IPCC projections show a global range for sea level rise between 0.32 meters and 1.01 meters by 2100 (Intergovernmental Panel on Climate Change (IPCC), 2020). Additionally, other uncertain factors like economic growth and population growth influence flood risk. The range between the 5th and 95th quantile of the population projections by 2100 of the United Nations (2019) lays between nearly 10 billion people and almost 14 billion people indicating a considerable uncertainty margin.

Haasnoot et al. (2013) invented a method able to effectively act on the changing climate while remaining flexible to be able to still adjust to future uncertainties. This method is called Dynamic Adaptive Policy Pathways (DAPP). DAPP is an approach made up out of the concepts of Adaptation Pathways and Adaptive Policy-making. The concept of Adaptation Pathways is used as an analytical approach to set up different sets of possible solutions applicable to various external developments over time. The creation of such pathways can be seen in Figure 1.1a.

Whereas adaptation pathways provide insight into the order of actions, adaptive policy-making provides a step-wise approach for developing a basic plan which can be adapted to changing circumstances. Adaptive policy-making consists of 5 different steps:

1. Setting the scope of a project.
2. Developing a basic plan.
3. Increasing the robustness of the plan.
4. Setting up a monitoring system.
5. Monitoring and reacting to triggers when needed.

This is also shown in more detail in Figure 1.1b. It is clear that both concepts provide support in decision-making when dealing with deep uncertainty. Specifically on choosing the near-term actions, while keeping other options open. Although both approaches offer support in the decision-making process, both methods also have their limitations. Where adaptation pathways give no guidance to decision-makers in translating the pathway into an actual plan, adaptive policy-making does not provide information on the desired sequence of measures. Therefore, combination of both approaches results into a complementing dynamic adaptive plan consisting of the 10 steps shown in Figure 1.2. This plan contains a selected adaptation pathway with Adaptation Tipping Points (ATPs) and trigger values. ATPs are the points in time the current measures are no longer satisfactory to reach the objectives. Trigger values are values to initiate subsequent actions. These values and points help decision-makers to determine when what actions are required.



(a) Stepwise policy analysis to construct Adaptation Pathways

(b) The Adaptive Policymaking approach to designing a dynamic adaptive plan

Figure 1.1: The principles of Adaptation Pathways and Adaptive Policymaking (Haasnoot et al., 2013)

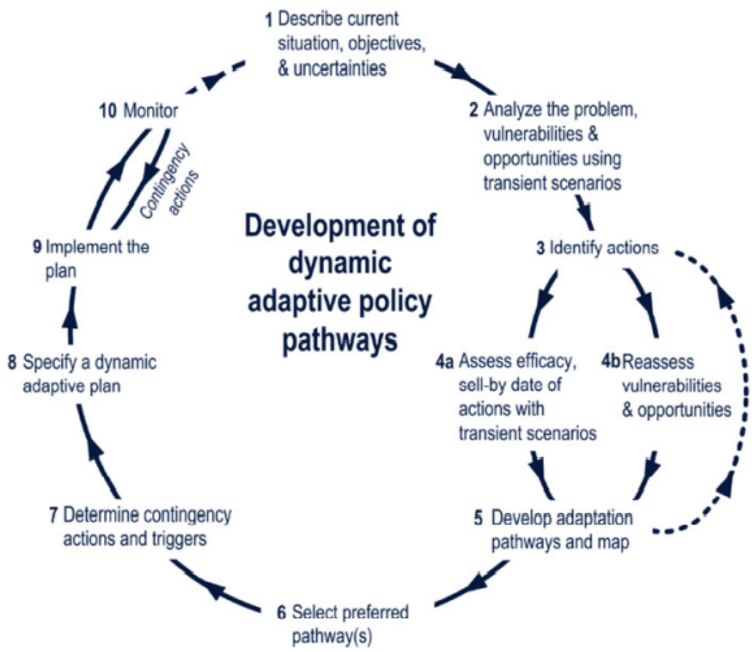


Figure 1.2: The Dynamic Adaptive Policy Pathways approach (Haasnoot et al., 2013)

1.2. Problem definition

DAPP is an approach that has been developed in research. The approach has for that purpose been applied to simplified illustrations, but not yet to more detailed master-planning as can be seen in Table 1.1. As a result, multiple issues will be encountered when using the DAPP-approach to obtain a detailed adaptive policy plan. This section will describe the expected issues to be faced when applying DAPP to more detailed master-planning.

Table 1.1: Overview of available literature

Source	Level of detail	Selection Method	Exclusions
Haasnoot et al. (2013)	Describes the systematic methodology and applies to a conceptual case study of the lower Rhine delta	Not specified	No insight is given in a suitable approach of selecting an AP
Haasnoot et al. (2020)	A select number of measures is included and tested for two scenarios for a case study of the Waal river	CBA	A limited number of measures and scenarios is included
Buurman and Babovic (2016)	A conceptual methodology to prevent pluvial flooding for a case study in Singapore has been worked out	CBA	No guidance given on how to interpret the evaluation of the pathways and no guidance given on defining the probability of occurrence
Vrinds (2021)	Detailed adaptation pathways of flood defences for the Rhine-Meuse estuary	MCDA & CBA	Compares performances of pathways based on scenarios, limited amount of pathways assessed, lack of optimizations for certain SLR
van de Watering (2021)	Systematically described how DAPP can be applied for the coastal defence of a case study in Singapore	MCDA & CBA	No insight is given into what conditions to use when scoring
de Ruig et al. (2019)	Detailed evaluation over time with limited number of pathways for the coastal defence of Los Angeles	CBA	Provides no insight into how to obtain values for uncertainties other than SLR
van den Broek (2019)	Multiple uncertainties are included to enhance coastal protection and stormwater management in Mozambique	CBA	Not all possible pathways are assessed, lack of clarity provided to decision-makers and no clear selection strategy
Ke et al. (2016)	Systematically describes how DAPP can be applied to the city of Shanghai	Not specified	Limited number of possible measures assessed

After analysing the problem, vulnerabilities and opportunities, DAPP requires the creation of adaptation pathways. Schoemaker et al. (2016) showed that the number of possible flood risk strategies combinations at the first timing of implementation is equal to:

$$N_{strategies} = (1 + \tau)^n \tag{1.1}$$

in which n is the number of independent measures and τ is the number of possible implementation timings. This would already result in 2.82 $*10^{12}$ possible strategies when assuming 8 dike sections and possible reinforcement once every year between 2016 and 2050. Since DAPP considers the far future (e.g. until 2100 or 2200), possible flood risk strategies for consecutive years still have to be added. The height of measures can also be adjusted. Finally, a pathway consists of a sequence of measures meaning that consecutive measures have to be included as well. This all results in a near-infinite number of possible flood risk strategies. Therefore, guidance is desired in dealing with the high amount of possible pathways. A substantial part of the considered literature just assesses a limited amount of possible pathways making it possible to exclude the potentially most optimal strategies. van Berchum et al. (2020) identified a method to quickly screen potential flood risk strategies. However, in this article ”only” 500 flood risk strategies were screened which meant that the initial strategies already had to be pre-selected. This pre-selection required was done with a toolbox not applicable yet to adaptation pathways. Dam (2021) created a framework to screen and optimise different measures. However, the rising sea level is not included in this framework and pathways including subsequent measures are not included as well.

Next to that, the performance of those pathways has to be evaluated under varying conditions. Scenarios can be applied to reduce the amount of required evaluations. However, applying scenarios can lead to cognitive biases according to Hoffmann (2017). Examples of such biases are considering the middle scenario as a baseline or seeing one scenario as optimistic and the other as pessimistic when having a scheme based on two scenarios. Even more importantly, he states that it is possible that scenarios do not cover the full range of future possibilities. A substantial part of the considered literature makes use of a limited number of scenarios. This can result in less effective pathways in not considered futures.

Identification of the preferred pathway is currently often done via a Multi-Criteria Decision Analysis (MCDA) and/or a Cost-Benefit Analysis (CBA) as can be seen in Table 1.1. A MCDA can be used to make a selection of the most promising strategies and afterwards a more detailed CBA can be used to select the preferred pathway. The economic assessment of a pathway is, however, highly dependent on the timing of implementation of subsequent measures, which depends on uncertainties like the rising sea level, and economic parameters (Marchau et al., 2019), making it a not straightforward process. Marchau et al. (2019) states that ”further refinement, in particular due to the sensitivity of the evaluation to variation in the discount rate and the timing of tipping points” is therefore required. The influence of changing circumstances needs to be assessed in order to do so. However, there is no current framework able to take into account more uncertainties than the sea level rise alone.

Additionally, Dynamic Adaptation Pathways are planned to be applied to the coastal adaptation project of the Southeast Coast of Singapore (van de Watering, 2021). Within this strategy, it is assumed that the selected pathway is the desired pathway under all conditions. Different values for the uncertainties, like discount rate and sea level rise, can alter the input of the MCDA (leading to increased or reduced effectiveness of measures) and CBA (leading to different benefits and costs) resulting in a different desired pathway. Haasnoot et al. (2020) used different scenarios to perform the economic evaluation but again, not all possible futures might be incorporated. Therefore, it can be possible that an upfront decided preferred adaptation pathway may in the end not be the desired pathway under certain circumstances. In order to prevent this, robustness can play an important factor in selecting the desired pathway. Robustness is in this thesis defined as the ability to perform in widely ranging conditions. However, Marchau et al. (2019) state that ”What is desirable or robust for one stakeholder might not be robust for another, giving rise to robustness conflicts”. Therefore, the level of performance and the conditions should be well-defined before being able to assess the robustness of pathways to ensure the selected pathway performs in varying conditions.

Finally, triggers to start with subsequent (corrective) actions need to be set to complete the Dynamic Adaptive Policy Pathways-approach as can be seen in step 7 of Figure 1.2. These trigger values (or signal values) are included in the Dutch law as can be seen in the Figure 1.3. These triggers should prevent the actual safety level from dropping below the minimum required safety level. The decline in safety level is significantly influenced by the uncertain rate of sea level rise. It might be necessary to alter these trigger values in the case of acceleration of the sea level rise. An increased rate leads to a more rapid decline in safety level and therefore less time to prepare subsequent measures. On the other hand, too conservative trigger values results in an inefficient investment strategy as postponed investment can be discounted. Setting appropriate trigger values can therefore be not-straightforward as they should always provide enough time to implement the following measures but should also not be triggered too early as this would result in less cost-efficient investments. They should, also, still at all times provide decision-makers insight into when to apply what measure.

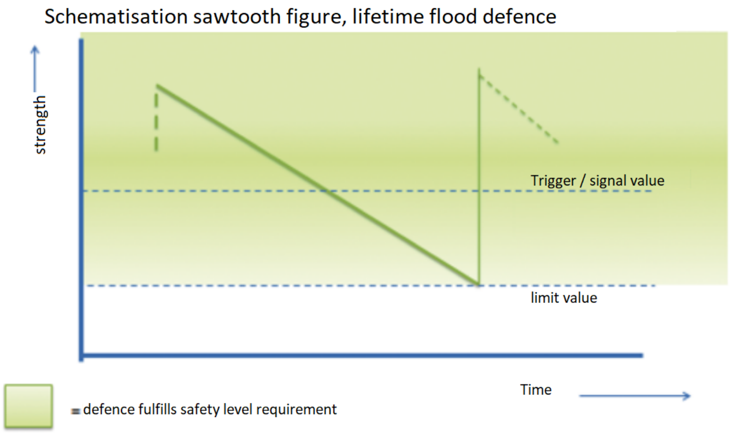


Figure 1.3: Trigger values used in the Dutch flood defence (“Wijziging van de Waterwet en enkele andere wetten”, 2016)

In general, DAPP is a promising approach to be able to deal with uncertainties in flood risk management strategies. However, several refinements of the approach are required before being able to obtain a detailed adaptive masterplan. First of all, an approach should be found to deal with extremely high numbers of possible flood risk reduction strategies. Next to that, a selection procedure specified to the situation of the project area is needed before being able to choose the desired pathway. This pathway should be robust and/or flexible enough to function in uncertain conditions. For this, a method should be found to assess the robustness of a pathway. Finally, trigger values should still give enough time to implement required subsequent actions without jeopardizing the main goal of the DAPP-approach: clearly describing when to implement what measure.

1.3. Objective and scope

1.3.1. Research questions

Section 1.2 showed the need for a long-term approach able to coop with the deep uncertainties of external factors. DAPP turns out to be a promising approach to create plans that sufficiently perform under broadly varying conditions but still can be adapted over time when desired. However, this approach has not been widely applied resulting in many unsolved issues when implementing this in real cases. This results into the following main research question:

How can the Dynamic Adaptive Policy Pathways (DAPP) approach be used to create and select effective flood risk strategies under highly uncertain conditions?

The answer to this main research question can be used to create a framework that automatically provides a long-term plan for project areas to adapt to the changing climate. The sub-questions will focus on specific steps of the Dynamic Adaptive Policy Pathways approach as shown in Figure 1.2. The sub-questions are:

1. **What uncertainties can affect the effectiveness of flood risk reduction strategies?**
   It is essential to identify the uncertainties of the system before being able to come up with effective flood risk strategies. This also requires analysing the current flood risk management system including identifying opportunities and vulnerabilities. This corresponds to steps 1 and 2 of Figure 1.2.
2. **How can the creation of possible adaptation pathways be implemented in flood risk management?**
   It is essential to identify possible adaptation pathways before being able to select a single adaptation pathway. Identifying possible APs includes the identification of Adaptation Tipping Points. This corresponds to step 3 up to and including step 5.
3. **Can different conditions lead to a different preferred adaptation pathway? If so, how can the approach be adjusted to assess more combinations of conditions?**
   The assumption of just having to change the timing in actions like proposed by van de Watering (2021), is checked for unforeseen scenarios. A selection procedure has to be specified and the full range of possible futures has to be defined in order to answer this research question. This corresponds to step 6 of the DAPP-approach.
4. **When should triggers to initiate (corrective) actions be set for the selected pathway in uncertain conditions?**
   Triggers are essential to ensure the desired level of flood safety. The trigger values should provide enough time to prepare subsequent actions but also should not provide an abundance of time as this would lead to cost-inefficiency. Simultaneously, they should give decision-makers insight into when to apply what measure. The answer to this sub-question should provide all necessary information to perform steps 7 and 8.

The first eight steps of Dynamic Adaptive Policy Pathways-approach, as shown in Figure 1.2, can be conducted after answering the sub-questions above. This will be applied to a fictive and real-life case. The implementation and monitoring stage can be executed with the information given in the earlier steps and therefore will not be specified further in this thesis.

1.3.2. Scope

The Adaptation Pathways derived from the sub-questions will focus on adaptation to coastal flooding. Waves are disregarded within this thesis. The interaction with possible measures to adapt to pluvial and fluvial flooding can still be assessed in the selection procedure. The generic approach that will be obtained in this thesis will be tested with a fictive case. Afterwards, it will be applied to a case study on the East Coast of Singapore.

1.4. Report overview

This chapter introduced the broader context of the thesis. The research gap within this context was sketched in the problem definition and was followed by the research questions and scope. Chapter 2 provides the methodology that will be used to answer the research questions. It also contains background on the uncertainties present in flood risk management and the existing methods to select suitable flood risk measures.

A framework that can be used to work with these uncertainties has been created and is described in detail in Chapter 3. This framework was used to generate possible adaptation pathways, test their performance in various conditions, define trigger values and evaluate the pathways. Chapter 4 describes the application of the framework to a fictive case. Afterwards, the framework will be applied to the South East Coast of Singapore as described in Chapter 5. The discussion and conclusion & recommendations can respectively be found in Chapters 6 and 7.

2 Methodology

2.1. Research method

A literature study was conducted to find the uncertainties affecting the effectiveness of flood risk reduction strategies. Flood risk strategies across the world have been analysed, especially those at places vulnerable to flooding. This literature study was used to answer the first research question. Additionally, the literature study also focused on identifying ways of economic optimisation. Afterwards, a framework had been created that can create and evaluate different pathways in certain scenarios to each other. The framework automatically generates pathways within a solution space restricted by a selection of measures and sequences. Optimisation of the desired safety level of measures can be done via the identified ways of optimisation. The working of this framework is in more detail discussed in Chapter 3.

The framework was used to answer research questions 2-4 as it creates pathways, evaluates the influence of changing circumstances on those pathways and identifies trigger values. The most promising flood risk strategies were also obtained via this framework. These strategies were subsequently probabilistically assessed to test their robustness and effectiveness in the full range of possible futures. This is schematised in Figure 2.1. The framework and probabilistic analysis were first applied to a fictive case to check whether it gave logical outcomes. Afterwards, the framework was applied to a project area along the City-East Coast of Singapore.

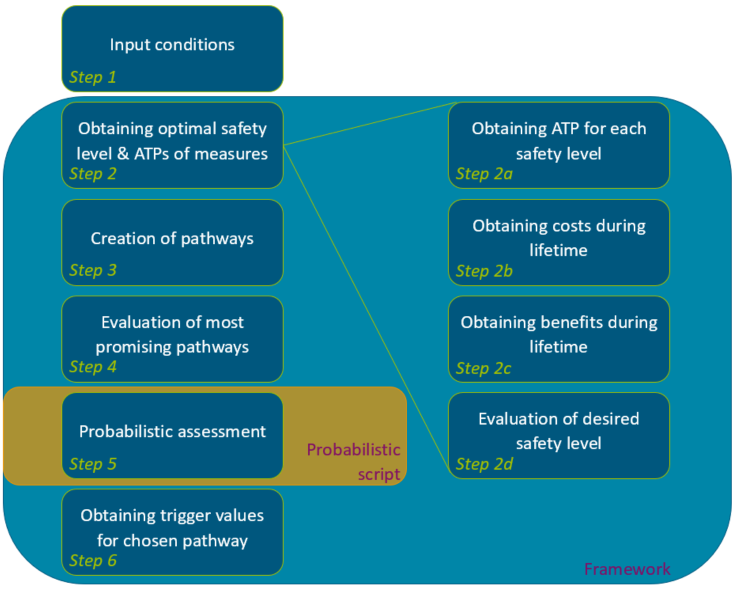


Figure 2.1: The overview with the outcomes of the framework and probabilistic assessment

2.2. Background

2.2.1. Uncertainties in flood risk

One would have to define the uncertainties before being able to coop with them. Therefore, this section describes the uncertainties that can affect the flood risk management strategies in the long-term. Both the safety level and the economic evaluation of measures can determine which strategy is desired. Uncertainties which can affect either of the two can therefore, also have an effect on the desired flood risk management strategy.

Water levels

The probability of occurrence of a certain water level partly determines the total risk and therefore influences the investment that can be made to reduce the risk. The probabilities contain several uncertainties. The return periods of the extreme water levels can be obtained by applying an extreme value analysis to the data acquired by measurements. These measurements can contain measurement uncertainties. Also, the data is generally of a relatively short period of time and can result in an inaccurate analysis. The uncertainty can be reduced by using longer measurement series when available. Jonkman, Steenbergen, et al. (2021) states that one should differentiate between 3 types of uncertainty, namely physical, statistical and model uncertainties and therefore, this inaccuracy can be seen as statistical uncertainty. Jonkman, Steenbergen, et al. (2021) suggests to account for statistical uncertainties by applying a predictive distribution. The model uncertainty accounts for the discrepancy between real-life and the model as a result of e.g. a wrong distribution function. The model uncertainty can be accounted for by applying a model uncertainty, most often applied as a normal or lognormal distribution (Jonkman, Steenbergen, et al., 2021). An accurate model has a μ close to 1. This model factor can also be used to include natural disasters like tsunamis.

Damages

Risk has been defined as the probability of a flood event (hazard) multiplied by the consequences. The probability of a flood event has already been described and the consequences consist out of the vulnerability and the values (Kron, 2005). The vulnerability can be estimated by using damage functions. The maximum possible value also has to be defined. Huizinga et al. (2017) has created both. These functions and values are estimates specific to locations and conditions of a flood. Huizinga et al. (2017) included standard deviations in the functions and maximum amount of damage. These can be used to describe the uncertainty within the damages. Calibrations can result in lower standard deviations. Wever (2022) showed that the damage models inherently contain uncertainty. However, for some classes (e.g. agriculture) the uncertainty can be decreased by calibration. For land-use classes like residential and critical assets, it is more difficult to reduce the uncertainty and the damage can even considerably vary locally. The level of accuracy is also dependent on spatial information like the elevation map, as the damage estimate is calculated with the inundation depth which is influenced by the accuracy of the elevation map.

Changing climate

The rising sea level is a threat to the coastlines across the world and the magnitude of it influences the best action that can be taken to combat it. Coastal cities and countries are not capable of limiting the rising sea levels themselves and are dependent on global efforts. Next to that, a lot on the changing climate and the melting of the ice caps is still unknown. This all makes the sea level rise a deep uncertainty. Predictions of the IPCC sketch different scenarios related to global CO2 emissions leading to the a global sea level rise. The range can be found in Table 2.1. Intergovernmental Panel on Climate Change (IPCC) also included a low-likelihood, high-impact scenario in their report, leading to ice sheet instability processes and a sea level rise approaching 2 meters. Despite the low likelihood, the scenario cannot be ruled out as the impact on the global coastlines would be major. Local sea level rise can differ from the global sea level rise.

Table 2.1: The median values for IPCC projections for mean sea-level rise (Intergovernmental Panel on Climate Change (IPCC), 2020)

Scenario	Description	Sea level rise range 2100 [m]
SSP1-2.6	Global CO2-emission will be net zero around 2050	0.32-0.62
SSP2-4.5	Global CO2-emission are reduced significantly, reaching net zero after 2050	0.44-0.76
SSP5-8.5	CO2-emission double from current levels by 2100	0.63-1.01

The changing climate does not only result in higher sea levels but possibly also results in an increase in the frequency and intensity of storms as a result of the rising sea temperatures. Tom Knutson (2021) showed a possible relation between the Power Dissipation Index (PDI) and local tropical Sea Surface Temperatures (SSTs) for the Atlantic Ocean. The PDI is an aggregate measure of expressing hurricane activity by combining frequency, intensity and duration.

When assuming such a direct link based on statistical correlations, the PDI could potentially increase by approximately 300% (Tom Knutson, 2021) as can be observed in the upper figure of Figure 2.2. However, Swanson (2008) states that the PDI is also correlated to other SST indices, especially that of the tropical mean SST. The lower graph of Figure 2.2 is obtained when assuming this relationship and shows a negligible impact of this intensity.

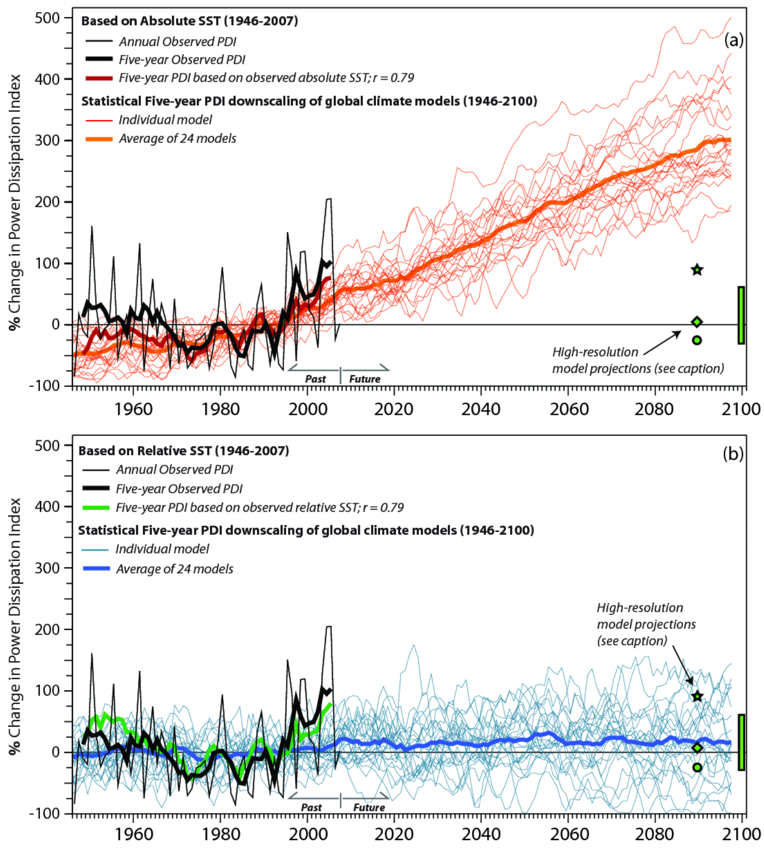


Figure 2.2: Increase in PDI for two different assumptions (Tom Knutson, 2021)

When solely considering statistics of the past, Tom Knutson (2021) states that the data record of Atlantic hurricanes does not provide compelling evidence for a significant increase as a result of climate change. He states that this can also be due to an overestimation of the factor accounting for the missed observed storms at the start of the data due to the limited observing network or statistical coincidence. Chen et al. (2021), however, state that the impact in South East Asia is already detectable with longer and more intense storms. The study also states that the landfill intensity will increase by 2 m/s (6%) and sustain 4.9 hours (56%) longer based on a high-resolution global model according to the Representative Concentration Pathway 8.5 scenario. These studies show that little is known on relation between an increased SST and the intensity, frequency and duration of storms. Since these factors can influence the storm surge and as a result the probability of occurrence for extreme events, these factors should be taken into account as deep uncertainties.

Subsidence
Land deformation can play a major role in flood risk management as can be seen in cities like Jakarta. Subsidence can have a similar effect as sea level rise as it results in a reduced difference in the level of land and water level. Subsidence occurs at a local scale and is dependent on local conditions like soil types and the extraction of groundwater. Therefore, subsidence should be examined locally and when it turns out to be considerable, it should be taken into account.

Discount rate
The discount rate can refer to both a social and economic term. The economic term is dependent on the type of funding (Gallo, 2014) making it company- or country-specific. When the funds are paid with money available, the discount rate describes the rate of return investors expect when making investments. When the investments are paid by loans, the interest rate can be used. This interest rate often accounts for inflation and therefore is automatically included when using the interest rate. For countries the interest rate is often used as countries usually do not have investors. The interest rate can significantly impact the desired strategy for coastal strategy.

The social discount rate is used to valuate possible futures. The discount rate for climate adaptation projects can differ from other projects that require large investments. The social discount rate includes the preferences of society for certain measures (The London School of Economics and Political Science, 2018). This can for example be the case when decision-makers decide that future generations should not carry the burden of climate adaptation. Therefore, when decision-makers decide to use a social discount rate, the discount rate is decoupled from the interest rate, and it can be considered deterministic.

The discount rate can counteract an increase in costs as result of the inflation and the increase in risk as a result of socio-economic growth. However, this is only the case when the base years are the same. If e.g., growth and inflation rates are expressed from 2023 and are both equal to 1% and the NPV in the year 2023 is calculated with a discount rate of 1%, the outcome would be the same to the situation in which all rates would be equal to 2%.

Economic growth rate
Economic growth can influence the value at risk in the future. This can significantly impact the strategy for coastal protection as higher risk can make more expensive measures economically desirable. The growth rate is, however, site-specific and depends on many factors and therefore can be considered as deep uncertainty. This rate does not directly have to be proportional to economic growth indicators like the Gross Domestic Product (GDP) growth rate as it is also dependent on development plans for specific areas. However, the change in GDP provides an indication of the increase in value on a national and long-term scale.

Population growth
The value of a human life can be expressed in monetary value to be able to maximise safety with limited resources (Card & Mooney, 1977). Population growth can therefore, under constant conditions, lead to increased economic risk when the costs of a human life stays constant (else this can become another variable). The costs of a human life are country-specific. The population projection is dependent on many factors and therefore is uncertain. The 5th and 95th quantile of the United Nations (2019) projections ranges between nearly 10 billion people and almost 14 billion people, indicating a considerable uncertainty margin.

Inflation

The required investment costs and the operation & maintenance costs increase due to inflation. This can result in a situation in which measures are no longer economically desired in the future while it might currently be economically desired. This is the case when the increase in costs is larger than the increase in risk. Therefore, inflation should be accounted for. Inflation can be caused by the demand being greater than the production, increasing the cost of production and increasing wages to keep up with the rising prices (Fernando, 2022). As these are all uncertainties, the inflation rate is uncertain as well and should be accounted for.

Costs

The costs of the measures are estimated to assess whether they are cost-effective. However, these cost estimates are usually given as deterministic values but in fact are uncertain. Dam (2021) proposed to use log-normal distributions to probabilistically describe the investment and operational & maintenance costs as shown in Figure 2.3. The mean and standard deviation should be estimated for each measure individually and can be derived from literature.

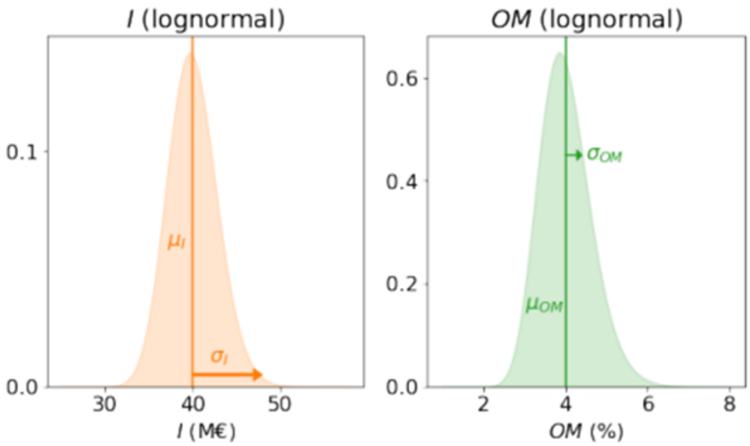


Figure 2.3: Example distributions of the considered stochastic variables I and OM with the adjustable parameters μ_I, σ_I, μ_{OM} and σ_{OM} (Dam, 2021)

Effectiveness measures

Flood defences can have different failure mechanisms and these are dependent on both the load and resistance (Jonkman, Jorissen, et al., 2021). The load is dependent on the hydraulic conditions that can lead to failure and these have been described above. The resistance is dependent on site-specific conditions for which a model can be set up to obtain the probability for different failure mechanisms containing the physical, statistical and model uncertainties as defined by Jonkman, Steenbergen, et al. (2021).

2.2.2. Cost-Benefit Analysis

In general, a Cost-Benefit Analysis (CBA) is performed with deterministic values. A CBA can be used to obtain the optimal safety level of measures. A safety level is optimal when it has the highest Net Present Value (NPV) or Benefit Cost-ratio (BCR). The definitions of the NPV and BCR are shown in Equations 2.1 and 2.2. Both definitions can lead to different desired optimal safety levels. When one would have numerous investment options, it can be desired to maximise the BCR as it leads to high returns relative to the investments and therefore, describes the economic efficiency of an investment. In cases with limited investment options maximising the NPV can be desired.

$$NPV = B_{PV} - C_{PV} \tag{2.1}$$

$$BCR = \frac{B_{PV}}{C_{PV}} \tag{2.2}$$

The costs consist of the investment costs and operation and maintenance costs as can be seen in Figure 2.4a and are discounted as following (Jonkman, Steenbergen, et al., 2021):

$$C_{PV} = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} + C_0 \tag{2.3}$$

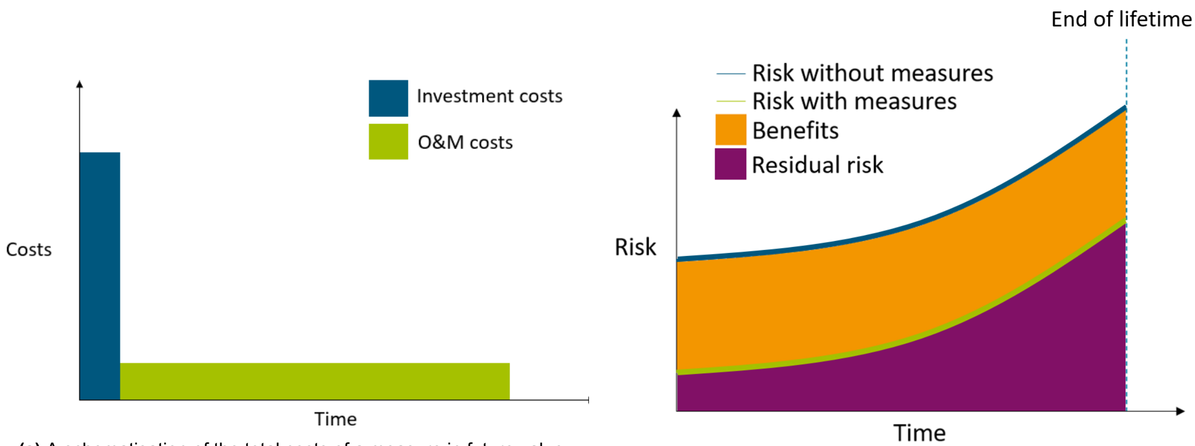
in which the C_t are the costs in the year t and r is the discount rate. The benefits consist of the reduced risk as a result of the measures as can be seen in orange in Figure 2.4b. The risk with and without measures can be obtained by applying the following equation:

$$\text{Annual risk} = \sum_{p=1,10,100,..}^{P} (\frac{1}{P_p} - \frac{1}{P_{p+1}}) * \frac{D_p + D_{p+1}}{2} \tag{2.4}$$

in which P is the return period for a certain water level and D is the expected corresponding damage for these water levels. Now the benefits of the measures can easily be obtained for the lifetime of certain measures by applying the following equation:

$$B_{PV} = \sum_{t=1}^{T} \frac{R_{t,nm} - R_{t,m}}{(1+r-g)^t} \tag{2.5}$$

in which B_{PV} is the benefit as a result of risk reduction in the present value, $R_{t,nm}$ is the risk in year t when no measures will be applied, $R_{t,m}$ is the residual risk in year t when measures are applied, r is the discount rate and g is the socio-economic growth rate. The discount rate is the expected rate of return on investments. Now, Equations 2.1 and 2.2 can be used to acquire the NPV and BCR.



(a) A schematisation of the total costs of a measure in future value without inflation

(b) The residual risk and benefits

Figure 2.4: the costs and benefits of flood measures

Investment tipping points

The moment of investment is essential when applying adaptation pathways as the NPV can significantly differ for different transition times. de Ruig et al. (2019) found that adaptation pathways can have 'investment tipping points' defined as "an inefficient investment in time of the initial strategy, that will prevent further transitions later in time to reach economic efficiencies that were possible before the investment tipping point". This means that pathways should be optimised in such a way that a transition is performed before the investment tipping point. The investment tipping point can differ for certain scenarios (e.g. rates of sea level rise) and therefore these conditions should be monitored in order to prevent crossing the investment tipping point.

2.2.3. Optimisation by minimizing total costs

Another way of determining the optimal safety level of a measure is by minimizing the total costs. This can be used when the safety level requirement is stricter than the economic optimisation as a result of for example, the individual or societal criterion. The total costs can be obtained as following:

$$C_{tot} = I + OM + R_{res} \tag{2.6}$$

in which C_{tot} is the total costs, I is the investment costs, OM is the Operation & Maintenance costs and R_{res} is the residual risk after applying the measures. These correspond to respectively the blue, green and purple areas in Figure 2.4 An optimal safety level is reached when the total costs reach a minimum. The investment costs will increase for higher safety levels while the residual risk decreases, creating an optimum as can be seen in Figure 2.5.

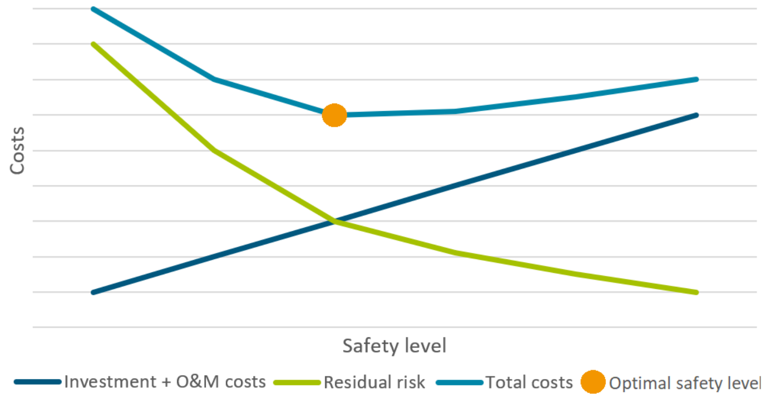


Figure 2.5: Conceptual plot of the optimal safety level shown in red

Again, the residual risk from the future has to be converted to the present value in order to come to the optimal safety level. Equation 3.3 can be used to obtain this. The optimal safety level can only be determined when the lifetime of possible options is equal.

When one would want to compare different lifetimes, the concept of Equivalent Annual Costs (EAC) can be used. This concept enables to compare measures with different lifespans to each other and also compares it to the situation where no measures are applied. This method can indicate the best time of investment, with which the adaptation tipping points can be determined. This method can be applied by using the following formula (Schoemaker et al., 2016):

$$EAC = \frac{C_{tot}}{Annuity} \tag{2.7}$$

in which the Annuity factor can be described as:

$$A_{t^*,i} = \sum_{t=1}^{t^*} \frac{1}{(1+r)^t} = \frac{1 - \frac{1}{(1+r)^{t^*}}}{r} \tag{2.8}$$

in which r is the discount rate and t^* is the valid duration of the measure. It can be seen that EAC is the total costs obtained as described in Section 2.2.3 divided by the annuity factor. The annuity factor enables to compare measures with different lifespans to each other and therefore can also be applied to obtain the equivalent annual NPV and compare the NPV of strategies with different lifespans.

2.2.4. Probabilistic assessment

A measure or a sequence of measures (a pathway) can be chosen based on a deterministic analysis like a CBA but a selection can also be made with a probabilistic assessment. An example of such a probabilistic assessment is Real Options Analysis. Real Options Analysis (ROA) was introduced by Myers (1977) to provide guidance in investing in oil and gas fields with uncertain prices. A simplified example of such an analysis can be seen in Figure 2.6. This example contains three options to extract a natural resource. These three options lead to different costs and benefits affecting the net present value. The outcome is also dependent on the prices of this natural resources. In this simplified case, a high and low price can be assumed. This results into a range of possible outcomes for each option. Decision-makers can decide whether they prefer an option with a wide range but a high profit or rather choose a narrow range with lower profits. In reality, the outcome can be influenced by many more uncertainties and the price can also, for instance, be moderate.

These uncertainties can be described using a distribution to account for this. This would result in more possible outcome and subsequently more bins than in the histograms of the simplified example. The histograms can indicate the degree of robustness for all possible investment options. This can guide decision-makers in determining a cost-efficient investment strategy for the long term. As flood risk management is exposed to many uncertainties, like the rising level, this approach might provide insight into the choices yet to make. Therefore, ROA was identified as a possible approach to apply to the Singapore coastline by Buurman and Babovic (2016). One would have to assign probabilities to possible futures when conducting ROA. When applying this together with adaptation pathways, the range of economic performances of pathways (e.g. NPV) can be compared to each other to see whether the ranges of the outcomes differ. These ranges can be useful because flexibility has significant value in civil engineering projects due to long project durations, technical complexity and the large influence of the boundary conditions (Verschuure, 2008). Therefore, a pathway with a lower deterministic NPV can be preferred over one with a higher NPV as a result of the narrower range of probabilistic outcomes.

ROA requires to analyse all possible investment options. It is not feasible to analyse all the possible pathways as a result of the high amount of pathways. Therefore, this method can be used to compare the most promising pathways out of the deterministic synthesis to each other to see whether they differ in robustness. As ROA will only be applied to the most promising options instead of all possible investment options, it will in this thesis be referred to as probabilistic assessment instead of ROA.

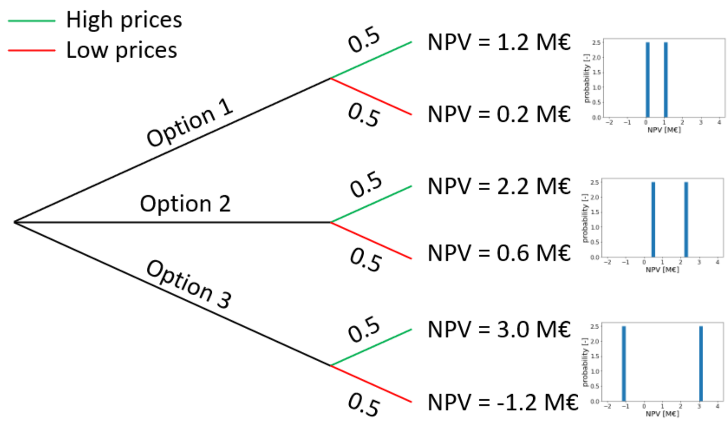


Figure 2.6: A simplified example of ROA

3
Framework based on DAPP approach

Deltares created the "Pathways Generator" (2017) to be able to explore policy pathways in an interactive way and eventually score the created pathways. This tool does not automatically provide pathways and therefore requires insight into the required sequence and heights of measures. The assessment of those pathways is done in a qualitative way making it vulnerable to subjectivity. The tool is limited to dealing with one single uncertainty which makes it impossible to assess the impact of a combination of uncertainties. As the tool also does not give any insight into the trigger values, which are part of the DAPP-approach, a new tool will be developed in excel that will provide a fully dynamic policy plan and is able to deal with multiple uncertainties. This plan should also provide clarity to decision-makers, while simultaneously being cost-efficient and effective. Sub-questions 2-4 can be answered by applying the tool as it will automatically create possible pathways, assess the performance in varying conditions by altering the input-conditions and automatically generate the trigger values for certain conditions. The robustness of pathways is probabilistically assessed by a separate script account for the full range of possible futures.

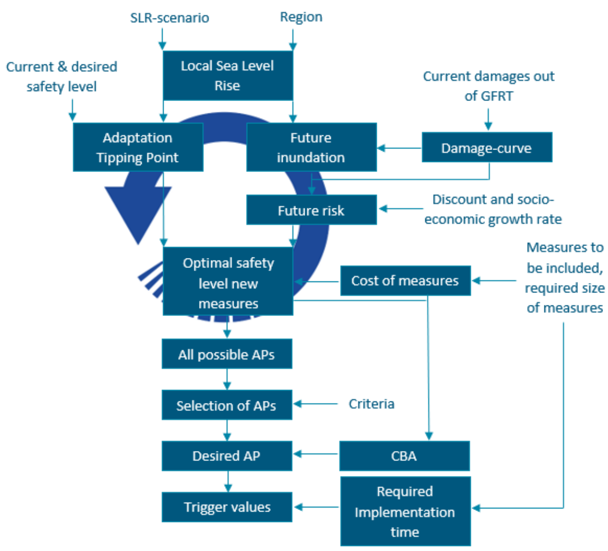


Figure 3.1: The outline of the constructed tool

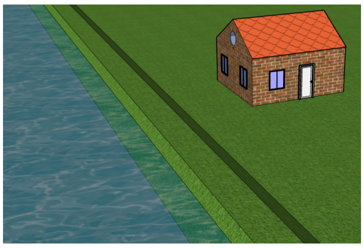
The assumptions made within the tool can be found in Section 3.1. These assumptions are required to obtain different pathways and their dimensions as schematised in Figure 3.1. This chart shows the required input-parameters that will be described in Section 3.2 and the obtained outcomes by performing the calculations that are described in greater detail in Section 3.3. The additional script to test the robustness of pathways is explained in Section 3.4. A description of the outcomes of the tool and the script provide can be found in Section 3.5.

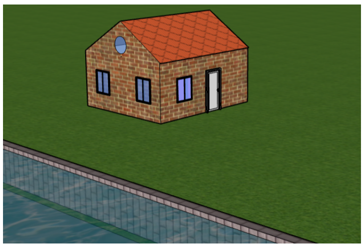
3.1. Assumptions

The framework that has been created contains some assumptions in order to simplify the highly complex real-life cases. First of all, the framework assumes no previous measures have been applied. Next to that, the framework has a limited solution space. The adaptation pathways are built up of a selection of measures. These measures are described in Table 3.1 and illustrated in Figure 3.2.

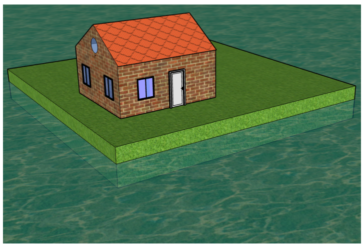
Table 3.1: All measures included in the tool

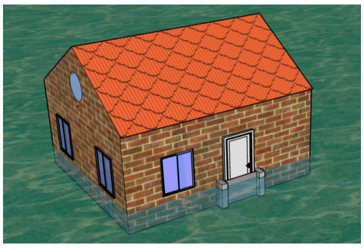
Measure	Description	Spatial scale
Levee system	The levee system protects the area from flooding until the water level exceeds the crest height. The length of the levee system has to be filled in in the ”Required length of levee to increase safety level”. The height of the levee system depends on the optimal safety level. A visualisation of a levee system can be found in Figure 3.2a and an illustration of the inundation curve can be found in Figure 3.3b.	Regional level
Flood wall	The flood wall functions in a similar way as the levee system. The differences are the investment and operational costs. A visualisation of a flood wall can be found in Figure 3.2b and an illustration of the inundation curve can be found in Figure 3.3b.	Regional level
Deployable flood wall	The deployable flood wall functions in a similar way as the levee system and flood wall. The differences are the investment and operational costs. An example of a possible deployable flood wall can be found in Figure 3.2c and an illustration of the inundation curve can be found in Figure 3.3b. The maximum height of a deployable flood wall depends on the type of deployable flood wall. This height is by default set to 2 meters.	Regional level
Landfill	The project area is elevated with a landfill altering the safety level and inundation depths when flooding. The landfill can only be applied in building areas. A visualisation of a landfill can be found in Figure 3.2d and an illustration of the inundation curve can be found in Figure 3.3b.	Regional level
Dryproofing	Dryproofing prevents water from flowing into buildings and therefore prevents any damage from happening inside buildings. When the water level exceeds the height to which dryproofing is applied, the inundation equals the water depth outside buildings and the damage function is altered as shown in the example in Figure 3.3a in which dryproofing is applied until 1 meter. A visualisation of dryproofing can be found in Figure 3.2e. The height to which dryproofing can depend on the site characteristics and the type of dryproofing that is being applied. This height is by default set to 1.5 meters which is the maximum height for dryproofing by local flood walls according to FEMA (2013). The residual risk is calculated by applying a factor to account for the damage that occurs to buildings compared to the total damage. This ratio is by default set to 1 (which means that 100% of the damage is occurring inside buildings).	Building level
Elevation	Elevation of the buildings does not prevent the project area to be inundated. As a result of the elevation, damage occurs at a greater inundation depth as is illustrated in Figure 3.3a in which the buildings are 1 meter elevated. A visualisation of elevation can be found in Figure 3.2f. The maximum elevation height is by default set to 3 meters (approximately 1 storey). The residual risk is calculated by applying a factor to account for the damage that occurs to buildings compared to the total damage. This ratio is by default set to 1 (which means that 100% of the damage is occurring inside buildings). Elevation can only be applied in building areas.	Building level
Storm surge barrier	The barrier prevents water from flowing into a basin. An example of a storm surge barrier can be seen in Figure 3.2g. One can differentiate between two types of barriers in this framework. The first type assumes all risk can be neglected for the complete lifetime of the barrier. This means the barrier is built very robust and will function for all sea level scenarios. The second type of barrier assumes a probability of failure for the closure of the barrier. This means that the probability of a water level is multiplied by the failure probability of closure as illustrated in Figure 3.3c. The type of barrier has to be chosen in the input.	Regional level

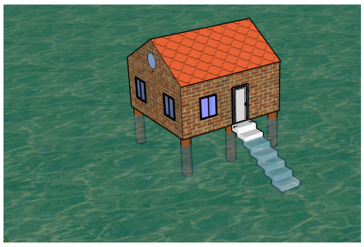

(a) Levee system


(b) Flood wall


(c) Deployable flood wall (Flood control international)

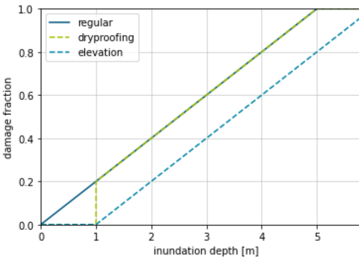

(d) Landfill


(e) Dryproofing

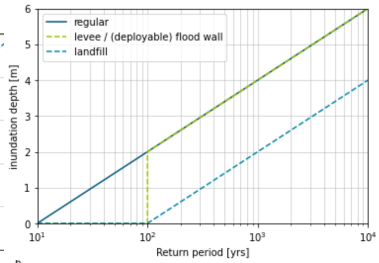

(f) Elevation


(g) Storm surge barrier (Holland)

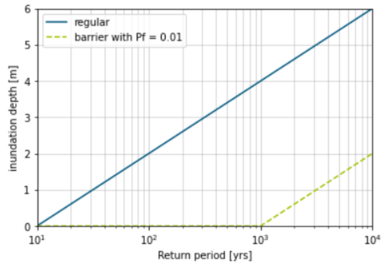
Figure 3.2: Illustration of the measures available in the framework



(a) The damage functions for dryproofing / elevation of 1 meter



(b) The inundation curves for levee / (deployable) flood wall and landfill with a safety level of 100 years



(c) The inundation curve for a barrier with failure probability of 1%

Figure 3.3: The effects of the measures

The safety level is altered when applying a levee system, (deployable) flood wall, landfill or barrier while dryproofing and elevation alter the damage function as can be seen in Figure 3.3. Dryproofing and elevation of buildings do not prevent the land from inundating. The inundation can be expected as only local measures are taken and therefore the inundation is regarded to be acceptable. In this case, the actual safety level is equal to the safety level of the local measures instead of the land. To illustrate, the safety level of the schematisation in Figure 3.4 is assumed to be 100 years instead of 10 years.

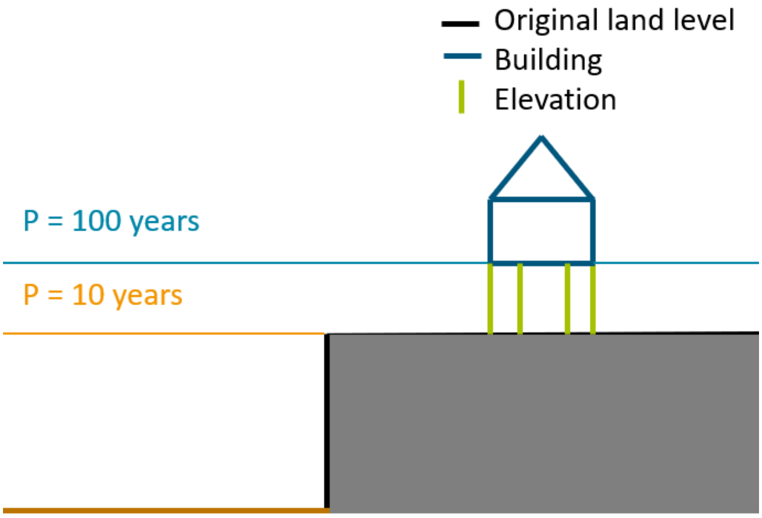


Figure 3.4: An illustration of the safety level of Dryproofing / Elevation

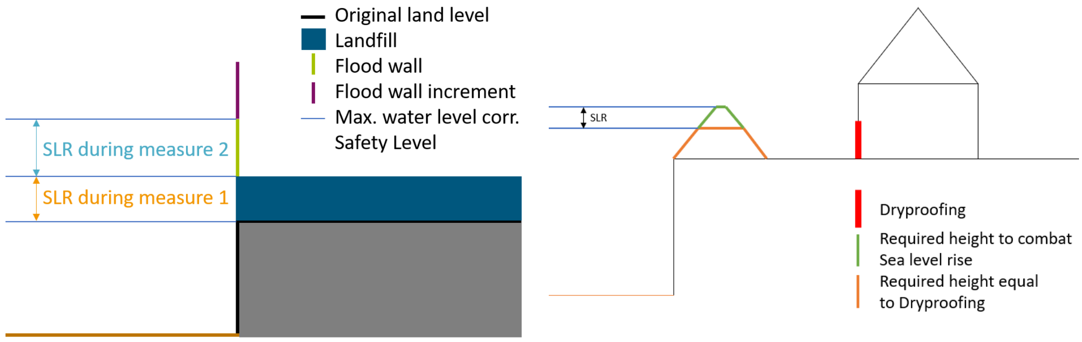
The sequence of measures is limited to the most logical sequences to limit the number of pathways that have to be calculated. The following sequences are excluded:

- Landfill and elevation can only be applied as first measure as they are restricted to building areas.
- Dryproofing can not be applied after a levee, flood wall or deployable flood wall as this would likely result in heights exceeding the maximum height to which dryproofing can be applied as the height of the previous measure(s) have to be added to the required height. The application of dryproofing after the landfill has not been included in this thesis.
- No measures are possible after applying the barrier as the barrier is not an adaptable measure and therefore is desired to be postponed as far as possible in time. Therefore, a barrier would only be feasible when it covers the entire span of the adaptive plan or when used as final measure.
- The deployable flood wall can only be raised once as it should still be deployable and therefore is limited by its size. Next to that, it cannot be raised at all when applied as second measure after dryproofing or elevation. This is because of the fact that the rate if sea level rise is increasing even for the lowest sea level rise scenario and therefore, this would likely lead to required deployable flood wall heights exceeding the maximum height.
- A levee, flood wall or deployable flood wall is excluded when one of the others has been applied previously.

This leads to the adaptation pathways that are included in this framework. They can be found in Table 3.2. An example of such a pathway is consecutively a landfill, a flood wall and a flood wall increase (AP22) as can be seen in Figure 3.5a. The height of the consecutive measure is equal to the difference in water levels corresponding to that of the desired safety level and that of the safety level of the applied measures. Measures applied after dryproofing and elevation form an exception as they do not result in a complementing effect with the consecutive measures as is illustrated in Figure 3.5b. Therefore, the height of the dryproofing / elevation applied as first measure should be added to the required height of the consecutive measures.

Table 3.2: All Adaptation Pathways included in the framework

Pathway	Measures + order in time
Adaptation Pathway 1	Levee
Adaptation Pathway 2	Levee + Barrier
Adaptation Pathway 3	Levee + Levee increase
Adaptation Pathway 4	Levee + Levee incr. + Barrier
Adaptation Pathway 5	Levee + Levee incr. + Levee incr.
Adaptation Pathway 6	Flood wall
Adaptation Pathway 7	Flood wall + Barrier
Adaptation Pathway 8	Flood wall + Flood wall increase
Adaptation Pathway 9	Flood wall + Flood wall incr. + Barrier
Adaptation Pathway 10	Flood wall + Flood wall incr. + Flood wall incr.
Adaptation Pathway 11	Deployable flood wall
Adaptation Pathway 12	Deployable flood wall + Barrier
Adaptation Pathway 13	Deployable flood wall + Depl. flood wall increase
Adaptation Pathway 14	Deployable flood wall + Depl. FW incr. + barrier
Adaptation Pathway 15	Landfill
Adaptation Pathway 16	Landfill + Barrier
Adaptation Pathway 17	Landfill + Levee
Adaptation Pathway 18	Landfill + Levee + Barrier
Adaptation Pathway 19	Landfill + Levee + Levee incr.
Adaptation Pathway 20	Landfill + Flood wall
Adaptation Pathway 21	Landfill + Flood wall + Barrier
Adaptation Pathway 22	Landfill + Flood wall + Flood wall incr.
Adaptation Pathway 23	Landfill + Deployable flood wall
Adaptation Pathway 24	Landfill + Deployable flood wall + Barrier
Adaptation Pathway 25	Barrier
Adaptation Pathway 26	Dryproofing
Adaptation Pathway 27	Dryproofing + Barrier
Adaptation Pathway 28	Dryproofing + Levee
Adaptation Pathway 29	Dryproofing + Levee + Barrier
Adaptation Pathway 30	Dryproofing + Levee + Levee incr.
Adaptation Pathway 31	Dryproofing + Flood wall
Adaptation Pathway 32	Dryproofing + Flood wall + Barrier
Adaptation Pathway 33	Dryproofing + Flood wall + Flood wall incr.
Adaptation Pathway 34	Dryproofing + Deployable flood wall
Adaptation Pathway 35	Dryproofing + Deployable flood wall + Barrier
Adaptation Pathway 36	Elevation
Adaptation Pathway 37	Elevation + Barrier
Adaptation Pathway 38	Elevation + Levee
Adaptation Pathway 39	Elevation + Levee + Barrier
Adaptation Pathway 40	Elevation + Levee + Levee incr.
Adaptation Pathway 41	Elevation + Flood wall
Adaptation Pathway 42	Elevation + Flood wall + Barrier
Adaptation Pathway 43	Elevation + Flood wall + Flood wall incr.
Adaptation Pathway 44	Elevation + Deployable flood wall
Adaptation Pathway 45	Elevation + Deployable flood wall + Barrier



(a) A visualisation of Adaptation Pathway 22

(b) The additional required height illustrated when levee applied after dryproofing

Figure 3.5: Visualisation of pathways

Additionally, some uncertainties defined in Section 2.2.1 have been disregarded in the framework. The uncertainties of increased intensity & duration of storms are not included. This means that if the sea level rises 1 meter that the safety level is the same if, for instance, the ground is raised by 1 meter. When one would want to account for this, the distribution of the water level can be altered. Risks as a result of other failure mechanisms (e.g. internal erosion) than the water level exceeding the top of measures are also not included in this framework. This means that overtopping must be negligible as a result of low waves or the measure should be able to withstand high volumes of overtopping preventing a breach. This also means that the measures need to be robust to the other failure mechanisms. As overtopping / overflow is by default assigned the highest reliability targets (Rijkswaterstaat, 2015) and for the other failure mechanisms counter-measures can be taken to prevent them, this assumption can be justified to obtain a first-order impression of the effectiveness of flood defence measures.

Next to that, the water levels resulting in inundation are assumed to last long enough for the hinterland to fill up completely. It depends on the characteristics of the site area if this assumption can be justified. The inundation depths and therefore damages and risk are overestimated if this is not the case. This can result in an overestimation of the NPV of measures and therefore, a higher safety level than is desired. A more detailed description of requirements of project areas is given in Appendix A. The extreme water levels are assumed to be distributed according to the Gumbel distributions as this distribution can fit extreme water levels accurately in general (Wahl et al., 2017). Finally, the desired safety level is assumed to be at least as high as the economic optimum meaning that is economically not desired to increase the safety level before the minimum required safety level is reached. This will prevent investment tipping points to be crossed.

3.2. Input-parameters

The framework will use the input of the Global Flood Risk Tool and some basic characteristics of the project area. The input that is required for this framework is described in Appendix B. The costs of the measures have been predefined and can be altered when more local and accurate costs parameters are known. The standard costs parameters can be found in Tables 3.3 and 3.4. These construction costs are linearly increasing but restricted by a minimum height. This minimum value is by default set to 0.5 meters. This means that when e.g. a levee of 0.25 meters is being calculated, the costs are equal to that of a 0.5 meters levee since else it would lead to unrealistically low costs for low measures. The time it takes to implement measures has also been predefined and can be found in Table 3.5. These values are not based on literature and are solely used to illustrate how trigger values can be obtained within the framework. It would, therefore, require additional research to obtain reliable values and so they can be changed when desired.

Table 3.3: Construction costs for the different measures

Measure	Costs	Unit	Source
Levee	10,000	€/m/m	Royal HaskoningDHV (2018)
Flood wall	5,000	€/m/m	Jonkman et al. (2013)
Deployable flood wall	5,200	€/m/m	Aerts (2018)
Landfill	25	€/m/m^2	Jonkman et al. (2013)
Dryproofing	8,700	€/m/building	Aerts (2018)
Elevation	52,000	€/m/building	Appendix Aerts (2018)
Barrier	1,200,000	€/m	Jonkman et al. (2013)

Table 3.4: Operation & Maintenance costs for the different measures

Measure	Annual O&M [%]	Source
Levee	0.2	Jonkman et al. (2013)
Flood wall	0.5	Aerts (2018)
Deployable flood wall	5	Aerts (2018)
Landfill	0.2	Jonkman et al. (2013)
Dryproofing	2	Aerts (2018)
Elevation	0.2	Aerts (2018)
Barrier	5	Jonkman et al. (2013)

Table 3.5: The time it takes to implement different measures

Measure	Time required to implement measure	Unit	Minimum required time [years]	Maximum required time [years]
Levee	1	year/m/km	1	10
Levee increase	0.5	year/m/km	1	5
Flood wall	1	year/m/km	1	10
Flood wall increase	0.5	year/m/km	1	5
Deployable flood wall	0.2	year/m/km	1	5
Depl. flood wall increase	0.1	year/m/km	1	2
Landfill	2	year/m/km^2	2	20
Dryproofing	0.5	year/m/building	1	5
Elevation	0.5	year/m/building	1	5
Barrier	15	year/km	10	50

3.3. Calculations

3.3.1. Obtaining optimal safety level

This section describes how the optimal safety level is determined in the framework. This corresponds to step 2 of Figure 2.1. Adaptation tipping points have to be obtained to do so. Adaptation tipping points have in Section 1.1 been defined as points in time current measures are no longer satisfactory to reach the objectives. Sea level rise results in a decrease of the safety level. When the safety level requirement is no longer met, an ATP is reached as can be seen in Figure 3.6. The ATPs are determined by subtracting the annual sea level rise from the water level corresponding to the current actual safety level. When this exceeds the water level corresponding to the desired safety level at the moment of implementation, an adaptation tipping point has been reached. The local sea level rise for 2040, 2060 and 2100 are based on the projections of the Intergovernmental Panel on Climate Change (IPCC) (2020). The sea level rise for the years in between is linearly interpolated. The sea level rise of 2200 is estimated by linearly extrapolating the rate of sea level rise between 2060 and 2100. The period 1995-2014 forms the baseline for the projections. The water level of the current and desired safety level is obtained by rewriting the equation of the Cumulative Density Function for the Gumbel distribution (Equation 3.1) to Equation 3.2.

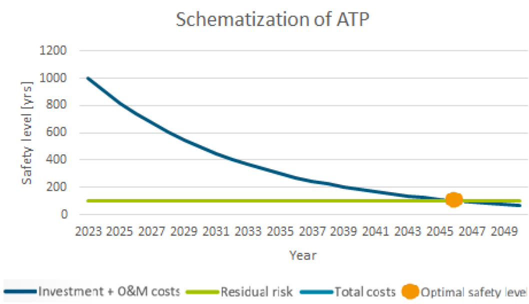


Figure 3.6: A schematisation of the ATP

$$F(x;\mu,\beta) = e^{-e^{-(x-\mu)/\beta}} \tag{3.1}$$

$$x = -\ln(-\ln(F)) * \beta + \mu \text{ in which } F = 1 - \frac{1}{T_R} \tag{3.2}$$

in which F is the cumulative probability, x is the water level corresponding to a Return Period (T_R) and β and μ are parameters of the Gumbel distribution. An example is given in Box 3.1. At the moment a measure is implemented, the water level corresponding to the optimal safety level of a measure is the new water level. An additional freeboard can be added when desired. This can be desirable when the Gumbel distribution is relatively flat. The sea level rise is subtracted again until a subsequent ATP is reached and the process repeats itself. Equation 3.2 is also used to obtain the water levels for the return periods 10 years, 100 years, 1,000 years, 10,000 years, 50,000 years, 100,000 years and 500,000 years.

Illustration 3.1: Obtaining ATP

For this illustration, a deployable flood wall with a safety level of 1,000 years in 2023 is applied to a project area. The required safety level of the project area is 100 years. The assumed sea level rise is 1 cm/year is assumed. The β and μ are respectively assumed to be 0.1 and 2.

The water levels corresponding to the current and desired safety level can easily be obtained by filling in Equation 3.2:

$$\text{WL}_{2023} = -\ln\left(-\ln\left(1-\frac{1}{1{,}000}\right)\right) * 0.1 + 2 = 2.69 \text{ m}$$

$$\text{WL}_{desired} = -\ln\left(-\ln\left(1-\frac{1}{100}\right)\right) * 0.1 + 2 = 2.46 \text{ m}$$

This means that with a sea level rise of 1 cm/year, it takes 23 years until the SLR is bigger than the difference and therefore the ATP is reached. An additional freeboard can be added when desired. Therefore, a new measure should be implemented in the year 2047. This can be seen in the schematisation of Figure 3.6 as well. When the safety level is afterwards increased to 1,000 years again by applying a new measure, it means that the height of the subsequent measure is 23 cm as well.

The optimal safety level of measures can be determined in different ways as described in Chapter 2. The NPV and BCR can be maximized or the total costs can be minimised to obtain an optimal safety level for measures. For all methods, the costs of implementation of measures have to be obtained. These have to be discounted in order to compare different times of expenses. The costs can be obtained in the PV as following (Jonkman, Steenbergen, et al., 2021):

$$C_{PV} = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} + C_0 \tag{3.3}$$

in which the C_t are the costs in the year t and r is the discount rate. The costs consist of the investment costs and operation & maintenance costs. The construction costs assumed for Europe can be found in Table 3.3 and the operation & maintenance costs are expressed in a percentage of the construction costs which can be found in Table 3.4. The costs, however, still have to be corrected for inflation which has been done as following:

$$C_{incl,infl} = C_0 * (1+i)^t \tag{3.4}$$

in which $C_{incl,infl}$ are the costs including inflation, C_0 are the costs at the year of the data on costs, i is the interest rate and t is the number of years after the data on costs. An illustration of obtaining the total costs for one single measure can be found in Box 3.2. The operation & maintenance costs of previous measures are included in consecutive measures for the pathways consisting of multiple measures. No O&M costs are included in the year of increasing the height of a measure. When applying a different measure (e.g. a levee after a landfill), O&M costs are included for the year a consecutive measure is applied. The O&M costs of previous measures are not included when applying the barrier that always functions as previous measures no longer are required. This is not the case for the barrier with a certain failure probability.

Illustration 3.2: Obtaining costs

For this illustration, the deployable flood wall is assumed to have a height of 1 meter and a length of 1000 meters. The wall is constructed in the year 2023. This levee has a lifetime of 23 years as could be seen in Box 3.1. The inflation rate and discount rate are respectively 2% and 4%. The construction costs can easily be obtained with Equation 3.4 and Table 3.3 as following:

I_{2023} = 1 m * 1000 m * 5,200 €/m/m * $(1+0.02)^{2023-2018}$ = 5.741 M €

The O&M costs excluding inflation can now be easily obtained with Table 3.4 as following:

$O\&M_{2023}$ = 5% * 5.74 m € = 0.287 M €

The total costs over the lifetime are now displayed in the table below. The total costs in present value at implementation are obtained by applying Equation 3.3.

year	2023	2024	2045	2046	
Investment costs [M€]	5.741	0	0	0	
O&M costs excl. infl. in FV [M€]	0	0.287	0.287	0.287	
O&M costs incl. infl. in FV [M€]	0	0.293	0.444	0.453	
O&M costs incl. infl. in PV [M€]	0	0.282	0.187	0.184	
Total costs in PV [M€]	5.741	0.282	0.187	0.184	**11.015**

The benefits consist of the obtained risk reduction in the future. The annual risk can be obtained by applying the following equation:

$$\text{Annual risk} = \sum_{p=1,10,100,..}^{P} \left(\frac{1}{P_p} - \frac{1}{P_{p+1}}\right) * \frac{D_p + D_{p+1}}{2} \tag{3.5}$$

in which P is the return period for a certain water level (the safety levels of 1, 10, 100, 1000, 10,000, 50,000, 100,000 and 500,000 are included in the framework) and D is the expected corresponding damage for these safety levels. The expected damage can be obtained by using the damage function and the expected inundation depth. The damage function is automatically generated from the damages that are required as input and correspond to a certain inundation depth. The inundation depth can be determined by subtracting the water level corresponding to the actual safety level from the water level corresponding to the damage. The damages for these return periods can be obtained from the Global Flood Risk Tool. These damages have to be entered as input for the tool. The difference between the water level of the actual safety level is subtracted from the water level at which damage occurs for the first time and this is the inundation that belongs to the lowest damage. This process is repeated for the water level with the second lowest damage, and so on.

When applying dryproofing or elevation, damage can still occur below the safety level of the measure (outside of the buildings) and this damage has to be accounted for. This can be done by applying the damages as shown in Equation 3.6 for dryproofing and in Equation 3.7 for elevation.

$$D_{dryproofing} = \begin{cases} \text{if } d_{inundation} \leq h_{dryproofing}, & (1 - r_{dam,buildings}) * D_{nm} \\ \text{if } d_{inundation} > h_{dryproofing}, & D_{nm} \end{cases} \tag{3.6}$$

in which $D_{dryproofing}$ is the damage when applying dryproofing, $d_{inundation}$ is the inundation depth of the project area, $h_{dryproofing}$ is the height of the applied dryproofing, $r_{dam,buildings}$ is the ratio of damage occurring at buildings compared to the total damage and D_{nm} is the damage when no measures would be applied for the total area.

$$D_{elevation} = \begin{cases} \text{if } d_{inundation} \leq h_{elevation}, & (1 - r_{dam,buildings}) * D_{nm} \\ \text{if } d_{inundation} > h_{elevation}, & r_{dam,buildings} * D_{wm,full,area} + (1 - r_{dam,buildings}) * D_{nm} \end{cases} \tag{3.7}$$

in which $D_{elevation}$ is the damage when applying elevation, $d_{inundation}$ is the inundation depth of the project area, $h_{elevation}$ is the height of the applied elevation, $r_{dam,buildings}$ is the ratio of damage occurring at buildings compared to the total damage, D_{nm} is the damage when no measures would be applied for the total area and $D_{wm,full,area}$ is the damage when the full area would be elevated.

Illustration 3.3: Risk at implementation

A linear damage function with a maximum damage of 100 €/m at 2 meters depth is assumed for this illustration. The area has a size of 0.1 km^2. The safety level is assumed to be equal to 1,000 years at the moment of implementation. The inundation depth consists of the water level above the safety level and the height of a measure when the water level is higher than the measure. No socio-economic growth is assumed. The same Gumbel distribution as in Box 3.1 is used and the following damage is obtained:

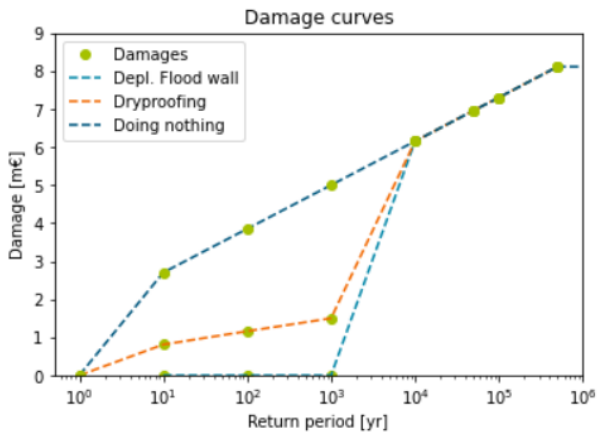
Return Period [years]	Water level [m]	Inundation depth [m]	Damage [m€]
10	2.23	0	0
100	2.46	0	0
1,000	2.69	0	0
10,000	2.92	1.23	6.15
50,000	3.08	1.39	6.96
100,000	3.15	1.46	7.30
500,000	3.31	1.62	8.11

The damage curve of the table above is displayed in the end of this box. The annual risk is approximated with Equation 3.5:

$$\text{Annual Risk}_{2023} = \left(\frac{1}{1{,}000} - \frac{1}{10{,}000}\right) * \frac{0+6.15}{2} + \left(\frac{1}{10{,}000} - \frac{1}{50{,}000}\right) * \frac{6.15+6.96}{2} + \left(\frac{1}{50{,}000} - \frac{1}{100{,}000}\right) * \frac{6.96+7.30}{2} + \left(\frac{1}{100{,}000} - \frac{1}{500{,}000}\right) * \frac{7.30+8.11}{2} + \frac{8.11}{500{,}000} = 3441 \text{ €/year}$$

When applying dryproofing or elevation, the damage that is not prevented (outside the buildings) by the measures should be accounted for as well. The damage after implementing dryproofing can now be obtained when assuming a ratio accounting for the damages occurring at buildings of 0.7 and applying Equation 3.6. These can be found in the last column. A damage factor of 0.7 indicates that 70% of the damage would occur at buildings if no measures would be applied. The damage curve can be found in the bottom right corner. The risk can now be applied in a similar way as above.

Return Period [years]	In. depth [m]	Damage no meas. [m€]	Damage drypr. [m€]
10	0	2.70	0.81
100	0	3.85	1.16
1,000	0	5.00	1.50
10,000	1.23	6.15	6.15
50,000	1.39	6.96	6.96
100,000	1.46	7.30	7.30
500,000	1.62	8.11	8.11



The annual risk with and without measures is calculated at the moment of implementation and at the end of the lifetime of measures by using Equation 3.5. A more efficient way of calculation had to be found for the intermediate years as calculating it in the same way as at the end and beginning of the lifetime would require an enormous amount of calculations for the different safety standards, different measures and different lifetimes.

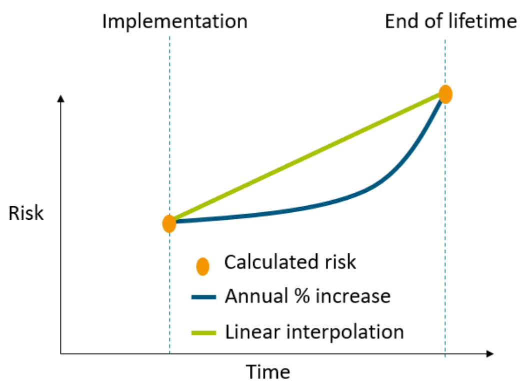


Figure 3.7: A schematisation of applying linear interpolation and an annual percentage increase

Linear interpolation and using an annual percentage increase were identified as methods to more efficiently calculate the risk of the intermediate years. Both methods are illustrated in Figure 3.7. The methods are tested for a case and compared to the extensive calculation as done in Box 3.3 (which can be found in Appendix C) to see whether the methods gave reliable results. The annual percentage increase can be calculated by rewriting Equation 3.8 to Equation 3.9.

$$R_{end} = R_{start} * (1+g)^t \tag{3.8}$$

$$g = \left(\frac{R_{end}}{R_{start}}\right)^{\frac{1}{t}} - 1 \tag{3.9}$$

The outcome of the fictive case can be seen in Table 3.6. It also includes the outcomes with altered input conditions. The extreme and mildest SLR-scenario both show that linear interpolation gives a considerably different result than when performing the calculation annually. A possible explanation for this is that the economic value annually increases by percentage instead of linearly. This also explains why when an annual percentage increase is applied, a reasonable estimate of the annual risk is obtained. The influence of different input-parameters are checked and it clearly shows that applying an annual percentage increase gives the same order of total risk during the lifetime of a measure. Therefore, an annual percentage increase will be used to obtain the annual risk of intermediate years. This method is illustrated in Box 3.4.

Table 3.6: Different methods to calculate the annual risk of the intermediate years efficiently

	Way of calculation	Total Risk [M €]	Rel. change [%]
Extreme SLR-scenario	Annual calculation	3.2	-
	Linear interpolation	8.7	+175%
	Annual % increase	2.5	-20%
Mildest SLR-scenario	Annual calculation	3.5	-
	Linear interpolation	18.6	+427%
	Annual % increase	3.5	-0%
Changing the discount rate to 1%	Annual calculation	10.4	-
	Linear interpolation	26.0	+149%
	Annual % increase	8.5	-19%
Changing the socio-economic growth rate to 1%	Annual calculation	2.2	-
	Linear interpolation	6.4	+200%
	Annual % increase	1.7	-20%

Whenever, there is no residual risk after implementation of the measures (for the measures with the highest safety standards), the risk is calculated for the second year of the lifetime of the measure as the sea level rise results in risk.

Illustration 3.4: Risk during lifetime

The annual risk at the end of the lifetime of the deployable flood wall can be calculated in a similar way as in Box 3.3. The only difference is that the sea level rise until the last year of the lifetime has to be added. This results in inundation for the high water-event with a return period of 1,000 years while without the sea level rise, this event did not result in inundation. This results in an annual risk in 2046 of 345,003 €/year when disregarding socio-economic growth. The annual percentage increase can now be obtained by applying Equation 3.9:

$$g = \left(\frac{345{,}003}{3{,}441}\right)^{\frac{1}{23}} - 1 = 22\%$$

Now the annual risk of the intermediate risk can easily be obtained with Equation 3.8 as is displayed in the table below.

year	**2023**	**2024**	**2045**	**2046**	
Annual risk in FV [€]	3,441	4,205	282,371	345,003	
Annual risk in PV [€]	3,441	4,043	119,148	139,977	**921,008**

The benefits can now be calculated and converted to the present value at the time of implementation as the lifetime differs for different safety levels. Equation 3.3 is adjusted for this purpose leading to the following equation:

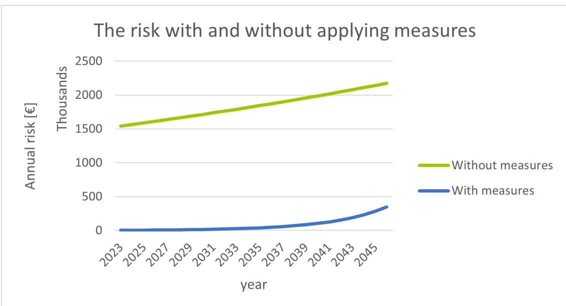
$$B_{PV} = \sum_{t=1}^{T} \frac{R_{t,nm} - R_{t,m}}{(1+r)^t} \tag{3.10}$$

in which B_{PV} are the benefits in present value as a result of risk reduction, $R_{t,nm}$ is the risk in year t when no measures will be applied, $R_{t,m}$ is the residual risk in year t when measures are applied and r is the discount rate. The discount rate is the expected rate of return on investments. An illustration of this calculation is shown in Box 3.5.

Illustration 3.5: Benefits

The annual risk without implementation of the 1-meter high flood wall can also be calculated in a similar way as done in Box 3.4. These results are displayed in the table below. Afterwards, Equation 3.10 has been used to obtain the benefits. This is also displayed in the figure below with the reduced risk defined as the area between the two lines.

year	**2023**	**2024**	**2045**	**2046**	
Risk with implementation in FV [k€]	3	4	282	345	
Risk without implemenation in FV [k€]	1,541	1,663	2,141	2,174	
Risk reduction in FV [k€]	1,538	1,560	1,859	1,829	
Benefits in PV [k€]	1,538	1,500	784	742	**27,453**



As both the benefits and costs are now known, the Net-Present Value (NPV) can simply be calculated:

$$NPV = B_{PV} - C_{PV} \tag{3.11}$$

When the NPV turns out positive, it is worthwhile to invest in the proposed measures. The efficiency of the investments can be easily obtained from the Benefit-Cost ratio (BCR):

$$BCR = \frac{B_{PV}}{C_{PV}} \tag{3.12}$$

Another way to determine the desired safety level is to minimize the total costs as following:

$$C_{tot,PV} = I + OM + R_{res} \tag{3.13}$$

in which $C_{tot,PV}$ is the total costs in Present Value, I is the investment costs, OM is the operation and maintenance costs, and R_{res} is the residual risk. The optimal safety level can now be determined depending on the desired optimisation method filled in at the input-sheet (NPV, B/C-ratio or total costs). When one would want to take the lifetime of measures into account, Equivalent Annual Costs can be applied by dividing the total benefits and costs by the annuity. The annuity factor can be obtained as following:

$$A_{t^*,i} = \sum_{t=1}^{t^*} \frac{1}{(1+r)^t} = \frac{1 - \frac{1}{(1+r)^{t^*}}}{r} \tag{3.14}$$

in which r is the discount rate and t is the lifetime of measures. An example of all the different methods can be found in Box 3.6. After the selection of choice in the desired optimisation method, a safety level with a corresponding ATP is selected and the process repeats itself for subsequent measures.

Illustration 3.6: Economic optimisation

The NPV, BCR and total costs can be calculated with the outcomes of the previous illustrations. Equations 3.11, 3.12 and 3.13 are used to obtain:

NPV = 27.453 M € - 11.015 M € = 16.438 M €
BCR = 27.453 M € / 11.015 M € = 2.49
C_{tot} = 27.453 M € + 0.921 M € = 28.374 M €

This calculation is done for a deployable flood wall with a safety level of 1,000 years at the moment of implementation. The same has to be done for the other safety levels and the desired safety level of a measure is the safety level with either the highest NPV, the highest BCR or the lowest total costs. The annuity factor can be used to compare the different lifetimes as a result of the different safety levels. The total NPV or the total costs should be divided by the annuity factor to do this. The annuity factor can be calculated with Equation 3.14. Applying a discount rate of 4% and a lifetime of 5 years gives:

Annuity factor = $\frac{1-\frac{1}{(1+0.04)^{24}}}{0.04}$ = 15.2

This results into an annual Net Present Value and Equivalent Annual Costs of:

NPV_{annual} = $\frac{16.438}{4.45}$ = 1.078 M € / year EAC = $\frac{6.901}{4.45}$ = 1.861 M € / year

As both the Benefits and the Costs are divided by the same annuity factor, the Benefit-Cost Ratio does not differentiate.

It is assumed that for the storm surge barrier no optimal safety level has to be derived as it is either restricted by the failure probability of closure or it is assumed to be robust enough for the residual risk to be negligible for the rest of its lifetime (dependent on the choice at the entry). When the latter option is chosen, the safety level is respected for its complete lifetime. When the barrier has a failure probability of closure, this failure probability is multiplied by the current safety level to obtain the safety level after the construction of a barrier. This is schematised in Box 3.7.

Illustration 3.7: Obtaining safety level after implementation of a barrier

The failure probability of closure of a barrier is assumed to be 10^{-4} for this illustration. The current safety level of the project area is assumed to be 100 years (or an annual failure probability of 10^{-2}). The new safety level can now easily be obtained as following:

$$P_{f,withbarrier} = P_{safety,level} * P_{barrier} = 10^{-2} * 10^{-4} = 1*10^{-6} \text{ -/year}$$

This is equal to a safety level of 1,000,000 years. The ATP can now be derived as done in Box 3.1.

3.3.2. Safety levels of pathways

The optimal safety level of individual measures has been derived. Now the pathways can be built out of the individual measures. This corresponds to step 3 of Figure 2.1. The relative difference between the land and water level is reduced by the sea level rise to obtain the annual safety level development. This reduction leads to a decrease in the safety level and accordingly, an increase in the probability of failure. From the actual water level corresponding to the current situation. When a measure is applied, the height of the measure is added to this water level. Afterwards, the safety is obtained as following:

$$SL = \frac{1}{1-F} \tag{3.15}$$

in which SL is the obtained safety level and F is the cumulative probability that can be obtained by applying Equation 3.1.

Illustration 3.8: Obtaining Safety levels over time

The rising sea level results in a lower safety level. The same deployable flood wall as previous illustrations has been used in this illustration. The deployable flood wall has a safety level of 1,000 years. The water level corresponding to this has been obtained in Box 3.1 and was equal to 2.69. The cumulative probability for subsequent years can be obtained by adjusting Equation 3.1 for SLR as following:

$$F(x;\mu,\beta) = e^{-e^{-(x-\Delta SLR-\mu)/\beta}} \tag{3.16}$$

The sea level rise of 1 cm/year is used to obtain the cumulative probability. The corresponding safety level is afterwards obtained with Equation 3.15. The results are shown in the table below.

year	**2023**	**2024**	**2045**	**2046**
Relative water level [m]	2.69	2.68	2.47	2.46
Cumulative probability [-/year]	0.999	0.998	0.991	0.990
Safety level	1,000	905	111	101

3.3.3. Evaluation

A selection has to be made before the probabilistic assessment can be applied. This selection is done with prerequisites and a CBA and corresponds to step 4 of Figure 2.1. Prerequisites are used to filter out pathways that are not desired by stakeholders. The following pre-requisites can be chosen to make a selection:

- Maximum investment costs;
- A positive NPV;
- Prevent lock-ins;
- The year until the safety requirement is at least respected;

The investment costs are obtained as described in Section 3.3.1. The only difference is that they are now being discounted to the present instead of the year of implementation. The NPV of a pathway is calculated in the CBA and the way of calculation is explained below. Pathways with only one subsequent action left are excluded when the option to prevent lock-ins is chosen. The end of the lifetime of the adaptation pathways are obtained with the ATPs described in Section 3.3.1.

The CBA is conducted by comparing the total investment and O&M costs to the benefits of the complete pathway in the present value. The benefits are obtained by subtracting the residual risk with implementation of measures from the risk without implementation of measures for the complete lifetime of the pathway. The costs and residual risks for the situation with measures have already been calculated as explained in Section 3.3.1. The risk without implementation of measures is calculated by obtaining the inundation depth, damage and annual risk for all years of the pathway (as described in Section 3.3.1). Now the benefits can easily be obtained by subtracting the residual risk with implementation of the measures from the risk without implementation of measures. This is illustrated in Box 3.9. The total costs (investment, O&M and residual risk) are also obtained for every pathway. Afterwards, the pathways that do not fulfill the prerequisites are filtered out and the most optimal pathway is chosen dependent on the method of optimization as has been illustrated in Box 3.6.

Illustration 3.9: CBA of entire pathway

All costs and residual risks from the moment of implementation until the last year of the lifetime of the last measure are discounted to obtain a CBA of the entire pathway. All values have already been discounted to the moment of implementation of the measure. At the moment the previously described deployable flood wall reached its ATP, another fictive measure was applied for this illustration. The total cost and residual risk during their lifetime have been obtained in the table below.

	Measure 1	**Measure 2**	
Year of impl.	2023	2047	
Costs in value at impl. [m€]	11.015	17.500	
R_{res} in value at impl. [m€]	0.921	1.500	
Costs in PV [m€]	10.591	6.565	**17.156**
R_{res} in PV [m€]	0.886	0.563	**1.448**

The total risk when no measures would be applied for the same period is assumed to be €40 million in present value. This means that the total benefits can now easily be obtained as following:

$$B_{PV} = 40 \text{ m€} - 1.448 \text{ m€} = 38.552 \text{ m €}$$

The NPV, BCR and Total costs can now be obtained:

$$NPV = 38.552 \text{ m €} - 17.156 \text{ m €} = 21.396 \text{ m €}$$
$$BCR = 38.552 \text{ m €} / 17.156 \text{ m €} = 2.25$$
$$C_{tot} = 17.156 \text{ m €} + 1.448 \text{ m €} = 18.604 \text{ m €}$$

When one would decide to apply the annuity factor to compare the different lifetimes of different safety levels, the total NPV or the total costs should be divided by the annuity factor as done in Box 3.6.

3.3.4. Trigger values

The trigger values that should initiate subsequent actions. This is done for the selected pathway and therefore performed in step 6 of Figure 2.1. The trigger values for this pathway can be obtained by subtracting the time it takes to implement a certain measure, which can be seen in Table 3.5, from the adaptation tipping point. Afterwards the corresponding sea level rise at that moment in time is obtained by using the sea level rise scenario that has to be filled in as input. The values that can be found in the table are not based on literature and solely are used to illustrate how trigger values could be obtained within the framework. It would, therefore, require additional research to obtain reliable values.

Illustration 3.10: Obtaining trigger-values

The required time to implement the previously described deployable flood wall of 1 meter high and 1,000 meters long can be obtained from Table 3.5 and a simple calculation:

$$T_{required} = 1 \text{ m} * 1 \text{ km} * 0.1 \text{ year/m/km} = 0.1 \text{ year}$$

However, this is lower than the minimum value meaning that the time it takes is equal to the minimum required time of 1 year. This means that with a sea level rate of 1 cm/year, action should be taken when the sea level is 22 cm higher than at the beginning of 2023.

3.4. Probabilistic assessment

Uncertain values like the socio-economic growth rate were used as deterministic input for the framework. This allowed for an evaluation of pathways with different combinations of input-parameters. However, applying scenarios might result in incomplete coverage of the range of possible futures as stated in Section 1.2. Therefore, a probabilistic assessment can be applied to evaluate the three most promising pathways to see whether they perform sufficiently for the full range of possible futures. This probabilistic assessment is a separate python-script that will use input on pathways from the previously described framework and corresponds to step 5 out of Figure 2.1. These pathways will be assessed by including distributions for the costs estimates, potential benefits, sea level rise, socio-economic growth rate, discount rate and inflation rate as can be seen in Table 3.7. A Monte Carlo simulation in which random values out of these distributions are used for each simulation. The NPV will be obtained with these random values for each simulation. This is schematised for a single measure and simulation in Figure 3.8. The calculations done to obtain the ATP, costs, benefits and NPV for this probabilistic assessment are described in respectively Sections 3.4.1, 3.4.2, 3.4.3 and 3.4.4. Section 3.4.5 describes how pathways consisting of multiple measures can be assessed.

Table 3.7: The distributions used in the probabilistic assessment

Parameter	Distribution
Investment costs	Lognormal
O&M costs	Lognormal
Risk reduction	Lognormal
Sea level rise	Fit through the IPCC quantiles
Socio-economic growth rate	Normal
Discount rate	Normal
Inflation rate	Normal

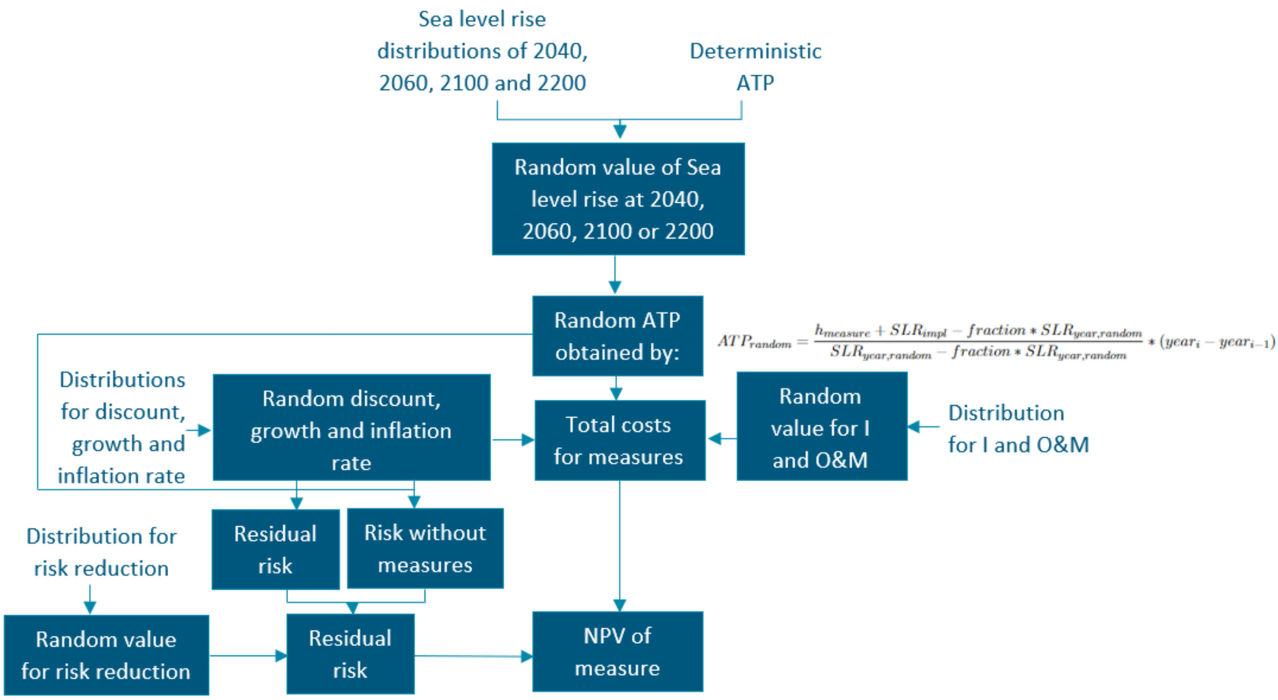


Figure 3.8: A schematisation of the application of probabilistic assessment for a single measure and simulation

3.4.1. Adaptation Tipping Point

A random value is taken for the sea level rise. This value is dependent on when the deterministic ATP is expected. When the deterministic ATP is expected to be in between 2060 and 2100, the SLR distribution of 2100 is used to obtain a random value for the sea level rise in 2100. The ATP with the randomly obtained sea level rise is afterwards determined as following:

$$ATP_{random} = \frac{h_{measure} + SLR_{impl} - fraction * SLR_{year,random}}{SLR_{year,random} - fraction * SLR_{year,random}} * (year_i - year_{i-1}) + year_{i-1} \quad (3.17)$$

in which h is the height between the safety level of the applied measure and the height corresponding to the required safety level, SLR$_{impl}$ is the sea level rise that has taken place at the moment of implementation of the measure, SLR$_{year,random}$ is the random value of sea level rise either at the year 2040, 2060, 2100 or 2200 dependent on the deterministic ATP, fraction is the fraction between the SLR of year$_i$ and year$_{i-1}$ where year$_i$ is either 2060, 2100 or 2200 and year$_{i-1}$ is either 2040, 2060 and 2100. This random rate of sea level at the years 2040, 2060, 2100 and 2200 is obtained by multiplying the median sea level rise according to the IPCC-projections by a random value obtained from a distribution to account for the uncertainty in the sea level rise scenario. The same random value is used for the SLR in different years as they are correlated. This results in the same ATP as in the Excel-framework when taking 1 as randomly obtained value for the sea level rise. Box 3.11 illustrates how such ATPs are obtained in the probabilistic assessment.

Illustration 3.11: Obtaining ATP

The ATP can be obtained by applying Equation 3.17. This equation requires the height between the levels of the new and required safety level. The same parameters as previous illustrations are used for this example. This means that β = 0.1, μ = 2, the new safety level is 1,000 and the required safety level is 100 years. This results in a height of 23 cm between the new and required level (Box 3.1). The SLR at the moment of implementation (2023) is assumed to be 0 cm to keep this example simple. The deterministic ATP has been calculated in Box 3.1 and equals 2047. A linear SLR of 1 cm/year has been assumed which means that the SLR in 2060 will be 0.37 meters. A random value can now be taken from the distribution of the SLR in 2060. To show that the outcome of this equation gives the same result as in the deterministic approach, a sea level rise of 0.37 meters in 2060 is assumed. As the SLR is assumed to be linear, the fraction of SLR taken place in 2040 compared to 2060 is equal to $\frac{SLR_{2040}}{SLR_{2060}} = \frac{0.17}{0.37} = 0.46$. This gives:

$$\text{ATP}_{random} = \frac{0.23+0-0.46*0.37}{0.37-0.46*0.37} * (2060-2040) + 2040 = 2046$$

which means that 2046 is the last year of the measure and a new measure has to be implemented in 2047. When the random value turns out to be 0.5 m instead of 0.37, this results into:

$$\text{ATP}_{random} = \frac{0.23+0-0.46*0.5}{0.5-0.46*0.5} * (2060-2040) + 2040 = 2040$$

which means that 2040 is the last year of the measure and a new measure has to be implemented in 2041. This could be expected as the rate of sea level rise is happening at a faster rate.

3.4.2. Costs

The deterministic investments costs obtained in the framework are used as input for the probabilistic assessment. These obtained investment costs are afterwards separately multiplied by a random value obtained from a Log-normal distribution with the mode at 1 and the standard deviation dependent on the type of measure. This is done to account for the uncertainty. The annual O&M costs are subsequently obtained by multiplying the investment costs by the percentages in Table 3.4. These are afterward multiplied by a random value obtained from a Log-normal distribution with the mode at 1 and the standard deviation dependent on the type of measure. Inflation results in an annual increase of costs. All costs can be discounted to the present as described in Section 3.3.1. The inflation rate and discount rate are also randomly obtained from the distributions.

3.4.3. Benefits

The risk after implementation of measures is calculated by obtaining the inundation depth and using Equation 3.5. The optimal safety level has already been obtained in the excel framework and therefore considerably less calculations have to be run. Therefore, the risk of the intermediate years can be obtained in a similar way instead of applying an annual percentage increase. The risk is also calculated for the situation when no measures are applied. This residual risk is subtracted from the total risk without applying the measures for the complete pathway. These form the benefits of a pathway and are subsequently multiplied by a normalized Log-normal distribution to account for the uncertainty. This is also done with a randomly obtained socio-economic growth and discount rate (the same one as used to obtain the costs).

3.4.4. NPV

The NPV can now simply be obtained for the measures by bringing all the costs and benefits of the complete pathway to the present value with the previously obtained discount rate and subtracting the costs from the benefits. This is similar to the calculation described in Section 3.3.3.

3.4.5. Consecutive measure

Consecutive measures are run with the same randomly obtained discount rate, socio-economic growth rate, inflation rate and factor accounting for the variability in risk reduction. The ATP is obtained in a similar way as described in Section 3.4.1 except for the fact that no completely random value for sea level rise is taken but this value is correlated to the randomly obtained sea level rise at the first measure as they are related. This is done by dividing the randomly obtained sea level rise for the first measure by the expected sea level rise. Then, this factor is multiplied by the expected sea level rise for the second measure. This is illustrated in Box 3.12. As the uncertainty in the costs of measures are assumed to be uncorrelated for different measures, these values are again randomly obtained for subsequent measures.

Illustration 3.12: SLR for consecutive measures

The randomly obtained value for sea level rise was 0.5 meters in the last example of Box 3.11 while the deterministic value of sea level rise was equal to 0.37 meters. The factor accounting for the difference in randomly and deterministically obtained value is therefore equal to $\frac{0.37}{0.5}$ = 0.74. Assuming a deterministic ATP of 2085 for the consecutive measure and an expected SLR of 1 meter in 2100, the randomly obtained SLR in 2100 can now be calculated as following:

$$\text{SLR}_{2100,random} = \text{factor} * \text{SLR}_{2100,deterministic} = 0.74 * 1 \text{ m} = 0.74 \text{ m}$$

The ATP of the consecutive measure can now be calculated as done in Box 3.11.

3.5. Output-parameters

The excel-framework and the python-script provide the following outputs:

Adaptation Pathways-scheme

This scheme provides an overview of all possible pathways with their Adaptation Tipping Points. The safety level of each pathway plotted over time can also be observed in this scheme. A second overview is given in which the pathways that do not fulfill the requirements are filtered out.

CBA

The costs and benefits are calculated for each adaptation pathway. This calculation has been explained in Section 3.3.3. Afterwards, the NPV, B/C-ratio and Total costs are calculated with the costs and benefits and Equations 3.11, 3.12 and 3.13. Then, it is checked whether the pathways satisfy the criteria specified in the prerequisites-sheet. Finally, the optimal pathway is selected out of all pathways and out of the pathways which satisfy the earlier specified criteria.

Trigger-values

This output-sheet provides the trigger values for the selected pathway. These trigger values are obtained as explained in Section 3.3.4 and give the sea level at which action has preparation for implementation of subsequent measures have to be initiated.

Probabilistic assessment

A range of different NPVs forms the outcome of the probabilistic assessment for a selection of pathways. The outcome can be used to compare the robustness of the selected pathways.

4
Fictive case

In this chapter, the framework described in Chapter 3 is applied to a fictive case to see whether it gives reliable results. Afterwards, the probabilistic assessment is applied to the selected pathway. The site characteristics of the case are described in Section 4.1. The results of the framework and the probabilistic assessment can be found in Section 4.2. The results are evaluated and compared to the outcomes obtained with different input-parameters in Section 4.3.

4.1. Input

The geometry, water levels and damage are required as input before obtaining results out of the framework. A flat area of 100 x 50 meters with residential land-use is assumed as geometry. The project area is visualised in Figure 4.1. It is assumed that the land surrounding the project area is elevated and water cannot flow in from other sides than the sea. Now, it can clearly be seen that a levee or (deployable) flood wall should be located at the long side along the sea. Therefore, the required length for a levee or (deployable) flood wall is assumed to be 100 meters. A barrier can be used to close off the bay and is assumed to be approximately 50 meters long. The area to which a landfill can be applied is equal to the entire project area and is 5,000 m^2. Finally, dryproofing and elevation can be applied to 10 buildings that will be built in the area.

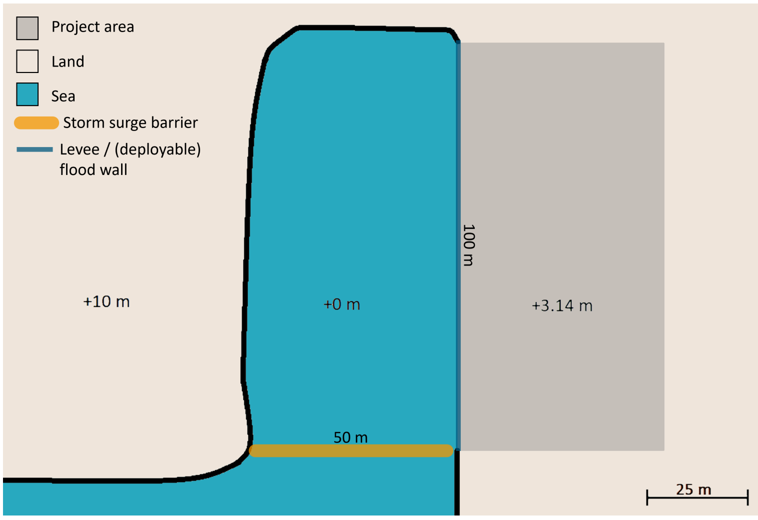


Figure 4.1: Visualisation of the fictive case

The water level is assumed to be Gumbel distributed with β = 0.15 and μ = 2.8. This results in the water levels that can be seen in Figure 4.2. It is here assumed that the waves can be neglected and the high water levels are caused solely by surges.

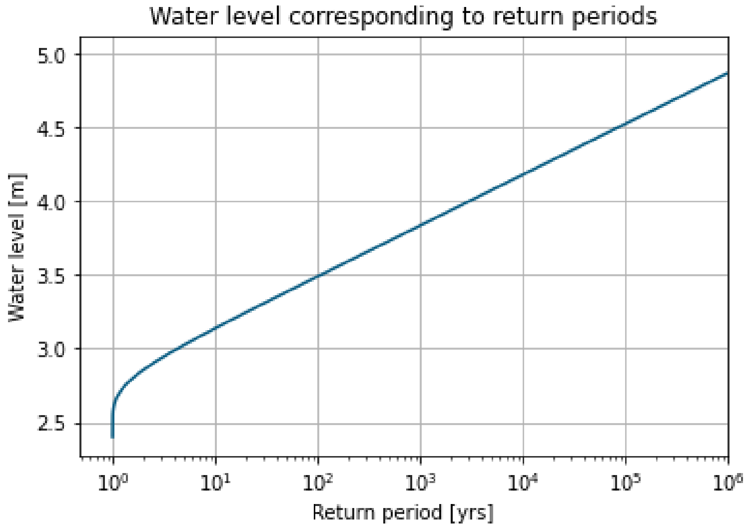
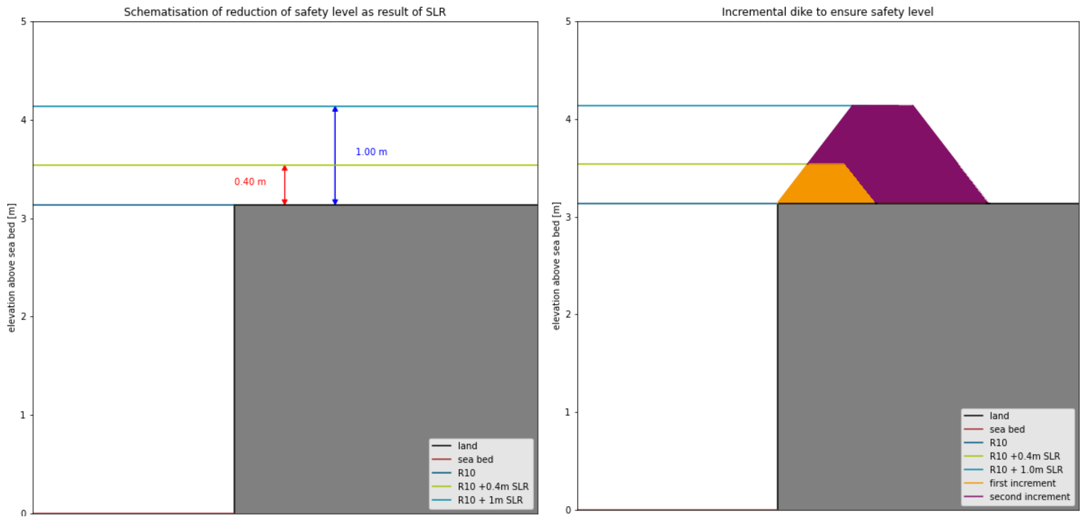


Figure 4.2: Return periods with their corresponding water levels for the fictive case

The Dutch damage function for residential land-use derived by Huizinga et al. (2017) was used to obtain the expected damages for the different return periods. The maximum damage was estimated to be 168 €/m^2 in 2010. The latest (2021) CPI with 2010 as a baseline is 120.5 (The World Bank, n.d.). This results in a maximum damage of 202 €/m^2 when correcting it for the CPI. This function is valid for the entire project area as it is land-use based. The current safety level is 10 years as the level of the land equals the water level corresponding to a return period of 10 years. This is schematised in Figure 4.3a. The 95th quantiles of the mid-term and long-term sea level rise of the SSP5-8.5-scenario for Western Europe are also shown as these are required for a more accurate damage function. An illustration of a measure that can be applied to keep the same safety level is shown in Figure 4.3b.



(a) The reduction in the safety level as a result of SLR schematised

(b) A measure that can be applied to keep the same safety level after SLR

Figure 4.3: The consequence of SLR schematised

The expected damage obtained by using the inundation depth (water level - elevation) and the damage functions can be found in Table 4.1. The damages are displayed in a graph in Figure 4.4.

Table 4.1: Water levels for different return periods for the fictive case

Return Period	Damage [k€]	Damage when SLR = +0.4m [k€]	Damage when SLR = +1.0m [k€]
10	0	202	404
100	178	329	475
1,000	313	424	545
10,000	413	494	613
50,000	462	542	649
100,000	483	563	665
500,000	531	611	702

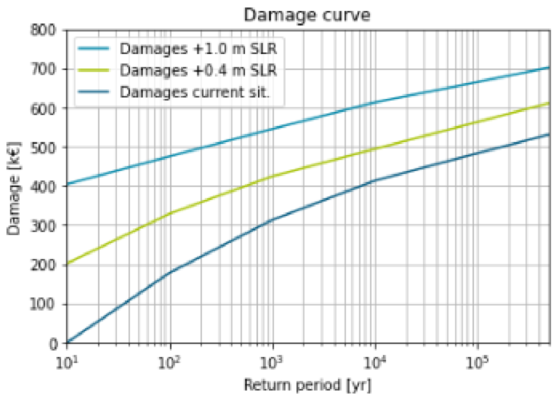


Figure 4.4: The damages for different water levels

The required safety level was assumed to be equal to 100 years. A value of 4% was assumed for the discount rate as this is the prescribed discount rate for infrastructure projects in The Netherlands (Research Programme on the Economic Effects of Infrastructure, n.d.). The average inflation rate of The Netherlands of this century is used as input and is equal to 2% (Macrotrends, 2020). The socio-economic growth rate is assumed to be equal to the GDP growth and is equal to 1% in The Netherlands in this century (The World Bank, 2022). The pathways were evaluated according to the SSP5-8.5-scenario. The discount rate, inflation rate and socio-economic growth rate were all assumed to have a Coefficient of Variation of 0.1 for the probabilistic assessment. Finally, the barrier was assumed to always function and have a lifetime of 100 years and optimizations are done based on the highest NPV. A Lognormal function with μ = 0.001 and σ = 0.01 is used to account for the uncertainty in investment costs, O&M costs and the risk reduction. The uncertainty within a sea level rise scenario is assumed to be normally distributed and to have a Coefficient of Variation of 0.1. All Coefficients of Variation are initial assumptions and their sensitivity is evaluated in Section 4.3. The input-conditions of the framework and probabilistic assessment can be found in Tables 4.2 and 4.3.

Table 4.2: The input-parameters for the fictive case

Input	Value
Region	Northern Europe
Desired protection level	100 years
Actual protection level	10 years
Req. length of levee to increase safety level	100 meters
Buildings that require dryproofing / elevation	10 buildings
Req. barrier length	50 meter
Protection area	5,000 m^2
Year of data	2021
Currency	Euro
β and μ of the Gumbel distribution	β = 0.15 m and μ = 2.8 m
Damage	See Table 4.1
Sea level rise scenario	SSP3-7.0
Socio-economic growth rate	1%
Discount rate	4%
Inflation rate	2%
Measures to include	All
Safety level of the barrier	A set protection level for a lifetime of 100 years
Determination of the optimal safety level	NPV
Apply the annual cost / benefits	no

Table 4.3: The distributions used in the probabilistic assessment

Parameter	Distribution	Parameters
Investment costs	Lognormal	λ = 0.001 and ζ = 0.01
O&M costs	Lognormal	λ = 0.001 and ζ = 0.01
Risk reduction	Lognormal	λ = 0.001 and ζ = 0.01
Sea level rise	Normal	μ = 1 and σ = 0.1
Socio-economic growth rate	Normal	μ = 1 and σ = 0.1
Discount rate	Normal	μ = 1 and σ = 0.1
Inflation rate	Normal	μ = 1 and σ = 0.1

4.2. Results

The outcome of the framework can be seen in Figure 4.5. All possible adaptation pathways are displayed for the fictive case in this figure. It can be seen that the first measure is implemented in the year 2023 (the first possible year of implementation). As all measures are assumed to be possible, all pathways are possible. It can also be seen that the lifetime of the measures differs which means that the safety level at the moment of implementation differs as well. Not all measures last until 2200 and therefore, not all pathways might be desired.

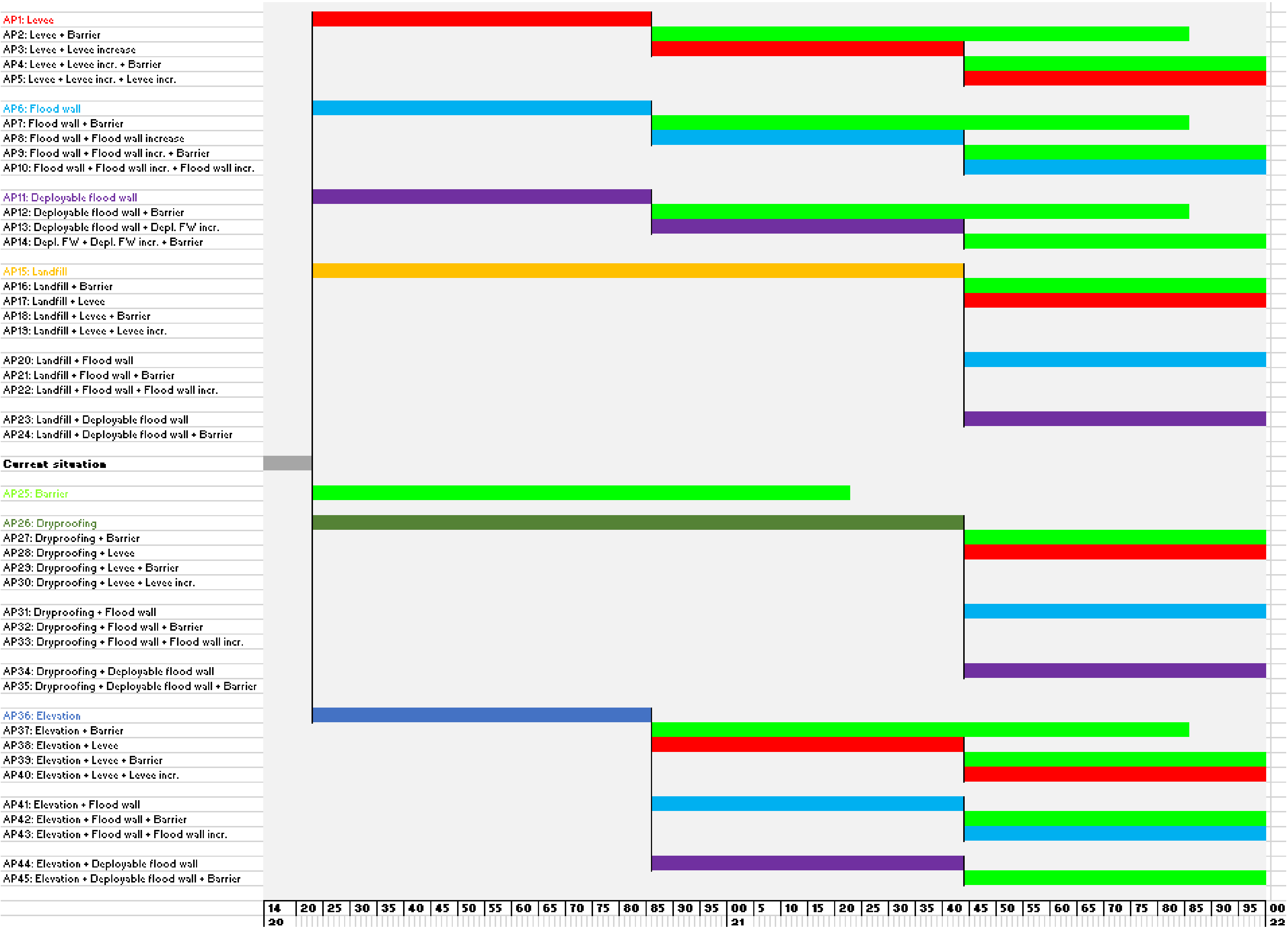
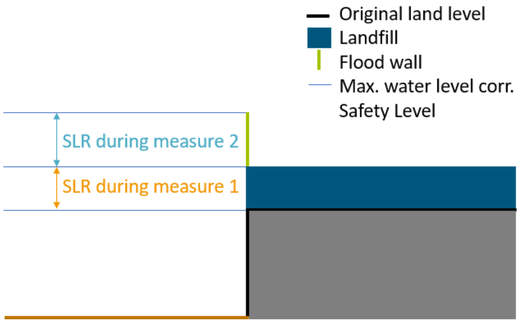
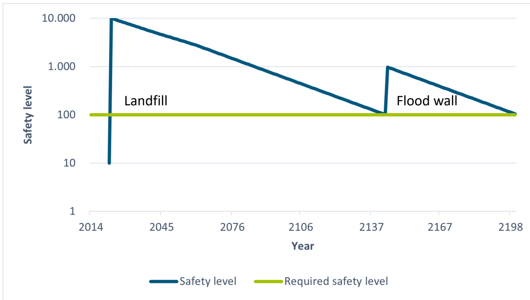


Figure 4.5: All possible Adaptation Pathways possible for the fictive case

The adaptation pathway with the highest NPV(€1.8m) is pathway 20. The first measure of this pathway is a landfill. The area is relatively small and therefore, the cost of implementing a landfill are low resulting in an effective first flood risk measure. A flood wall is implemented at the moment the safety level requirement is no longer met as can be seen in Figure 4.6a. The measures have safety levels at the moment of implementation of respectively 10,000 and 1,000 years as is displayed in Figure 4.6b. This pathway satisfies the safety requirements until at least 2200 for this scenario. The first measure is implemented in 2023 and the consecutive measure is implemented in 2144. The landfill has a height of 1.05 meters and the subsequent flood wall has a height of 0.35 meters.



(a) A schematisation of the measures applied in AP20



(b) The safety level over time for AP20 for the fictive case on a log-scale

Figure 4.6: Schematisation of AP20

The first measure has to be implemented instantly making the first trigger value irrelevant. Actions to prepare the flood wall have to be initiated 1 year before the actual implementation. This corresponds to 2043 and a sea level rise of 70 cm relative to the present and a safety level of 101 years.

The total CBA can be seen in Figure 4.7. The year in which the pathway ends is also given. The NPV is highly negative when a barrier is immediately applied (pathway 25). This could be expected as the area that is protected by the measure is relatively small while the measure is extremely costly. It can also be observed that the NPV of pathways in which the barrier is applied as second measure (e.g. pathway 2) is considerably less negative as a result of the discount rate.

Pathway	Measures in order	End date	Total investment costs in PV [€]	Total benefits in PV [€]	NPV [€]	B/C-ratio	Total Costs [€]	Total Costs [€ / year]
Adaptation Pathway 1	Levee	2085	807.081	1.225.550	418.470	1,52	824.854	36.040
Adaptation Pathway 2	Levee + Barrier	2185	60.375.979	1.925.504	-58.450.475	0,03	60.393.753	2.419.799
Adaptation Pathway 3	Levee + Levee increase	2143	937.743	1.791.567	853.824	1,91	958.787	38.688
Adaptation Pathway 4	Levee + Levee incr. + Barrier	2200	17.294.368	1.944.437	-15.349.932	0,11	17.315.413	693.261
Adaptation Pathway 5	Levee + Levee incr. + Levee incr.	2200	982.410	1.943.716	961.305	1,98	1.004.176	40.204
Adaptation Pathway 6	Flood wall	2085	443.878	1.225.550	781.672	2,76	461.652	20.171
Adaptation Pathway 7	Flood wall + Barrier	2185	60.012.777	1.925.504	-58.087.273	0,03	60.030.550	2.405.247
Adaptation Pathway 8	Flood wall + Flood wall increase	2143	526.098	1.791.567	1.265.469	3,41	547.143	22.078
Adaptation Pathway 9	Flood wall + Flood wall incr. + Barrier	2200	16.882.724	1.944.437	-14.938.287	0,12	16.903.768	676.780
Adaptation Pathway 10	Flood wall + Flood wall incr. + Flood wall incr.	2200	555.633	1.943.755	1.388.122	3,50	577.359	23.116
Adaptation Pathway 11	Deployable flood wall	2085	1.090.909	1.243.324	152.416	1,14	1.108.682	48.441
Adaptation Pathway 12	Deployable flood wall + Barrier	2185	60.659.807	1.925.504	-58.734.303	0,03	60.677.580	2.431.171
Adaptation Pathway 13	Deployable flood wall + Depl. flood wall increas	2143	1.439.879	1.791.567	351.688	1,24	1.460.923	58.949
Adaptation Pathway 14	Deployable flood wall + Depl. FW incr. + barrier	2200	17.796.504	1.944.437	-15.852.067	0,11	17.817.548	713.365
Adaptation Pathway 15	Landfill	2143	152.915	1.810.612	1.657.697	11,84	154.914	6.251
Adaptation Pathway 16	Landfill + Barrier	2200	16.509.540	1.963.482	-14.546.059	0,12	16.511.540	661.076
Adaptation Pathway 17	Landfill + Levee	2200	191.282	1.962.505	1.771.224	10,26	194.257	7.778
Adaptation Pathway 18	Landfill + Levee + Barrier	2200	2.201.216	1.962.505	-238.711	0,89	2.204.192	88.250
Adaptation Pathway 19	Landfill + Levee + Levee incr.	2200	195.031	1.962.505	1.767.474	10,06	198.007	7.928
Adaptation Pathway 20	Landfill + Flood wall	2200	174.342	1.962.505	1.788.164	11,26	177.317	7.099
Adaptation Pathway 21	Landfill + Flood wall + Barrier	2200	2.184.277	1.962.505	-221.771	0,90	2.187.252	87.571
Adaptation Pathway 22	Landfill + Flood wall + Flood wall incr.	2200	180.138	1.962.505	1.782.367	10,89	183.114	7.331
Adaptation Pathway 23	Landfill + Deployable flood wall	2200	219.734	1.962.505	1.742.771	8,93	222.710	8.917
Adaptation Pathway 24	Landfill + Deployable flood wall + Barrier	2200	2.229.669	1.962.505	-267.163	0,88	2.232.644	89.389
Adaptation Pathway 25	Barrier	2122	202.445.963	1.679.608	-200.766.355	0,01	202.445.963	8.261.415
Adaptation Pathway 26	Dryproofing	2143	187.190	1.806.885	1.619.695	9,65	192.917	7.784
Adaptation Pathway 27	Dryproofing + Barrier	2200	16.543.815	1.959.755	-14.584.061	0,12	16.549.542	662.597
Adaptation Pathway 28	Dryproofing + Levee	2200	345.201	1.959.073	1.613.873	5,68	351.608	14.077
Adaptation Pathway 29	Dryproofing + Levee + Barrier	2200	2.355.135	1.959.073	-396.062	0,83	2.361.543	94.550
Adaptation Pathway 30	Dryproofing + Levee + Levee incr.	2200	356.794	1.959.073	1.602.280	5,49	363.201	14.542
Adaptation Pathway 31	Dryproofing + Flood wall	2200	276.630	1.959.073	1.682.443	7,08	283.038	11.332
Adaptation Pathway 32	Dryproofing + Flood wall + Barrier	2200	16.633.255	1.959.073	-14.674.182	0,12	16.639.663	666.205
Adaptation Pathway 33	Dryproofing + Flood wall + Flood wall incr.	2200	282.427	1.959.073	1.676.647	6,94	288.834	11.564
Adaptation Pathway 34	Dryproofing + Deployable flood wall	2200	1.691.274	1.959.073	267.800	1,16	1.697.681	67.970
Adaptation Pathway 35	Dryproofing + Deployable flood wall + Barrier	2200	3.701.208	1.959.073	-1.742.135	0,53	3.707.616	148.443
Adaptation Pathway 36	Elevation	2085	419.682	1.235.446	815.764	2,94	427.560	18.681
Adaptation Pathway 37	Elevation + Barrier	2185	59.988.580	1.935.400	-58.053.181	0,03	59.996.458	2.403.881
Adaptation Pathway 38	Elevation + Levee	2143	780.099	1.799.357	1.019.258	2,31	793.354	32.012
Adaptation Pathway 39	Elevation + Levee + Barrier	2200	17.136.724	1.952.226	-15.184.498	0,11	17.149.979	686.637
Adaptation Pathway 40	Elevation + Levee + Levee incr.	2200	827.293	1.951.718	1.124.425	2,36	841.056	33.674
Adaptation Pathway 41	Elevation + Flood wall	2143	620.829	1.799.357	1.178.527	2,90	634.084	25.586
Adaptation Pathway 42	Elevation + Flood wall + Barrier	2200	16.977.455	1.952.226	-15.025.228	0,11	16.990.709	680.260
Adaptation Pathway 43	Elevation + Flood wall + Flood wall incr.	2200	652.891	1.951.545	1.298.654	2,99	666.654	26.691
Adaptation Pathway 44	Elevation + Deployable flood wall	2143	892.013	1.799.357	907.344	2,02	905.267	36.528
Adaptation Pathway 45	Elevation + Deployable flood wall + Barrier	2200	17.248.638	1.952.226	-15.296.412	0,11	17.261.893	691.118

Figure 4.7: The CBA for all considered pathways

Table 4.4: The three most promising flood risk strategies

Pathway	Measures	Year of impl. 1st measure	Year of impl. 2nd measure	NPV [€]
AP20	Landfill + Flood wall	2023	2144	1,788,000
AP17	Landfill + Levee	2023	2144	1,771,000
AP23	Landfill + Deployable Flood Wall	2023	2144	1,743,000

The three most promising pathways can be found in Table 4.4. The probabilistic assessment can be used to compare the robustness of these pathways. As this fictive case functions as an illustration of the method, the probabilistic assessment has been applied only to the most promising pathway of the framework (pathway 20) to see whether that assessment works as expected. The output of the framework has been used to fill in the probabilistic assessment. The safety level at the moment of implementation is 9.43 years, the year of implementation of the first measure is 2023 and the height of the first and subsequent measure are respectively 1.05 m and 0.35 m (the measures of Figure 4.6).

The script that has been produced to perform the probabilistic assessment was tested by taking a deterministic value of 1 instead of using distributions to account for uncertainty. This outcome should comparable to the outcome of the framework and resulted into ATPs of 2144 and 2201 for AP20. The O&M in PV at the moment of implementation of measures were respectively €13.9k and €484k. The total NPV is €1.8 million. The script to obtain these values can be found in Appendix D.1. Afterwards, the distributions were used to perform 10,000 simulations. In this way the performance of pathway 20 could be tested in varying conditions as can be seen in Figure 4.8. The script can be found in Appendix D.2. It can be seen that the mode of the obtained NPVs equals the deterministically obtained value. It can, however, also be observed that some simulations lead to a considerably different NPV (up to 3 times higher and lower).

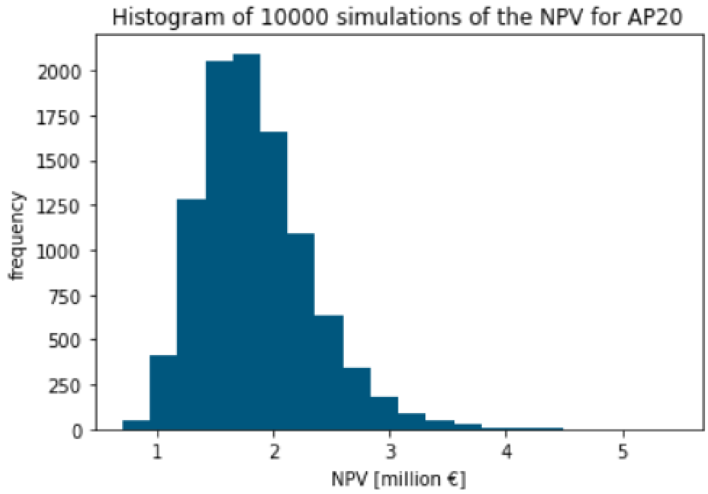


Figure 4.8: The probabilistic assessment applied to AP20 for the fictive case

4.3. Evaluation

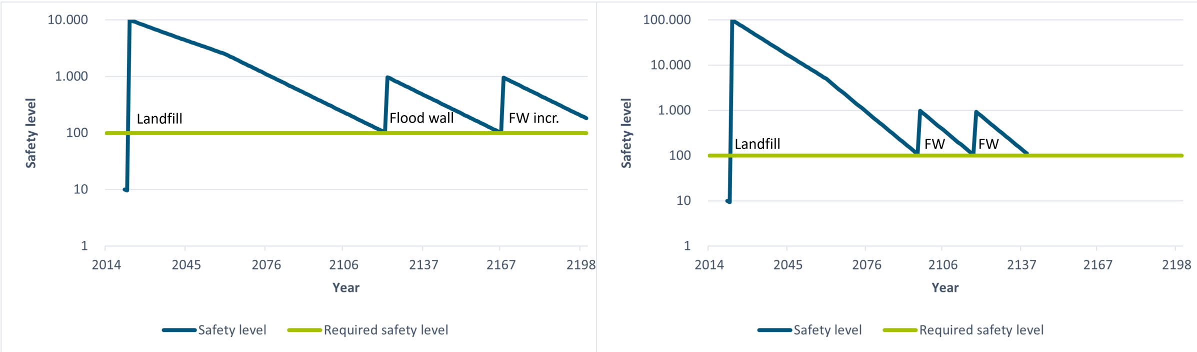
The framework and the script created to perform the probabilistic assessment are evaluated in this section. Some calculations have been done to check whether the outcomes were correct. Also, the input has been changed to see whether the altered input resulted in outcomes that could be expected. Section 4.3.1 describes the evaluation of the framework while Section 4.3.2 describes the evaluation of the probabilistic assessment.

4.3.1. Framework

To see whether the outcomes gave a reliable result, the results have been evaluated. The outcomes have been checked with hand calculations as described in Appendix E. The results of the hand calculations turned out to be similar to results of the framework. Additionally, the input-conditions have been altered to assess whether the framework gave logical results and therefore can be used to provide clarity in changing conditions.

First, the SSP5-8.5-scenario was used instead of the SSP3-7.0-scenario. This resulted in the same desired AP. The increased sea level rise results in the ATPs occurring sooner as can be seen in Figure 4.9a. An additional increment is required to satisfy the safety level requirement until 2200. Despite these additional costs, the NPV is higher than the original situation as a result of the increased amount of prevented risk. This can be seen back in Table 4.5. The BC-ratio decreases as a result of the increased required costs.

When using the 95th quantile of the SSP5-8.5-scenario, the optimal safety level increases as can be seen in Figure 4.9b. This is due to the increased amount of prevented risk and the fact that the ATP occurs earlier if the safety level is not increased resulting in fewer benefits. Despite the shorter time span in which the pathway is effective, the NPV is higher than that of the other scenarios. The rate of sea level rise influences the trigger value for which action of subsequent measures is required. This can be seen back in the trigger value of the second measure which is slightly higher for a more severe sea level rise scenario (108 years vs. 101 years). This difference is likely to increase when the implementation time of an applied measure increases. The second measure is now assumed to be a storm surge barrier. The implementation time of a storm surge barrier has been assumed to be at least 15 years. This would result in a more considerable difference (479 years vs. 177 years) as can be seen in Figure 4.10 in which the storm surge barrier is assumed to have a constant safety level of 10,000 years. The difference in implementation time of measures also shows that when a trigger value is set for a measure with a short implementation time (like the flood wall increment), it does not provide enough time for measures with longer implementation times (like the storm surge barrier). This can result in the exclusion of subsequent measures.



(a) The safety level over time for AP22 for the fictive case for SSP5-8.5 on a log-scale

(b) The safety level over time for AP22 for the fictive case for the 95th quantile of SSP5-8.5 on a log-scale

Figure 4.9: Adjusted sea level rise-scenario for the fictive case

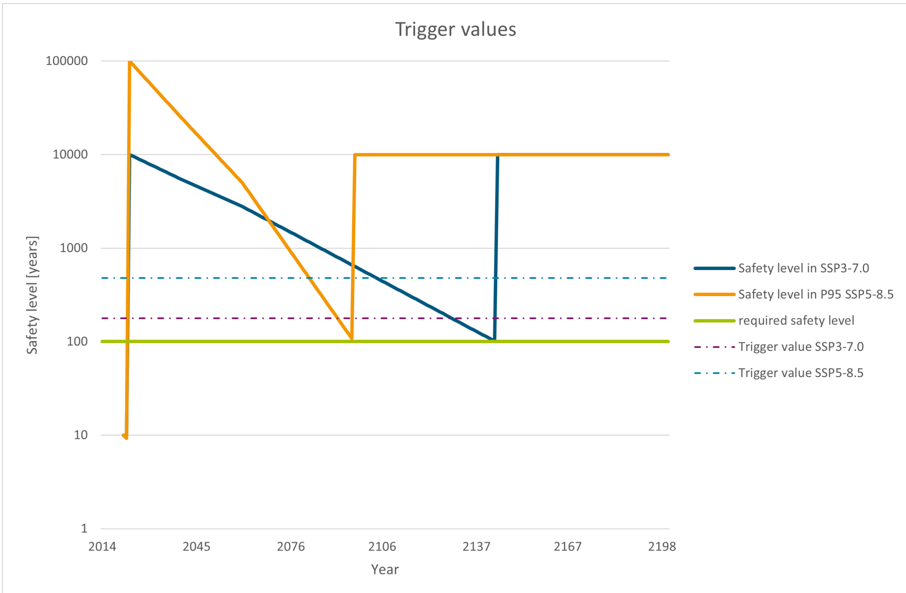


Figure 4.10: Different trigger values for different sea level rise scenarios when implementing a storm surge barrier as second measure

Table 4.5: The outcome when applying the SSP5-8.5-scenario

	Measures	NPV [M€]	BC-ratio
SSP3-7.0	Landfill + Flood Wall	1.8	11.3
SSP5-8.5	Landfill + Flood Wall + Flood Wall increase	2.0	10.9
P95 SSP5-8.5	Landfill + Flood Wall + Flood Wall increase[1]	3.2	13.3

Raising the socio-economic growth rate to 3% with the original sea level rise scenario resulted in a higher optimal safety level for the first measure as can be seen in Figure 4.11. This could be expected as there is more value at risk in the future resulting in higher benefits making it economically desirable to invest in a higher safety level. The second measure is no longer necessary as a result of the higher safety level of the first measure. The NPV is considerably higher (see Table 4.6) due to the increased value in the area resulting in higher prevented risks and consequently, higher benefits.

[1]This pathway only lasts until 2140

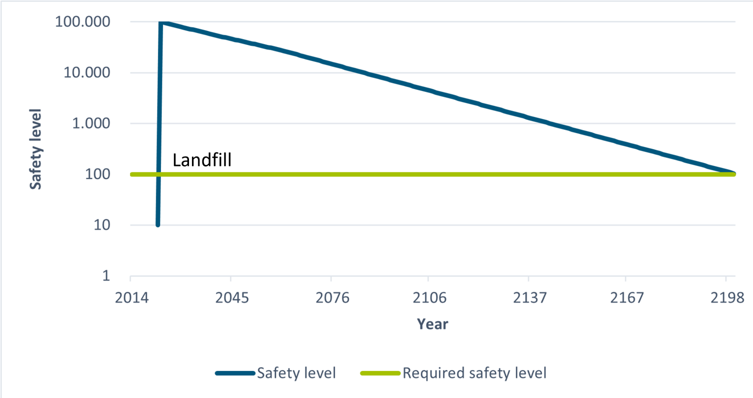


Figure 4.11: The safety level over time for AP20 for the fictive case with a 3% socio-economic growth rate on a log-scale

Table 4.6: The outcome when applying a 3% socio-economic growth rate

	Measures	NPV [M€]	BC-ratio
Socio-economic growth rate of 1%	Landfill + Flood Wall	1.8	11.3
Socio-economic growth rate of 3%	Landfill	8.4	42.1

A lower discount rate would theoretically make it less beneficial to postpone investments. It could also result in a higher optimal safety levels as benefits in the future have higher present value. This is what can be observed in Figure 4.12 where the discount rate was decreased to 2% compared to the original situation. It can be seen that the second measure is not necessary anymore as a result of the higher safety level of the first measure. The benefits of the future have a higher value resulting in a higher NPV as can be observed in Table 4.7. The outcome of the optimal safety level is equal to that with an increased socio-economic growth rate as the effect on the benefits is equal. The discounted costs are slightly higher resulting in a lower NPV than that of the situation with an increased growth rate.

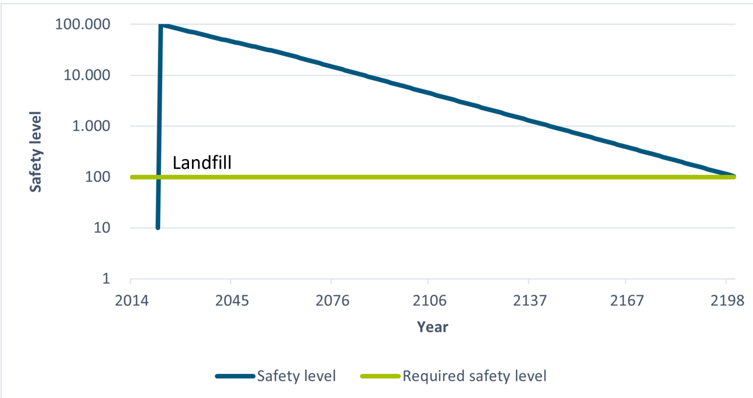


Figure 4.12: The safety level over time for AP20 for the fictive case with a 2% discount rate on a log-scale

Table 4.7: The outcome when applying a 2% discount rate

	Measures	NPV [M€]	BC-ratio
Discount rate of 4%	Landfill + Flood Wall	1.8	11.3
Discount rate of 2%	Landfill	8.2	32.3

Additionally, the inflation rate was increased to 5% resulting in more expensive future measures and consequently lower optimal safety levels for future measures. This is what can be observed in Figure 4.13 in which the safety level of the landfill is decreased from 10,000 to 1,000 compared to the original situation. The safety level of the flood wall cannot be reduced as a lower safety level would not satisfy the safety level requirement. A flood wall increase is required to satisfy the safety level requirement until 2200. As a result of the increased costs due to inflation and additional required increment, the NPV decreases as well as can be observed in Table 4.8. It can be seen that the effect of an increased inflation rate is less than that of an increased socio-economic growth rate. This could be expected as the NPV is positive and therefore the benefits are larger than the costs. The same relative change on a smaller number logically has a smaller impact.

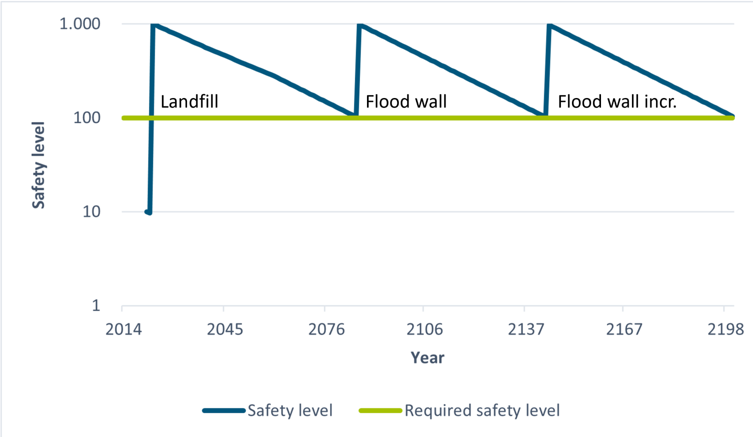


Figure 4.13: The safety level over time for AP22 for the fictive case with a 5% inflation rate on a log-scale

Table 4.8: The outcome when applying a 5% inflation rate

	Measures	NPV [M€]	BC-ratio
Inflation rate of 2%	Landfill + Flood Wall	1.8	11.3
Inflation rate of 4%	Landfill + Flood Wall + Flood Wall increase	-1.5	0.6

Finally, the short side of the area has been increased to 500 meters while keeping the other input-parameters the same as can be seen in Figure 4.14. This means that the total area changed to 100 x 500 meters and the expected damage increased as well. This is done to check whether the geometry can affect the most effective measure. The total expected damage had to be obtained again as the increased size results in more value at risk. The damage function applied to the original situation was used to obtain the expected damages. The damages increased by tenfold as the area increased by tenfold. The expected damages can be found in Table 4.9. The number of buildings to which elevation or dryproofing could be applied to was assumed to be to ratio to the increase in area size and therefore 10 times larger as well.

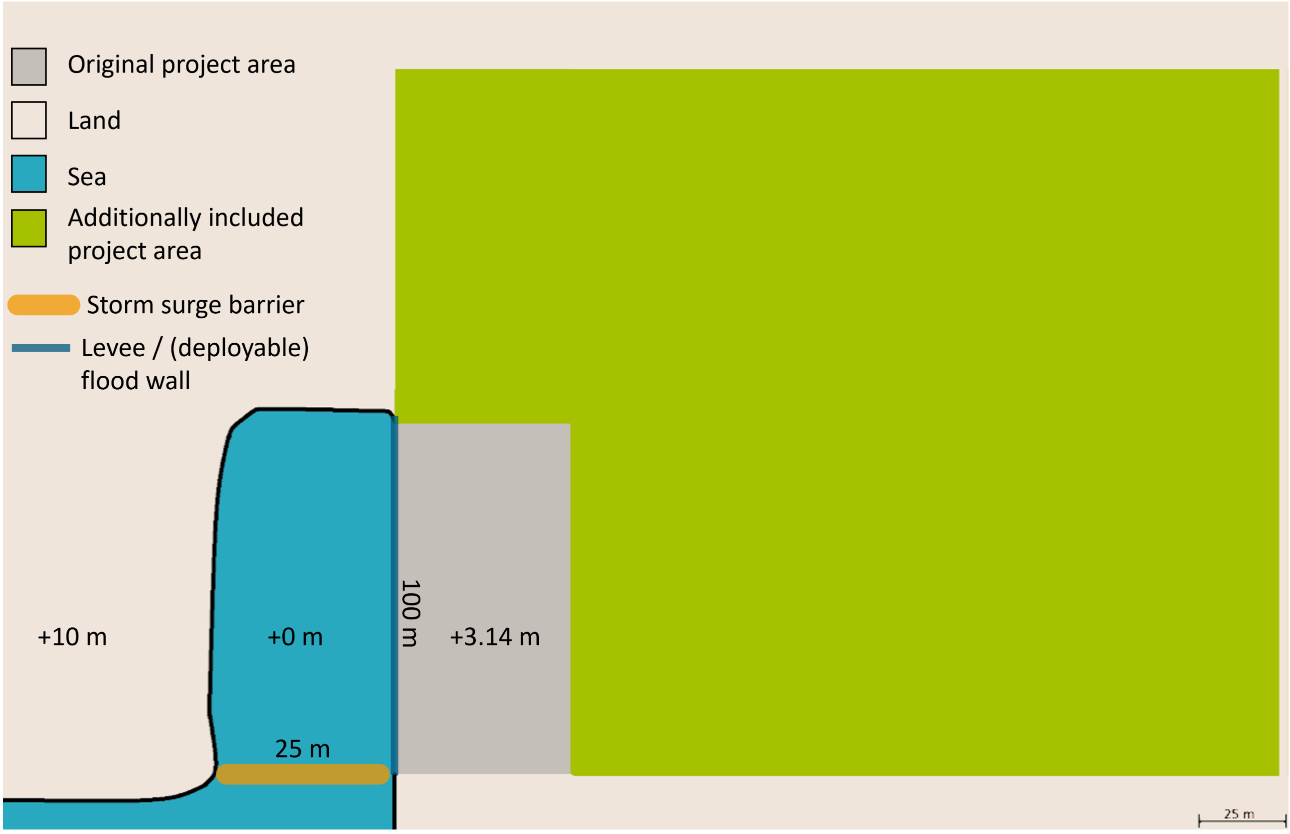


Figure 4.14: Visualisation of the increased project area

Table 4.9: Water levels for different return periods for the fictive case with increased area

Return Period	Expected damage [k€]	Expected damage when SLR = +0.4m [k€]	Expected damage when SLR = +1.0m [k€]
10	0	2,020	4,040
100	1,800	3,290	4,752
1,000	3,127	4,239	5,451
10,000	4,129	4,937	6,127
50,000	4,617	5,425	6,492
100,000	4,827	5,635	6,650
500,000	5,314	6,107	7,016

The most optimal pathway turned out to be the pathway with a flood wall and a flood wall increase (AP8) with a safety level of respectively 10,000 and 1,000 years as can be seen in Figure 4.15. The safety level development over time looks the same as the original situation. Only now different measures are used to achieve this. This could be expected as the costs of elevation, dryproofing and applying a landfill increased while the costs of a levee, flood wall, deployable flood wall and barrier remained the same for similar safety levels. The CBA of the adjusted case with the increased area can be seen in Figure 4.16. The investments costs of the previously mentioned measures are not equal to those of Figure 4.7 as a result of the increased benefits which resulted in higher optimal safety levels and therefore also higher and more expensive measures. This can be seen back in the most promising pathway 8 consisting out of a flood wall and a flood wall increase. The flood wall previously had a safety level of 1,000 years while the increased size of the area lead to an increase in optimal safety level to 10,000 years. The comparison between the original and adjusted best-performing pathway can be seen in Table 4.10. The NPV of the adjusted situation is higher as a result of the increased reduced risk. This outweighs the fact that the total costs of the measures applied in the original situation were lower.

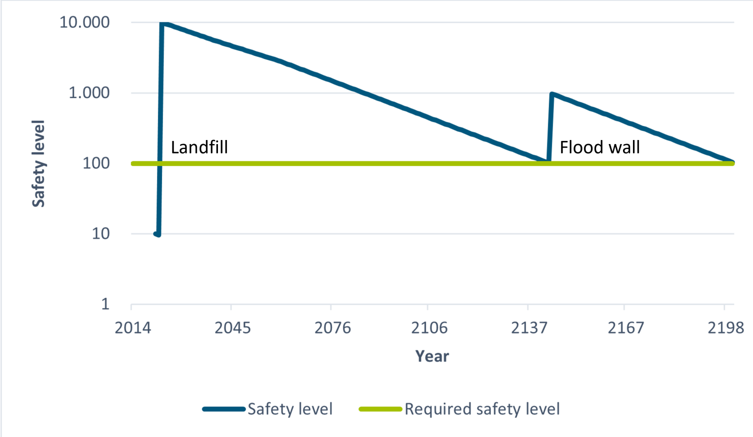


Figure 4.15: AP8 for the fictive case with increased size

Pathway	Measures in order	End date	Total investment costs in PV [€]	Total benefits in PV [€]	NPV [€]	B/C-ratio	Total Costs [€]	Total Costs [€ / year]
Adaptation Pathway 1	Levee	2143	1.223.322	18.068.848	16.845.527	14,77	1.280.587	51.672
Adaptation Pathway 2	Levee + Barrier	2200	17.579.947	19.597.545	2.017.598	1,11	17.637.212	706.145
Adaptation Pathway 3	Levee + Levee increase	2200	1.267.985	19.590.734	18.322.750	15,45	1.332.060	53.332
Adaptation Pathway 4	Levee + Levee incr. + Barrier	2200	3.277.920	19.590.734	16.312.815	5,98	3.341.995	133.804
Adaptation Pathway 5	Levee + Levee incr. + Levee incr.	2200	1.279.578	19.590.734	18.311.157	15,31	1.343.653	53.796
Adaptation Pathway 6	Flood wall	2143	689.018	18.068.848	17.379.830	26,22	746.283	30.113
Adaptation Pathway 7	Flood wall + Barrier	2200	17.045.644	19.597.545	2.551.902	1,15	17.102.908	684.753
Adaptation Pathway 8	Flood wall + Flood wall increase	2200	718.548	19.590.734	18.872.186	27,26	782.623	31.334
Adaptation Pathway 9	Flood wall + Flood wall incr. + Barrier	2200	2.728.483	19.590.734	16.862.252	7,18	2.792.558	111.806
Adaptation Pathway 10	Flood wall + Flood wall incr. + Flood wall incr.	2200	724.344	19.590.734	18.866.390	27,05	788.420	31.566
Adaptation Pathway 11	Deployable flood wall	2085	1.090.909	12.433.242	11.342.333	11,40	1.268.647	55.430
Adaptation Pathway 12	Deployable flood wall + Barrier	2185	60.659.807	19.255.038	-41.404.768	0,32	60.837.545	2.437.581
Adaptation Pathway 13	Deployable flood wall + Depl. flood wall increas	2200	1.720.295	19.466.170	17.745.875	11,32	1.908.935	76.428
Adaptation Pathway 14	Deployable flood wall + Depl. FW incr. + barrier	2200	3.730.230	19.466.170	15.735.940	5,22	3.918.870	156.901
Adaptation Pathway 15	Landfill	2143	1.529.152	18.106.122	16.576.970	11,84	1.549.143	62.509
Adaptation Pathway 16	Landfill + Barrier	2200	17.885.777	19.634.819	1.749.041	1,10	17.905.769	716.897
Adaptation Pathway 17	Landfill + Levee	2200	1.575.889	19.625.055	18.049.166	12,45	1.605.644	64.285
Adaptation Pathway 18	Landfill + Levee + Barrier	2200	3.585.824	19.625.055	16.039.231	5,47	3.615.579	144.758
Adaptation Pathway 19	Landfill + Levee + Levee incr.	2200	1.587.482	19.625.055	18.037.573	12,36	1.617.237	64.750
Adaptation Pathway 20	Landfill + Flood wall	2200	1.558.949	19.625.055	18.066.106	12,59	1.588.704	63.607
Adaptation Pathway 21	Landfill + Flood wall + Barrier	2200	3.568.884	19.625.055	16.056.171	5,50	3.598.639	144.079
Adaptation Pathway 22	Landfill + Flood wall + Flood wall incr.	2200	1.564.745	19.625.055	18.060.309	12,54	1.594.501	63.839
Adaptation Pathway 23	Landfill + Deployable flood wall	2200	1.604.341	19.625.055	18.020.713	12,23	1.634.096	65.425
Adaptation Pathway 24	Landfill + Deployable flood wall + Barrier	2200	3.614.276	19.625.055	16.010.779	5,43	3.644.031	145.897
Adaptation Pathway 25	Barrier	2122	202.445.963	16.796.081	-185.649.882	0,08	202.445.963	8.261.415
Adaptation Pathway 26	Dryproofing	2143	1.871.902	18.068.848	16.196.947	9,65	1.929.166	77.843
Adaptation Pathway 27	Dryproofing + Barrier	2200	18.228.527	19.597.545	1.369.018	1,08	18.285.792	732.112
Adaptation Pathway 28	Dryproofing + Levee	2200	2.088.170	19.590.734	17.502.565	9,38	2.152.245	86.170
Adaptation Pathway 29	Dryproofing + Levee + Barrier	2200	4.098.104	19.590.734	15.492.630	4,78	4.162.180	166.642
Adaptation Pathway 30	Dryproofing + Levee + Levee incr.	2200	2.099.762	19.590.734	17.490.972	9,33	2.163.838	86.634
Adaptation Pathway 31	Dryproofing + Flood wall	2200	2.019.599	19.590.734	17.571.135	9,70	2.083.675	83.424
Adaptation Pathway 32	Dryproofing + Flood wall + Barrier	2200	4.029.534	19.590.734	15.561.201	4,86	4.093.609	163.897
Adaptation Pathway 33	Dryproofing + Flood wall + Flood wall incr.	2200	2.025.395	19.590.734	17.565.339	9,67	2.089.471	83.657
Adaptation Pathway 34	Dryproofing + Deployable flood wall	2200	2.135.209	19.590.734	17.455.525	9,18	2.199.285	88.053
Adaptation Pathway 35	Dryproofing + Deployable flood wall + Barrier	2200	4.145.144	19.590.734	15.445.590	4,73	4.209.219	168.525
Adaptation Pathway 36	Elevation	2085	4.196.820	12.354.460	8.157.641	2,94	4.275.601	186.811
Adaptation Pathway 37	Elevation + Barrier	2185	63.765.718	19.353.995	-44.411.723	0,30	63.844.499	2.558.060
Adaptation Pathway 38	Elevation + Levee	2200	4.781.363	19.554.952	14.773.589	4,09	4.881.221	195.430
Adaptation Pathway 39	Elevation + Levee + Barrier	2200	6.791.298	19.554.952	12.763.654	2,88	6.891.156	275.903
Adaptation Pathway 40	Elevation + Levee + Levee incr.	2200	4.792.956	19.554.952	14.761.996	4,08	4.892.814	195.895
Adaptation Pathway 41	Elevation + Flood wall	2200	4.572.430	19.554.952	14.982.522	4,28	4.672.288	187.065
Adaptation Pathway 42	Elevation + Flood wall + Barrier	2200	6.582.364	19.554.952	12.972.588	2,97	6.682.222	267.537
Adaptation Pathway 43	Elevation + Flood wall + Flood wall incr.	2200	4.578.226	19.554.952	14.976.726	4,27	4.678.084	187.297
Adaptation Pathway 44	Elevation + Deployable flood wall	2143	4.742.053	17.993.567	13.251.514	3,79	4.874.599	196.693
Adaptation Pathway 45	Elevation + Deployable flood wall + Barrier	2200	21.098.678	19.522.264	-1.576.414	0,93	21.231.224	850.039

Figure 4.16: The CBA for all considered pathways for the fictive case with increased size of the project area

Table 4.10: The outcome when increasing the size of the project area by a factor 10

	Measures	NPV [M€]	BC-ratio
Original	Landfill + Flood Wall	1.8	11.3
Adjusted	Flood Wall + Flood Wall	18.9	27.3

4.3.2. The probabilistic assessment

The robustness of pathways was assessed by a probabilistic assessment. The probabilistic assessment is in fact a Real Options Analysis reduced to a limited selection of pathways. A python script has been written to conduct this assessment. Deterministic values were first filled in to see whether the script gave outcomes comparable to those of the deterministic framework. The ATPs and the O&M of the measures in the script turned out to be exactly equal to the values obtained in the framework. The NPV of the script and the framework also turned out to be comparable. There is a minor difference between the NPV of the script and the excel-framework (1.78 M€ vs 1.79 M€). This discrepancy can occur as a result of the restriction to the year 2200 of the excel while the script does not have such a restriction. As the present value after the year 2200 is very low as a result of the discount rate, these differences are very small. Especially for this case in which the ATP would be reached soon after or even in 2200.

Additionally, the optimal safety level had already been obtained in the excel framework and therefore considerably fewer calculations had to be run. Therefore, the script allowed for an exact calculation (and not applying the annual percentage increase) of the risk of the years in between implementation and the last year of its lifetime. The differences were expected to be minor as could be seen in Table 3.6. Therefore, the NPV of AP20 obtained by the framework was expected to be approximately equal to the outcome of deterministic script. As this was the case, it validates the use of the annual percentage increase of risk in the framework. Since, above it was concluded that the results of the framework are reliable, the script is also assumed to give reliable results given the comparable results.

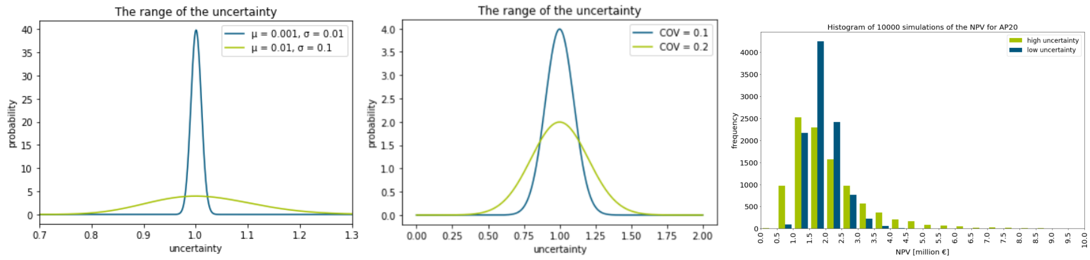
The deterministic values were afterwards replaced by randomly obtained variables out of the defined distributions given in Section 4.1 and a Monte Carlo analysis of 10,000 simulations was done. The mode of the outcome of the probabilistic assessment, which can be seen in Figure 4.8, is comparable to that of the deterministic outcome of the deterministic framework which can be seen in Figure 4.7. The probability of having a value above the mode is higher than that of obtaining a NPV below the mode. This could be expected as a result of the lognormal distributions that have been applied to account for the uncertainty in the investment costs, O&M costs and benefits.

The uncertainty of costs and effectiveness of different measures may differ. The range of the uncertainties is adjusted to see the impact of a different range of uncertainty. The adjusted distributions can be found in Table 4.11.

Table 4.11: The adjusted distributions used in the probabilistic assessment

Parameter	Distribution	Former parameters	Adjusted parameters
Investment costs	Lognormal	λ = 0.001 and ζ = 0.01	λ = 0.01 and ζ = 0.1
O&M costs	Lognormal	λ = 0.001 and ζ = 0.01	λ = 0.01 and ζ = 0.1
Risk reduction	Lognormal	λ = 0.001 and ζ = 0.01	λ = 0.01 and ζ = 0.1
Sea level rise	Normal	μ = 1 and σ = 0.1	μ = 1 and σ = 0.2
Socio-economic growth rate	Normal	μ = 1 and σ = 0.1	μ = 1 and σ = 0.2
Discount rate	Normal	μ = 1 and σ = 0.1	μ = 1 and σ = 0.2
Inflation rate	Normal	μ = 1 and σ = 0.1	μ = 1 and σ = 0.2

The Log-normal distributions are changed to μ = 0.01 and σ = 0.1. The PDFs of the originally used distribution and the adjusted distribution can be seen in Figure 4.17a. It can clearly be seen that the adjusted distribution contains a wider range of uncertainty. Also, the Coefficient of Variation for the discount rate, inflation rate and socio-economic growth rate are increased from 0.1 to 0.2. The PDFs of the original and adjusted distributions can be seen in Figure 4.17b. The outcome of the adjusted probabilistic assessment is expected to have a wider range of outcomes as a result of the increased uncertainty. This is what can be seen in the outcome in Figure 4.17c.



(a) The distributions used to account for uncertainty in the costs

(b) The distributions used to account for uncertainty in the rates

(c) NPV of adjusted probabilistic applied to AP20

Figure 4.17: The adjusted probabilistic assessment

A wider range of outcomes can be a reason not to choose a certain pathway as an extremely low outcome is more likely to occur compared to a more narrow range. The range in outcome can be evaluated by means of a ratio of the 5th quantile and 95th quantile. Such a ratio can be obtained by using the following equation:

$$Ratio = \frac{|\mathrm{P}95 - \mathrm{P}5|}{max(|\mathrm{P}95|, |\mathrm{P}5|)} \tag{4.1}$$

The 5th quantile and 95th quantile of the outcome with a relatively low range of uncertainty were equal to respectively 1.21 M€ and 2.80 M€ while those obtained with a relatively high range of uncertainty were equal to 0.87 M€ and 4.52 M€. This results in a ratio of 0.57 when assuming a relatively low range of uncertainty and 0.81 when assuming a relatively high range of uncertainty. The ratio would be 0 if there would be no difference between both quantiles. Therefore, when using this ratio, a low range of uncertainty would be preferred. Logically, also other quantiles can be used to obtain such a ratio. Another indicator for the robustness of pathways is the percentage that is performing better than in the framework. The range of uncertainty did not significantly affect the outcome as the relatively low range of uncertainty resulted in 52% of the outcomes being higher than that of the framework while for the relatively high range 50% resulted in a higher NPV. The limited impact can likely be ascribed to the marginal effect of skewed distributions in this case.

4.3.3. Conclusion of fictive case

The framework resulted in different possible pathways shown in Figure 4.5. The framework has been validated with hand calculations and also altering the input-parameters lead to the expected changes in the outcome. Therefore, it can be concluded that the framework can be used as a tool able to create and select promising flood risk reduction strategies. A point of improvement is the unrealistically long lifetimes of individual measures. These long lifetimes may be longer than the technical lifetime and also prevent a fully adaptive approach that anticipates on changing future conditions. Therefore, the lifetime of measures is restricted in the next case study. In the original situation, a flood wall of 35 centimeters was constructed as second measure. As the linear relationship assumed for the construction costs is unrealistic for such low heights, a minimum height before this linear relation starts is assumed for the next case study. Every height below this minimum value will have the same costs as the minimum value. This value is by default set to 0.5 meters. This will automatically prevent extremely short lifetimes of measures that can occur with risk-averse strategies in which the safety level requirement is far above the economic optimum.

Despite the necessary adjustments, it was concluded that the results of the framework are reliable. Therefore, the framework could be used to assess the impact of different uncertainties. The discount rate and the socio-economic growth rate turned out to greatly affect the NPV. Increasing the socio-economic growth rate by 2% and reducing the discount rate by 2% both lead to a multiplication of the NPV close to a factor of 5. The considerable impact of the socio-economic growth rate can likely be ascribed to the fact that it affects the reduced risk and therefore the benefits. As the benefits are bigger than the costs, this effect is likely to be more considerable than that of the inflation rate. The increased size of the area also turned out to greatly affect the NPV and the desired measure. However, the area cannot be considered as uncertainty.

The obtained trigger value for the selected pathway turned out to be dependent on the sea level rise scenario. This underlines the importance of monitoring of the actual sea level rise. The fictive case also illustrated how obtaining the trigger value for the planned subsequent measure could result in a loss in flexibility due to the exclusion of other possible subsequent measures.

The script used to conduct the probabilistic assessment gave comparable results as the framework when the same deterministic input was used. Therefore, it can be concluded that the results of the script are reliable and the script can be used to conduct the probabilistic assessment. The probabilistic assessment has been conducted using a Monte Carlo simulation. The most promising pathway of the framework was assessed using narrow and wide distributions for the uncertainties. Logically, a wider range of uncertainty also resulted in a wider range of possible outcomes. When defining the uncertainty for each individual measure and pathway, this probabilistic assessment can be used to compare the robustness of pathways. The ratio between the 5th and 95th quantile and the percentage having a higher outcome than that of the framework can be used as indicators of the robustness.

5
Case Study: South East Coast of Singapore

The aim of this chapter is to apply the framework to a real-life case. The South East Coast of Singapore is used as case study. The broader context of this case study is sketched in Section 5.1. The characteristics of the case study are described in Section 5.2. Section 5.3 describes the input used for the framework. The outcome of the framework can be found in Section 5.4 and an evaluation of that outcome can be found in Section 5.5.

5.1. Introduction to the case

Socio-economic developments and climate change cause a great increase in the flood risk of many places, especially that of coastal cities like Singapore. Singapore is a city-state situated at the southern tip of the Malay peninsula. Although, it never experienced major coastal flooding, it is a flat and low-lying country and therefore extra vulnerable to coastal flooding when the sea level rises. IPCC projections show median sea level rise ranging between 0.38 meters to 0.79 meters by 2100 for the coast of Singapore (Intergovernmental Panel on Climate Change (IPCC), 2020). The Singapore government has decided to anticipate on the changing climate. Three approaches have been outlined in order to do so (NCCS Singapore, n.d.):

- Understanding climate change,
- Mitigating climate change and,
- Adapting to climate change.

Besides the above-mentioned approaches, Singapore also set other goals. The ongoing plans and programs are:

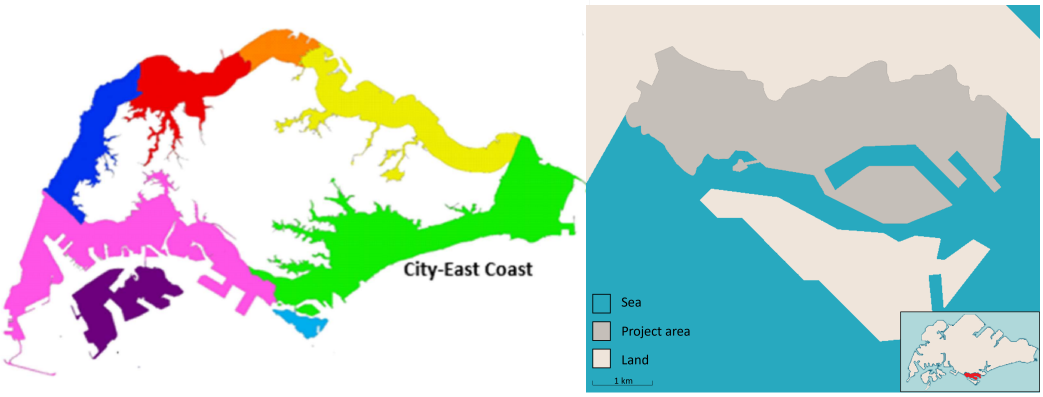
- Singapore Blue Plan focussing on enhancing the marine ecosystem,
- Singapore Green Plan focussing on sustainable development,
- Integrated Urban Coastal Management focussing on applying integral coastal management including enhanced accessibility, protection and ecology by incorporating multi-functional use, et cetera.

All these different programs and plans generally have a common part but also complement each other. Reaching all objectives of the ongoing plans and programs asks for an integral plan that guides decision-makers in what measures to take when. This integral plan should not only result in increased protection against coastal flooding but also enhance liveability, sustainability and flexibility.

The East Coast was identified as most vulnerable area to climate change due to currently present flooding issues, critical assets and plans for future developments (PUB, 2021). The East Coast extends from Changi Beach Park in the north-east, to Labrador Park in the south-west as shown in green in

Figure 5.1a. In order to still reach the required safety level in the future, while simultaneously coping with the deep uncertainties, a long-term approach for the City-East coast of Singapore is envisioned by the government of Singapore. Royal HaskoningDHV has been selected to work out this approach focusing on mitigation and adaptation to anticipate to the changing climate. Dynamic Adaptive Policy Pathways (DAPP) has been identified as the approach to do so and therefore, this case study is suitable to apply the framework to.

This case study will focus on a smaller area within the East Coast-region. Area C is chosen as project area for this case study and will from now on be referred to as project area. It can be seen in Figure 5.1b. This project area is chosen as it independently functions, represents Singapore as a whole and has sufficient data availability. The barrier island of Sentosa is excluded from the project area as it contains many rock cliffs making it less vulnerable to flooding. The project area is further analysed in Section 5.2. It is important to emphasise that this case study is conducted with the aim of showing how the framework and probabilistic assessment can be applied to a real situation rather than a detailed study on the conditions. The assumptions made to obtain the required input are made with publicly available information. This means that with more detailed information the outcome can be considerably different.



(a) The location of the study area (Hussain, 2021)

(b) The study area further zoomed in (PUB, 2021)

Figure 5.1: The location of the study area

5.2. Characteristics of study area

The characteristics of the study area have been analysed in Section 5.2.1. The damages in the current situation have been defined in Section 5.2.2. An analysis of the uncertainties that can influence the future flood risk strategy can be found in Section 5.2.4. The required safety standards have been defined in Section 5.2.3.

5.2.1. Current situation

General

The project area has been defined in Section 5.1. The area contains high-value assets like shopping malls and other landmarks such as the Marina Bay Cruise Centre Singapore and exclusive property called Reflections at Keppel Bay condominium. It also contains an island called Brani Island and a large container terminal is situated on that island. The land lease for this terminal expires in 2027 and the land is allowed to be returned earlier which could facilitate an alteration of the current land use as the government wants to consolidate container port facilities at Tuas (Urban Redevelopment Authority, 2019). Two other terminals (Keppel Terminal and Tanjong Pagar Terminal) can be found on the mainland and also these lease contracts from the State expire in 2027 allowing for future land use changes. There are existing plans to incorporate Area C into the Greater Southern Waterfront (GSW) extending from Pasir Panjang (the most eastern part of the project area) to Marina South (just east of the project area) (Urban Redevelopment Authority, 2019). This may result in different land-uses and corresponding values in the project area in the future. The current land use map can be seen in Figure 5.2. This map has been made with open data retrieved from the Singaporean Urban Redevelopment Authority. It can be seen that the terminals are currently indicated as reserved sites. Some adjustments have been made in order to make the land-use map a better representation of reality. These can be found in Table G.1 in Appendix G.

The area is currently not densely populated as the terminals take up a lot of space. However, this might change as well due to future changes in land-use. In Figure 5.3, it can be seen that the area is relatively flat along the waterfront making it a suitable area to apply the framework to. This map was created with data obtained from Maxar (2022). The publicly accessible DEM-map has been adjusted since a large area of the port and Brani-island consists of pile decks as can be seen in Figure 5.5. Therefore, one would expect an equal altitude for the entire area of the pile decks. As that is not the case in the publicly accessible DEM-map, the altitude of these areas have been changed to 3 meter which is approximately the average altitude of the area and the required height for this newly constructed land at the moment of implementation. Next to that, some buildings have been constructed on higher grounds while this is not included in the DEM. These buildings have been identified on a site visit. The buildings that are elevated have already been raised in the DEM and therefore, applying a threshold would result in having a too high threshold compared to reality. These adjustments to the DEM-map can be found in more detail in Table G.2. The coastline mainly consists of hard shores of which approximately 10 kilometers is located on the mainland and almost 5 kilometers is located at Brani island.

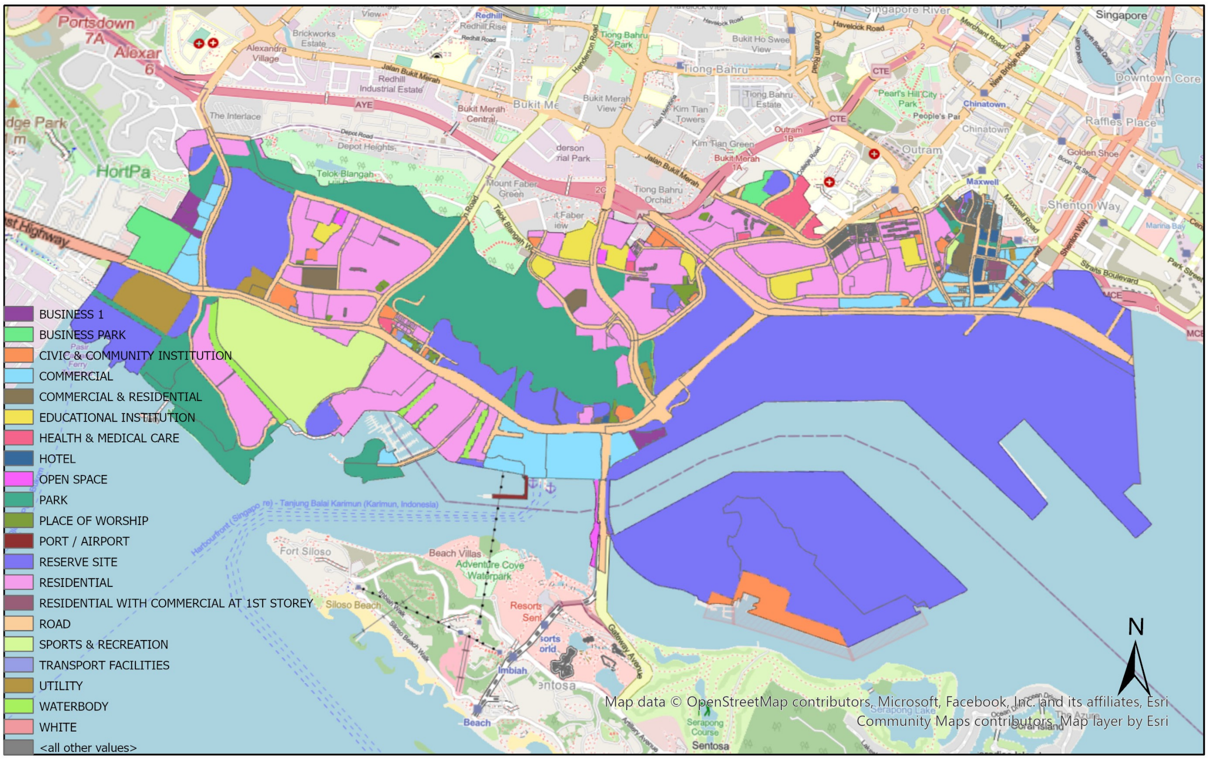


Figure 5.2: The land-use of the project area made with data retrieved from Urban Redevelopment Authority (2019)

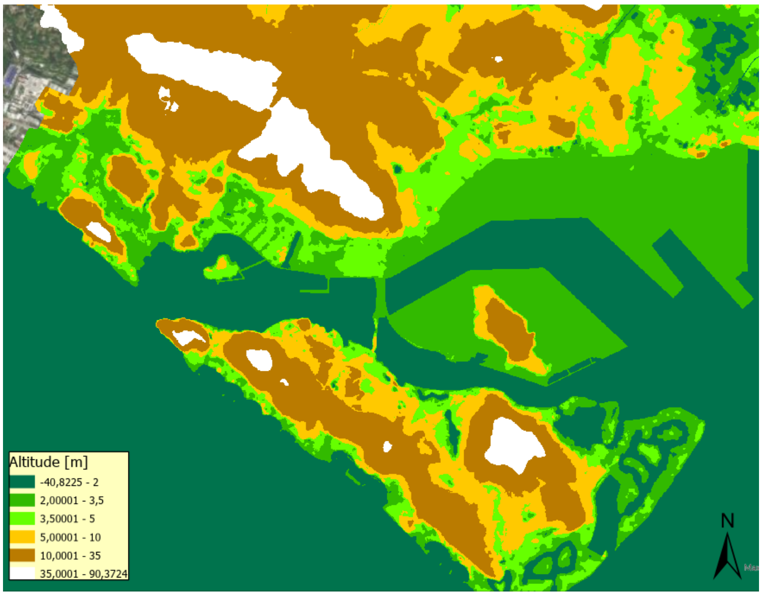


Figure 5.3: Elevation map of project area made with data retrieved from Maxar (2022)

The wave conditions of the City-East coast are very mild as can be seen in Figure 5.4. The conditions in Area C can be expected to be even milder as Area C is sheltered from waves by Sentosa island.

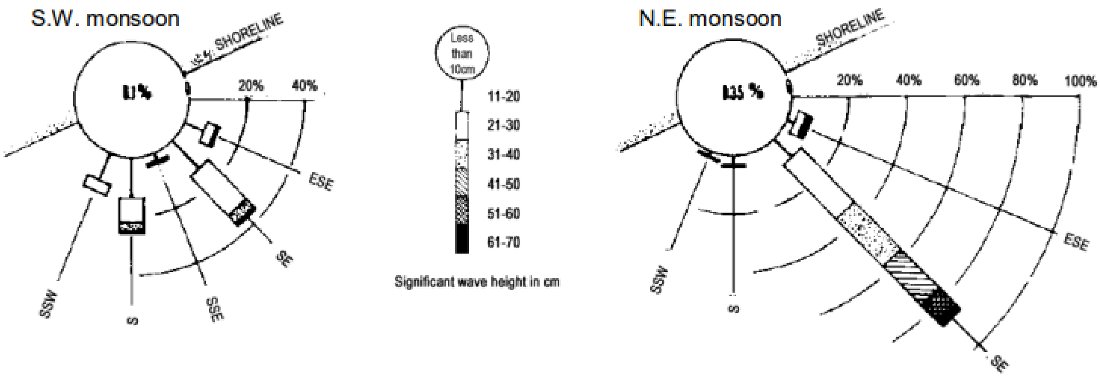


Figure 5.4: Significant wave heights in cm and dominant direction of approach at East Coast Park, resulting from measurements performed during periods from August to November 1972 and April to July 1973 (S.W. monsoon, left panel) and from December 1972 to March 1973 (N.E. monsoon, right panel) (Chew et al., 1974)

Existing structures & biodiversity

The original platform level of the area has been raised as a result of previous developments. The coastal protection consists of vertical walls, pile decks and revetments as can be seen in Figure 5.5. Several areas also have a distinct biodiversity like mangroves, reefs and inter-tidal areas as can been in Figure 5.6. The area with mangroves also contains the Bakau Pasir (Rhizophora stylosa) which is rare and also endemic to the region (Yeo, 2011).

Figure 5.5: The current coastal protection with self-taken pictures supplemented with pictures of Google Maps

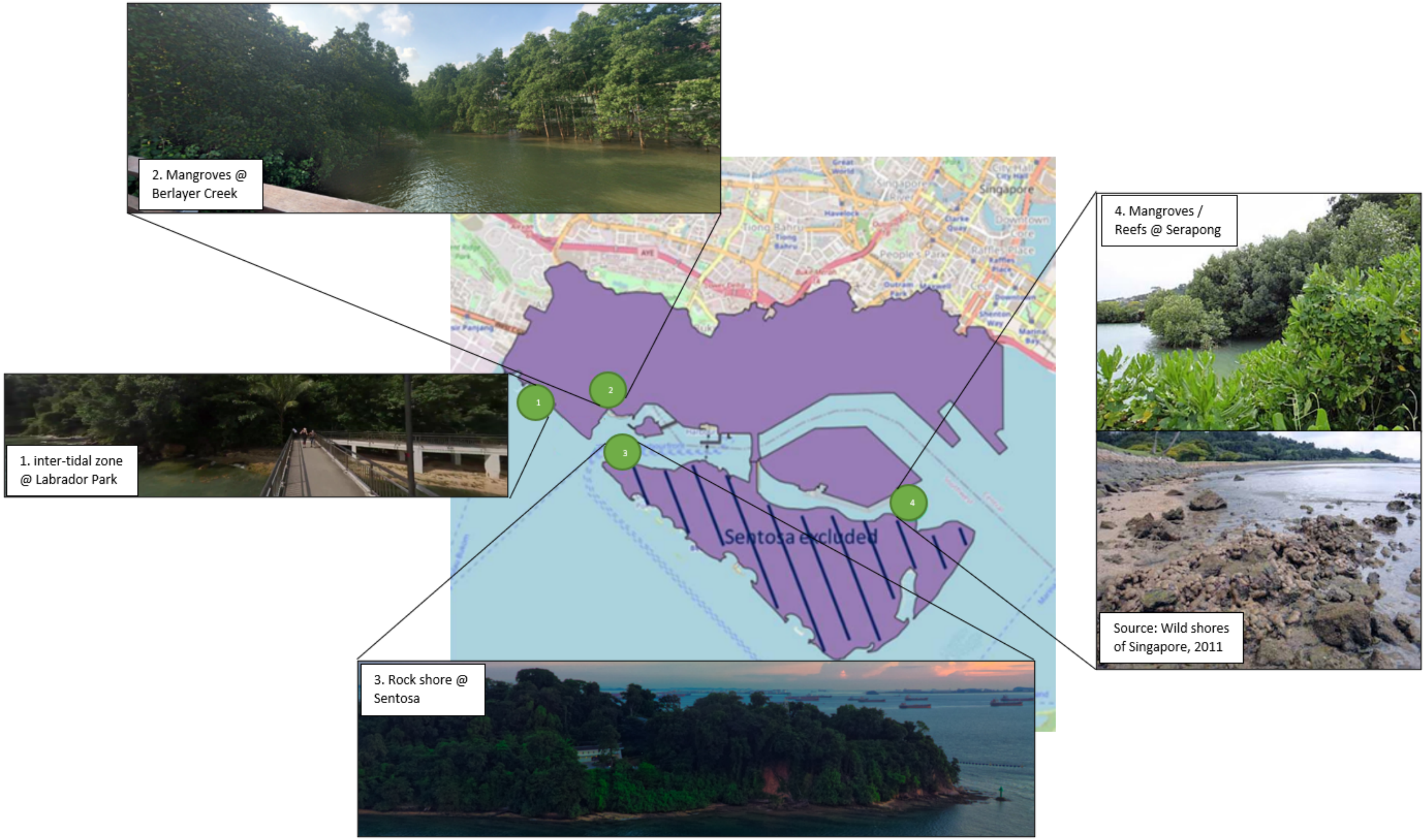


Figure 5.6: Biodiverse distinct areas with self-taken pictures supplemented with pictures of Google Maps

Water levels
High water levels in Singapore are generally caused by prolonged (lasting for several days in duration) northeast winds over the South China Sea (Cannaby et al., 2016). These winds usually tend to coincide with the northeast monsoon. Sufficient time to take temporary measures can be assumed as the winds have to prolong for several days and can be predicted weeks in advance (Terzi et al., 2019).

An extreme value-analysis was conducted to describe the extreme water levels of the Singapore East-Coast. The hourly water levels of Tanjong Pagar of the University of Hawaii: Sea Level center (2018) were used for this. Tanjong Pagar is located in the project area. This data is of research quality which means it is adjusted for e.g. level adjustments, timing shifts and outliers. The data set contains 31 years of data ranging from 1988 until 2018. Since sea level rise is a process that has already been ongoing for some time, the water levels have been adjusted to have the same reference level. A linear relation was assumed for this, resulting in an annual increase of 3.49 mm/year as can be seen in Figure 5.7.

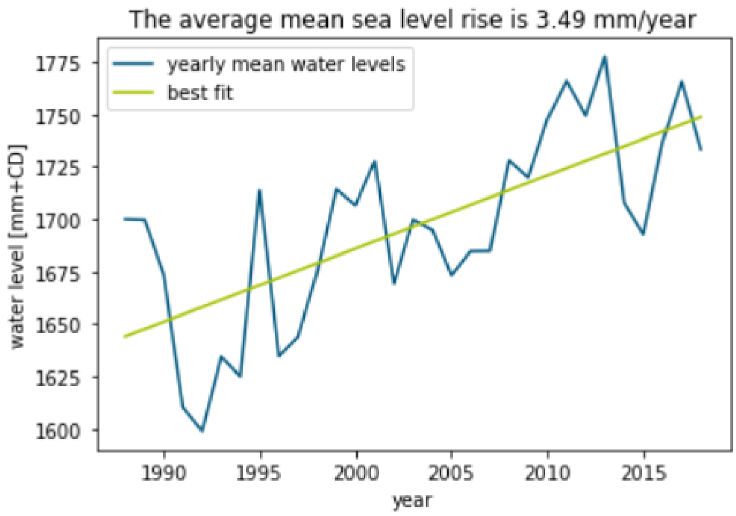
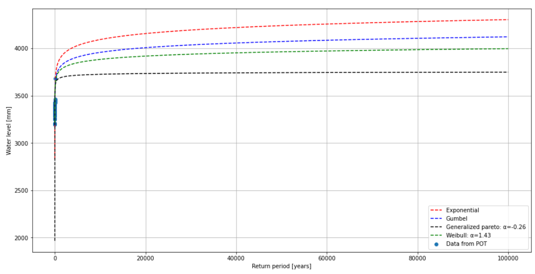
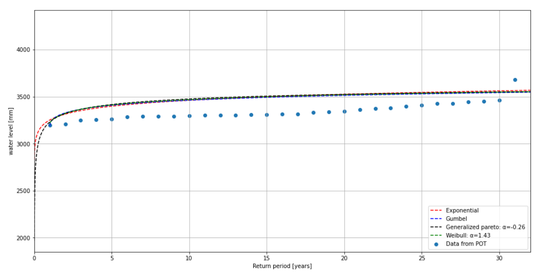


Figure 5.7: The increase in Mean Sea Level

Subsequently, 2022 was taken as reference year. As an illustration, for the year 2000, 22 times the mean sea level rise has to be added to the original water level to obtain the adjusted water level. Afterwards, several distributions were fitted to the data as can be seen in Figure 5.8. The Root Mean Square error was obtained for all distributions.



(a) The Exponential, Gumbel, Generalized Pareto and Weibull distributions fitted to the data



(b) A zoom-in on the data points

Figure 5.8: Different distributions fitted for Tanjong Pagar for the adjusted dataset

The generalized pareto turned out to have the lowest Root Mean Square error for an α-value of -0.26 while the other distributions gave a RMS error of comparable size. In studies like Cannaby et al. (2016), the extremes are described with Gumbel distributions because of a good match between observation and modeling. Therefore, the Gumbel-distribution was used to describe the extreme water levels. This Gumbel distribution has a γ of 1.677 meters and a β of 0.071 meters. The obtained water levels for certain return periods can be observed in Figure 5.9. The return periods with corresponding water levels are shown in Chart Datum (CD) in Table 5.1 and . A value of 1,652 mm is subtracted to obtain the water level in mm Singapore Height Datum (SHD). It turns out that the decimation heights are small. They are smaller than 20 centimeters for increases of the return period by a factor of 10. The python-code written to obtain the water levels for certain return periods can be found in Appendix D.3.

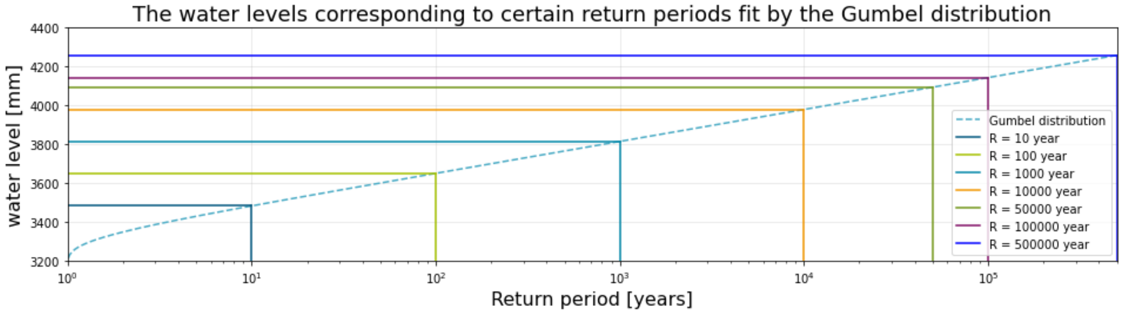


Figure 5.9: The Gumbel distribution fitted through the adjusted water levels

Table 5.1: Return periods obtained for a Gumbel distribution fitted through the adjusted data of University of Hawaii: Sea Level center (2020)

Return Period	Water level [m +CD]	Rel. water level [m +SHD]
10	3.49	1.84
100	3.66	2.00
1,000	3.82	2.17
10,000	3.99	2.33
50,000	4.10	2.45
100,000	4.15	2.49
500,000	4.27	2.61

The highest water event of the data has been used to assess the duration of extreme events. This event took place in December 1999 and the water levels are converted to 2022 water levels by including the sea level rise. Figure 5.10 shows that the storm surge lasts for several days and the water level varies as a result of the tide. During the storm surge, multiple peaks take place with one peak being marginally larger than the others. All these peaks approximately last for 2-3 hours.

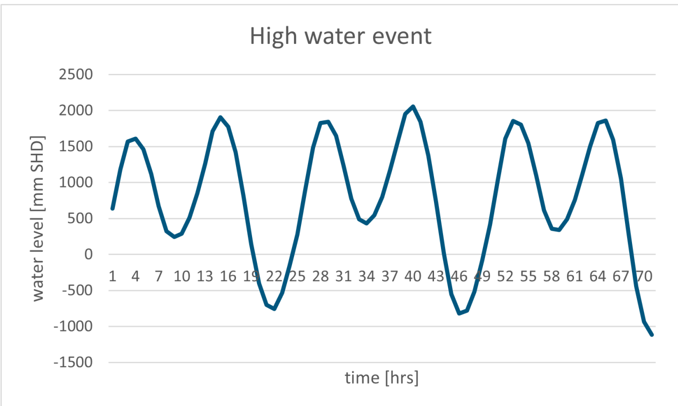


Figure 5.10: The high water event of December 1999 converted to 2022 water levels based

5.2.2. Damages

The severity of the expected damage is both dependent on the characteristics of the flood and the characteristics of the land-use. The characteristics of a certain flood can be described by flood-damage curves while the type of land-use determines the maximum possible damage. The damage for certain water levels will be modelled with the obtained damage curves in this section.

Damage curves

Factors like depth, duration and velocity can influence the amount of damage caused by floods. Macdonald et al. (2012) stated that the water depth is to be the most limiting factor for such damages. Therefore, depth-damage curves can be used in order to derive an estimate of the expected damages for certain floods. These curves can be derived analytically, empirically, synthetically or with a combination of these. Analytical curves are generally obtained via laboratory-tests. However, this requires a monotone area in order to be applicable. As this is not true and also indirect damages can significantly influence the total damage, these curves are not valid in this case study. Empirical curves are derived from earlier floods in the area. As there has not been any major coastal flooding, this is not possible for this project area. Therefore, damage curves are obtained from relevant literature for the land-classes defined in Figure 5.2. These curves and their derivation can be found in Appendix F.

Maximum damage

The maximum possible damage had to be defined to obtain the expected damage for certain flooding conditions. Huizinga et al. (2017) states that the maximum damage is dependent on several characteristics like:

- a calculation of the depreciated value as a share of construction cost,
- a calculation of the value of content,
- the size of the building footprint,
- proportion of the un-damageable part and,
- an adjustment for the material used.

The maximum damage has been derived for the different land-uses in Singapore taking into account the characteristics mentioned above. These, as well as the complete damage functions, can be found in Appendix F.

Total damage in project area

The total damage corresponding to extreme water levels can now be modelled with the damage curves and the land-use. The Global Flood Risk Tool of Royal HaskoningDHV will be used to determine the damages for different return periods. An inundation map can be made out of an elevation map and water levels when the bathtub approach is used. These water levels are coupled to certain return periods and can be obtained by performing an extreme value analysis like done in Section 5.2.1. With the inundation maps, land use maps, water areas, project boundaries and damage functions, the tool calculates the damage. This is visualised in Figure 5.11. It is important to realise that the tool uses input from a hydraulic model when high water events last for a limited period or when waves significantly influence flooding and the land does not simply overflow according to the bathtub-principle. As the waves are limited and the extreme water event takes sufficiently long, the bathtub approach has been used.

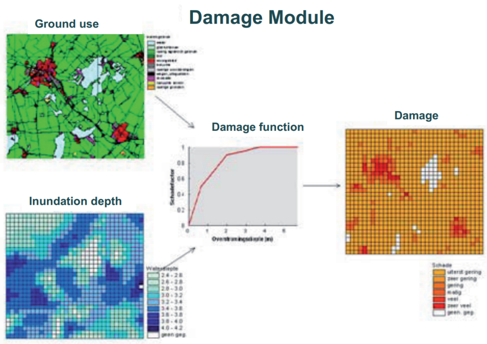


Figure 5.11: Damage modules (*Flood Risks and Safety in the Netherlands (Floris)*, 2005)

Input Global Flood Risk Tool

Publicly accessible input is used in the tool in order to estimate the damages. As previously stated, the topographic maps, the water areas, damage functions, land-use maps, the project boundaries and the hydraulic conditions are required to obtain the expected damages. The static hydraulic conditions and the damages have already been obtained in this section and in Section 5.2.1. Also, the land-use map has already been shown in Figure 5.2. As the reserved site will be included in the Greater Southern Waterfront, the land-use is changed to residential.

A map of the water areas had to be created including the water areas on the land. The boundaries of the area, as defined in Section 5.1, have been mapped. The topographic map of Figure 5.3 was also used to model the damages. The water levels obtained in Section 5.2.1 have been used as input in the GFRT. Additionally, 1.4 and 3.4 meters was added to these water levels and also modelled to obtain an accurate damage function for the area even for the extreme sea level rise scenarios.

Output Global Flood Risk Tool

The expected damage can be obtained with the input described in the section above. In Figure 5.12, it can be seen that severe damage starts to occur for water levels higher than 3 meters. Therefore, the actual safety level is assumed to be equal to the return period corresponding to a 3.00 meters water level. This means that no damage is assumed below that level, as the damage that occurs for water levels below 3 meters is very local and limited and therefore is likely to be the result of a modelling inaccuracy. Table 5.1 shows that all water levels corresponding to the return periods assessed by the framework are below this level meaning that currently no damages are expected.

The damages of Table 5.2 indicate what potential effect sea level rise can have on this. The table shows the damages corresponding to the sea level rise according to the SSP5-8.5 scenario in 2100. The damages corresponding to the current situation and for the situations with a sea level rise of 1.4 and 3.4 meters according to the 95th quantile of the SSP5-8.5 sea level rise scenario in 2100 and 2200, are used by the framework to create the damage function of the entire area. These damages can be found in Tables H.1a, H.1b and H.1c. The risk maps for the three scenarios can be seen in Appendix H. This extreme scenario is used to ensure an accurate flood damage function for all sea level rise scenarios.

(a) The damage corresponding to a water level of 3.00 meter

(b) The damage corresponding to a water level of 3.01 meter

Figure 5.12: Damage maps of the project area

Return Period	Damage [m SGD]
10	0
100	0
1,000	0
10,000	3,670
50,000	4,890
100,000	5,230
500,000	6,320

Table 5.2: Damages in current situation +0.82m SLR

5.2.3. Required Safety level

The required safety level of this area are still being assessed and is dependent on more detailed future development plans which are not publicly available. In general, it can be said that the safety standards of Singapore are high. A newly created polder at Pulau Tekong for instance has a safety level of 100,000 years against wave overtopping (Housing & Development Board, 2016). As the conditions are similar to that of the polder and both areas are under the same governance, the safety standards of the project area are also likely to be high. A safety level of 10,000 years is assumed based on expert opinion (Bos, n.d.).

5.2.4. Future uncertainty

The analysis of the water levels is conducted with data from the past. There are several factors which may change the sea level in the future. Additionally, socio-economic developments can influence the desired flood risk strategy and therefore should be identified. All future uncertainties related to the situation in Singapore are identified below.

Sea level rise

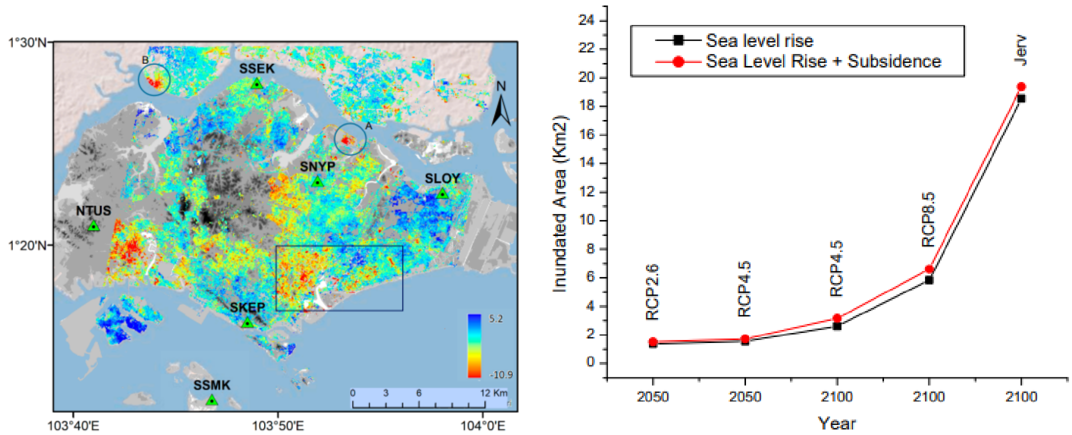
The sea level rise was identified as uncertainty in Section 2.2.1. The sea level rise varies across the globe and the range for South-East Asia can be found in Table 5.3. Intergovernmental Panel on Climate Change (IPCC) also included a low-likelihood, high-impact scenario in their report, leading to ice sheet instability processes and a sea level rise of 1.77 meters. Despite the low likelihood, the scenario cannot be ruled out as the impact on the Singapore coastline would be major. The sea level here represents the median estomate per scenario. However, Singapore calculates with the upper bound of the range 0.62-1.02 meters for the SSP5-8.5 scenario (The Strait Times, 2022). This thesis uses the median values of the different scenarios.

Table 5.3: The median values for IPCC projections for mean sea-level rise (Intergovernmental Panel on Climate Change (IPCC), 2020)

Scenario	Description	Sea level rise 2060 [m]	Sea level rise 2100 [m]
SSP1-2.6	Global CO2-emission will be net zero around 2050	0.25	0.48
SSP2-4.5	Global CO2-emission are reduced significantly, reaching net zero after 2050	0.27	0.60
SSP3-7.0	CO2-emission stabilize around current levels and fall mid-century reaching net zero after 2100	0.29	0.71
SSP5-8.5	CO2-emission double from current levels by 2100	0.32	0.82
95th quantile of SSP5-8.5	The 95th quantile of the scenario described above	0.59	1.4

Subsidence

Subsidence can negatively affect the flood safety in Singapore. The estimated annual deformation rate based on data between 2011 and 2016 lay between +5.2 mm/year and -10.9mm/year where negative values imply land subsidence (Catalao et al., 2020). This can be seen in Figure 5.13a. The figure also shows that the subsidence in the project area is very marginal or even not present. The values found are similar to the studies conducted by Catalao et al. (2013) and Wan et al. (2014). Since these studies used different time intervals and since the fact that Singapore is tectonically stable, Catalao et al. (2020) concluded that the subsidence rate of Singapore did not change significantly in the last decade. The relative impact of land subsidence depends on the climate scenario previously discussed as can be seen in Figure 5.13b. This figure shows that the relative impact of subsidence in Singapore is minor compared to the sea level rise. Therefore, the subsidence of Singapore is neglected in this case study.



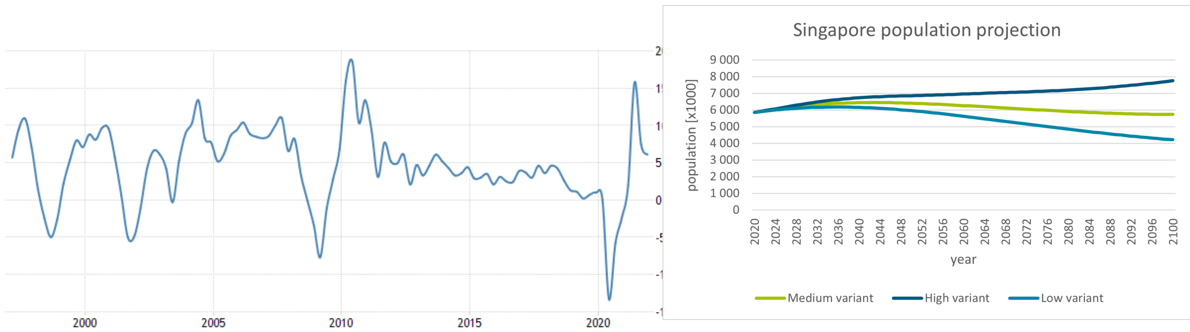
(a) Annual land deformation rates estimated by the Persistent Scatterers Interferometry (PSI) (Catalao et al., 2020)

(b) Relative impact of land subsidence for different climate scenarios (Catalao et al., 2020)

Figure 5.13: Land subsidence in Singapore

Socio-economic growth rate

The socio-economic growth rate is a combination of economic growth and increase in population. It was concluded in Section 2.2.1 that the annual GDP growth rate forms a good indicator for the increase in value at risk. The Singapore annual GDP growth rate can be seen in Figure 5.14a.



(a) Singapore annual GDP growth rate (Singapore Statistics, 2022)

(b) Singapore population projections for different scenarios (United Nations, 2019)

Social growth can be described by accounting for the population growth when the costs of a human life stay constant (else this can become another variable). Quah et al. (2009) have estimated that the value of a statistical life in Singapore is between 850,000 SG$ (US$615,950) and 2.05 million SG$ (US$1.49 million). This has been calculated in 2009 and therefore should still be indexed. By then the value was comparable to those of South Korea and Taiwan but was lower than that of the United States and Australia.

The change in population size is dependent on many factors and therefore is uncertain. This can be seen in the projections of the United Nations (2019) in Figure 5.14b. The medium variant of the population projections shows an approximately stable population size resulting in no additional population at risk within the same area. Therefore, the population growth is not included and the socio-economic growth rate is assumed to solely consist of the increase in GDP. The derivation of the average socio-economic growth rate of 2.0% and a standard deviation of 0.3% can be found in Appendix I.2. The uncertainty is likely to be slightly underestimated as the uncertainty in population projections is not included in this analysis. Since the high water events, like shown in Figure 5.10, have relatively low rising rates and are predictable, the human risk can be considered to be low, and therefore, this simplification to obtain a first-order estimate of the socio-economic growth rate can be justified.

Discount rate

The choice of discount rate can be considered to be political when a social discount rate as described in Section 2.2.1 is applied. The discount rate is assumed to be a social discount rate in this thesis as it is a climate adaptation project and therefore it can be argued that measures are desired to prevent future generations from carrying the burden of the changing climate. Therefore, the discount rate is deterministic. The choice of discount rate is dependent on the economic situation of a country. The World Bank applies an upper limit of 10% for underdeveloped countries and an upper limit of 6% for developed countries. As Singapore is a developed country and it is a goal of the government to anticipate immediately, the discount rate is assumed to be 4%.

Inflation rate

Inflation results in measures becoming increasingly expensive to implement. Also, the costs of operation and maintenance get increasingly expensive. The derivation of the average socio-economic growth rate of 1.5% and a standard deviation of 0.1% can be found in Appendix I.1. Singapore's historic inflation rates have been used for this.

Increased occurrence & intensity of storms

The literature assessed in Section 2.2.1 showed no prevailing evidence of an increased occurrence, duration and intensity of storms in general. Cannaby et al. (2016) have quantified the effects of the increased intensity specifically on the coast of Singapore. This research used four climate models to simulate the impact of the changing climate and the rising sea level. The increase in sea level change counteracts the increase in intensity and therefore no statistical changes in skew surge events were found. Likewise, no large changes in significant wave height could be observed. The bandwidth for the uncertainties does however include slight increases as can be seen in Tables 5.15a and 5.15b. As the central estimate even showed a decrease in wave-height and wind set-up, the increased occurrence & intensity of storms will not be considered in this thesis. The government of Singapore does on the other hand include an increased occurrence and intensity of storm surge (Fu, 2022). This assumption can result in significantly higher assumed water levels and therefore, measures that have to be implemented earlier and bigger measures.

Period/years	2	20	100	1000	10 000
Lower	−15	−460	−730	−1260	−2030
Central	−30	−140	−220	−390	−620
Upper	80	190	290	490	780

(a) The expected changes in wave-height

Period/years	2	20	100	1000	10 000
Lower	−20	−40	−63	−90	−120
Central	0	−10	−20	−20	−30
Upper	20	20	30	50	60

(b) The expected changes in the wind set-up

Figure 5.15: The changes in intensity of storms in mm/century according to Cannaby et al. (2016)

Tsunamis

A tsunami is a major wave caused by a mechanism that is able to move an enormous amount of water. An example of such a mechanism is an earthquake. However, not all earthquakes can cause tsunamis as tectonic plates sliding horizontally do not move enough water (KNMI, n.d.). The same source states that vertical movement of the tectonic plates is required and should be of sufficient magnitude (> 7). Additionally, this movement should not be too deep beneath the bottom surface(KNMI, n.d.). Finally, the KNMI states that the water depth below which an earthquake takes place influences the impact of a tsunami. When the earthquake takes place in a shallow part of the ocean, the change in water level between the location of the earthquake and the coast is relatively small as a result of a relatively small change in wavelength.

The tectonic plates causing major earthquakes are shown in Figure 5.16. It can clearly be seen that for most angles Singapore is not directly exposed to tsunamis as it is protected by land mass in between the plate boundaries and Singapore. This is what happened when the land mass of the island of Sumatra protected Singapore in 2004 from the disastrous tsunami resulting in more than 230,000 fatalities in Asia (NU, 2019). The tsunami did not reach the Strait of Melaka and therefore, did not even affect water levels in Singapore.

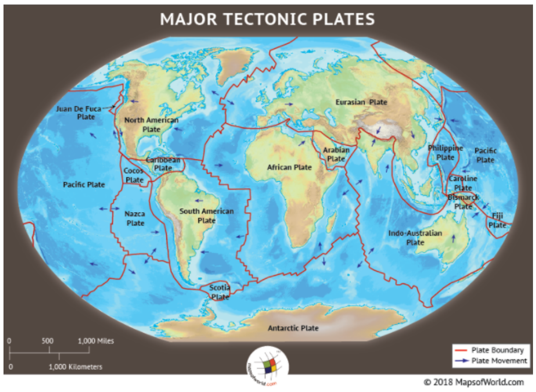


Figure 5.16: The tectonic plates of the world (Maps of World, 2018)

However, the impact of a tsunami is theoretically likely to be experienced when the location of the earthquake would be more northern, e.g. close to the Nicobaren islands. This could lead to waves propagating through the Strait of Melaka and reaching Singapore. Thai seismologist, Dr. Smith Dharmasaroja, stated after the 2004 tsunami that the epicentre for future earthquakes is likely to be further north than before. Therefore, the possibility of a tsunami more north should not be ruled out and the effects of such a tsunami should be considered. This was done by Suppasri et al. (2012) by modelling the impact of earthquakes at several locations in the Indian Ocean. The normative earthquake lead to waves propagating into the Strait of Malacca and resulted in a maximum wave of approximately 1 meter at the coast of Singapore.

Collision of tectonic plates can also occur in the South China Sea. Dao et al. (2009) modelled a wave height of 40 to 60 cm from a fault rupture in the Manilla trench while Huang et al. (2009) stated a maximum water level increase of approximately 0.80 m for an earthquake in the Manilla trench. Finally, tsunamis can also be generated by submarine landslides or eruptions (Observatory, n.d.). This could happen on the Sunda shelf, the shelf on which Singapore is located. However, these events are impossible to predict as they can have different magnitudes and can happen in many locations.

Singapore has not experienced major tsunamis in recent history and therefore, are not included in the data on water levels. However, this does not provide any guarantees for the future. Theoretically, earthquakes, eruptions and landslides could result in a tsunami reaching the coast of Singapore. Therefore, tsunamis are an uncertainty which could lead to waves of 1 meter. As the probability of a tsunami occurring simultaneously with an extreme event is extremely low and the relatively low wave caused by the tsunami on the Singaporean coast, tsunamis will not be considered in this thesis.

5.3. Input

The framework to come up with various adaptation pathways can only be applied when the site characteristics fulfills the requirements described in Appendix A. One of the requirements is that the area should completely fill up when inundation occurs. The area in which risk occurs is shown in Figure 5.17 and illustrates the expected area to be flooded. The area and length of the waterfront that is inundated can be derived from these maps and were estimated to be respectively 6 km^2 and 17.1 km.

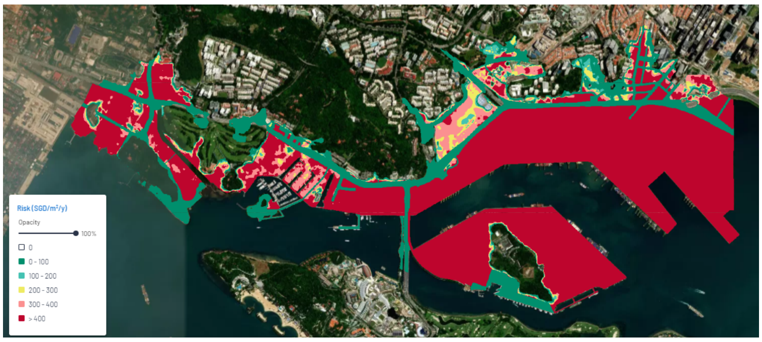


Figure 5.17: Area at which inundation takes place

The time it takes to fill up the area can now be derived in a similar way as in Appendix A with an assumed height of measures of 2 meter and m = 0.8. This results in the graph shown in Figure 5.18. Even with a very limited water depth above the measures, the peak lasts long enough for the area to fill up as can be seen in Figure 5.10 and therefore, it can be concluded that this criterion is met. The height difference within the area is limited as can be seen in Figure 5.3, no initial measures have been taken in the area, the waves are very low resulting in limited overtopping and the extreme water levels can be described according to the Gumbel distribution as can be seen in Figure 5.8 and therefore, the framework can be applied to the area.

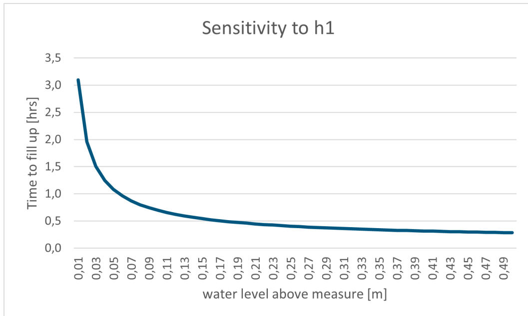
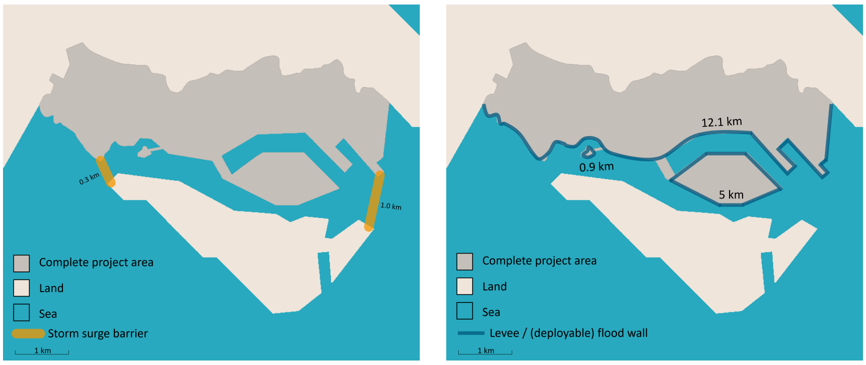


Figure 5.18: Time required to fill up

The framework is first used to see whether the storm surge barrier is a desired solution for the area as this would impact almost the complete area. If this turns out not to be desired, the spatial scale can be reduced to be able to apply a more local approach. As the area contains already constructed buildings, applying a landfill and elevation is not possible. The implementation of levees is also impossible since the area partly contains a pile deck as can be seen in Figure 5.5. The other measures are possible.

The area that has been modelled to potentially inundate contains 676 buildings. Dryproofing would have to be applied to all of them to be fully effective. The dimensions of the other possible measures can be seen in Figure 5.19. It can be seen in Figure 5.19a that additional measures are required for the coastal stretch that is unaffected by the storm surge barrier. This leads to an underestimation of the actual costs when applying the storm surge barrier. These additional costs can be neglected in the first-order assessment as the storm surge barrier is considerably more costly than the additional required measures. When the storm surge barrier turns out to be a more cost-effective measure than the alternative solutions, an additional, more accurate analysis is required with the inclusion of the costs related to additional measures required for the unaffected coastal stretch. When the storm surge barrier turns out to be less cost-effective compared to alternative solutions, this analysis suffices as including the additional required measures would make it even less cost-effective.



(a) The required barrier length

(b) The required length for levee / (deployable) flood wall

Figure 5.19: The required dimension of the measures

An analysis was conducted to see whether applying a barrier at Area C of the Singapore City-East Coast is desired. The input of the framework used to conduct this analysis can be found in Table 5.4. The damages occurring on Sentosa island are assumed to be negligible as the cliffs prevent any inundation. It is important to emphasise the fact that the outcome is dependent on the assumptions made (e.g. assuming no additional future storm surge). When one would use different assumptions based on different or newly available knowledge, the outcome could be considerably different.

Table 5.4: The input-parameters for the Singapore City-East Coast

Input	Value	Source
Region	South-East Asia	-
Desired protection level	10,000 years	Section 5.2.3
Actual protection level	$123{*}10^6$	The return period corresponding to the water level determined in Section 5.2.3
Req. length of levee to increase safety level	17.1 km	Figure 5.19b
Buildings that require dryproofing / elevation	676 buildings	The amount of buildings that the maximum inundated area contains
Req. storm surge barrier length	1.3 km	Figure 5.19a
Protection area	6 km^2	The flooded area in the most extreme scenario
Year of data	2022	The year for which the damage and the water levels are derived
Currency	SGD	Currency of Singapore
β and μ of the Gumbel distribution	β = 0.071 m and μ = 1.677 m	Section 5.2.1
Damage	See Tables H.1a, H.1b and H.1c	Section 5.2.2
Sea level rise scenario	SSP5-8.5	This scenario is used by the government of Singapore for future planning
Socio-economic growth rate	2%	Appendix I.2
Discount rate	4%	Based on the economic situation of Singapore as described in Section 5.2.1
Inflation rate	1.5%	Appendix I.1
Measures to include	Flood wall, deployable flood wall, dryproofing and barrier	The only measures that are possible due to restrictions of project area like existing buildings and pile decks
Safety level of the barrier	A set protection level for a lifetime of 200 years	The barrier is assumed to be robust under all conditions during its lifetime
Determination of the optimal safety level	Maximising the NPV	Gives the highest NPV
Divide by the annuity factor for optimisation	no	Gives the highest NPV
Freeboard added to measures	0.75 m	Gives the highest NPV

The costs of measures are adjusted to the situation in Singapore. A multiplication factor of 2 has been applied to obtain the unit costs for a levee, (deployable) flood wall and landfill compared to costs defined for The Netherlands. This is the same multiplication factor as has been used to obtain the damage functions in Appendix F. The results are in line with the unit costs for Singapore in the cost database of Royal HaskoningDHV. This database has also been used to obtain the unit costs for dryproofing, elevation and barrier. The unit costs for Singapore can be found in Table 5.5.

Table 5.5: Construction costs for the different measures in Singapore

Measure	Costs	Unit
Levee	20,000	€/m/m
Flood wall	10,000	€/m/m
Deployable flood wall	10,400	€/m/m
Landfill	50	€/m/m^2
Dryproofing	12,000	€/m/building
Elevation	80,000	€/m/building
Barrier	1,200,000	€/m

It turned out that the storm surge barrier is the least cost-effective measure when Table 5.4 is used as input for the framework. The total costs (Investments, O&M costs and residual risk combined) of the barrier are more than 0.5 billion SGD during the lifetime while for instance, a flood wall would cost over 10 times less. The same can be seen for other sea level rise scenarios. Therefore, the barrier is not considered anymore for further optimisations of the flood risk reduction strategy. For this optimisation, the Area C was split up into 5 separate areas as can be seen in Figure 5.20. These areas can be split up because they already function independently (Area C4 and C5) or the area is almost entirely separated due to height differences. Only limited measures are needed to fully function independently (Area C1, C2 and C3) as can be seen in Figure 5.3. The division of areas is also based on the land use as new developments are planned for some of the areas and therefore measures like a landfill and elevation are possible. Finally, some of the areas are constructed on pile decks as can be seen in Figure 5.5 (Area C3 and C5) and therefore applying a landfill would require the space below the pile deck also to be filled as it is likely that the pile deck is not able to support a landfill on top.

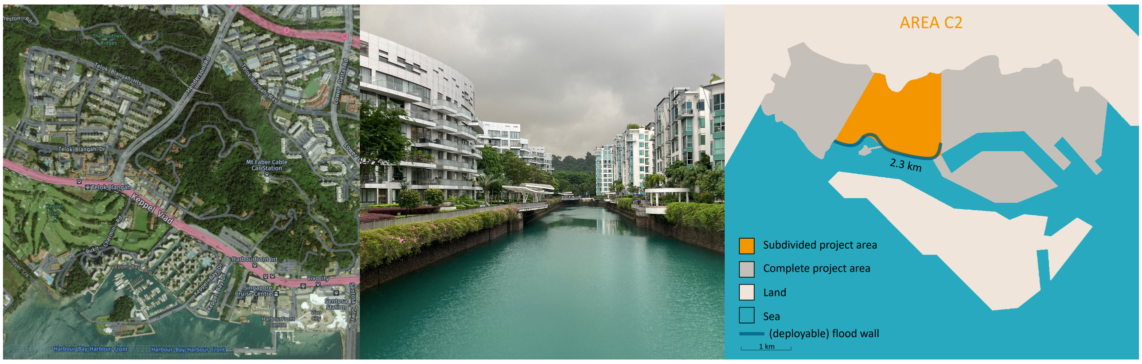
(a) Area C1 **(b)** Area C2 **(c)** Area C3

(d) Area C4 **(e)** Area C5

Figure 5.20: Area C split up into separate areas

Area C2 is used as a case study to illustrate how the framework and probabilistic assessment can be used to obtain a long-term flood risk strategy. Area C2 is an area that already contains buildings. Therefore it is not possible to elevate buildings or apply a landfill. Due to the existing buildings, there is not enough space to implement a levee and therefore, the pathways with levees are excluded as well. A satellite image of the area can be seen in Figure 5.21a. The inlets which can be seen in the satellite image are shown from the ground in Figure 5.21b. As previously concluded, the barrier is not the best option for the area and therefore the adaptation pathways with the barrier as a measure are also excluded.

The required dimension of the (deployable) flood wall can be seen in Figure 5.21c. It can be seen that the wall has been extended in the east to prevent inflow from that side due to its low elevation. The required length of the (deployable) flood wall does not include the inlets that can be seen in Figure 5.21b as it is assumed that a relatively cheap solution can be found to close them off during high water events. If this assumption does not turn out to be true, the synthesis has to be redone with the required length of the (deployable) flood wall around the inlets included.



(a) Satellite view (Maxar, 2022) **(b)** The inlets **(c)** Required dimensions

Figure 5.21: Area C2

This all leads to the input-parameters in Table 5.6. Most of the input-parameters are equal to those used for the larger area and therefore will not be further explicated. The damages have been modelled in a similar way as done for the complete area. The damage corresponding to the SSP5-8.5 scenario in 2100 can be found in Table 5.8. The damages that were used to define the damage function of Area C2 can respectively be found in Figure 5.22 and Tables H.2a, H.2b and H.2c. The risk maps can be found in Figure H.2 in Appendix H. As the same current safety level is assumed as was assumed for the bigger area, the current situation results in no damage. Maximum lifetimes have to be included to prevent unrealistically long lifetimes like in the fictive case. The maximum design lifetimes of measures that are assumed for this case can be found in Table 5.7. The damage occurring in Area C2 is approximately 10% of the total damage of Area C.

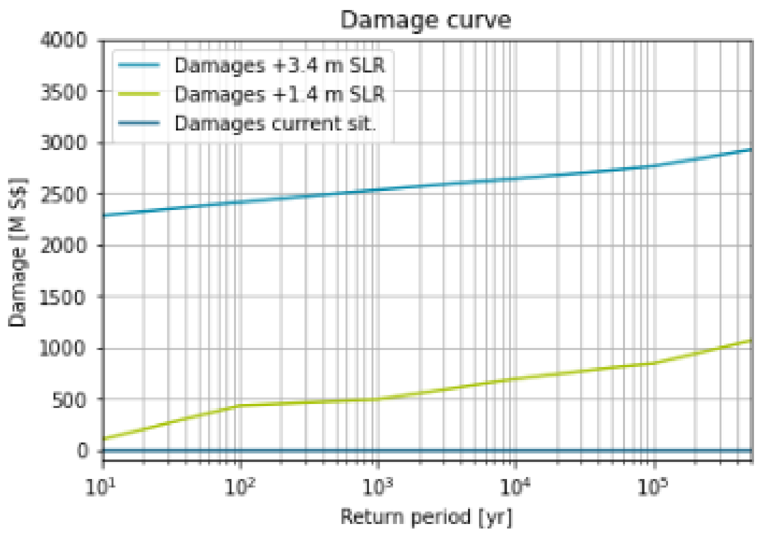


Figure 5.22: The damages of Area C2 used as input for the framework

Table 5.6: The input-parameters for the Area C2 within the Singapore City-East Coast

Input	Value	Source
Region	South-East Asia	-
Desired protection level	10,000 years	Section 5.2.3
Actual protection level	$123 * 10^6$	The return period corresponding to the water level determined in Section 5.2.3
Req. length of levee to increase safety level	2.3 km	Figure 5.21c
Buildings that require dryproofing / elevation	113 buildings	The amount of buildings that the maximum inundated area contains
Protection area	0.762 km^2	The flooded area in the most extreme scenario
Year of data	2022	The year for which the damage and the water levels are derived
Currency	SGD	-
β and μ of the Gumbel distribution	β = 0.071 m and μ = 1.677 m	Section 5.2.1
Damage	See Tables H.1a, H.1b and H.1c	Section 5.2.2
Sea level rise scenario	SSP5-8.5	The sea level rise scenario for which the Singapore government wants to make the design
Socio-economic growth rate	2.0%	Appendix I.2
Discount rate	4%	Political choice
Inflation rate	1.5%	Appendix I.1
Measures to include	Flood wall, deployable flood wall, dryproofing	Not all measures are applicable everywhere
Determination of the optimal safety level	Maximizing NPV with limited lifetime	Gives the highest NPV
Divide by the annuity factor for optimisation	no	Gives the highest NPV
Freeboard added to measures	0.75 meter	Gives the highest NPV

Table 5.7: The maximum lifetime for measures applied in Singapore

Measure	Max. lifetime [years]
Levee	50
Flood wall	50
Deployable flood wall	50
Landfill	100
Dryproofing	25
Elevation	100
Barrier	100

Return Period	Damage [m SGD]
10	0
100	0
1,000	0
10,000	143
50,000	260
100,000	283
500,000	365

Table 5.8: Damages in current situation +0.82m SLR

5.4. Results

5.4.1. Application of framework

The framework has been used to create pathways by maximising the NPV of individual measures. A detailed analysis of the possible ways of optimisation and which one to use when can be found in Appendix J. As a result of the relatively narrow water level distribution, the level corresponding to a e.g. 500,000 years return period was not considerably higher than the level corresponding to a 50,000 years return period. This resulted in measures with low heights and correspondingly short lifetimes. An additional 0.75 meters was added to each measure to prevent this en to obtain the highest possible NPV.

The outcome of the framework is shown in Figure 5.23. It can be seen that no measures are required until 2092 for the assumed conditions. Afterwards, a (deployable) flood wall or dryproofing can be applied. There are only two adaptation pathways that satisfy the safety level requirement until 2200. A 75 cm flood wall constructed in 2092 with consecutive flood wall increments of 63 cm in 2142 and 30 cm in 2192 is one of them (AP10). The other pathway consists of consecutively 42 cm of dryproofing applied in 2092, 106 cm of flood wall (including the additional 42 cm of dryproofing as both measures do not have a complementing effect) in 2117 and a 46 cm flood wall increment applied in 2167 (AP33). The safety levels over time of both pathways can be found in Figure 5.24. It can be seen that the safety level after implementation of a subsequent measure is not equal to either 100,000 or 500,000 years as 0.75 meters of freeboard has been added.

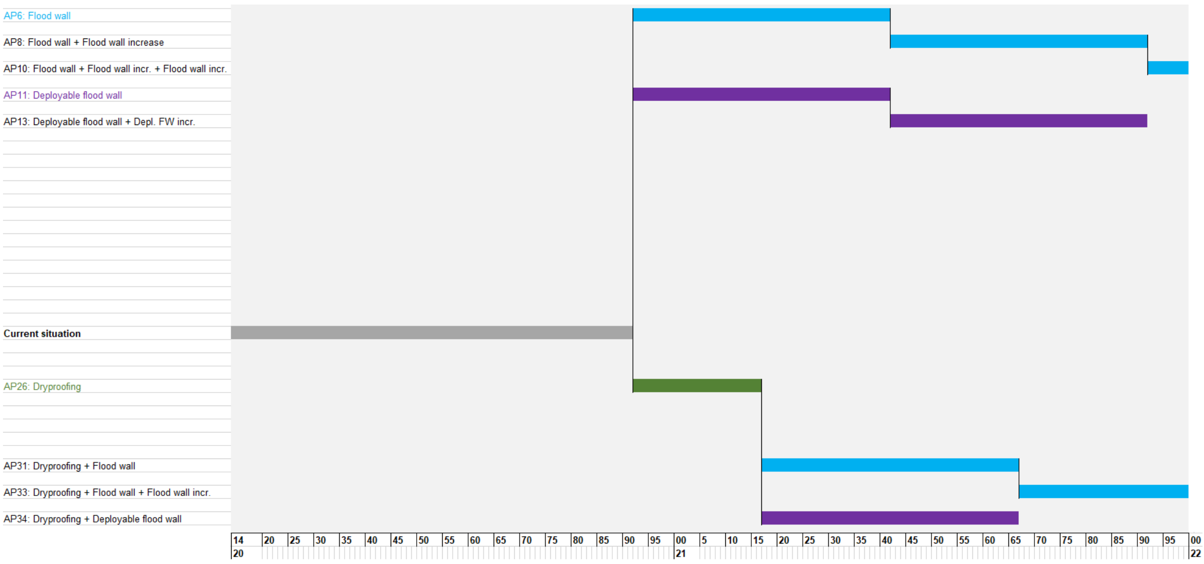
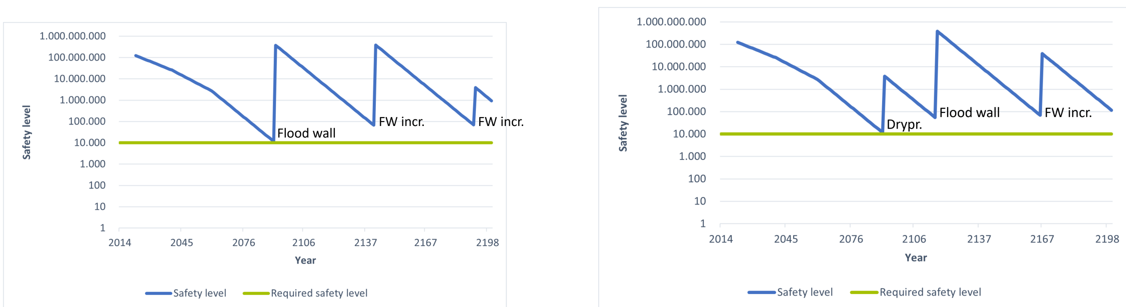


Figure 5.23: The possible pathways for Area C2 for the SSP5-8.5 scenario



(a) Adaptation Pathway 10 for Area C2

(b) Adaptation Pathway 33 for Area C2

Figure 5.24: Possible APs for Area C2 for the SSP5-8.5 scenario

Table 5.9: The outcome for Area C2

Measures	NPV [M SGD]	BC-ratio	Total costs [M SGD]
AP10	750	114	6.7
AP33	752	155	4.9

In Table 5.9 it can be seen that for both pathways the benefits are over a factor of 100 higher than the costs. This is the result of the high sea level rise resulting in an extremely high annual risk when nothing is done. The difference in NPV of both pathways is relatively small as a result of this high annual risk without implementation of measures. Stated differently, implementing measures in the long-term is very cost-effective if the conditions turn out to be equal to those assumed. The difference in BCR and total costs is more significant. The total costs (investment, O&M and residual risk) of AP10 are equal to 6.7 million SG$ while that of AP33 is equal to 4.9 million SG$. This is mainly due to the fact that dryproofing is a relatively cheap solution for the area making it possible to postpone more expensive measures like the flood wall.

5.4.2. Application of probabilistic assessment

The robustness of both pathways can qualitatively be assessed by altering the sea level rise scenario. AP33 would require an additional measure when one would use the 95th quantile of the SSP5-8.5 scenario. Without this additional measure, the NPV of AP10 would be higher as the pathway lasts longer. The lowest included SLR-scenario would for both pathways result in the last increment not being necessary anymore and a slightly negative NPV, with AP33 still performing better (-0.2 M vs -0.9 M SGD). To include all possible futures and all uncertain parameters the probabilistic assessment can be used.

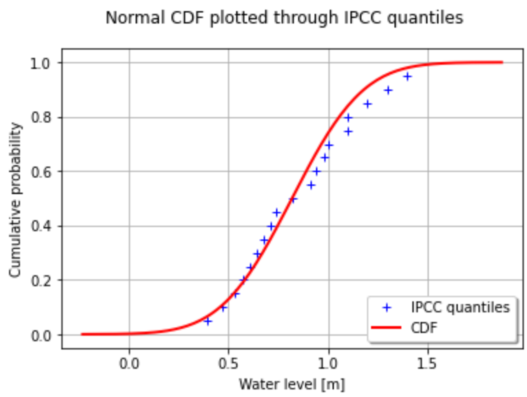


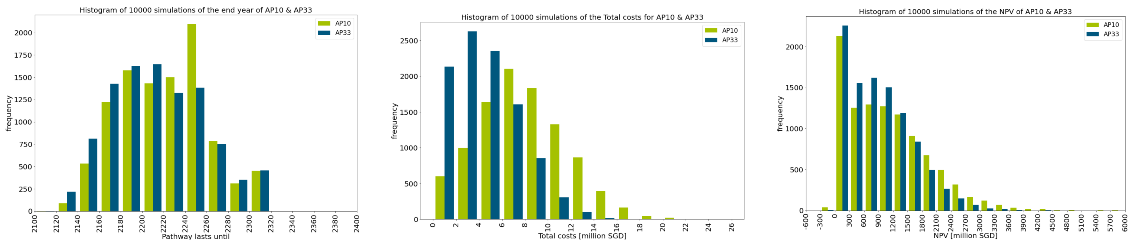
Figure 5.25: A normal distribution fitted through the IPCC SSP5-8.5 projections

This probabilistic assessment provides more insight into the robustness of the pathways. This might be decisive as the difference in NPV of both pathways is relatively small. Therefore, a probabilistic assessment of both pathways was conducted to assess their robustness. For this assessment, the discount rate is taken as deterministic as it is assumed to be a social discount rate. The normal distributions for the inflation and socio-economic growth rate have a mean of respectively 1.5% and 2% and a standard deviation of 0.1% and 0.5% as defined in Appendix I. The uncertainty in the costs has been estimated based on the cost database of Royal HaskoningDHV and the costs are modelled with a standard deviation that can be found in Table 5.10. These cannot become negative and therefore, they have been transformed to LogNormal distributions as can be seen in the last column. The uncertainty in sea level rise has been determined by using the quantiles for the sea level rise predictions of 2100 for the SSP5-8.5 scenario. These can be found in Figure 5.25. A CDF of a normal distribution has been fitted through these quantiles. This has been done by using the 50th quantile as mean and the difference between the 50th and 16th quantile as standard deviation (equal to the definition of the standard deviation). The 5th quantile is taken as the lower limit else this could theoretically result in sea level decline for the SSP5-8.5 scenario. It is assumed that the effectiveness of measures is part of the design criteria. Therefore, no distribution is applied to account for the effectiveness of measures.

Table 5.10: The uncertainty in the costs of measures

Measure	STD Investment costs [%]	STD O&M [%]	I transformed to LN distr.	O&M transformed to LN distr.
Flood wall	20	10	LN(λ = -0.0196, ζ = 0.198)	LN(λ = -0.00497, ζ = 0.0997)
Dryproofing	20	10	LN(λ = -0.0196, ζ = 0.198)	LN(λ = -0.00497, ζ = 0.0997)

The results of the probabilistic assessment can be seen in Figure 5.26. A peak with the histogram of the NPV can be observed between the 0 and 300 million SGD. This peak is caused by the fact that the sea level rise was restricted by a minimum equal to the 5th quantile. The second highest peak is at the outcome of the framework as could be expected. Furthermore, it can be seen that the total costs of AP10 are higher than those of AP33. This could also be seen in the framework. However, the NPV of the AP33 is in general slightly lower than that of AP10. This is likely due to the fact that for more simulations AP10 ends earlier than AP33 minimizing the obtained benefits. This results in a slightly wider range of possible outcomes for AP10. The outcome of the probabilistic assessment is 58% of the time higher than that of framework for AP10 (750 M SGD). This percentage is equal to 51% for AP33. These percentages might also be influenced by the fact that framework is restricted until 2200 while the probabilistic assessment. A sensitivity analysis to this restriction is therefore conducted in Section 5.5.2. The ratio between the 5th and 95th quantile is equal to 0.64 for AP10 and to 0.54 for AP33. In this case, the wider range for AP10 mainly results in a higher NPV and not in lower NPV. Therefore, the probabilistic assessment shows that AP10 is preferred.



(a) Last year of the pathway **(b)** Total costs of the pathway **(c)** NPV of the pathway

Figure 5.26: The outcome of the probabilistic assessment

5.5. Evaluation

5.5.1. Evaluation of the outcome

Two pathways turned out to fulfill the safety level requirement until 2200 for the input-conditions. The framework showed that AP33 resulted in a slightly higher NPV than AP8. A probabilistic assessment showed no big differences between both APs. The limitation of this probabilistic assessment is that the pathway is assumed to be fixed. Adjustments of pathways can, however, be made in real-life to adjust to changing conditions. Therefore, the probabilistic assessment forms a bottom estimate as pathways can further be optimised at the moment more is known about the uncertainties. When the sea level rise for instance turns out to be more severe than anticipated, the height of the applied measure can be increased resulting in more benefits.

The economic and technical evaluation has been conducted in this thesis. However, selecting the desired pathway is also dependent on the preferences of local stakeholders. Although a local stakeholder has not been included in this thesis, the advantages and disadvantages of both pathways will be explicated so that a pathway can be selected. Dryproofing is the first measure that is applied in AP33. Dryproofing prevents water from flowing into buildings but it does lead to water on the street. It is assumed that this does not lead to damage, but it can be inconvenient and undesirable. Next to that, dryproofing is a measure that is not permanent. This means that when a high water event is expected, measures have to be correctly installed. This should not lead to problems under normal circumstances as high water events can be predicted in time. The flood wall does not have these limitations and therefore it is likely that AP10 instead of AP33 is preferred by local stakeholders despite its higher costs. The trigger values for AP10 for SSP5-8.5 can now be set as can be seen in Table 5.11. Trigger values have been defined as the safety level at which action needs to be initiated in order to implement subsequent measures to prevent the safety level from dropping below the minimum required safety level. As has been concluded during the fictive case study, the trigger values may significantly vary when the SLR is not equal to the design situation. Therefore, the SLR has to be monitored constantly and trigger values have to be updated according to the actual sea level rise.

Table 5.11: The trigger values for AP10 for SSP5-8.5

	Year of impl. m1	Trigger value [yrs]	Year of impl. m2	Trigger value [yrs]	Year of impl. m3	Trigger value [yrs]
AP10	2092	14,000	2142	67,000	2192	69,000

It could be observed that the chosen sea level rise scenario significantly influences the NPV of a pathway and its trigger values. It determines the amount of risk occurring in the future and therefore influences the optimal safety level. However, the sea level rise that will actually occur is currently still unknown. Postponing investments can reduce the uncertainty in the sea level rise. The discount rate can also make it favorable to postpone investments until the moment the reduced risk as a result of the measures outweigh the costs. However, investments can no longer be postponed when the safety level impends to drop below the required safety level. The policy of Singapore is to design for high-end scenarios like the SSP5-8.5 as has been done in this case study.

Although this choice did not lead to a different type of desired first measure, it did result in a higher initial optimal height of the flood wall compared to designing for the lowest sea level rise scenario. As a higher initial height leads to higher investment costs, it raises the question of whether designing for a high sea level rise scenario is desirable. To evaluate this, the NPV of AP10 is obtained with the height of the first measure being optimised according to a low and high sea level rise scenario (SSP1-2.6 and SSP5-8.5) and afterwards exposed to both the high and low sea level rise scenario. The results can be seen in Table 5.12. The absolute difference turns out to be small for both scenarios. The relative difference of the outcome in NPV is, however, large for a design according to the high sea level rise scenario while the actual occurring sea level rise turns out be following the SSP1-2.6-scenario. This might be explained by the fact that investments would be less costly as they could be postponed to the future and therefore discounted, without the reduced risk (benefits) severely being affected. Designing according to a low sea level rise scenario while it turns out to be a higher sea level rise scenario might postpone part of the investment costs of the initial measure but can also lead to the subsequent ATP occurring sooner resulting in the subsequent measure being required earlier and its corresponding investment costs having a higher present value. Therefore, this cannot be considered as a general truth.

Table 5.12: Outcome of design for high and low SLR for AP10

SLR happening	SLR designed for	NPV [M SGD]	% change
Low	Low	-0.9	-
Low	High	-1.4	-57%
High	High	750	-
High	Low	750	0%

5.5.2. Sensitivity analysis

Sensitivity to assumed input conditions

The Singaporean government wants to anticipate on climate change and studies are being conducted to quantify the impact of climate change on its coasts. Most of these studies are either not publicly accessible or not finished at the moment of writing. There are, nonetheless, press releases stating that the government wants to anticipate to the 95th quantile of the SSP5-8.5 scenario and also want to include increased storm surges (The Strait Times, 2022). When one would have to include the increased storm surge, the parameters of the Gumbel distribution would alter resulting into higher water levels. The increased storm surge that is assumed to perform a sensitivity analysis is based on the storm surges applied for locations close to the project area and can be found in Table 5.13 (Bos, n.d.). These additional surges were added to the initial water levels and a new Gumbel distribution was fitted through these newly obtained water levels resulting in the distribution that can be seen in Figure 5.27. This newly obtained Gumbel distribution in combination with the 95th quantile of the SSP5-8.5 instead of the median, was used to obtain the outcome of the framework as can be seen in Figure 5.28. It can be seen that measures have to be implemented considerably earlier (2038 vs 2092). Immediate action would even be required when one would want to include more than 0.15 meter of additional freeboard to account for the effect of waves. It is therefore clear that the assumed sea level rise and increased storm surge ascribed to the changing climate, greatly affect the outcome.

Table 5.13: The assumed additional storm surge

Return period [years]	10	100	1,000	10,000	100,000
Additional surge [m]	0.1	0.2	0.4	0.5	0.6

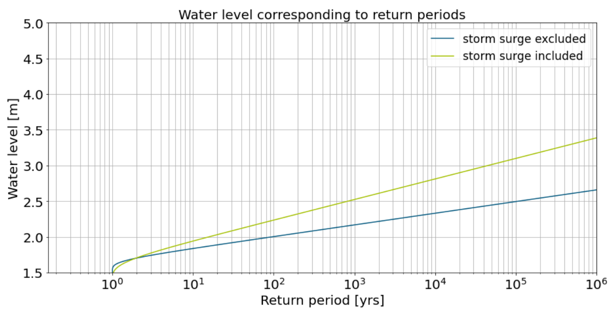


Figure 5.27: The newly obtained Gumbel distribution when including increased storm surge

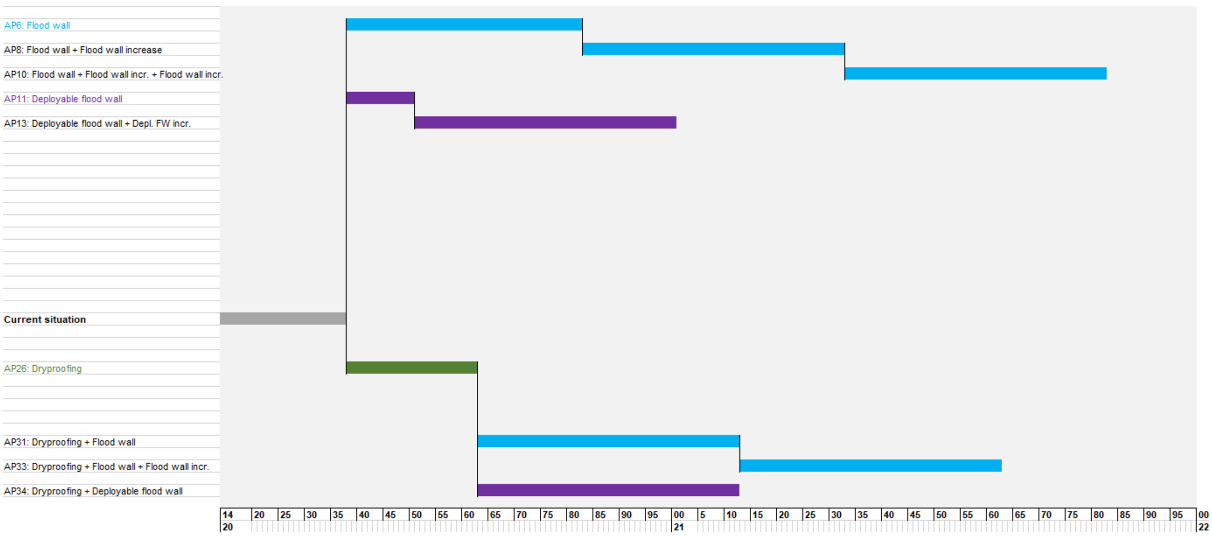


Figure 5.28: The outcome when assuming extreme SLR and include an increase in storm surge

Table 5.14 shows that the NPVs of both pathways are increased as a result of the more extreme conditions and therefore, increased benefits. It can also be seen that AP10 performs better than AP33, opposite to the outcome obtained when excluding the additional storm surge and using the median of SSP5-8.5. This is likely the result of the lifetime of AP33 being longer than that of AP10 as this was not the case before due to the restriction until 2200.

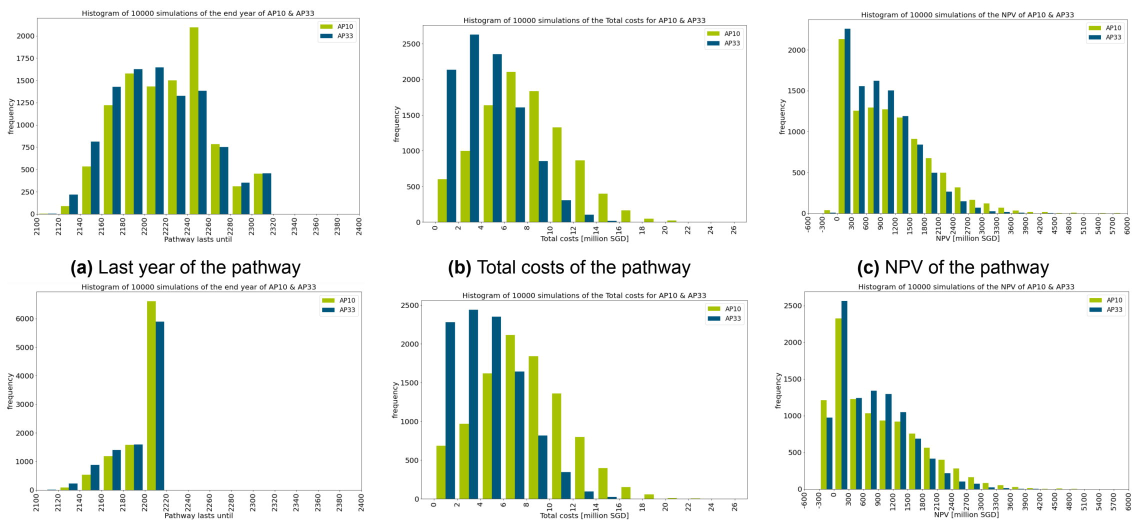
Table 5.14: The economic evaluation of the pathways

Pathway	End year	NPV [M SGD]	BCR
AP10	2182	2,600	88
AP33	2162	2,000	79

Sensitivity to restriction until 2200

To assess the influence of the restriction of the framework until 2200, the probabilistic assessment is also restricted until 2200 and compared to the one without restriction. The outcome can be seen in Figure 5.29. The first row shows the outcome of the probabilistic assessment without restricting it until 2200. The second row shows the results when the time horizon is restricted until 2200, like done in the framework. It can be seen that no major differences can be observed in the obtained total costs.

The NPV is slightly underestimated with the restriction. This can also be seen back in the percentage being higher than framework. The percentage being higher than the framework is now 47% and 44% for respectively AP10 and AP33 while it used to be 58% and 51%. The NPV was maximised in the framework, and the benefits after 2200 are not included, resulting in a relatively low safety level at 2200 and therefore low benefits. It can be seen that the restriction of the framework has some effects when there is some additional safety margin above the safety level requirement left. This effect is likely to increase for high socio-economic growth and inflation rates and for low discount rates. The same trends can still be observed with this restriction and therefore the restriction can still be justified. However one should be aware of the effects and understand for what conditions this effect is likely to be considerable when using the framework.



(a) Last year of the pathway

(b) Total costs of the pathway

(c) NPV of the pathway

(d) Last year of the pathway with restriction until 2200

(e) Total costs of the pathway with restriction until 2200

(f) NPV of the pathway with restriction until 2200

Figure 5.29: The outcome of the probabilistic assessment with a restriction until 2200

5.5.3. Conclusion of case study

Many lessons can be learned from the application of the framework and probabilistic assessment to the case study of Singapore, characterised by a narrow water level distribution. First of all, it turned out that the current flood risk is low when disregarding the increased storm surge as a result of climate change. Flood risk reduction measures that can be applied to ensure a high level of flood safety were not necessary until 2092 in that case. When the increased storm surge was included and an extremely high sea level rise scenario was assumed, these measures turned out to be required more than 50 years earlier, indicating a substantial sensitivity.

The storm surge barrier turned out to be a factor of 10 more costly compared to the alternatives, independent of the chosen sea level rise scenario. Therefore, the storm surge barrier can be concluded not to be the desired solution for the area. Two pathways consisting out of the multiple individual measures turned out to satisfy the safety level requirement until 2200. One pathway consists of a flood wall and subsequently 2 flood wall increments and the other one consists of dryproofing and subsequently a flood wall and a flood wall increment. The latter turned out to be performing slightly better in the framework but also turned out to be less robust. As dryproofing can lead to inundation of the land for high water events with a return period lower than the safety standard while Singapore has set the goal to protect its coastlines and prevent inundation of the land, the pathway solely consisting of flood wall turns out to be the most suitable solution for the project area.

6 Discussion

The discussion is divided into the validation of the framework and probabilistic assessment, an analysis of the outcomes of the case studies, the implication of the applied method and the limitations to this method.

6.1. Validation

6.1.1. Framework

Validation of the framework is required to see whether the results of the framework are in line with existing research and can therefore be considered as reliable. The framework has been validated with the methods described in Chapter 2. This validation can be found in Appendix E.

A noteworthy observation in the fictive case was that the pathways consisted of individual measures with long lifetimes. Afterwards, it was concluded that lifetimes that exceed the technical lifetime of individual measures should be restricted. In this way an adaptive approach is ensured. The importance of restricting the individual lifetimes of measures is emphasised by Haasnoot et al. (2020) as well who stated that ”In a changing climate, it is imperative to evaluate non-individual investments, but pathways derived from sequences of investments, taking into account their operational and societal lifetime”.

A difference with the economic evaluation of entire pathways of the approach used by Haasnoot et al. (2020) is the use of transfer costs. Transfer costs have there been defined as ”the costs of course correction in light of changing circumstances” which means that they explicitly reflect the cost of maintaining flexibility in the face of deep uncertainty. The transfer costs have not been included in the framework due to a lack of literature on appropriate values for different measures and sequences. This can lead to an underestimation of the actual costs resulting in a preference for pathways consisting of multiple different measures or increments as transfer costs ”helps to make the consequences of certain pathways explicit and therefore amenable to long-term planning under uncertainty”.

Additionally, the framework makes use of a minimum required safety level. This safety level requirement is often specified per project area and based on economic optimisation, societal safety and/or individual safety. Individual and societal safety are both related to the number of fatalities in a flood and also affect the economic optimum as costs can be addressed to the loss of life. The number of fatalities in a flood has been estimated by Jonkman (2007) and is dependent on the evacuation and mortality fraction resulting in:

$$N = F_d(1 - F_E)N_{PAR} \tag{6.1}$$

in which N is the estimated number of fatalities, F_D is the mortality fraction, F_E is the evacuation fraction and N_{PAR} is the estimated number of people at risk. The mortality fraction is dependent on flood characteristics like the rising rate, inundation depth and velocities. This fraction can evolve over time with increased water levels and the possibility of a breaching-scenario. The evacuation fraction can also be different than in the initial situation. Therefore, the individual and/or societal safety criterion can evolve over time. Likewise, the value of an area can increase which affects the economic optimisation. Therefore, it is likely that the safety level requirements evolve over time as all criteria potentially affecting it, evolve too. This means that the required safety level should be reassessed over time which can lead to a stricter safety level requirement in the future.

The framework has been used to create and evaluate pathways for different sets of scenarios. This means that the framework should be applicable to all sea level rise scenarios which makes it impossible to apply a simplification as a constant sea level rise rate like done in *Impact zeespiegelstijging op hoogwaterveiligheid* (2019). Therefore, other methods had to be used to obtain the optimal safety level. The methods used in the framework to conduct the optimisation have their limitations as well as described in Appendix J. However, they have been adjusted by restricting lifetimes and applying a minimum height before the linear costs relation starts, to ensure executable pathways.

After the creation and evaluation of pathways, trigger values are obtained for the desired pathway as part of the DAPP-approach. These trigger values are directly related to the sea level rise in this thesis. However, subsequent actions can also be desired as a result of socio-economic developments, knowledge and innovation and societal preferences like described in Haasnoot et al. (2018). Changing circumstances could result in different desired subsequent measures. Different measures can have different trigger values as for instance could be seen in the fictive case in which the trigger value corresponding to a storm surge barrier was significantly higher than that of flood wall increment for the same sea level rise scenario (177 years vs. 101 years). Changing conditions can also have an effect on the trigger values. This was obtained in the fictive case in which the trigger value for the storm surge barrier was equal to 479 years for the 95th quantile of the SSP5-8.5 scenario while the trigger value was equal to 177 years for the median of the SSP3-7.0 scenario. A similar conclusion was drawn in Haasnoot et al. (2018) where it was stated that these values ”not only depend on the action itself and how quickly it can be activated, but also on the situation in which the action needs to be implemented”.

6.1.2. Probabilistic assessment

The probabilistic assessment has been conducted to test the performance of pathways in the full range of possible futures. However, not all of the identified uncertainties have been included in the probabilistic assessment. The water levels and damages have been identified as being uncertain as a result of statistical and model uncertainties. Nevertheless, they were not included in the probabilistic assessment as a result of insufficient data. The probabilistic assessment would have been more in line with the reality if these would have been included. Next to that, the probabilistic assessment is applied to a selection of pathways. Assessing all pathways probabilistically can prevent a pathway that performs well in the probabilistic assessment, but not for the assumed conditions in the framework, from not being included in the selection of pathways.

The adaptation pathways that were probabilistically assessed, were assumed to be fixed. This means that the type and height of subsequent measures is based on the input, even when that assumed input turns out to significantly differ from reality. Therefore, subsequent measures can further be optimised in conditions other than anticipated. The probabilistic assessment in this thesis consequently forms a bottom estimate of range of possible outcomes of a certain pathway. Flexible pathways will be valued better when including that optimisation. This is what could be seen back in a case study conducted by Buurman and Babovic (2016) in which pathways with the flexibility to combine different strategies, performed better in terms of net benefits than an inflexible solution. The value of flexibility is likely to increase as uncertainty (variability) increases.

6.2. Analysis of results

6.2.1. Fictive case

The intention of the fictive case was to ascertain whether the framework resulted in reliable solutions and workable pathways. A sensitivity analysis was conducted to assess the influence of changed input-parameters. Marchau et al. (2019) called the economic evaluation of pathways ”a not straightforward process in particular due to the sensitivity of the evaluation to variation in the discount rate and the timing of adaptation tipping points (ATPs)”. The outcome of the fictive case turned out to also be sensitive to a changing discount rate. However, the influence of the socio-economic growth rate turned out to be considerable as well. This could be expected as the growth rate can (partly) nullify the effect of the discount rate. The timing of the ATP turned out to be dependent on the chosen sea level rise scenario and the applied safety level of measures. A more severe sea level rise scenario resulted in ATPs occurring sooner. A higher safety level simultaneously mitigated this effect. This makes it impossible to directly link the timing of the ATP to one of the input-parameters of the framework. It could be observed that investment costs were reduced when the ATP occurred later as a result of postponed and consequently discounted investments. This showed that the ATP can have a considerable effect. However, the impact of this is dependent on both the inflation rate and the ratio between the costs and benefits (reduced risk) and therefore is case-dependent.

The pathways that were automatically generated by the framework resulted in measures in the order of centimeters. This accuracy conflicts with the practical feasibility during construction and might therefore be undesirable. Nonetheless, these obtained heights were used as input for the probabilistic assessment. This assessment showed that the variability of outcomes increases as the uncertainties increase. This result is intuitive, but it confirms that the probabilistic assessment can be used to assess the robustness of pathways. The outcome of the probabilistic assessment was almost equal to that of the framework indicating that the restriction until 2200 of the framework did not affect the outcome.

6.2.2. Case study: South East coast of Singapore

It turned out that the outcome was heavily influenced by the used sea level rise scenario and by whether the effects of increased storm surge were ex- or included. The publicly accessible research that has been used in this thesis concluded that the increased storm surge will not heavily affect the water levels in Singapore. This is not in line with the press releases of the Singaporean government. As a result, obtained results published by the Singaporean government might significantly differ to the obtained results in this case study. Next to that, an assumption for the discount rate was made. It has been concluded that the discount rate can be related to the inflation rate and as the inflation rate at the moment of writing is historically high, this can also have its effect on the discount rate and consequently affect the desired flood risk strategy.

Additionally, the framework only contains a limited solution space consisting of a selected set of measures. Measures like wetproofing are not included in the framework, are not assessed and therefore, a more suitable solution might be existing. The solutions that are obtained in this case study also have an accuracy in the order of centimeters which might conflict with the practical feasibility during construction.

Two pathways that are obtained within the solution space turned out to satisfy the safety level requirement until 2200. These were assessed using the probabilistic assessment. This assessment was influenced by the fact that AP10 had a higher remaining safety level in 2200 as can be seen in Figure 5.24. As more severe sea level rise can result in the ATP occurring sooner, AP10 is more robust to that situation. Despite the fact that the outcome of both pathways did not significantly differ, it can potentially have a more prominent effect on the results as the timing of the ATP was identified to considerably affect the economic evaluation. This effect is likely to be less prominent when flexibility, to anticipate to different conditions than expected, is included in the probabilistic assessment. The results of the probabilistic assessment were also influenced by the restriction until 2200 of the framework. It seemed that for both pathways more than 50% performed better than the framework but when also restricting the probabilistic assessment it turned out to be less than 50% for both cases. Therefore, one should realise that this restriction can influence the percentage having a higher outcome than the framework. This is especially the case with low discount rates and high socio-economic growth and inflation rates.

The evaluation of the obtained results of the case study showed that under- or over-adaptation resulted in limited differences in absolute numbers. This is what also could be seen back in the case study conducted by de Ruig et al. (2019). The relative difference, however, turned out to be bigger in this case study. Though, one should be careful with drawing general conclusions as it is, among others, dependent on the ratio between costs of measures and value in the area.

6.3. Implications of the developed method

This framework is aimed to identify effective and robust pathways to ensure the desired level of flood safety on the long-term. After the creation of these pathways, they are economically evaluated under a wide range of futures. The advantage is that all possible scenarios can be easily evaluated with the framework. Any sea level rise rate can be used unlike the method applied in *Impact zeespiegelstijging op hoogwaterveiligheid* (2019) which is restricted to a constant SLR-rate. This makes it possible to see what effect input-parameters have on the outcome and get a feel for the effectiveness of measures for specific project areas. This includes getting a feel for a first-order estimate of the costs and benefits of measures and pathways. The probabilistic assessment can be used to evaluate these pathways under all possible futures.

6.4. Limitations of the developed method

Appendix A describes when the framework and probabilistic assessment can be used to obtain reliable results. This means that the framework and the probabilistic assessment can only be applied to project areas that are in line with these requirements. Additionally, it is assumed that the reduction in safety level is solely caused by the sea level rise. However, the reduced safety level can also be the result of land subsidence or reduced performance of the measures ("Wijziging van de Waterwet en enkele andere wetten", 2016). In the case study, land subsidence was assumed to be negligible. The strength of measures was assumed to remain the same over time as a result of an effective maintenance program. The use of the framework can therefore be justified. However, the framework requires some minor adjustments to include land subsidence and/or reduced strength when this is required for a particular case. Finally, one should also be aware of the restricted solution space when applying the framework.

7 Conclusion & recommendations

7.1. Conclusion

The objective of this thesis was to develop a method able to create and select effective adaptation pathways under uncertain conditions. A framework and probabilistic assessment have for that purpose been developed. This framework and assessment in combination with the literature study, have been used to answer the sub-questions. The answers can be found in the following paragraphs. Thereafter, these answers are used to answer the main research question.

Sub-question 1: What uncertainties can affect the effectiveness of flood risk reduction strategies?

This research question has been addressed by identifying uncertainties in literature that turn out to affect flood risk reduction strategies worldwide. It turned out that a distinction can be made between uncertainties as some can directly affect the actual and future safety level of an area, like the sea level rise rate and others can directly affect the economic evaluation of flood risk measures, like the discount rate and the socio-economic growth rate. To assess the influence of both uncertainties, a framework that automatically creates and evaluates flood risk strategies in line with the Dynamic Adaptive Policy Pathways (DAPP) approach has been developed. This framework made it possible to easily alter the conditions and assess the impact of these alterations on the effectiveness of flood risk strategies. This framework has been applied to a fictive case and a case study along the South East Coast of Singapore.

A small area, on which damage occurs according to a standard damage function retrieved from literature, was assumed for the fictive case. The discount rate and the socio-economic growth rate turned out to greatly affect the Net Present Value (NPV) and Cost-Benefit Ratio (CBR). The NPV even increased by a factor of 5 for both subtracting 2% from the discount rate and adding 2% to the socio-economic growth rate. Although the discount rate is often fixed and a political choice, the fictive case shows that a decrease in the discount rate results in higher safety levels and therefore less flexible solutions. Showing this sensitivity therefore might affect the choice of discount rate to obtain results in line with an envisaged strategy (e.g. flexible or inflexible solutions). Uncertainties like the inflation rate turned out to have a less significant impact on the effectiveness of flood risk strategies. The inflation rate affects the costs and the socio-economic growth rate affects the reduced risk and therefore benefits. The benefits were larger than the costs in the fictive case as the NPV was positive, and therefore, it is likely that the influence of both uncertainties is impacted by the ratio between the benefits and costs.

The case study along the City East Coast of Singapore showed that the outcome was very sensitive to both the sea level rise scenario assumed and whether or not to account for increased storm surge ascribed to climate change. Flood risk reduction measures turned out to be required more than 50 years earlier when assuming the 95th quantile instead of the median of the same sea level rise scenario and including increased storm surge. This substantial sensitivity is likely to be amplified as a result of the narrow distribution of water levels which is characteristic of the specific project area, i.e. a relatively small difference ($\sim$15 centimeters) between water levels that differ a factor 10 in return period. Therefore the sensitivity will not be as substantial everywhere. It does, however, illustrate the importance of assessing adaptation pathways in the full range of possible futures. Land subsidence was irrelevant to both the fictive case and the case study. However, the influence of such an uncertainty should be assessed per case study as it is very case-specific.

Sub-question 2: How can the creation of possible adaptation pathways be implemented in flood risk management?
The creation of possible adaptation pathways can be implemented in flood risk management by applying the framework that has been created for this thesis. This framework automatically creates adaptation pathways out of optimised individual measures and calculates the total costs and flood risk reduction (benefits) of the obtained pathways. This enables comparing the effectiveness of pathways for set conditions. The framework requires the damages, corresponding to certain water levels, to obtain the damage function of a project area. These damages can be modelled with damage modules like the Global Flood Risk Tool (GFRT). The obtained damages and other basic information like dimensions and conditions, are used by the framework to create flood risk reduction strategies out of individual measures. These individual measures are economically optimised to reduce the amount of possible flood risk strategies. The points in time the safety level requirement is no longer met is identified per individual measure. These points in time are called Adaptation Tipping Points (ATPs). A new measure is applied after such an ATP. The framework also includes an economic evaluation of all pathways to be able to compare the effectiveness of different possible adaptation pathways. The framework can be used to get a feel of which measures are effective in what conditions for specific project areas. It can also be used to assess the sensitivity to uncertain conditions as has been done for the first sub-question and to obtain the conditions for which a different adaptation pathway turns out to be more effective.

The framework has been applied to the fictive case to verify its use as a tool to create adaptation pathways as prescribed by the DAPP approach. The framework turned out to create pathways in which the ATPs of individual measures exceeded the end of the technical lifetime of measures. Long lifetimes usually correspond to high safety levels. High safety levels result in high investment costs and when the conditions turn out to be less severe, investments have already been made and cannot be adjusted to the actual occurring conditions. As the DAPP approach should allow for flexibility, it is in this perspective also necessary to restrict the lifetime.

It was also found in the fictive case that a more severe SLR could result in shorter lifetimes of measures. Especially in combination with a narrow distribution and a high required safety level as a result of a risk-averse strategy, it can lead to practically infeasible heights (lower than 10 cm). The value at which the linear cost relation starts, was by default set to 0.5 meters to prevent these practically infeasible heights from occurring. Measures with lower heights than this minimum value would therefore have the same costs as measures with a height equal to the value. As the benefits of pathways with a height lower than this value will be lower, these measures will automatically not be chosen by the framework. After these adjustments, the framework could be used to obtain possible adaptation pathways in line with the DAPP approach as has been illustrated in the case study of the South East Coast of Singapore. It turned out to be necessary to add an additional freeboard to the height of the applied measures as a result of the narrow water level distribution. This case study also showed that it can be necessary to subdivide a project area as measures can have different scales of impact.

Sub-question 3: Can different conditions lead to a different preferred adaptation pathway? If so, how can the approach be adjusted to assess more combinations of conditions?
This research question has been addressed by applying the framework to the fictive case and to the case study in Singapore. An increase in size of the fictive case resulted in the flood wall being the most effective first measure instead of the landfill illustrating that the characteristics of a project area can determine which flood risk reduction strategy is most effective. The effectiveness of adaptation pathways is also dependent on the assumed conditions and for that fictive case specifically, especially on the assumed discount rate and socio-economic growth rate. Subtracting 2% from the discount rate for instance resulted in an increase in safety level and correspondingly in an increased height of the first measure, making the application of the second measure no longer necessary. A different adaptation pathway was therefore desired and the NPV increased by a factor of 5. Choosing the 95th quantile of

a sea level rise scenario instead of the median and including the increase in storm surge for the case study, resulted in measures being required over 50 years earlier and a different pathway having the highest NPV.

Both cases illustrate that a different pathway can be preferred if the conditions are different than assumed. This outcome cannot be considered a surprise as, for instance, increased sea level rise intuitively leads to higher levees. However, the sensitivity of these cases to the assumed conditions is considerable. Selecting such a pathway should therefore not been done based on an estimation of the conditions like done in the framework but the effectiveness of pathways should also be examined in the full range of futures.

As the framework that has been developed does not evaluate the performance for the full range of futures, the approach has been supplemented with a probabilistic assessment able to assess the robustness of pathways. This is done by means of a Monte Carlo simulation. A robust pathway will have a narrow range of outcomes in comparison to a frail pathway. Choosing such a pathway reduces the chance of considerable underperformance compared to the design conditions. This could be seen back in the probabilistic assessment of the fictive case in which an increased range of uncertainty resulted in a considerably lower 5th quantile (NPV of 0.87 M€ vs. 1.21 M€) and a considerably higher 95th quantile (NPV of 4.52 M€ vs. 2.80 M€). The percentage of outcomes being higher than the NPV obtained out of the framework, was not severely affected by this wider range (50% vs. 52%). This can, however, be the case when the impact of skewed distributions is more considerable. For example, when the socio-economic growth rate is described using a skewed distribution. The case study showed that the pathway solely consisting of a flood wall and flood wall increments was slightly more costly but also turned out to be more robust. 58% of the simulations lead to a NPV higher than 750 M SGD while this was 51% for the pathway with dryproofing as first measure and subsequently a flood wall and a flood wall increment. Additionally, dryproofing can lead to inundation of the land for high water events with a return period lower than the safety standard while Singapore has set the goal to protect its coastlines and prevent inundation of the land. Therefore, the pathway consisting of a flood wall and flood wall increments turns out to be the most suitable flood risk reduction strategy for the case study.

When actions have to be taken to prevent the actual safety level from dropping below the required one while uncertainties like the sea level rise remain uncertain, conditions have to be assumed as input for the framework. In that case, the case study of Singapore showed that under-adaptation is preferred over over-adaptation as over-adaptation turned out to have higher relative impact on the NPV. Under-adaptation can be defined as a design being based on conditions less severe than the actual conditions while over-adaptation is the opposite. However, as this is dependent on the combination of damages, costs of measures, required safety level, the discount rate and other factors, this should not be considered the general truth and should be evaluated for each individual project area.

Sub-question 4: When should triggers to initiate (corrective) actions be set for the selected pathway in uncertain conditions?
Trigger values should initiate actions to prevent the actual safety level from dropping below the required safety level. The fictive case showed that the chosen sea level rise scenario can affect the magnitude of trigger values. The trigger value changed from a return period of flooding of 177 years to 479 years when a more severe sea level rise was assumed. The DAPP approach should facilitate flexible strategies and prevent the exclusion of subsequent measures as a result of too limited time to implement them. This could be seen back in the fictive case, where trigger values of the selected pathway resulted in insufficient time to implement other measures, like a storm surge barrier, without the actual safety level dropping below the required one. To ensure the flexibility of being able to choose all of the possible subsequent measures, trigger values should be set for the measure with the longest implementation time.

The trigger values used in the framework are directly related to the sea level rise and the maximum lifetime of measures. However, subsequent actions can also be desired as a result of socio-economic developments, knowledge and innovation and societal preferences. This can for instance be the case when innovation reduces the price of measures making it more attractive to apply measures.

Main research question: How can the Dynamic Adaptive Policy Pathways (DAPP) approach be used to create and select effective flood risk strategies under highly uncertain conditions?

A method has been developed enabling the creation and selection of adaptation pathways according to the DAPP approach. This method uses a framework that automatically builds these pathways out of individual measures that have economically been optimised. A selection of pathways can be made based on prerequisites and a Cost-Benefit Analysis (CBA). The framework makes it easy to evaluate numerous scenarios by simply adjusting the input. The damages that are required as input can be modelled with damage modules like the GFRT. As applying scenarios does not evaluate the performance of a pathway in the full range of futures, it might happen that the actual conditions severely differentiate from the assumed conditions and the NPV of the flood risk strategy is drastically decreased. The probabilistic assessment can be used to evaluate the performance of the selection of pathways in the full range of possible futures and select a robust flood risk strategy. The framework can afterwards be used to obtain trigger values for the selected pathway. These triggers should provide enough time to implement subsequent measures while allowing for flexibility. Continuous monitoring of the actual sea level rise is required as these trigger values are influenced by it.

7.2. Recommendations

The DAPP approach is a relatively new approach that had not widely been applied at the moment of writing. This resulted in an approach in which complications had to be solved using trial and error. Therefore, not all aspects of the DAPP-approach could be worked out in the same level of detail resulting in the following set of recommendations. The recommendations are ordered by priority. More accurate outcomes will be obtained if these recommendations are followed and therefore this would also result in a more accurate outcome for the case study of Singapore.

1. **Include transfer costs**
   Transfer costs explicitly reflect the cost of maintaining flexibility in the face of deep uncertainty. Including them leads to a more reliable cost estimate of adaptation pathways. The transfer costs can be included in absolute numbers or as a ratio between the transfer costs and total costs. When applying a ratio for this, it be can applied to different amounts of unit costs. Compiling these estimates requires additional research.
2. **Incorporate adaptability within the probabilistic assessment**
   Incorporating adaptability within the probabilistic approach allows for measures that are adapted to the actual circumstances. In the current probabilistic assessment, the type and safety level of subsequent measures are fixed. Adjusting the type and safety level of subsequent measures to the actually occurring conditions, leads to a more accurate assessment.
3. **Apply the probabilistic assessment to all pathways**
   The probabilistic assessment has so far been applied to a selection of pathways as this process has not been automated yet, unlike the deterministic assessment. Automating this process allows for assessing all created pathways probabilistically.
4. **Include the uncertainty of damages and water levels in the probabilistic assessment**
   The damages and water levels have been filled in as deterministic while they comprise statistical and model uncertainty. One would have to define the range of uncertainty before being able to include them.
5. **Annual reassessment of the required safety level time**
   The increase in risk can lead to a stricter safety level requirement over time. An annual reevaluation of this requirement can be implemented to account for this.
6. **Incorporate a wider range of trigger values**
   The current framework uses the implementation time of subsequent measures. Changing circumstances can make it desirable to adjust the timing or type of subsequent measures. Additionally, trigger values to account for socio-economic developments, knowledge and innovation and societal preferences can be included.
7. **Expand the solution space**
   Expanding the solution space increases the chance of the most suitable solution being chosen. This can be done by increasing the number of measures and including additional sequences of measures. Wetproofing can for instance be included.
8. **Ensure practical feasibility of construction**
   The obtained height of measures had an accuracy in the order of centimeters which conflicted with the practical feasibility during construction. Therefore, the height of measures should be rounded off to the nearest 10 centimeters. This would affect the costs of measures, the timing of the ATP and it may result in equal heights for different safety levels.
9. **Increase the applicability of the framework**
   Appendix A explicated the requirements that project areas had to comply with before the framework could be used. Including phenomena like waves in the frameworks increases the applicability of the framework.

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A
Requirements project area

Not all projects areas are suitable to apply the framework to. This is the result of multiple assumptions and simplifications made in the framework. Therefore, a project area has to fulfill the following requirements:

- Water should not be able to flow in via land (independent functioning area);
- Limited height differences within the area;
- Overtopping is not strong enough to cause a breach (either not a lot of overtopping due to mild conditions or strong measures);
- Low vulnerability to other failure mechanisms than overflow (else counter-measures have to be taken in order to prevent);
- No initial measures have been applied yet;
- Extreme water levels can be described according to Gumbel distribution;
- The area fills up completely.

The latter requirement is dependent on the characteristics of the site area. The equation to obtain the discharge over a weir with free flow can be used check this assumption. That equation is as following:

$$\mathrm{Q} = m * L * \frac{2}{3} * \sqrt{\frac{2}{3} * g} * h_1^{\frac{3}{2}} \tag{A.1}$$

in which Q is the discharge in m^3/s, m is the discharge coefficient, L is the length of the measure, g is the gravitational constant and h_1 is the water depth above the height of the measure. The default value for the discharge coefficient is 0.8 (RioNed, 2019). This formula is just valid until $h_2 > 2/3 h_1$ (RioNed, 2019), with h_1 and h_2 defined in Figure A.1. Since this is almost equal to the complete inundation depth, the equation can be used to assess whether an area complies to this criterion. The time it takes to fill up the area versus the water depth above a measure is plotted in Figure A.2a with A/L = 10,000 m, an assumed measure height of 2 meter and m = 0.8. It can be seen that low water depths result in longer fill up times which may lead to an overestimation of the damage if the high water event do not last long enough. The time it takes to fill up the area versus the ratio between the total area and the length of the measures is plotted in Figure A.2b with h_1 = 0.2 m, the height of the measure is 2 meter and m = 0.8. It can clearly be seen that the time it takes to fill up the area exponentially increases. An area is suitable when the time corresponding to the ratio of the project area is smaller than the duration of the extreme water levels. The time it takes to fill up the area versus the ratio between the total area and the length of the measures is plotted in Figure A.2c for h_1 = 0.2 m, A/L = 10,000 m and m = 0.8. It can be seen that the time it takes to fill up the area increases for higher measures. This means that when the β of the Gumbel distribution is large or the SLR is extreme, measures are required to be higher and this assumptions needs to be reassessed.

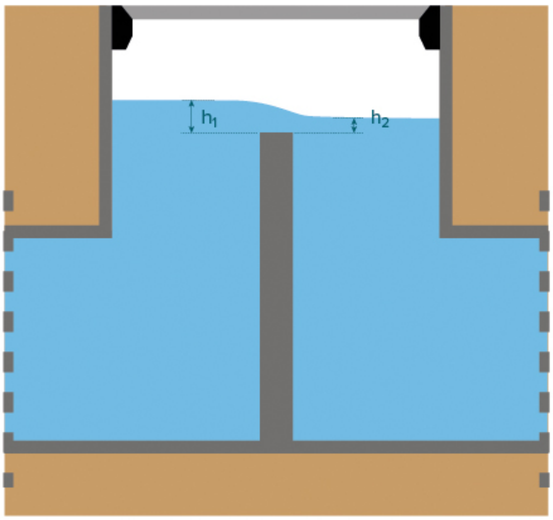
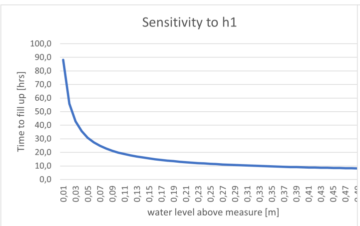
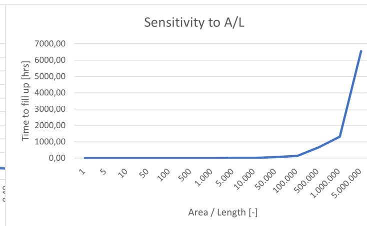


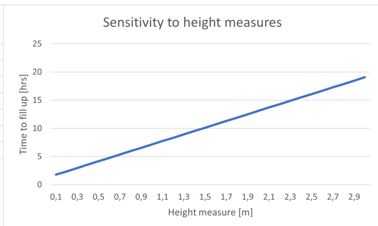
Figure A.1: h_1 and h_2 visualised (RioNed, 2019)



(a) Sensitivity to water levels of time required to fill up



(b) Sensitivity to ratio Area and Length of time required to fill up



(c) Sensitivity to height of measures of time required to fill up

Figure A.2: A sensitivity analysis for the time required to fill up

B

Required input

Table B.1: The required input-parameters

Input	Description	Has an influence on
Region [-]	The region the site is in. A choice can be made between regions in the world	- the local sea level rise - the costs of implementing measures
Desired protection level [yrs]	This is the protection level that has to be reached at all times	- the moment a new measure will be applied
Actual protection level [yrs]	The protection level which is currently true	- the damage curves - moment of implementation of first measure
Req. length of levee to increase safety level [m]	The length of a levee that has to be built to protect the complete area	- the investment, operation and maintenance costs of the levee
Buildings that require dryproofing / elevation [-]	The number of buildings that require dryproofing / elevation to be implemented	- the investment, operation and maintenance costs of dryproofing / elevation
Req. barrier length [m]	The length of a barrier that has to be built to protect the complete area	- the investment, operation and maintenance costs of the barrier
Protection area [km^2]	The area of the site	- the investment, operation and maintenance costs of the landfill and dryproofing
Year of data [-]	The year of the data of the current protection level, water level and damage	- the amount of SLR already has taken place - when socio-economic growth starts - the year of the present value
Currency [-]	The currency in which the input and output will be shown	- the currency of the input and output of damage and CBA
β and μ of the Gumbel distribution [m]	The parameters of the Gumbel distribution	- the water levels corresponding to RPs - the safety level of WLs
Damage [in millions]	The corresponding damages of certain return periods	- the current and future annual risk - the damage curves
Sea level rise scenario [-]	The scenario of sea level rise	- the amount of sea level rise - the moment a new measure is required
Socio-economic growth rate [%]	The increase in value in the area per year due to social and economic changes	- the future annual risk
Discount rate [%]	A rate to bring future benefits or costs in the present value	- the value of the future risk and investments
Inflation rate [%]	The rate at which prices increase over time resulting in a reduction of the value of money	- the costs of measures in the future
Measures to include [-]	The measures that have to be included to build up adaptation pathways. The measures that can be included can be found in table 3.1	- the measures that will be included in the automatically created pathways
Safety level of the barrier [yrs]	The way the safety level of the barrier has to be defined; either by a certain failure probability of closure or by a set protection level	- the required input to define the safety level of the barrier

Determination of the optimal safety level [-]	The way the optimal safety level of a certain measure is determined: either by a B/C-ratio, NPV or total costs	- the choice of the optimal safety level of a measure
Divide by the annuity factor for optimisation	If the NPV or total costs have to be divided by the annuity factor to obtain the optimal safety level	- the way optimal safety level is determined - the way the optimal AP is chosen

C
Input conditions

Site-specific characteristics				
region		South East Asia		
desired protection level	1.000	year		
actual protection level	100	year		
required length of levee to increase safety level	100	m		
required barrier length	20	m		
Required length dryproofing	1.000	m		
Protection area	0,100	km2		
Current conditions				
year of data	2022			
Currency	EURO			
Gumbel distribution	beta =	0,09	mu =	2,8

	Current situation				Situation with +		0,5	m SLR	Situation with +		2	m SLR
Return period	**Water level**		**Corresp. Damage in millions**		**Water level**		**Corresp. Damage in millions**		**Water level**		**Corresp. Damage in millions**	
10	3,00	+m ref	-	EURO	3,50	+m ref	0,75	EURO	5,00	+m ref	5,50	EURO
100	3,21	+m ref	-	EURO	3,71	+m ref	1,25	EURO	5,21	+m ref	6,50	EURO
1.000	3,42	+m ref	0,50	EURO	3,92	+m ref	2,25	EURO	5,42	+m ref	7,00	EURO
10.000	3,63	+m ref	1,00	EURO	4,13	+m ref	3,00	EURO	5,63	+m ref	7,40	EURO
50.000	3,77	+m ref	1,50	EURO	4,27	+m ref	3,50	EURO	5,77	+m ref	7,80	EURO
100.000	3,84	+m ref	2,00	EURO	4,34	+m ref	4,00	EURO	5,84	+m ref	8,10	EURO
500.000	3,98	+m ref	2,50	EURO	4,48	+m ref	4,50	EURO	5,98	+m ref	8,30	EURO
max damage	7	+m ref	9,00	EURO								

Future conditions		
Sea level rise scenario	P95 SSP5-8.5	
Socio-economic growth rate	2	%
Discount rate	4	%
Inflation rate	1	%

Measures to include

Solutions to take into account

- ☑ Levee system
- ☑ Flood wall
- ☑ Deployable flood wall
- ☑ Landfill
- ☑ Dryproofing
- ☑ Wetproofing
- ☑ Barrier:
  - ○ with a failure probability for the closure of: 0,005 %
  - ◉ always functions with a lifetime of: 150 year

Figure C.1: The case used to compare interpolation and growth rate to obtain risk for the intermediate years

D
Python-functions

D.1. ROA deterministic check

In [1]:

```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import numpy.random as rnd
import pandas as pd
from pandas import read_csv
from IPython.display import display
import matplotlib.dates as mdates
import openturns as ot
import openturns.viewer as viewer
import random
from numpy import log as ln
```

In [2]:

```
def Damage(x): #in millions
    global D
    if x == 0:
        D = 0
    elif x > 0 and x <=0.35:
        D = x/0.35*0.178
    elif x > 0.35 and x <=0.4:
        D = (x-0.35)/0.05*(0.024)+0.178
    elif x > 0.4 and x <= 0.7:
        D = (x-0.4)/0.3*0.111+0.202
    elif x > 0.7 and x <= 0.75:
        D = (x-0.7)/0.05*0.016+0.313
    elif x > 0.75 and x <=1:
        D = (x-0.75)/0.25*0.075+0.329
    elif x > 1 and x <=1.04:
        D = (x-1)/0.04*0.009+0.404
    elif x > 1.04 and x <=1.10:
        D = (x-1.04)/0.06*0.011+0.413
    elif x > 1.1 and x <=1.29:
        D = (x-1.1)/0.19*0.038+0.424
    elif x > 1.29 and x <= 1.35:
        D = (x-1.29)/0.06*0.013+0.462
    elif x > 1.35 and x <= 1.39:
        D = (x-1.35)/0.04*0.008+0.475
    elif x > 1.39 and x <= 1.44:
        D = (x-1.39)/0.05*0.011+0.483
    elif x > 1.44 and x <= 1.63:
        D = (x-1.44)/0.19*0.037+0.494
    elif x > 1.63 and x <= 1.69:
        D = (x-1.63)/0.06*0.012+0.531
    elif x > 1.69 and x <= 1.70:
        D = (x-1.69)/0.01*0.002+0.543
    elif x > 1.70 and x <= 1.79:
        D = (x-1.70)/0.09*0.019+0.545
    elif x > 1.79 and x <= 2.03:
        D = (x-1.79)/0.24*0.047+0.564
    elif x > 2.03 and x <= 2.04:
        D = (x-2.03)/0.01*0.002+0.611
    elif x > 2.04 and x <= 2.29:
        D = (x-2.04)/0.25*0.036+0.613
    elif x > 2.29 and x <= 2.39:
        D = (x-2.29)/0.10*0.016+0.649
    elif x > 2.39 and x <= 2.63:
        D = (x-2.39)/0.23*0.037+0.665
    elif x > 2.63 and x <= 6:
        D = (x-2.63)/3.37*0.318+0.702
    else:
        D = 1.02
    return D
```

In [3]:
```
def SLR(year_impl):
    global SLR_implm
    if year_impl <= 2040:
        SLR_implm = (year_impl - 2014)/(2040-2014) * 0.14
    elif year_impl <= 2060:
        SLR_implm = (year_impl - 2040)/(2060-2040) * 0.1 + 0.14
    elif year_impl <= 2100:
        SLR_implm = (year_impl - 2060)/(2100-2060) * 0.24 + 0.24
    elif year_impl <=2200:
        SLR_implm = (year_impl - 2100)/(2200-2100) * 0.6 + 0.48
    return SLR_implm
```

In [4]:
```
def LY_fun(height_wm_req, year_impl): #height is difference between new and required leve
    global LY
    SLR_impl = SLR(year_impl)
    if height_wm_req <= 0.14-SLR_impl:
        r = 1 #random.normalvariate(1, 0.1)
        x = r*0.14
        y = 2040
        LY = (height_wm_req+SLR_impl)/(x)*(2040-2014)+2014  #Last year of lifetime
        SLR_nextm = (LY-2014)/(2040-2014)*x
    elif height_wm_req <= 0.24-SLR_impl:
        r = 1 #random.normalvariate(1, 0.1)
        x = r*0.24
        y = 2060
        LY = (height_wm_req+SLR_impl-(0.14/0.24)*x)/(x-(0.14/0.24)*x)*(2060-2040)+2040
        SLR_nextm = (LY-2040)/(2060-2040)*(x-(0.14/0.24)*x)+(0.14/0.24)*x
    elif height_wm_req <= 0.48-SLR_impl:
        r = 1 #random.normalvariate(1, 0.1)
        x = r*0.48
        y = 2100
        LY = (height_wm_req+SLR_impl-(0.24/0.48)*x)/(x-0.5*x)*(2100-2060)+2060
        SLR_nextm = (LY-2060)/(2100-2060)*(x-0.5*x)+0.5*x
    else:
        r = 1 #random.normalvariate(1, 0.1)
        x = r*1.08
        y = 2200
        LY = (height_wm_req+SLR_impl-(0.48/1.08)*x)/(x-(0.48/1.08)*x)*(2200-2100)+2100
        SLR_nextm = (LY-2100)/(2200-2100)*(x-(0.48/1.08)*x)+(0.48/1.08)*x
    return int(LY), r, SLR_nextm
```

In [5]:
```
def SLR_array(r, year_impl, year_end, SLR_impl):
    SLR2040 = r*0.14
    SLR2060 = r*0.24
    SLR2100 = r*0.48
    SLR2200 = r*1.08
    years_lifetime = np.arange(2014, 2401, 1)
    SLR_array = np.ones(len(years_lifetime))
    for i in range(len(SLR_array)):
        if i <=26:
            SLR_array[i] = i*SLR2040/(2040-2014)
        elif i <= 46:
            SLR_array[i] = (i-26)*(SLR2060-SLR2040)/(2060-2040)+SLR2040
        elif i <= 86:
            SLR_array[i] = (i-46)*(SLR2100-SLR2060)/(2100-2060)+SLR2060
        else:
            SLR_array[i] = (i-86)*(SLR2200-SLR2100)/(2200-2100)+SLR2100
    return SLR_array[year_impl-2014:year_end-2014+1]-SLR_impl
```

In [6]:
```
def LY_cons_fun(height_wm_req, r, SLR_impl): #height is difference between new and require
```

```
    global LY
    if height_wm_req <= 0.1-SLR_impl:
        x = r*0.14
        y = 2040
        LY = (height_wm_req+SLR_impl)/(x)*(2040-2014)+2014  #Last year of lifetime
        SLR_nextm = (LY-2014)/(2040-2014)*x
    elif height_wm_req <= 0.2-SLR_impl:
        x = r*0.24
        y = 2060
        LY = (height_wm_req+SLR_impl-0.5*x)/(x-0.5*x)*(2060-2040)+2040
        SLR_nextm = (LY-2040)/(2060-2040)*(x-0.5*x)+0.5*x
    elif height_wm_req <= 0.5-SLR_impl:
        x = r*0.48
        y = 2100
        LY = (height_wm_req+SLR_impl-0.4*x)/(x-0.4*x)*(2100-2060)+2060
        SLR_nextm = (LY-2060)/(2100-2060)*(x-0.4*x)+0.4*x
    else:
        x = r*1.08
        y = 2200
        LY = (height_wm_req+SLR_impl-0.4*x)/(x-0.4*x)*(2200-2100)+2100
        SLR_nextm = (LY-2100)/(2200-2100)*(x-0.4*x)+0.4*x
    return int(LY), SLR_nextm
```

In [7]:

```
def annual_risk(Saf_lev, beta, mu, heightmeasure): #hier wordt uitgegaan van de gumbel dis
    SL = [10, 100, 1000, 10000, 50000, 100000, 500000]
    x = np.ones(7)
    WL = np.ones(7)
    D = np.ones(7)
    WL_req = -ln(-ln(1-1/Saf_lev))*beta+mu
    for i in range(7):
        WL[i] = -ln(-ln(1-1/SL[i]))*beta+mu
        if SL[i] <= Saf_lev:
            x[i] = 0
        else:
            x[i] = WL[i] - WL_req + heightmeasure
        D[i] = Damage(x[i])*1000000
    Annual_risk = (1-1/SL[0])*D[0]/2+(1/SL[0]-1/SL[1])*(D[0]+D[1])/2+(1/SL[1]-1/SL[2])*(D
    return Annual_risk
```

In [8]:

```
def annual_risk_nm(WL_begin, SLR_LT, beta, mu): #hier wordt uitgegaan van de gumbel distr
    SL = [10, 100, 1000, 10000, 50000, 100000, 500000]
    x = np.ones(7)
    WL = np.ones(7)
    D = np.ones(7)
    for i in range(7):
        WL[i] = -ln(-ln(1-1/SL[i]))*beta+mu
        if WL[i] + SLR_LT <= WL_begin:
            x[i] = 0
        else:
            x[i] = WL[i] - WL_begin + SLR_LT
        D[i] = Damage(x[i])*1000000
    Annual_risk = (1-1/SL[0])*D[0]/2+(1/SL[0]-1/SL[1])*(D[0]+D[1])/2+(1/SL[1]-1/SL[2])*(D
    return Annual_risk
```

In [9]:

```
def risk_nm(year_impl, year_nextm, ac_Saf_lev, beta, mu, discount_rate, growth_rate, SLR_i
    SL_nm = np.ones(year_nextm-year_impl)
    SLR = SLR_array(r, year_impl, year_nextm-1, SLR_impl) #linear SLR assumed over lifeti
    Risk_nm = np.ones(year_nextm-year_impl)

    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    for i in range(year_nextm - year_impl):
```

```
        SL_nm[i] = 1/(1-np.exp(-np.exp(-(WL_begin-SLR[i]-mu)/beta)))
        Risk_nm[i] = annual_risk_nm(WL_begin, SLR[i], beta, mu) / (1+discount_rate)**(i) *
    return Risk_nm
```

In [10]:

```
def risk_wm(year_impl, year_nextm, ac_Saf_lev, Saf_lev_req, height_measure, beta, mu, disc
    SL_wm = np.ones(year_nextm-year_impl)
    SLR = np.ones(year_nextm-year_impl)
    Risk_wm = np.ones(year_nextm-year_impl)

    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    WLreq = -ln(-ln(1-1/Saf_lev_req))*beta+mu
    Saf_lev_wm = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-mu)/beta)))
    WLwm = -ln(-ln(1-1/Saf_lev_wm))*beta+mu
    for i in range(year_nextm - year_impl):
        SLR[i] = i*(SLR_impl-SLR_subs_measure)/(year_nextm-year_impl)
        SL_wm[i] = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-SLR[i]-mu)/beta)))
        Risk_wm[i] = annual_risk(SL_wm[i], beta, mu, height_measure+height_previous_meas)
    return Risk_wm
```

In [11]:

```
def risk_wm_landfill(year_impl, year_nextm, ac_Saf_lev, Saf_lev_req, height_measure, beta,
    SL_wm = np.ones(year_nextm-year_impl)
    SLR = np.ones(year_nextm-year_impl)
    Risk_wm = np.ones(year_nextm-year_impl)

    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    WLreq = -ln(-ln(1-1/Saf_lev_req))*beta+mu
    Saf_lev_wm = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-mu)/beta)))
    WLwm = -ln(-ln(1-1/Saf_lev_wm))*beta+mu
    for i in range(year_nextm - year_impl):
        SLR[i] = i*SLR_nextm/(year_nextm-2014)
        SL_wm[i] = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-SLR[i]-mu)/beta)))
        Risk_wm[i] = annual_risk(SL_wm[i], beta, mu, 0) / (1+discount_rate)**(i) *(1+growt
    return Risk_wm
```

In [12]:

```
def first_measure(year_impl, ac_Saf_lev, Saf_lev_req, height_measure, beta, mu, discount_r
    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    Saf_lev_wm = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-mu)/beta))) #verschil klopt
    difference_wm_req = -ln(-ln(1-1/Saf_lev_wm))*beta+mu - (-ln(-ln(1-1/Saf_lev_req))*beta
    LY1, r, SLR_nextm = LY_fun(difference_wm_req, year_impl) #deze height is de hoogte tus
    I = 1 * Inv1 * (1+inflation_rate)**(year_impl-2016) # discount rate is calculated now
    OM = np.ones(LY1-year_impl)
    for j in range(LY1-year_impl):
        OM[j] = 1 * perc_OM * I / (1+discount_rate)**(j+1) * (1+inflation_rate)**(j+1)
    OM_tot = np.sum(OM)
    Risk_wm =  sum(risk_wm_landfill(year_impl, LY1+1, ac_Saf_lev, Saf_lev_req, height_meas
    return LY1, Risk_wm, I, OM_tot, OM[-1]*(1+discount_rate)**(LY1-year_impl+1), r, SLR_ne
```

In [13]:

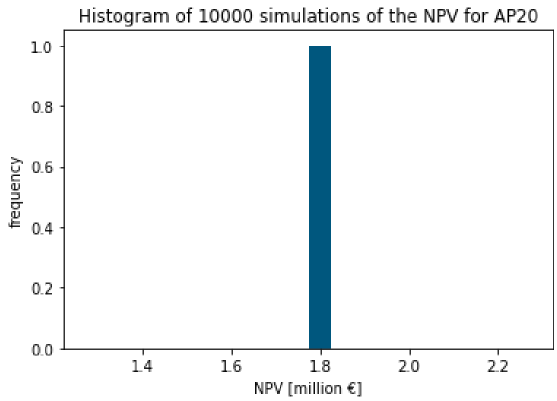
```
def consecutive_measure(year_impl, ac_Saf_lev, Saf_lev_req, height_measure, beta, mu, disc
    LY_cons, SLR_subs_measure = LY_cons_fun(height_measure, r, SLR_impl)  #deze height is
    I = 1 * Inv * (1+inflation_rate)**(year_impl-2016) # discount rate is calculated now -
    OM = np.ones(LY_cons-year_impl+1)
    for j in range(LY_cons-year_impl+1):
        OM[j] = 1 * perc_OM *I / (1+discount_rate)**(j) * (1+inflation_rate)**(j)
        OM[j] += OM_previous / (1+discount_rate)**(j+1) * (1+inflation_rate)**(j+1)
    OM[0] = OM_previous / (1+discount_rate)**(1) * (1+inflation_rate)**(1)
    #OM[0] = 0 only if a height increase is applied
    OM_tot = np.sum(OM)
    Risk_wm = sum(risk_wm(year_impl, LY_cons+1, ac_Saf_lev, Saf_lev_req, height_measure, b
    return LY_cons, Risk_wm, I, OM_tot, OM[-1]*(1+discount_rate)**(LY_cons-year_impl), SLF
```

In [14]:
```
def full_pathway(simulations, year_impl1, ac_Saf_lev, Saf_lev_req, height_measure1, height
    NPV = np.ones(simulations)
    for i in range(simulations):
        discount_rate = 4/100 # random.normalvariate(4/100, 0.4/100)
        inflation_rate = 2/100 # random.normalvariate(2/100, 0.2/100)
        socio_ec_growth_rate =  1/100 # random.normalvariate(1/100, 0.1/100)
        LY_1, Riskm1, I1, OM_tot1, OM1_LY, r, SLR_nextm1 = first_measure(year_impl1, ac_Sa
        LY_2, Riskm2, I2, OM_tot2, OM2_LY, SLR_nextm2 = consecutive_measure(LY_1+1, Saf_le
        Risknm = np.sum(risk_nm(year_impl1, LY_2, ac_Saf_lev, beta, mu, discount_rate, soc
        NPV[i] = 1 * (Risknm - Riskm1 - Riskm2/(1+discount_rate)**(LY_1+1-year_impl1)) -
        print(LY_1+1,LY_2+1)
        print(OM_tot1, OM_tot2)
        print(NPV / (1+discount_rate)**(year_impl1-2021) / 1000000)
    return NPV / (1+discount_rate)**(year_impl1-2021) / 1000000
```

In [17]:
```
simulations = 10000
plt.hist(full_pathway(1, 2023, 9.343, 100, 1.0494, 0.3461, 0.34607, 131460, 173033, 0, 0.0
plt.ylabel('frequency')
plt.xlabel('NPV [million €]')
plt.title('Histogram of {} simulations of the NPV for AP20'.format(simulations))
```

```
2143 2201
13874.899093055901 479480.6779763197
[1.77350363]
```

Out[17]:
```
Text(0.5, 1.0, 'Histogram of 10000 simulations of the NPV for AP20')
```



In [ ]:

D.2. ROA AP20

In [1]:

```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import numpy.random as rnd
import pandas as pd
from pandas import read_csv
from IPython.display import display
import matplotlib.dates as mdates
import openturns as ot
import openturns.viewer as viewer
import random
from numpy import log as ln
```

In [2]:

```
def Damage(x): #in millions
    global D
    if x == 0:
        D = 0
    elif x > 0 and x <=0.35:
        D = x/0.35*0.178
    elif x > 0.35 and x <=0.4:
        D = (x-0.35)/0.05*(0.024)+0.178
    elif x > 0.4 and x <= 0.7:
        D = (x-0.4)/0.3*0.111+0.202
    elif x > 0.7 and x <= 0.75:
        D = (x-0.7)/0.05*0.016+0.313
    elif x > 0.75 and x <=1:
        D = (x-0.75)/0.25*0.075+0.329
    elif x > 1 and x <=1.04:
        D = (x-1)/0.04*0.009+0.404
    elif x > 1.04 and x <=1.10:
        D = (x-1.04)/0.06*0.011+0.413
    elif x > 1.1 and x <=1.29:
        D = (x-1.1)/0.19*0.038+0.424
    elif x > 1.29 and x <= 1.35:
        D = (x-1.29)/0.06*0.013+0.462
    elif x > 1.35 and x <= 1.39:
        D = (x-1.35)/0.04*0.008+0.475
    elif x > 1.39 and x <= 1.44:
        D = (x-1.39)/0.05*0.011+0.483
    elif x > 1.44 and x <= 1.63:
        D = (x-1.44)/0.19*0.037+0.494
    elif x > 1.63 and x <= 1.69:
        D = (x-1.63)/0.06*0.012+0.531
    elif x > 1.69 and x <= 1.70:
        D = (x-1.69)/0.01*0.002+0.543
    elif x > 1.70 and x <= 1.79:
        D = (x-1.70)/0.09*0.019+0.545
    elif x > 1.79 and x <= 2.03:
        D = (x-1.79)/0.24*0.047+0.564
    elif x > 2.03 and x <= 2.04:
        D = (x-2.03)/0.01*0.002+0.611
    elif x > 2.04 and x <= 2.29:
        D = (x-2.04)/0.25*0.036+0.613
    elif x > 2.29 and x <= 2.39:
        D = (x-2.29)/0.10*0.016+0.649
    elif x > 2.39 and x <= 2.63:
        D = (x-2.39)/0.23*0.037+0.665
    elif x > 2.63 and x <= 6:
        D = (x-2.63)/3.37*0.318+0.702
    else:
        D = 1.02
    return D
```

In [3]:

```
def SLR(year_impl):
    global SLR_implm
    if year_impl <= 2040:
        SLR_implm = (year_impl - 2014)/(2040-2014) * 0.14
    elif year_impl <= 2060:
        SLR_implm = (year_impl - 2040)/(2060-2040) * 0.1 + 0.14
    elif year_impl <= 2100:
        SLR_implm = (year_impl - 2060)/(2100-2060) * 0.24 + 0.24
    elif year_impl <=2200:
        SLR_implm = (year_impl - 2100)/(2200-2100) * 0.6 + 0.48
    return SLR_implm
```

In [4]:

```
def LY_fun(height_wm_req, year_impl): #height is difference between new and required leve
    global LY
    SLR_impl = SLR(year_impl)
    if height_wm_req <= 0.14-SLR_impl:
        r = random.normalvariate(1, 0.1)
        x = r*0.14
        y = 2040
        LY = (height_wm_req+SLR_impl)/(x)*(2040-2014)+2014  #Last year of lifetime
        SLR_nextm = (LY-2014)/(2040-2014)*x
    elif height_wm_req <= 0.24-SLR_impl:
        r = random.normalvariate(1, 0.1)
        x = r*0.24
        y = 2060
        LY = (height_wm_req+SLR_impl-(0.14/0.24)*x)/(x-(0.14/0.24)*x)*(2060-2040)+2040
        SLR_nextm = (LY-2040)/(2060-2040)*(x-(0.14/0.24)*x)+(0.14/0.24)*x
    elif height_wm_req <= 0.48-SLR_impl:
        r = random.normalvariate(1, 0.1)
        x = r*0.48
        y = 2100
        LY = (height_wm_req+SLR_impl-(0.24/0.48)*x)/(x-0.5*x)*(2100-2060)+2060
        SLR_nextm = (LY-2060)/(2100-2060)*(x-0.5*x)+0.5*x
    else:
        r = random.normalvariate(1, 0.1)
        x = r*1.08
        y = 2200
        LY = (height_wm_req+SLR_impl-(0.48/1.08)*x)/(x-(0.48/1.08)*x)*(2200-2100)+2100
        SLR_nextm = (LY-2100)/(2200-2100)*(x-(0.48/1.08)*x)+(0.48/1.08)*x
    return int(LY), r, SLR_nextm
```

In [5]:

```
def SLR_array(r, year_impl, year_end, SLR_impl):
    SLR2040 = r*0.14
    SLR2060 = r*0.24
    SLR2100 = r*0.48
    SLR2200 = r*1.08
    years_lifetime = np.arange(2014, 2401, 1)
    SLR_array = np.ones(len(years_lifetime))
    for i in range(len(SLR_array)):
        if i <=26:
            SLR_array[i] = i*SLR2040/(2040-2014)
        elif i <= 46:
            SLR_array[i] = (i-26)*(SLR2060-SLR2040)/(2060-2040)+SLR2040
        elif i <= 86:
            SLR_array[i] = (i-46)*(SLR2100-SLR2060)/(2100-2060)+SLR2060
        else:
            SLR_array[i] = (i-86)*(SLR2200-SLR2100)/(2200-2100)+SLR2100
    return SLR_array[year_impl-2014:year_end-2014+1]-SLR_impl
```

In [6]:

```
def LY_cons_fun(height_wm_req, r, SLR_impl): #height is difference between new and require
```

```
    global LY
    if height_wm_req <= 0.1-SLR_impl:
        x = r*0.14
        y = 2040
        LY = (height_wm_req+SLR_impl)/(x)*(2040-2014)+2014  #Last year of lifetime
        SLR_nextm = (LY-2014)/(2040-2014)*x
    elif height_wm_req <= 0.2-SLR_impl:
        x = r*0.24
        y = 2060
        LY = (height_wm_req+SLR_impl-0.5*x)/(x-0.5*x)*(2060-2040)+2040
        SLR_nextm = (LY-2040)/(2060-2040)*(x-0.5*x)+0.5*x
    elif height_wm_req <= 0.5-SLR_impl:
        x = r*0.48
        y = 2100
        LY = (height_wm_req+SLR_impl-0.4*x)/(x-0.4*x)*(2100-2060)+2060
        SLR_nextm = (LY-2060)/(2100-2060)*(x-0.4*x)+0.4*x
    else:
        x = r*1.08
        y = 2200
        LY = (height_wm_req+SLR_impl-0.4*x)/(x-0.4*x)*(2200-2100)+2100
        SLR_nextm = (LY-2100)/(2200-2100)*(x-0.4*x)+0.4*x
    return int(LY), SLR_nextm
```

In [7]:

```
def annual_risk(Saf_lev, beta, mu, heightmeasure): #hier wordt uitgegaan van de gumbel dis
    SL = [10, 100, 1000, 10000, 50000, 100000, 500000]
    x = np.ones(7)
    WL = np.ones(7)
    D = np.ones(7)
    WL_req = -ln(-ln(1-1/Saf_lev))*beta+mu
    for i in range(7):
        WL[i] = -ln(-ln(1-1/SL[i]))*beta+mu
        if SL[i] <= Saf_lev:
            x[i] = 0
        else:
            x[i] = WL[i] - WL_req + heightmeasure
        D[i] = Damage(x[i])*1000000
    Annual_risk = (1-1/SL[0])*D[0]/2+(1/SL[0]-1/SL[1])*(D[0]+D[1])/2+(1/SL[1]-1/SL[2])*(D
    return Annual_risk
```

In [8]:

```
def annual_risk_nm(WL_begin, SLR_LT, beta, mu): #hier wordt uitgegaan van de gumbel distr
    SL = [10, 100, 1000, 10000, 50000, 100000, 500000]
    x = np.ones(7)
    WL = np.ones(7)
    D = np.ones(7)
    for i in range(7):
        WL[i] = -ln(-ln(1-1/SL[i]))*beta+mu
        if WL[i] + SLR_LT <= WL_begin:
            x[i] = 0
        else:
            x[i] = WL[i] - WL_begin + SLR_LT
        D[i] = Damage(x[i])*1000000
    Annual_risk = (1-1/SL[0])*D[0]/2+(1/SL[0]-1/SL[1])*(D[0]+D[1])/2+(1/SL[1]-1/SL[2])*(D
    return Annual_risk
```

In [9]:

```
def risk_nm(year_impl, year_nextm, ac_Saf_lev, beta, mu, discount_rate, growth_rate, SLR_i
    SL_nm = np.ones(year_nextm-year_impl)
    SLR = SLR_array(r, year_impl, year_nextm-1, SLR_impl) #linear SLR assumed over lifeti
    Risk_nm = np.ones(year_nextm-year_impl)

    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    for i in range(year_nextm - year_impl):
```

```python
        SL_nm[i] = 1/(1-np.exp(-np.exp(-(WL_begin-SLR[i]-mu)/beta)))
        Risk_nm[i] = annual_risk_nm(WL_begin, SLR[i], beta, mu) / (1+discount_rate)**(i) *
    return Risk_nm
```

In [10]:

```python
def risk_wm(year_impl, year_nextm, ac_Saf_lev, Saf_lev_req, height_measure, beta, mu, disc
    SL_wm = np.ones(year_nextm-year_impl)
    SLR = np.ones(year_nextm-year_impl)
    Risk_wm = np.ones(year_nextm-year_impl)

    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    WLreq = -ln(-ln(1-1/Saf_lev_req))*beta+mu
    Saf_lev_wm = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-mu)/beta)))
    WLwm = -ln(-ln(1-1/Saf_lev_wm))*beta+mu
    for i in range(year_nextm - year_impl):
        SLR[i] = i*(SLR_impl-SLR_subs_measure)/(year_nextm-year_impl)
        SL_wm[i] = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-SLR[i]-mu)/beta)))
        Risk_wm[i] = annual_risk(SL_wm[i], beta, mu, height_measure+height_previous_meas)
    return Risk_wm
```

In [11]:

```python
def risk_wm_landfill(year_impl, year_nextm, ac_Saf_lev, Saf_lev_req, height_measure, beta,
    SL_wm = np.ones(year_nextm-year_impl)
    SLR = np.ones(year_nextm-year_impl)
    Risk_wm = np.ones(year_nextm-year_impl)

    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    WLreq = -ln(-ln(1-1/Saf_lev_req))*beta+mu
    Saf_lev_wm = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-mu)/beta)))
    WLwm = -ln(-ln(1-1/Saf_lev_wm))*beta+mu
    for i in range(year_nextm - year_impl):
        SLR[i] = i*SLR_nextm/(year_nextm-2014)
        SL_wm[i] = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-SLR[i]-mu)/beta)))
        Risk_wm[i] = annual_risk(SL_wm[i], beta, mu, 0) / (1+discount_rate)**(i) *(1+growt
    return Risk_wm
```

In [12]:

```python
def first_measure(year_impl, ac_Saf_lev, Saf_lev_req, height_measure, beta, mu, discount_r
    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    Saf_lev_wm = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-mu)/beta))) #verschil klopt
    difference_wm_req = -ln(-ln(1-1/Saf_lev_wm))*beta+mu - (-ln(-ln(1-1/Saf_lev_req))*beta
    LY1, r, SLR_nextm = LY_fun(difference_wm_req, year_impl) #deze height is de hoogte tus
    I = random.lognormvariate(0.001,0.01) * Inv1 * (1+inflation_rate)**(year_impl-2016) #
    OM = np.ones(LY1-year_impl)
    for j in range(LY1-year_impl):
        OM[j] = random.lognormvariate(0.001,0.01) * perc_OM * I / (1+discount_rate)**(j+1)
    OM_tot = np.sum(OM)
    Risk_wm =  sum(risk_wm_landfill(year_impl, LY1+1, ac_Saf_lev, Saf_lev_req, height_meas
    return LY1, Risk_wm, I, OM_tot, OM[-1]*(1+discount_rate)**(LY1-year_impl+1), r, SLR_ne
```

In [13]:

```python
def consecutive_measure(year_impl, ac_Saf_lev, Saf_lev_req, height_measure, beta, mu, disc
    LY_cons, SLR_subs_measure = LY_cons_fun(height_measure, r, SLR_impl)  #deze height is
    I = random.lognormvariate(0.001,0.01) * Inv * (1+inflation_rate)**(year_impl-2016) # c
    OM = np.ones(LY_cons-year_impl+1)
    for j in range(LY_cons-year_impl+1):
        OM[j] = random.lognormvariate(0.001,0.01) * perc_OM *I / (1+discount_rate)**(j) *
        OM[j] += OM_previous / (1+discount_rate)**(j+1) * (1+inflation_rate)**(j+1)
    OM[0] = OM_previous / (1+discount_rate)**(1) * (1+inflation_rate)**(1)
    #OM[0] = 0 only if a height increase is applied
    OM_tot = np.sum(OM)
    Risk_wm = sum(risk_wm(year_impl, LY_cons+1, ac_Saf_lev, Saf_lev_req, height_measure, b
    return LY_cons, Risk_wm, I, OM_tot, OM[-1]*(1+discount_rate)**(LY_cons-year_impl), SLR
```

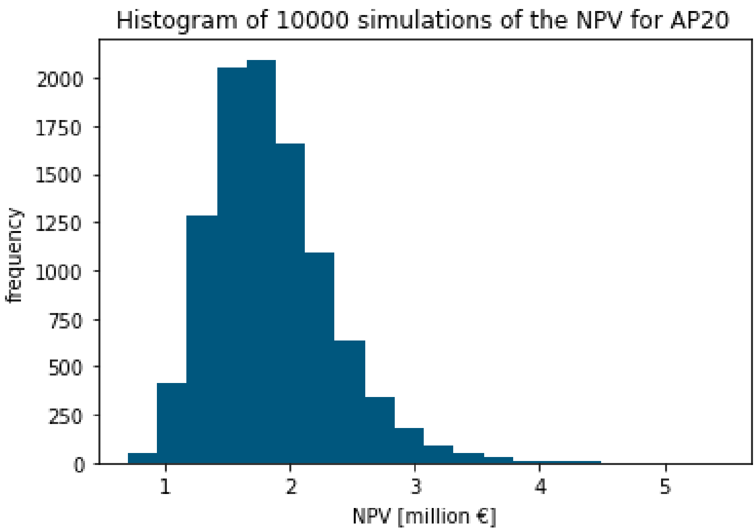
In [14]:

```
def full_pathway(simulations, year_impl1, ac_Saf_lev, Saf_lev_req, height_measure1, height
    NPV = np.ones(simulations)
    for i in range(simulations):
        discount_rate = random.normalvariate(4/100, 0.4/100)
        inflation_rate = random.normalvariate(2/100, 0.2/100)
        socio_ec_growth_rate =  random.normalvariate(1/100, 0.1/100)
        LY_1, Riskm1, I1, OM_tot1, OM1_LY, r, SLR_nextm1 = first_measure(year_impl1, ac_Sa
        LY_2, Riskm2, I2, OM_tot2, OM2_LY, SLR_nextm2 = consecutive_measure(LY_1+1, Saf_le
        Risknm = np.sum(risk_nm(year_impl1, LY_2, ac_Saf_lev, beta, mu, discount_rate, soc
        NPV[i] = random.lognormvariate(0.001,0.01) * (Risknm - Riskm1 - Riskm2/(1+discount
    return NPV / (1+discount_rate)**(year_impl1-2022) / 1000000
```

In [15]:

```
simulations = 10000
low_unc = full_pathway(simulations, 2023, 9.666, 100, 1.0494, 0.3461, 0.34607, 131460, 173
plt.hist(low_unc , color ='#00577E', bins=20)
plt.ylabel('frequency')
plt.xlabel('NPV [million €]')
plt.title('Histogram of {} simulations of the NPV for AP20'.format(simulations))
```

Out[15]: Text(0.5, 1.0, 'Histogram of 10000 simulations of the NPV for AP20')



In [16]:

```
def first_measure(year_impl, ac_Saf_lev, Saf_lev_req, height_measure, beta, mu, discount_r
    WL_begin = -ln(-ln(1-1/ac_Saf_lev))*beta+mu
    Saf_lev_wm = 1/(1-np.exp(-np.exp(-(WL_begin+height_measure-mu)/beta))) #verschil klopt
    difference_wm_req = -ln(-ln(1-1/Saf_lev_wm))*beta+mu - (-ln(-ln(1-1/Saf_lev_req))*beta
    LY1, r, SLR_nextm = LY_fun(difference_wm_req, year_impl) #deze height is de hoogte tus
    I = random.lognormvariate(0.01,0.1) * Inv1 * (1+inflation_rate)**(year_impl-2016) # di
    OM = np.ones(LY1-year_impl)
    for j in range(LY1-year_impl):
        OM[j] = random.lognormvariate(0.01,0.1) * perc_OM * I / (1+discount_rate)**(j+1) *
    OM_tot = np.sum(OM)
    Risk_wm =  sum(risk_wm_landfill(year_impl, LY1+1, ac_Saf_lev, Saf_lev_req, height_meas
    return LY1, Risk_wm, I, OM_tot, OM[-1]*(1+discount_rate)**(LY1-year_impl+1), r, SLR_ne
```

In [17]:

```
def consecutive_measure(year_impl, ac_Saf_lev, Saf_lev_req, height_measure, beta, mu, disc
    LY_cons, SLR_subs_measure = LY_cons_fun(height_measure, r, SLR_impl)  #deze height is
    I = random.lognormvariate(0.01,0.1) * Inv * (1+inflation_rate)**(year_impl-2016) # dis
    OM = np.ones(LY_cons-year_impl+1)
    for j in range(LY_cons-year_impl+1):
        OM[j] = random.lognormvariate(0.01,0.1) * perc_OM *I / (1+discount_rate)**(j) * (1
        OM[j] += OM_previous / (1+discount_rate)**(j+1) * (1+inflation_rate)**(j+1)
    OM[0] = OM_previous / (1+discount_rate)**(1) * (1+inflation_rate)**(1)
    #OM[0] = 0 only if a height increase is applied
```

```
    OM_tot = np.sum(OM)
    Risk_wm = sum(risk_wm(year_impl, LY_cons+1, ac_Saf_lev, Saf_lev_req, height_measure, h
    return LY_cons, Risk_wm, I, OM_tot, OM[-1]*(1+discount_rate)**(LY_cons-year_impl), SLR
```

In [18]:

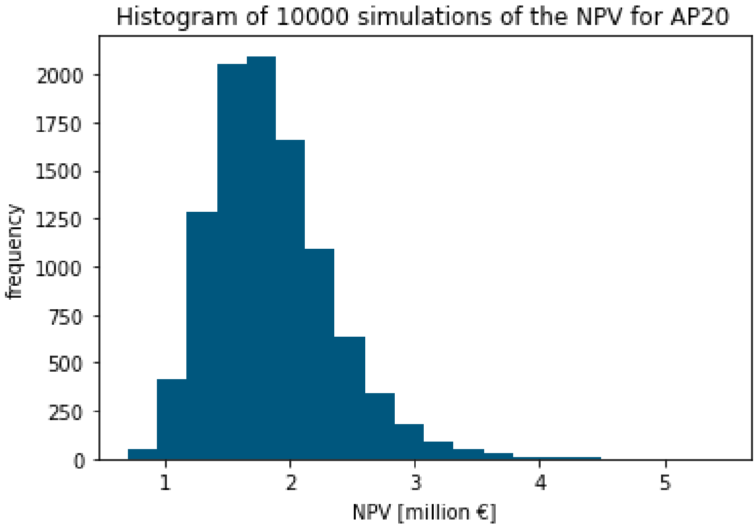
```
def full_pathway(simulations, year_impl1, ac_Saf_lev, Saf_lev_req, height_measure1, height
    NPV = np.ones(simulations)
    for i in range(simulations):
        discount_rate = random.normalvariate(4/100, 0.8/100)
        inflation_rate = random.normalvariate(2/100, 0.4/100)
        socio_ec_growth_rate =  random.normalvariate(1/100, 0.2/100)
        LY_1, Riskm1, I1, OM_tot1, OM1_LY, r, SLR_nextm1 = first_measure(year_impl1, ac_Sa
        LY_2, Riskm2, I2, OM_tot2, OM2_LY, SLR_nextm2 = consecutive_measure(LY_1+1, Saf_le
        Risknm = np.sum(risk_nm(year_impl1, LY_2, ac_Saf_lev, beta, mu, discount_rate, soc
        NPV[i] = random.lognormvariate(0.01,0.1) * (Risknm - Riskm1 - Riskm2/(1+discount_r
    return NPV / (1+discount_rate)**(year_impl1-2021) / 1000000
```

In [19]:

```
high_unc = full_pathway(simulations, 2023, 9.343, 100, 1.0494, 0.3461, 0.34607, 131460, 17
plt.hist(low_unc , color ='#00577E', bins=20)
plt.ylabel('frequency')
plt.xlabel('NPV [million €]')
plt.title('Histogram of {} simulations of the NPV for AP20'.format(simulations))
```

Out[19]:

```
Text(0.5, 1.0, 'Histogram of 10000 simulations of the NPV for AP20')
```

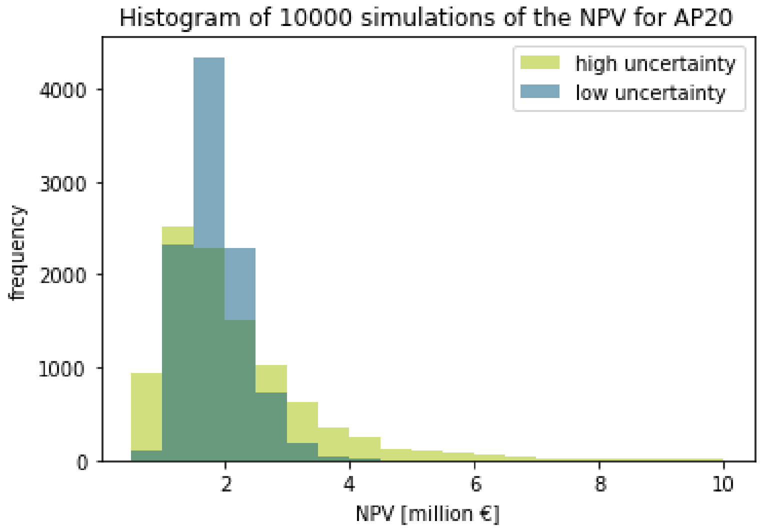


In [21]:

```
plt.hist(high_unc, bins=[0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6, 6.5, 7, 7.5, 8, 8
plt.hist(low_unc, bins=[0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6, 6.5, 7, 7.5, 8, 8.
plt.ylabel('frequency')
plt.xlabel('NPV [million €]')
plt.title('Histogram of {} simulations of the NPV for AP20'.format(simulations))
plt.legend()
```

Out[21]:

```
<matplotlib.legend.Legend at 0x1cee5943910>
```



Histogram of 10000 simulations of the NPV for AP20
high uncertainty
low uncertainty
frequency
4000
3000
2000
1000
0
2
4
6
8
10
NPV [million €]


```
In [ ]:
```

D.3. GEV water level

In [1]:

```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import numpy.random as rnd
import pandas as pd
from pandas import read_csv
from IPython.display import display
import matplotlib.dates as mdates
```

In [2]:

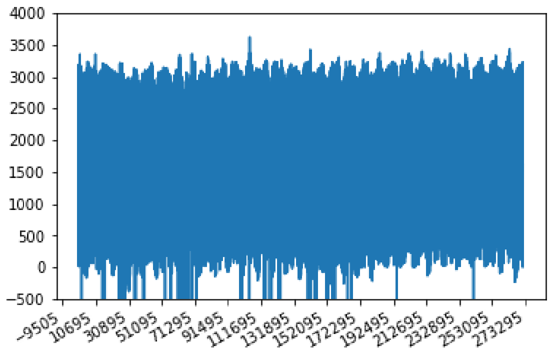
```
data = pd.read_csv('Sea_level_Data_Tanjong_Pagar.csv', index_col=0, skipinitialspace=True,
data['WL']
```

Out[2]:

```
year
1988.0    2520.0
1988.0    2610.0
1988.0    2490.0
1988.0    2170.0
1988.0    1690.0
           ...
2018.0    2380.0
2018.0    2300.0
2018.0    2120.0
2018.0    1850.0
2018.0    1620.0
Name: WL, Length: 271744, dtype: float64
```

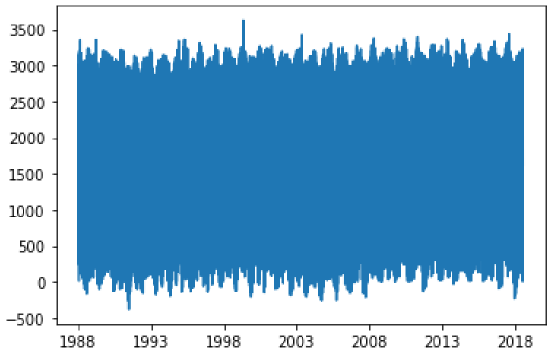
In [3]:

```
data.index = pd.to_datetime(data.index, format='%Y', errors='ignore')

plt.plot(data['WL'].dropna().values)
plt.gca().xaxis.set_major_locator(mdates.DayLocator(interval=20200))
plt.gcf().autofmt_xdate()
plt.ylim(-500, 4000);
```



In [4]:

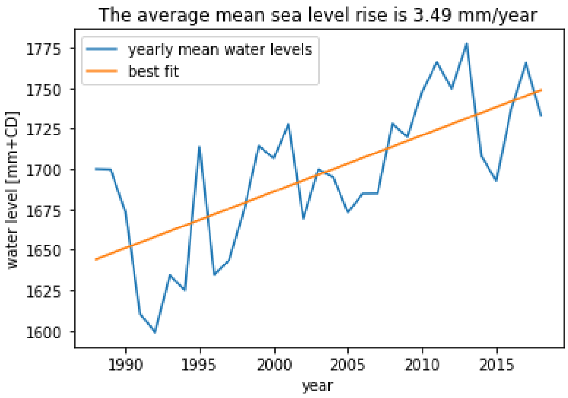
```
data = data['WL']

for i in range(len(data)):
    if data[i] < -500:
        data[i] = np.nan

plt.plot(data.dropna().values)
plt.xticks(np.linspace(0,255000,7), ['1988', '1993', '1998', '2003', '2008', '2013', '2018
```



In [5]:

```
yearly_max =np.ones(31)
yearly_mean =np.ones(31)
years = np.linspace(1988, 2018, 31)

for i in range(30):
    yearly_max[i] = data[i*8766:(i+1)*8766].max()
    yearly_mean[i] = data[i*8766:(i+1)*8766].mean()
yearly_max[30] = data[262992:271744].max()
yearly_mean[30] = data[262992:271744].mean()

print(yearly_max, yearly_mean)
plt.plot(years, yearly_mean, label='yearly mean water levels')
a, b = np.polyfit(years, yearly_mean, 1)
plt.plot(years, a*years+b, label = 'best fit')
plt.ylabel('water level [mm+CD]')
plt.xlabel('year')
plt.legend()
plt.title('The average mean sea level rise is {:.3} mm/year'.format(a))
print(a);
```

```
[3360. 3360. 3220. 3210. 3120. 3220. 3140. 3360. 3240. 3320. 3290. 3629.
 3202. 3269. 3270. 3220. 3430. 3230. 3313. 3278. 3289. 3380. 3270. 3400.
 3290. 3370. 3360. 3310. 3300. 3340. 3440.] [1700.03427651 1699.71943049 1673.53744389 161
0.29894375 1598.95953307
 1634.3613963  1624.93999746 1713.71949541 1634.60955124 1643.7477755
 1674.66381474 1714.29352397 1706.60002294 1727.59419886 1669.28357451
 1699.80321697 1694.88156346 1673.23889216 1684.69843267 1684.8108046
 1728.05795117 1719.83253479 1747.62974098 1766.03570614 1749.3693817
 1777.55509925 1707.9341775  1692.6914099  1736.54962355 1765.79329227
 1733.32198355]
3.487557320665418
```



In [6]:

```
yearly_max_adj = np.zeros(31)
for i in range(len(yearly_max)):
    yearly_max_adj[i] = yearly_max[i] + a*(len(yearly_max)-(i+1)-4) #gecorrigeerd tot 2014
    
mean = yearly_max_adj.mean()
std = yearly_max_adj.std()
```

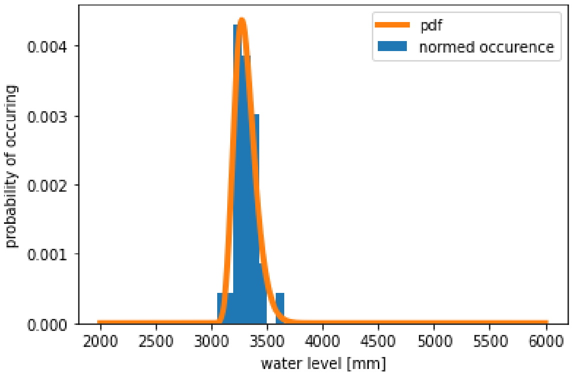
In [7]:

```
from scipy.stats import genextreme

shape_gev, location_gev, scale_gev = genextreme.fit(yearly_max)
print(shape_gev, location_gev, scale_gev)

input_WL = np.linspace(2000, 6000, 1000)
pdf_gev = genextreme.pdf(input_WL, shape_gev, loc=location_gev,
                         scale=scale_gev)
cdf_gev = genextreme.cdf(input_WL, shape_gev, loc=location_gev,
                         scale=scale_gev)
```

```
0.09251790449027092 3263.619388707063 84.46337398360578
```

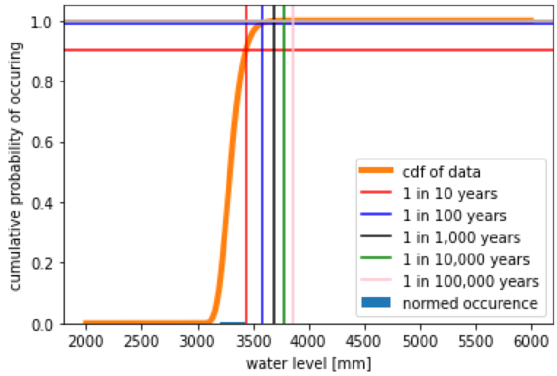
In [8]:

```
plt.hist(yearly_max, bins=40, range=(2000, 5000), density = True, label="normed occurence"
plt.plot(input_WL, pdf_gev, linewidth=4, label='pdf')
plt.ylabel('probability of occuring')
plt.xlabel('water level [mm]')
plt.legend();
```



In [9]:
```
plt.hist(yearly_max, bins=40, range=(2000, 5000), density=True, label="normed occurence")
plt.plot(input_WL, cdf_gev, linewidth=4, label='cdf of data')
plt.axhline(0.9, color='r')
WL_1_10 = np.interp(0.9, cdf_gev, input_WL)
plt.axvline(WL_1_10, color='r', label='1 in 10 years')
print('The water level with a return period of 10 years is', WL_1_10, 'mm')

plt.axhline(0.99, color='b')
WL_1_100 = np.interp(0.99, cdf_gev, input_WL)
plt.axvline(WL_1_100, color='b', label='1 in 100 years')
print('The water level with a return period of 100 years is', WL_1_100, 'mm')

plt.axhline(0.999, color='black')
WL_1_1000 = np.interp(0.999, cdf_gev, input_WL)
plt.axvline(WL_1_1000, color='black', label='1 in 1,000 years')
print('The water level with a return period of 1000 years is', WL_1_1000, 'mm')

plt.axhline(0.9999, color='green')
WL_1_10000 = np.interp(0.9999, cdf_gev, input_WL)
plt.axvline(WL_1_10000, color='green', label='1 in 10,000 years')
print('The water level with a return period of 10000 years is', WL_1_10000, 'mm')

plt.axhline(0.99999, color='pink')
WL_1_100000 = np.interp(0.99999, cdf_gev, input_WL)
plt.axvline(WL_1_100000, color='pink', label='1 in 100,000 years')
print('The water level with a return period of 100000 years is', WL_1_100000, 'mm')
plt.ylabel('cumulative probability of occuring')
plt.xlabel('water level [mm]')
plt.legend();
```

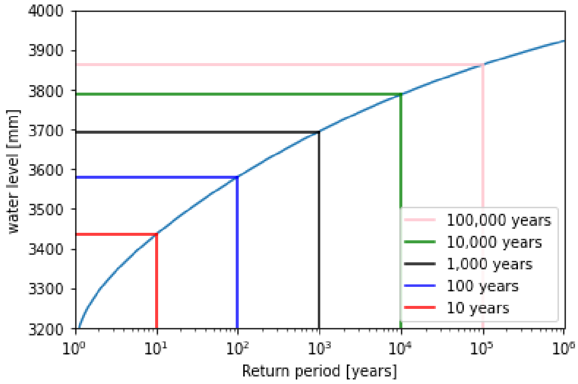
```
The water level with a return period of 10 years is 3435.2341703706616 mm
The water level with a return period of 100 years is 3580.0934001903656 mm
The water level with a return period of 1000 years is 3694.7445702610876 mm
The water level with a return period of 10000 years is 3787.2268911580113 mm
The water level with a return period of 100000 years is 3861.893594703078 mm
```



In [10]:
```
for i in range(len(cdf_gev)):
    if cdf_gev[i] < 0:
        cdf_gev[i] = np.nan
Return_period = 1 / (1 - cdf_gev)


plt.plot(Return_period, input_WL)
plt.ylim(3200, 4000)
plt.xlim(1, 1000000)
plt.xscale('log')
plt.xlabel('Return period [years]')
plt.ylabel('water level [mm]')
```

```
plt.plot()

plt.plot([1, 100000], [WL_1_100000, WL_1_100000], color='pink', label='100,000 years')
plt.plot([1, 10000], [WL_1_10000, WL_1_10000], color='green', label='10,000 years')
plt.plot([1, 1000], [WL_1_1000, WL_1_1000], color='black', label='1,000 years')
plt.plot([1, 100], [WL_1_100, WL_1_100], color='b', label='100 years')
plt.plot([1, 10], [WL_1_10, WL_1_10], color='r', label='10 years')

plt.plot([100000, 100000], [3200, WL_1_100000], color='pink')
plt.plot([10000, 10000], [3200, WL_1_10000], color='green')
plt.plot([1000, 1000], [3200, WL_1_1000], color='black')
plt.plot([100, 100], [3200, WL_1_100], color='b')
plt.plot([10, 10], [3200, WL_1_10], color='r')
plt.legend(loc='lower right');
```

```
C:\Users\922188\AppData\Local\Temp/ipykernel_20084/2864437533.py:4: RuntimeWarning: divide
by zero encountered in true_divide
  Return_period = 1 / (1 - cdf_gev)
```



In [11]:
```
for i in  range(len(yearly_max_adj)):
    yearly_max_adj[i] = round(yearly_max_adj[i])
print(yearly_max_adj)

shape_gev_adj, location_gev_adj, scale_gev_adj = genextreme.fit(yearly_max_adj)
print(shape_gev_adj, location_gev_adj, scale_gev_adj)

input_WL_adj = np.linspace(2000, 6000, 1000)
pdf_gev_adj = genextreme.pdf(input_WL_adj, shape_gev_adj, loc=location_gev_adj,
                         scale=scale_gev_adj)
cdf_gev_adj = genextreme.cdf(input_WL_adj, shape_gev_adj, loc=location_gev_adj,
                         scale=scale_gev_adj)
```

```
[3451. 3447. 3304. 3290. 3197. 3293. 3210. 3426. 3303. 3379. 3346. 3681.
 3251. 3314. 3312. 3258. 3465. 3261. 3341. 3302. 3310. 3397. 3284. 3410.
 3297. 3373. 3360. 3307. 3293. 3330. 3426.]
-5.571020941611099 3197.404998782228 2.256319550996495
```

In [12]:
```
Qi = []

for i in range(len(yearly_max_adj)):
    Qi.append(1- (i / (len(yearly_max_adj) + 1)))

yearly_max_adj.sort()
Return_period_values = np.ones(31)

for i in range(len(yearly_max_adj)):
    Return_period_values[i] = 1 + i
```

```
print(yearly_max_adj, Return_period_values)
```

```
[3197. 3210. 3251. 3258. 3261. 3284. 3290. 3293. 3293. 3297. 3302. 3303.
 3304. 3307. 3310. 3312. 3314. 3330. 3341. 3346. 3360. 3373. 3379. 3397.
 3410. 3426. 3426. 3447. 3451. 3465. 3681.] [ 1.  2.  3.  4.  5.  6.  7.  8.  9. 10. 11. 1
2. 13. 14. 15. 16. 17. 18.
 19. 20. 21. 22. 23. 24. 25. 26. 27. 28. 29. 30. 31.]
```

exponentional

In [13]:

```
beta_exp = std
gamma_exp = mean-beta_exp

RMSE_Final = 0
RMSE = 0

for i in range(len(yearly_max_adj)-1):
    H_exp_1 = gamma_exp + (beta_exp * (-np.log(Qi[i+1])))
    RMSE += ((H_exp_1 - yearly_max_adj[i+1]) ** 2)

RMSE_Final = RMSE/len(yearly_max_adj) ** .5

print(f'Minimum root mean square error = {RMSE_Final}')
```

```
Minimum root mean square error = 7471.852908515623
```

Gumbel

In [14]:

```
RMSE_Final = 0
RMSE = 0

beta_gum = std * np.sqrt(6) / np.pi
gamma_gum = mean - 0.5772 * beta_gum

for i in range(len(yearly_max_adj)-1):
    H_gum_1 = gamma_gum - (beta_gum * np.log(-np.log(1 - ((Qi[i+1])))))
    RMSE += ((H_gum_1 - yearly_max_adj[i+1]) ** 2)

RMSE_Final = RMSE/len(yearly_max_adj) ** .5

print(f'Minimum root mean square error = {RMSE_Final}')
print(beta_gum, gamma_gum)
```

```
Minimum root mean square error = 7106.916413011963
71.3628892913676 3301.366019215439
```

Generalized Pareto

In [15]:

```
RMSE_Final = []
alpha_par = np.arange(-3, 0, .01)

for i in alpha_par:
    RMSE = 0
    H_par = []
    beta_par = std * np.sqrt((1 - i)**2 * (1 - 2 * i))
    gamma_par = mean - (beta_par / (1 - i))

    for j in range(len(yearly_max_adj)):
```

```
        H_par.append(gamma_par + beta_par * (((Qi[j])**(-i) - 1) / i))
        RMSE += ((H_par[j] - yearly_max_adj[j]) ** 2)

    RMSE_Final.append(RMSE/len(yearly_max_adj) ** .5)

print(f'Minimum root mean square error = {min(RMSE_Final)}')
print(f'Index value of the minimum = {RMSE_Final.index(min(RMSE_Final))}')

alpha_par = alpha_par[RMSE_Final.index(min(RMSE_Final))]
print(f'Alpha_par for minimum error = {alpha_par:.2f}')

beta_par = std * np.sqrt((1 - alpha_par)**2 * (1 - 2 * alpha_par))
gamma_par = mean - (beta_par / (1 - alpha_par))
```

```
Minimum root mean square error = 6717.618575398874
Index value of the minimum = 274
Alpha_par for minimum error = -0.26
```

Weibull

In [16]:

```
from scipy.special import gamma as gamma_function
# Root mean square error
alpha_wei = np.arange(1,3.01,0.01)

RMSE_Final = []

for i in alpha_wei:
    RMSE = 0
    H_wei = []
    beta_wei = std / np.sqrt(gamma_function(1 + (2 / i)) - (gamma_function(1 + (1 / i)))**
    gamma_wei = mean - beta_wei * gamma_function(1 + (1 / i))

    for j in range(len(yearly_max_adj)):
        H_wei.append(gamma_wei + beta_wei * (-np.log((Qi[j])))**(1 / i))
        RMSE += ((H_wei[j] - yearly_max_adj[j]) ** 2)

    RMSE_Final.append(RMSE/len(yearly_max_adj) ** .5)

#print(RMSE_Final)
print(f'Minimum root mean square error = {min(RMSE_Final)}')
print(f'Index value of the minimum = {RMSE_Final.index(min(RMSE_Final))}')

# Final parameters
alpha_wei = alpha_wei[RMSE_Final.index(min(RMSE_Final))]
print(f'Alpha_wei for minimum error = {alpha_wei:.2f}')

beta_wei = std / np.sqrt(gamma_function(1 + (2 / alpha_wei)) - (gamma_function(1 + (1 / al
gamma_wei = mean - beta_wei * gamma_function(1 + (1 / alpha_wei))
print(len(yearly_max_adj[1:30]))
```

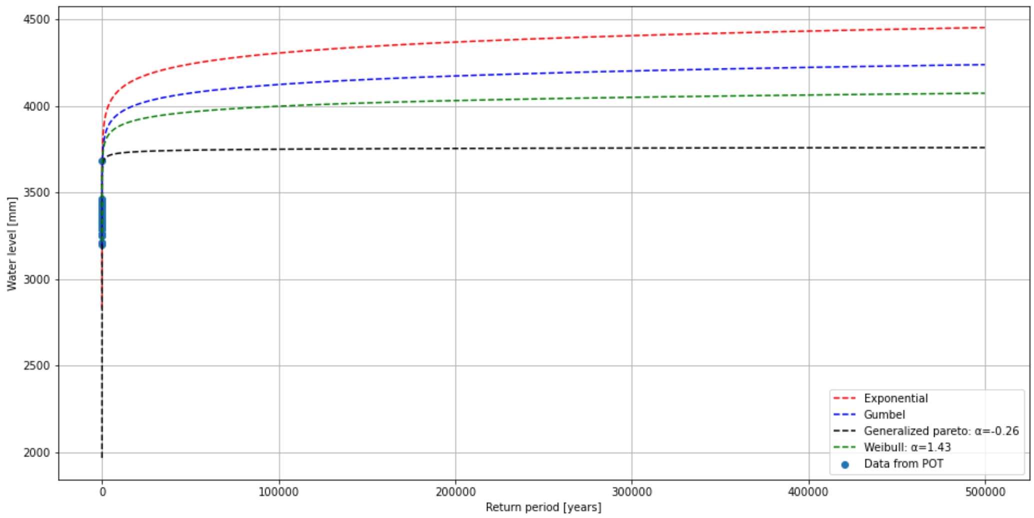
```
Minimum root mean square error = 6859.715530118372
Index value of the minimum = 43
Alpha_wei for minimum error = 1.43
29
```

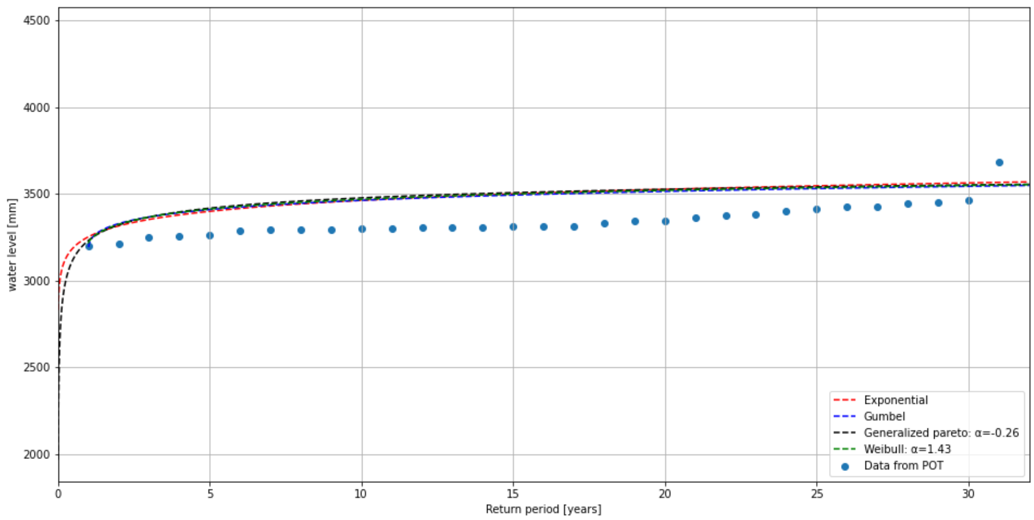
In [17]:

```
plt.figure(figsize=(16,8))

Return_period = np.arange(0.01, 500000.01, 0.01)

H_exp =  gamma_exp - (beta_exp * np.log(1 / (Return_period)))
plt.plot(Return_period, H_exp, 'red', linestyle='--', label='Exponential')
```

```
H_gum = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (Return_period)))))
plt.plot(Return_period, H_gum, 'blue', linestyle='--', label='Gumbel')

H_par = gamma_par + beta_par * (((1 / (Return_period))**(-alpha_par) - 1) / alpha_par)
plt.plot(Return_period, H_par, 'black', linestyle='--', label=f'Generalized pareto: \u03B1

H_wei = gamma_wei + beta_wei * (-np.log((1 / (Return_period))))**(1 / alpha_wei)
plt.plot(Return_period, H_wei, 'green', linestyle='--', label=f'Weibull: \u03B1={alpha_wei

plt.scatter(Return_period_values, yearly_max_adj, label='Data from POT')

plt.grid()
plt.xlabel('Return period [years]')
plt.ylabel('Water level [mm]')
plt.legend(loc='lower right')

plt.figure(figsize=(16,8))

plt.plot(Return_period, H_exp, 'red', linestyle='--', label='Exponential')
plt.plot(Return_period, H_gum, 'blue', linestyle='--', label='Gumbel')
plt.plot(Return_period, H_par, 'black', linestyle='--', label=f'Generalized pareto: \u03B1
plt.plot(Return_period, H_wei, 'green', linestyle='--', label=f'Weibull: \u03B1={alpha_wei
plt.scatter(Return_period_values, yearly_max_adj, label='Data from POT')
plt.xlim(0, 32)
plt.grid()
plt.xlabel('Return period [years]')
plt.ylabel('water level [mm]')
plt.legend(loc='lower right');
```

```
C:\Users\922188\AppData\Local\Temp/ipykernel_20084/1076034383.py:8: RuntimeWarning: divide
by zero encountered in log
  H_gum = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (Return_period)))))
C:\Users\922188\AppData\Local\Temp/ipykernel_20084/1076034383.py:8: RuntimeWarning: invali
d value encountered in log
  H_gum = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (Return_period)))))
C:\Users\922188\AppData\Local\Temp/ipykernel_20084/1076034383.py:14: RuntimeWarning: inval
id value encountered in power
  H_wei = gamma_wei + beta_wei * (-np.log((1 / (Return_period))))**(1 / alpha_wei)
```



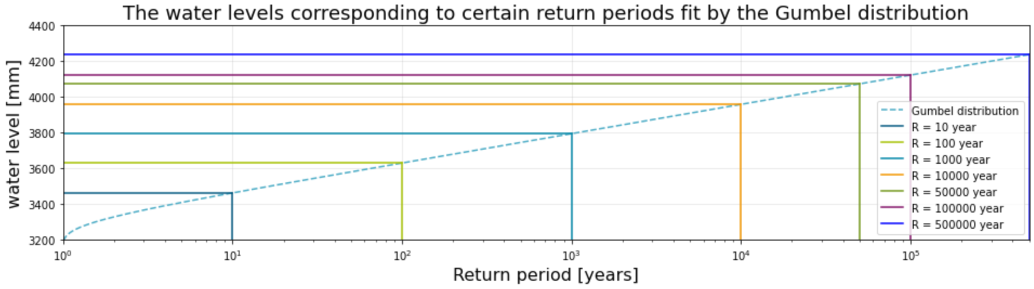


In [18]:

```
fig = plt.figure(figsize=(16,8))
ax = fig.add_subplot(2, 1, 1)
plt.plot(Return_period, H_gum, color='#4BACC6', linestyle='--', label=f'Gumbel distributio

H_gum_10 = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (10)))))
H_gum_100 = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (100)))))
H_gum_1000 = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (1000)))))
H_gum_10000 = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (10000)))))
H_gum_50000 = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (50000)))))
H_gum_100000 = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (100000)))))
H_gum_500000 = gamma_gum - (beta_gum * np.log(-np.log(1 - (1 / (500000)))))

plt.plot([0, 10], [H_gum_10, H_gum_10], color='#00577E', label='R = 10 year')
plt.plot([0, 100], [H_gum_100, H_gum_100], color='#A5C100', label='R = 100 year')
plt.plot([0, 1000], [H_gum_1000, H_gum_1000], color='#0086A8', label='R = 1000 year')
plt.plot([0, 10000], [H_gum_10000, H_gum_10000], color='#F39600', label='R = 10000 year')
plt.plot([0, 50000], [H_gum_50000, H_gum_50000], color='#72971B', label='R = 50000 year')
plt.plot([0, 100000], [H_gum_100000, H_gum_100000], color='#811066', label='R = 100000 yea
plt.plot([0, 500000], [H_gum_500000, H_gum_500000], color='blue', label='R = 500000 year')
plt.plot([10, 10], [3200, H_gum_10], color='#00577E')
plt.plot([100, 100], [3200, H_gum_100], color='#A5C100')
plt.plot([1000, 1000], [3200, H_gum_1000], color='#0086A8')
plt.plot([10000, 10000], [3200, H_gum_10000], color='#F39600')
plt.plot([50000, 50000], [3200, H_gum_50000], color='#72971B')
plt.plot([100000, 100000], [3200, H_gum_100000], color='#811066')
plt.plot([500000, 500000], [3200, H_gum_500000], color='blue')

ax.set_xscale('log')
plt.xlim(1, 500000)
plt.ylim(3200, 4401)
plt.grid(alpha=0.3)
plt.xlabel('Return period [years]', fontsize=16)
plt.ylabel('water level [mm]', fontsize=16)
plt.legend(loc='lower right')
plt.title(f'The water levels corresponding to certain return periods fit by the Gumbel dis

print(f'The water level for a return period of 10 years is {H_gum_10:.0f} mm')
print(f'The water level for a return period of 100 years is {H_gum_100:.0f} mm')
print(f'The water level for a return period of 1000 years is {H_gum_1000:.0f} mm')
print(f'The water level for a return period of 10000 years is {H_gum_10000:.0f} mm')
print(f'The water level for a return period of 50000 years is {H_gum_50000:.0f} mm')
```

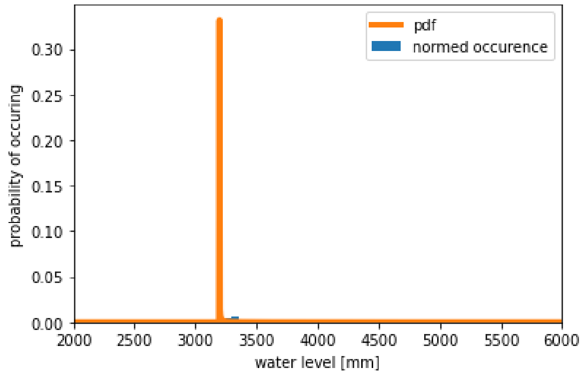
```
print(f'The water level for a return period of 100000 years is {H_gum_100000:.0f} mm')
print(f'The water level for a return period of 500000 years is {H_gum_500000:.0f} mm');
```

```
The water level for a return period of 10 years is 3462 mm
The water level for a return period of 100 years is 3630 mm
The water level for a return period of 1000 years is 3794 mm
The water level for a return period of 10000 years is 3959 mm
The water level for a return period of 50000 years is 4073 mm
The water level for a return period of 100000 years is 4123 mm
The water level for a return period of 500000 years is 4238 mm
```



In [19]:

```
plt.hist(yearly_max_adj, bins=20, range=(3000, 4000), density = True, label="normed occure
plt.plot(input_WL_adj, pdf_gev_adj, linewidth=4, label='pdf')
plt.ylabel('probability of occuring')
plt.xlabel('water level [mm]')
plt.xlim(2000, 6000)
plt.legend();
```

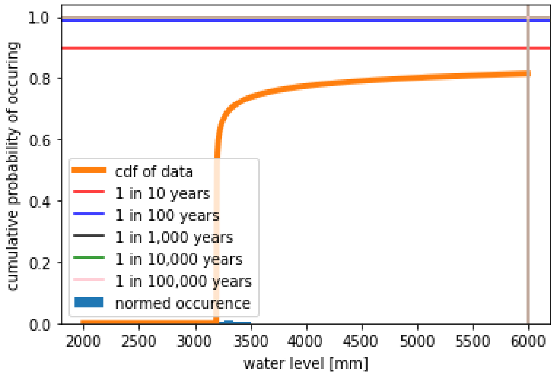


In [20]:

```
plt.hist(yearly_max_adj, bins=40, range=(2000, 5000), density=True, label="normed occurenc
plt.plot(input_WL, cdf_gev_adj, linewidth=4, label='cdf of data')
plt.axhline(0.9, color='r')
WL_1_10 = np.interp(0.9, cdf_gev_adj, input_WL)
plt.axvline(WL_1_10, color='r', label='1 in 10 years')
print('The water level with a return period of 10 years is', WL_1_10, 'mm')

plt.axhline(0.99, color='b')
WL_1_100 = np.interp(0.99, cdf_gev_adj, input_WL)
plt.axvline(WL_1_100, color='b', label='1 in 100 years')
print('The water level with a return period of 100 years is', WL_1_100, 'mm')

plt.axhline(0.999, color='black')
WL_1_1000 = np.interp(0.999, cdf_gev_adj, input_WL)
plt.axvline(WL_1_1000, color='black', label='1 in 1,000 years')
print('The water level with a return period of 1000 years is', WL_1_1000, 'mm')
```

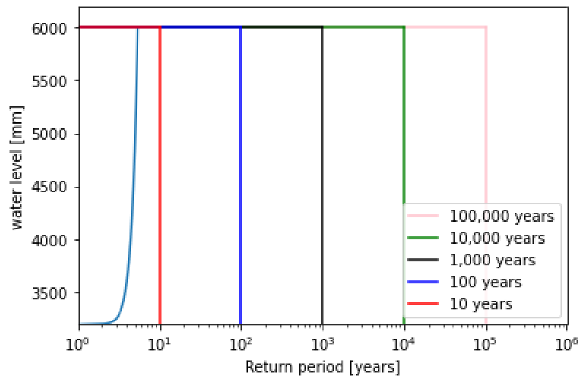
```
plt.axhline(0.9999, color='green')
WL_1_10000 = np.interp(0.9999, cdf_gev_adj, input_WL)
plt.axvline(WL_1_10000, color='green', label='1 in 10,000 years')
print('The water level with a return period of 10000 years is', WL_1_10000, 'mm')

plt.axhline(0.99999, color='pink')
WL_1_100000 = np.interp(0.99999, cdf_gev_adj, input_WL)
plt.axvline(WL_1_100000, color='pink', label='1 in 100,000 years')
print('The water level with a return period of 10000 years is', WL_1_100000, 'mm')
plt.ylabel('cumulative probability of occuring')
plt.xlabel('water level [mm]')
plt.legend();
```

```
The water level with a return period of 10 years is 6000.0 mm
The water level with a return period of 100 years is 6000.0 mm
The water level with a return period of 1000 years is 6000.0 mm
The water level with a return period of 10000 years is 6000.0 mm
The water level with a return period of 10000 years is 6000.0 mm
```



In [21]:

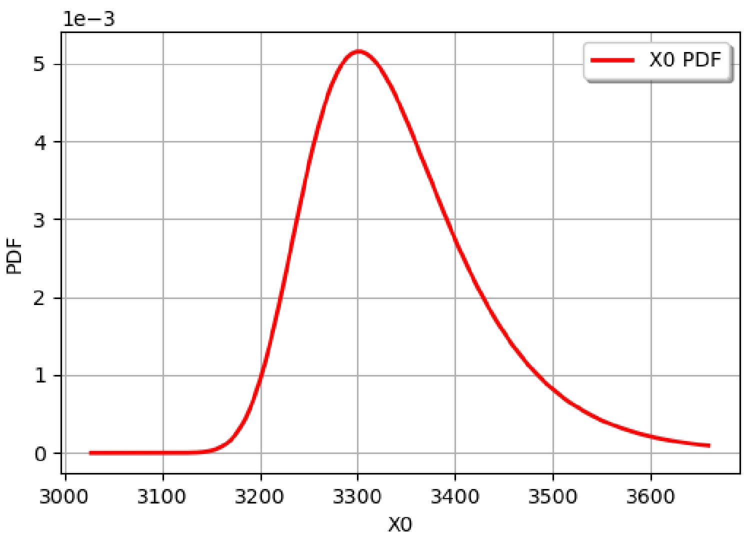
```
for i in range(len(cdf_gev_adj)):
    if cdf_gev_adj[i] < 0:
        cdf_gev_adj[i] = np.nan
Return_period = 1 / (1 - cdf_gev_adj)


plt.plot(Return_period, input_WL_adj)
plt.ylim(3200, 6200)
plt.xlim(1, 1000000)
plt.xscale('log')
plt.xlabel('Return period [years]')
plt.ylabel('water level [mm]')
plt.plot()

plt.plot([1, 100000], [WL_1_100000, WL_1_100000], color='pink', label='100,000 years')
plt.plot([1, 10000], [WL_1_10000, WL_1_10000], color='green', label='10,000 years')
plt.plot([1, 1000], [WL_1_1000, WL_1_1000], color='black', label='1,000 years')
plt.plot([1, 100], [WL_1_100, WL_1_100], color='b', label='100 years')
plt.plot([1, 10], [WL_1_10, WL_1_10], color='r', label='10 years')

plt.plot([100000, 100000], [3200, WL_1_100000], color='pink')
plt.plot([10000, 10000], [3200, WL_1_10000], color='green')
plt.plot([1000, 1000], [3200, WL_1_1000], color='black')
plt.plot([100, 100], [3200, WL_1_100], color='b')
plt.plot([10, 10], [3200, WL_1_10], color='r')
plt.legend(loc='lower right');
```



In [22]:

```
import openturns as ot
import openturns.viewer as viewer
WL_dist = ot.Gumbel(beta_gum, gamma_gum)
WL_dist.drawPDF()
```

Out[22]:



In [ ]:

E

fictive case

The total risk at the time of implementation of landfill as first measure has been calculated in order to do so. For a landfill with a safety level of 10,000 years at implementation, it means that inundation only occurs for water levels with a return period of higher than 10,000 years. The water levels with a return period of 50,000 years, 100,000 years and 500,000 years have consecutively an inundation depth of 0.24 m, 0.35 m and 0.59 m. Using the damages from the input, the damages corresponding to these inundation levels could be calculated giving damages of 0.12 million €, 0.17 million € and 0.27 million €. Equation 3.5 was used to obtain the annual risk giving:

$$\text{Annual risk} = \left(\frac{1}{10,000} - \frac{1}{50,000}\right) * \frac{0+0.12}{2} + \left(\frac{1}{50,000} - \frac{1}{100,000}\right) * \frac{0.12+0.17}{2} + \left(\frac{1}{100,000} - \frac{1}{500,000}\right) * \frac{0.17+0.27}{2} \frac{1}{500,000} * 0.27 = 8.68 \text{ €/year}$$

This value still has to be multiplied by the economic growth rate of 1%. As the latest data was from 2021, this gives:

$$Risk_{incl,ec,gr} = 8.68 * 1.01^{2023-2021} = 8.86 \text{ €}/year$$

which is similar to the risk that has been calculated in the framework. During its lifetime (between 2023 and 2130), the SLR is 0.69. Inundation at the end of the lifetime is therefore, consecutively 0.28 m, 0.63 m, 0.87 m, 0.97 m and 1.22 m for water levels corresponding to the return periods of 1,000, 10,000, 50,000, 100,000 and 500,000 years (WL_{impl} + $SLR_{lifetime}$ - level landfill). This is similar to the framework as well and therefore the risk at the end of the lifetime is also assumed to be correct.

The ATP of this measure has also been checked. This landfill is $WL_{10,000}$ - WL_{100} = 4.18 m - 3.49 m = 0.69 m above the required safety level. This means that the sea level rise has to be above 0.69 m from the moment of implementation of the measure (2023) before the measure does not fulfill the safety requirement again. The first year this happens for the SSP3-7.0-scenario is 2144. This means that the last year the safety requirement is met is 2143 as can be seen in Figure 4.5.

Finally, the costs of the landfill has been checked. The landfill is 0.69 m above the safety requirement. However, as the actual safety level is below the required safety level, the difference between them still has to be added to the height as well. This gives an additional $WL_{desired}$ - $WL_{current}$ = WL_{100} - WL_{10} = 0.35 m. Also, the sea level rise taking place between the data (2021) and the first possible year of implementation (2023), which is 0.01 m, has to be added. This gives a total required height of 1.05 m. The area is 5,000 m^2. With investments costs of 25 €/m/m^2 as can be seen in Table 3.3, this results in total investment costs of 132 k€. These costs have to be corrected for inflation from the year of the data (2016) resulting in total investment costs of:

$$I = 132 \text{ k€} * 1.02^{2023-2016} = 151 \text{ k€}$$

which is similar to the framework. The O&M costs are brought to the PV at time of implementation by Equation 3.3 and are 0.2% of the investment costs as defined in Table 3.4. The total O&M costs are 14 k € in PV at time of implementation as has been calculated in Figure E.1. This gave a similar result as in the framework and resulted in the total costs of 165 k€.

year	O&M excl. Inflation in FV	O&M incl. Inflation in FV	O&M incl. Inflation in PV	year	O&M excl. Inflation in FV	O&M incl. Inflation in FV	O&M incl. Inflation in PV	year	O&M excl. Inflation in FV	O&M incl. Inflation in FV	O&M incl. Inflation in PV	year	O&M excl. Inflation in FV	O&M incl. Inflation in FV	O&M incl. Inflation in PV
2023	0	0	0	2061	303	643	145	2099	303	1364	69	2137	303	2895	33
2024	303	309	297	2062	303	656	142	2100	303	1392	68	2138	303	2953	32
2025	303	315	291	2063	303	669	139	2101	303	1419	67	2139	303	3012	32
2026	303	321	286	2064	303	682	137	2102	303	1448	65	2140	303	3073	31
2027	303	328	280	2065	303	696	134	2103	303	1477	64	2141	303	3134	31
2028	303	334	275	2066	303	710	131	2104	303	1506	63	2142	303	3197	30
2029	303	341	270	2067	303	724	129	2105	303	1536	62	2143	303	3261	29,5
2030	303	348	264	2068	303	738	126	2106	303	1567	60				13.945
2031	303	355	259	2069	303	753	124	2107	303	1598	59				
2032	303	362	254	2070	303	768	122	2108	303	1630	58				
2033	303	369	249	2071	303	784	119	2109	303	1663	57				
2034	303	377	245	2072	303	799	117	2110	303	1696	56				
2035	303	384	240	2073	303	815	115	2111	303	1730	55				
2036	303	392	235	2074	303	832	113	2112	303	1765	54				
2037	303	400	231	2075	303	848	110	2113	303	1800	53				
2038	303	408	226	2076	303	865	108	2114	303	1836	52				
2039	303	416	222	2077	303	882	106	2115	303	1873	51				
2040	303	424	218	2078	303	900	104	2116	303	1910	50				
2041	303	433	214	2079	303	918	102	2117	303	1949	49				
2042	303	441	209	2080	303	936	100	2118	303	1988	48				
2043	303	450	205	2081	303	955	98	2119	303	2027	47				
2044	303	459	201	2082	303	974	96	2120	303	2068	46				
2045	303	468	198	2083	303	994	94	2121	303	2109	45				
2046	303	478	194	2084	303	1014	93	2122	303	2151	44				
2047	303	487	190	2085	303	1034	91	2123	303	2194	43				
2048	303	497	186	2086	303	1055	89	2124	303	2238	43				
2049	303	507	183	2087	303	1076	87	2125	303	2283	42				
2050	303	517	179	2088	303	1097	86	2126	303	2329	41				
2051	303	527	176	2089	303	1119	84	2127	303	2375	40				
2052	303	538	172	2090	303	1142	82	2128	303	2423	39				
2053	303	549	169	2091	303	1164	81	2129	303	2471	39				
2054	303	560	166	2092	303	1188	79	2130	303	2521	38				
2055	303	571	163	2093	303	1211	78	2131	303	2571	37				
2056	303	582	160	2094	303	1236	76	2132	303	2622	36				
2057	303	594	157	2095	303	1260	75	2133	303	2675	36				
2058	303	606	154	2096	303	1286	73	2134	303	2728	35				
2059	303	618	151	2097	303	1311	72	2135	303	2783	34				
2060	303	630	148	2098	303	1338	71	2136	303	2839	34				

Figure E.1: The Operation & Maintenance costs for Landfill applied as first measure for the fictive case

F

Derivation in Flood-Damage functions

Damage fractions
Huizinga et al. (2017) provides also damage curves of continents for different categories. These defined categories are residential buildings, commercial buildings, industrial buildings, transport, infrastructure-roads and agriculture and the damage function are shown in figure F.1. The database also contains the standard deviation for these continental curves. The maximum and minimum curves are shown in figure F.2.

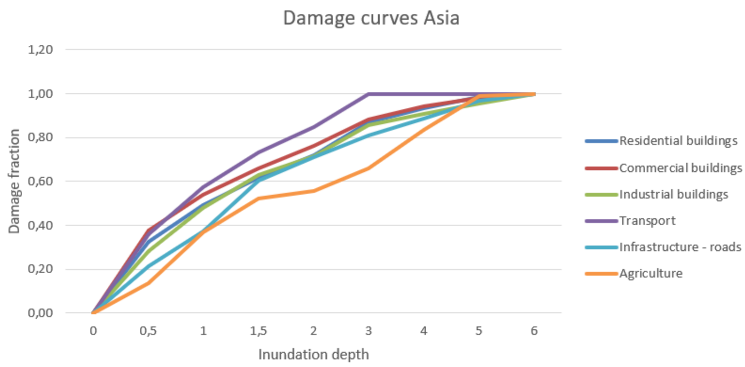


Figure F.1: Damage functions for Asia (Huizinga et al., 2017)

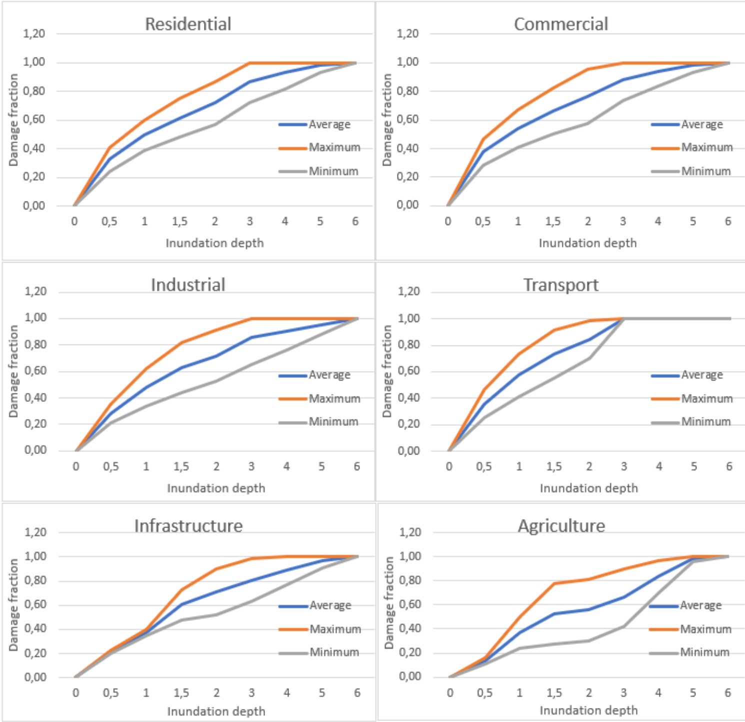


Figure F.2: The maximum and minimum damage functions for Asia (Huizinga et al., 2017)

For the land-uses which are not included in this module, the damage functions of "Schade en Slachtoffer Module" (2017) are used in which "Business 1" are food and drug industries and therefore the damage functions of commercial properties are used. The land-use category called "White" are offices and therefore the damage function of offices is used. For "Utility, the damage function for Industrial land-use is taken. The land-use category Airport/Port is not in this module as well and as there is no airport in the project area, the damage function defined for ports by Tebodin (2000) is used for this category. Another function that has not been defined is the commercial + residential-land-use for which the average between the curve of the commercial and residential is taken. The damage function for the residential with commercial at the first storey is altered with the result that the first three meters gives an equal damage as the commercial-land-use would give and afterwards, the damage would be equivalent to the damage that would occur with the land-use category residential.

Maximum damage

Huizinga et al. (2017) used the characteristics determining the maximum damage described in 5.2.2 in order to derive the maximum possible damage in Singapore. These can be seen in table F.1.

Table F.1: The maximum possible damage for Singapore in 2010 based on in €/m^2 (Huizinga et al., 2017)

	Building based			**Land-use based**
Category	**Structure**	**Content**	**Total**	**Total**
Residential	545	272	817	163
Commercial	564	564	1,129	339
Industrial	365	547	912	273
Agriculture	*not relevant*	*not relevant*	*not relevant*	9
Infrastructure	*not relevant*	*not relevant*	*not relevant*	97
Transport	*not relevant*	*not relevant*	*not relevant*	3,434

It can be converted to the present value with an average inflation rate based on the Consumer Price Index (CPI) with an average CPI of 1.50% since 2010 (The World Bank, n.d.). This results into the values for 2022 which can be seen in table F.2.

Table F.2: The maximum possible damage for Singapore in 2010 based on in €/m^2 (Huizinga et al., 2017)

	Building based			Land-use based
Category	**Structure**	**Content**	**Total**	**Total**
Residential	838	418	1,256	251
Commercial	867	867	1,736	521
Industrial	561	841	1,402	420
Agriculture	*not relevant*	*not relevant*	*not relevant*	14
Infrastructure	*not relevant*	*not relevant*	*not relevant*	150
Transport	*not relevant*	*not relevant*	*not relevant*	5,280

"Schade en Slachtoffer Module" (2017) is another reference providing damage for the land-use categories that have not been defined yet. The values for Residential, Commercial and Industrial in this source are considerably higher than the values found in Huizinga et al. (2017), and as flood damages are often underestimated, "Schade en Slachtoffer Module" (2017) is used for these categories. These damage date from 2017 and therefore are converted to the value for 2022 by using the CPI. Additionally, a factor is applied to account for the difference between value in The Netherlands. By comparing the pricing and value indicators of The Netherlands and Singapore shown in table F.3, a multiplication factor of 2 is chosen. As the housing prices went up considerably more than is accounted for with the CPI, an additional factor is used to increase the value of residential areas. Global Property Guide (n.d.) states that the prices went up with more than 25% between 2017 (the year of the source) and 2022. Therefore, this factor is used to make the value of residential buildings more in line with the reality. Lastly, a factor is added to account for the indirect damage. Johan Gauderis (2011) states that a 50% of the direct damage is a reasonable estimation for the indirect damage.

The complete damage function

The complete damage function can be found on the page 131.

Table F.3: Differences in value between The Netherlands & Singapore

catgory	Value in NL	unit	Source	Year	Value in NL in 2022	Value in SP	unit	Source	Year	Value in SP in 2022	unit	Factor 2022	Factor 2017	
average square meter prices for 120 m2 to buy	6.902,00	[€ / m2]	1	2017	11.305,48	14.373,00	[US$ / m2]	2	2019	14.411,91	[€ / m2]	1,27	1,66	in Amsterdam
average square meter prices for 120 m2 to buy	3.653,00	[€ / m2]	1	2017	6.169,92	14.373,00	[US$ / m2]	2	2019	14.411,91	[€ / m2]	2,34	3,14	in The Hague
average square meter prices for 120 m2 to rent	21,41	[€ / m2]	1	2017	21,94	39,47	[US$ / m2]	2	2019	41,13	[€ / m2]	1,87	1,61	in Amsterdam
average square meter prices for 120 m2 to rent	17,08	[€ / m2]	1	2017	20,17	39,47	[US$ / m2]	2	2019	41,13	[€ / m2]	2,04	2,02	in The Hague
GDP per capita	52.397,1	[US$ / capita]	3	2020	53.739,16	59.797,8	[US$ / capita]	3	2020	62.554,2	[US$ / capita]	1,16	1,41	
Residential	168	[€ / m2]	4	2010	202,25	163,00	[€ / m2]	4	2010	194,72	[€ / m2]	0,96	1,16	
Commercial	348	[€ / m2]	4	2010	418,96	339,00	[€ / m2]	4	2010	404,98	[€ / m2]	0,97	1,17	
Industrial	280	[€ / m2]	4	2010	337,09	273,00	[€ / m2]	4	2010	326,13	[€ / m2]	0,97	1,17	
Agriculture	5.591	[€ / ha]	4	2010	6730,98	93994,00	[€ / m2]	4	2010	112287,11	[ha / m2]	16,68	20,18	
Infrastructure	29,75	[€ / m2]	4	2010	35,82	97,38	[€ / m2]	4	2010	116,33	[€ / m2]	3,25	3,93	
Transport	877,18	[€ / m2]	4	2010	1056,03	3434,39	[€ / m2]	4	2010	4102,79	[€ / m2]	3,89	4,70	

sources

1 https://www.globalpropertyguide.com/Europe/Netherlands/Rental-Yields

2 https://www.globalpropertyguide.com/Asia/Singapore/Rental-Yields

3 https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

4 Huizinga et al Global (2017)

Table F.4: The Damage functions

Land-use category	Source	Max. damage [SGD]	0.2	0.5	0.75	1	1.25	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6
Beach area		0.00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Business 1	Huizinga et al.	7,440.64	0,15	0,38	0,46	0,54	0,60	0,66	0,76	0,82	0,88	0,91	0,94	0,96	0,98	0,99	1,00
Business park	Schade Slachtoffer module	54.28	0,22	0,55	0,60	0,65	0,70	0,75	0,90	0,93	0,95	0,98	1,00	1,00	1,00	1,00	1,00
Civic & community inst.	Schade Slachtoffer module	828.93	0,14	0,35	0,45	0,55	0,64	0,72	0,85	0,93	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Commercial	Huizinga et al.	7,440.64	0,15	0,38	0,46	0,54	0,60	0,66	0,76	0,82	0,88	0,91	0,94	0,96	0,98	0,99	1,00
Commercial & residential		6,178.38	0,14	0,36	0,44	0,52	0,58	0,64	0,74	0,81	0,88	0,91	0,94	0,96	0,98	0,99	1,00
Res. with com. at 1st storey		7,444.64	0,15	0,38	0,46	0,54	0,60	0,66	0,76	0,82	0,88	0,90	0,92	0,93	0,95	0,95	0,96
Educational institution	Schade Slachtoffer module	4,899.57	0,06	0,15	0,23	0,30	0,35	0,40	0,48	0,53	0,58	0,65	0,72	0,80	0,88	0,90	0,92
Health & medical care	Schade Slachtoffer module	9,739.94	0,06	0,15	0,23	0,30	0,35	0,40	0,48	0,53	0,58	0,65	0,72	0,80	0,88	0,90	0,92
Hotel	Schade Slachtoffer module	7,440.64	0,14	0,35	0,45	0,55	0,64	0,72	0,85	0,93	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Industrial	Huizinga et al.	7,386.37	0,11	0,28	0,38	0,48	0,56	0,63	0,72	0,79	0,86	0,89	0,91	0,94	0,96	0,98	1,00
Open space	Schade Slachtoffer module	296.05	0,12	0,30	0,45	0,60	0,65	0,70	0,80	0,84	0,88	0,92	0,95	0,98	1,00	1,00	1,00
Park	Schade Slachtoffer module	54.28	0,22	0,55	0,60	0,65	0,70	0,75	0,90	0,93	0,95	0,98	1,00	1,00	1,00	1,00	1,00
Place of worship	Schade Slachtoffer module	828.93	0,14	0,35	0,45	0,55	0,64	0,72	0,85	0,93	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Port / airport	Tebodin	656.15	0,06	0,15	0,23	0,30	0,33	0,35	0,38	0,47	0,55	0,56	0,57	0,65	0,72	0,73	0,74
Residential	Huizinga et al.	6,191.24	0,13	0,33	0,41	0,49	0,56	0,62	0,72	0,80	0,87	0,90	0,93	0,96	0,98	0,99	1,00
Road	Huizinga et al.	315.62	0,08	0,21	0,29	0,37	0,49	0,60	0,71	0,76	0,81	0,85	0,89	0,93	0,97	0,99	1,00
Sports & recreation	Schade Slachtoffer module	503.28	0,06	0,15	0,25	0,35	0,40	0,45	0,55	0,65	0,75	0,80	0,85	0,93	1,00	1,00	1,00
Transport facilities	Huizinga et al.	11,131.69	0,14	0,36	0,47	0,57	0,65	0,73	0,85	0,93	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Utility	Huizinga et al.	7,386.37	0,11	0,28	0,38	0,48	0,56	0,63	0,72	0,79	0,86	0,89	0,91	0,94	0,96	0,98	1,00
Waterbody		0.00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
White	Schade Slachtoffer module	6,330.47	0,06	0,15	0,23	0,30	0,35	0,40	0,48	0,53	0,58	0,65	0,72	0,80	0,88	0,90	0,92

G

Changes in Input GFRT

Table G.1: Changes in the land-use map

Input	Changes
Land-use map	- Filling in the empty fields within the map - The Land-use at Keppel Island have been changed to Park

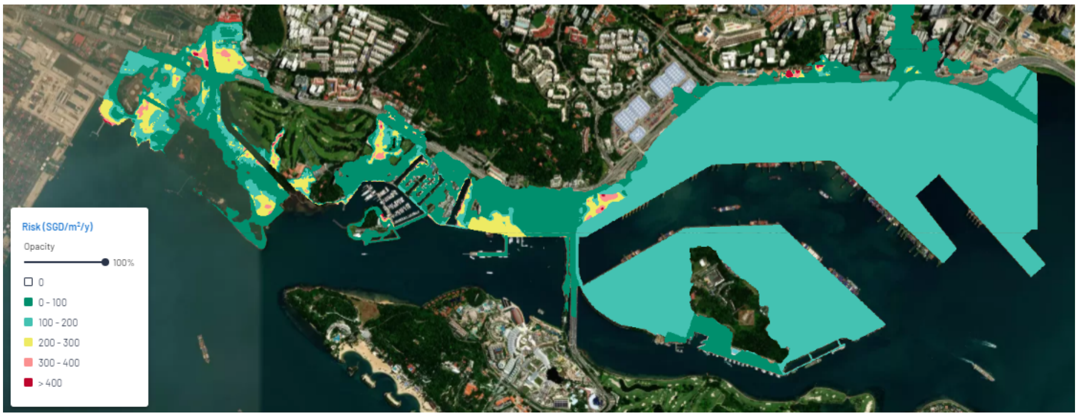
Table G.2: Changes in the DEM-map

Input	Changes
DEM-map	- Change the pile decks of the port on the mainland and Brani-island to an elevation of 3 meter. - A land reclamation next to the Singapore Cruise Terminal has been raised at the level of the surrounding land instead of the sea bed level. - The ground level below Vivo City has been raised to 4 meter. - The ground level below some buildings at Keppel Bay have been raised to 4 meter.

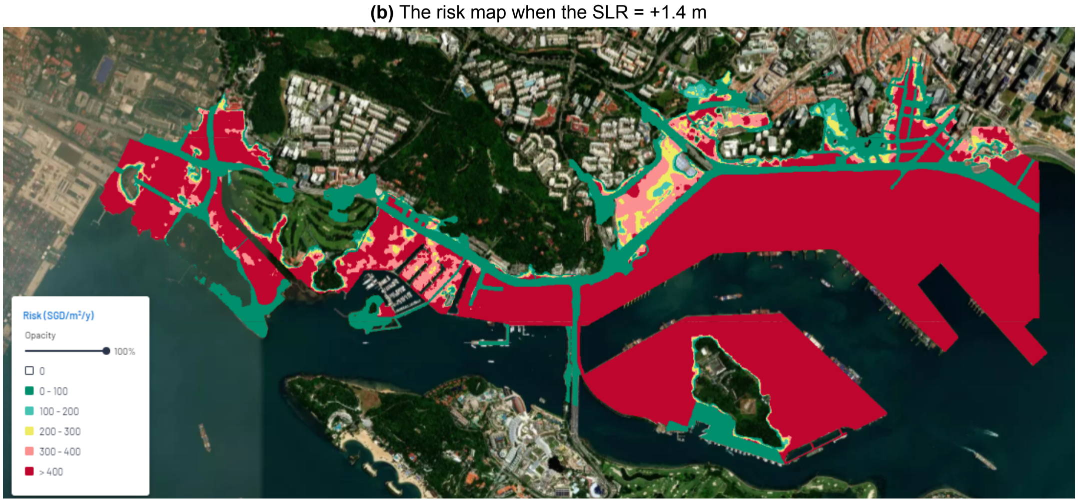
H

Preliminary results: Singapore-case study

(a) The risk map in the current situation



(b) The risk map when the SLR = +1.4 m



(c) The risk map when the SLR = +3.4 m

Figure H.1: Risk maps of the project area

Table H.1: The expected damages for three different scenarios

Return Period	Damage [m SGD]
10	0
100	0
1,000	0
10,000	0
50,000	0
100,000	0
500,000	0

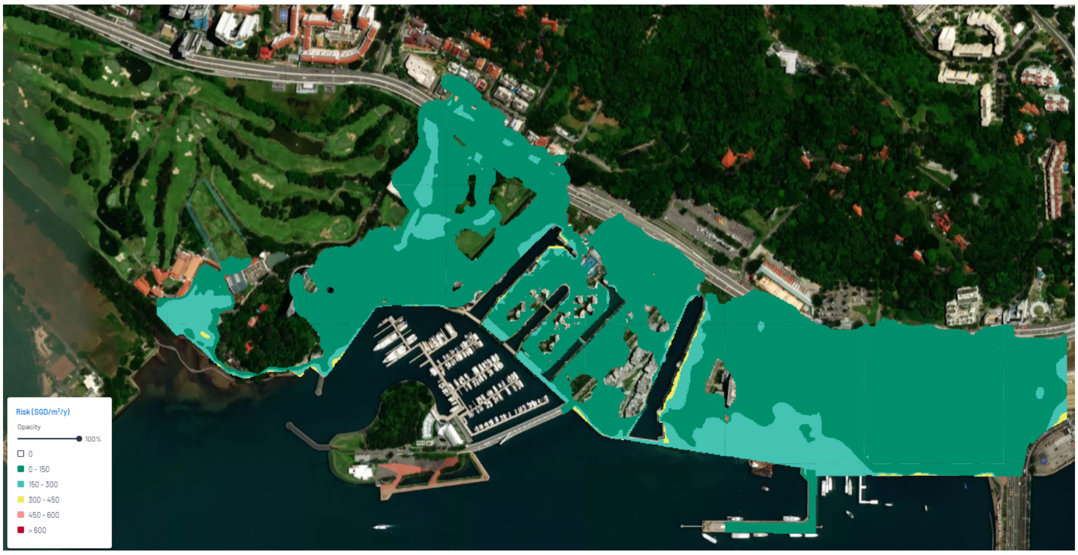
(a) Damages in current situation

Return Period	Damage [m SGD]
10	4,627
100	6,110
1,000	7,517
10,000	8,874
50,000	9,778
100,000	10,174
500,000	11,208

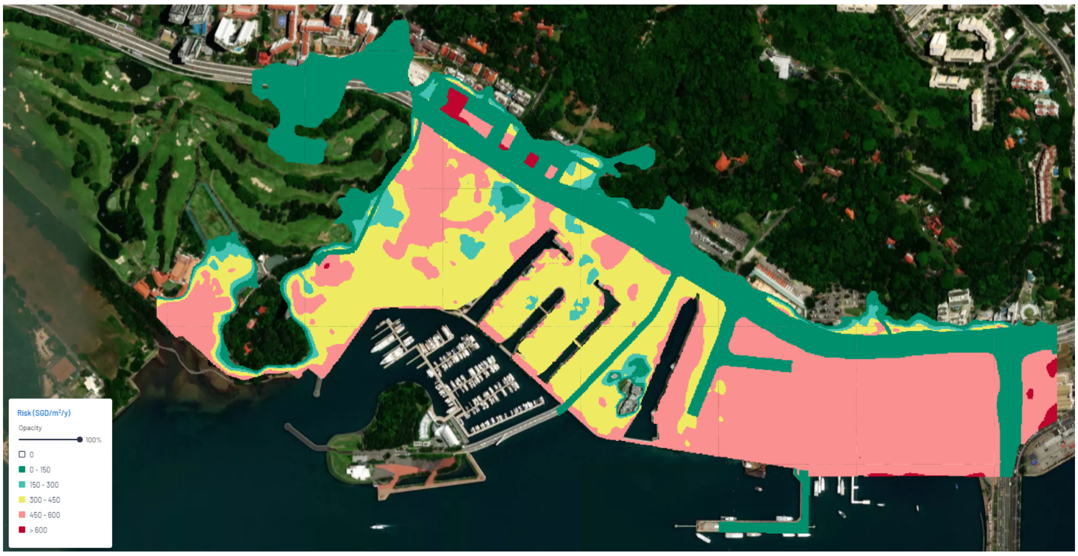
(b) Damages in current situation +1.4m SLR

Return Period	Damage [m SGD]
10	19,703
100	20,611
1,000	21,470
10,000	22,316
50,000	22,893
100,000	23,189
500,000	23,836

(c) Damages in current situation +3.4m SLR



(a) The risk map when the SLR = +1.4 m



(b) The risk map when the SLR = +3.4 m

Figure H.2: Risk maps of the project Area C2

Table H.2: The expected damages for two different scenarios

Return Period	Damage [m SGD]
10	0
100	0
1,000	0
10,000	0
50,000	0
100,000	0
500,000	0

(a) The expected damages for different return periods in the current situation

Return Period	Damage [m SGD]
10	100
100	430
1,000	490
10,000	690
50,000	800
100,000	840
500,000	1,060

(b) The expected damages for different return periods for 1.4 meter SLR

Return Period	Damage [m SGD]
10	2,280
100	2,410
1,000	2,530
10,000	2,640
50,000	2,720
100,000	2,760
500,000	2,920

(c) The expected damages for different return periods for 3.4 meter SLR

I
Input parameters Singapore-case

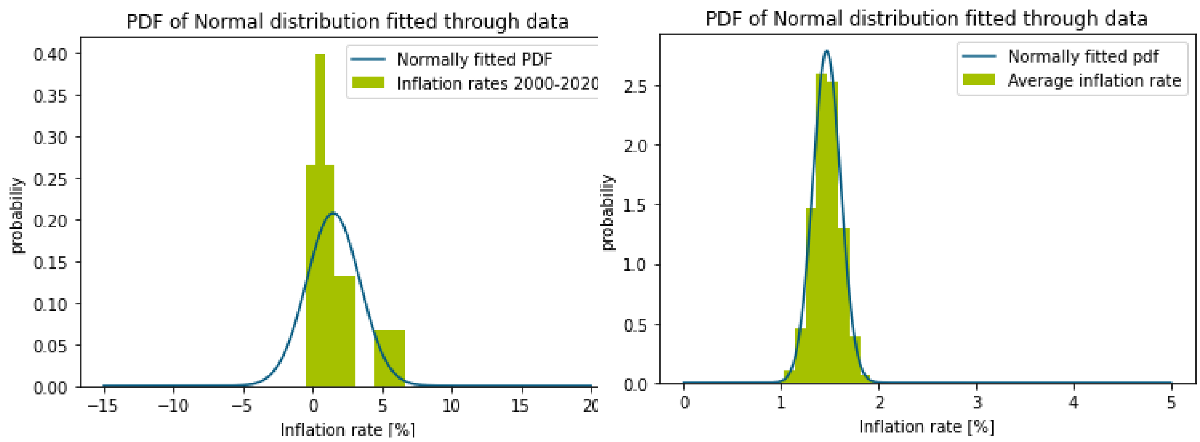
I.1. Inflation rate

An estimate of the inflation rate for the upcoming years is made with the inflation rates of the past. Although some studies suggests that positively skewed distributions better fit the inflation rate, the normal distribution is fitted through Singapore's inflation rates of this century as the normal distribution is a good first estimate for the inflation rate. Also, this case study is conducted to show the possible use of the adaptation pathways and the framework and not to be statistically completely accurate for which a more in-depth study would be required. Only the data of the period 2000-2020 has been used in order to be in the same economic phase.

Figure I.1a shows the PDF of the normal distribution fitted through the data. Random values are deducted from this distribution and the product of these values gives the total inflation in the year 2200. The average inflation can afterwards easily be calculated by using the following equation:

$$i_{av,annual} = \left(\prod_{t=1}^{T} (i_{t,random})^{\left(\frac{1}{T}\right)} - 1 \right) * 100 \tag{I.1}$$

in which i is the inflation rate and T is the amount of years for which the average inflation rate is obtained. The result of 10,000 simulations and a normal distribution plotted through them is shown in Figure I.1b. The mean does not change when applying a non-skewed distribution such as the normal distribution. However, the standard derivation is significantly decreased when the normal distribution is used. The mean annual average inflation rate until 2200 is 1.5% and the standard deviation is 0.1%.



(a) The average inflation rate (IMF, 2022)

(b) The obtained average inflation rate until 2200

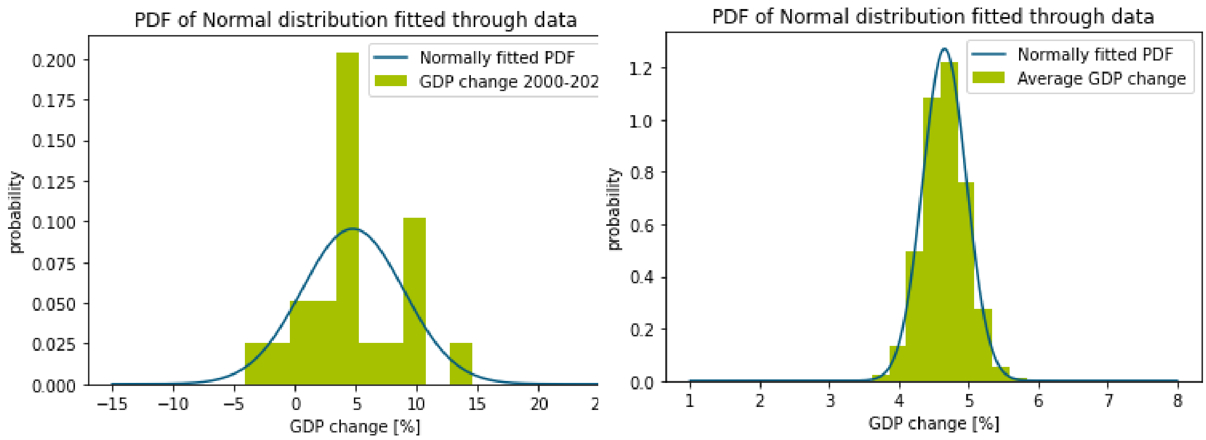
Figure I.1: The obtained average inflation rate for Singapore

I.2. GDP change

A similar approach as for the inflation rate is obtained for the change in GDP. The fit through the data is shown in Figure I.2a. The inflation rate is replaced by the percentage change in GDP to obtain the annual average percentage change of GDP resulting in the following equation:

$$\Delta GDP_{av,annual} = \left(\prod_{t=1}^{T} (GDP_{t,random})^{\left(\frac{1}{T}\right)} - 1 \right) * 100 \tag{I.2}$$

in which ΔGDP is the percentage change in GDP and T is the amount of years for which the average change in GDP rate is obtained. The result of 10,000 simulations and a normal distribution plotted through the 2000-2020 data is shown in Figure I.2b. Again, the mean does not change when applying a non-skewed distribution such as the normal distribution. However, the standard derivation is significantly decreased when the normal distribution is used. The mean annual GDP change until 2200 is 4.7% and the standard deviation is 0.3%.



(a) The average GDP change (Singapore Statistics, 2022)

(b) The obtained average GDP change until 2200

Figure I.2: The obtained average GDP change for Singapore

This socio-economic growth would double the value in the area every 15 years and the value in 2200 would be over 3,500 times as high as its current value. Beside the fact that this is unrealistic, it would not be sustainable as it would lead to inflation, labour shortages, excessive credit and trade difficulties ("Sustainable growth", 2020). Therefore, a sustainable growth rate of 2% with a similar standard deviation of 0.3% has been assumed in consultation with Matthijs Bos.

J

Economic optimisation

The optimal safety level of measures can be determined by maximising the NPV, maximising the annual NPV, maximising the BCR or minimising the EAC. All methods should lead to, on the one hand economic optimisation, but on the other hand practically feasible solutions.

When it is economically desirable to increase the safety level by implementing measures, maximising the NPV or the BCR is a suitable approach as discounting leads to devaluation of future value. This means that the benefits of the future are worth less. However, when the growth factor is larger than the discount rate, the increased value counteracts the discount rate leading to unrealistically long lifetimes. This is also the case when measures are relatively cheap relative to the prevented risk. A maximum lifetime has been implemented to prevent this. This is not only to ensure the technical lifetime of measures but also to ensure a step-wise adaptive approach. The BCR determines the economic efficiency of measures when the available budget is limited while the maximum NPV can be used when the project is not restricted to a certain project.

One could also account for the difference in lifetime of measures by dividing by the annuity factor. However, this insinuates that the same measure would have a similar effect in the future. The identified uncertainties may lead to a greater or reduced effect as a result of increased value, more expensive measures due to both inflation and more complex required measures to withstand more extreme conditions and increased impact due to greater inundation depth. As the lifetime is restricted and changes generally take place gradually, it can be used as first-order assessment. Since the framework has been created to provide insight into possible measures and to check the sensitivity of input-parameters, this satisfies.

The same principle can be applied to the total costs. This can be applied when the required safety level is above the economic optimum due to the individual or societal safety criterion or a general risk-averse flood risk strategy. This can potentially lead to very short lifetimes and therefore, a minimum height at which the linear cost starts has been implemented. In general, all methods have their limitations but do result in workable solutions and economically efficient solutions. However, when applying the framework, one should be aware of which method is most effective in which situation and one should be aware of the limitations of the used method.