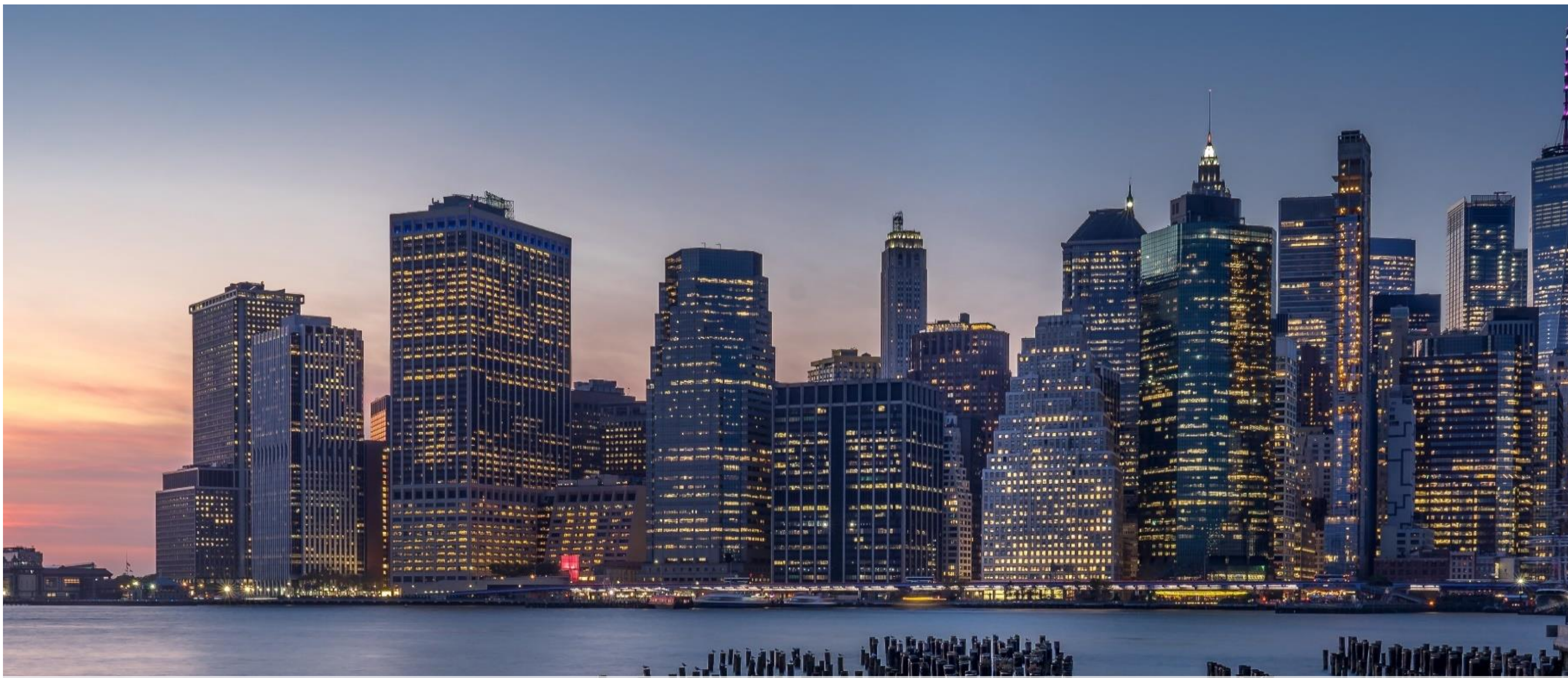
Master’s Thesis - Master Sustainable Business and Innovation



Assessing Climate-Related Flood Risk for Climate Adaptation in the Financial Sector

A Risk Assessment Framework for Future Flood Risk to Real-Estate

Author:

Jorn Krijgsman

5716039

j.n.krijgsman@students.uu.nl

Supervisor:

Prof. Dr. Kees Koedijk

Second reader:

Dr. Giovanna Capponi

Utrecht University | Faculty of Geosciences

17727 words

Utrecht University

PGGM

Abstract – 400 words

Introduction Climatic change results in an increase in flooding, posing a threat to the world's economic system. Especially real-estate assets are at risk. There is increasing demand for financially material climate-related risk information. While providers of this information exist, methodologies are proprietary, and results are divergent – indicating the need for a standardized flood risk assessment framework: *How can financial institutions quantify the financial risk posed by flooding to their real-estate portfolios in future climate change scenarios?*

Theory The literature illustrates an increasing need for financial firms to understand their risk to climate change. Current guidance to climate risk assessment exists in the form of general recommendations. However, these are often too vague. At the same time, global coverage flood models exist that predict flood occurrence in future climate change scenarios. The research defines climate-related flood risk in financial and hydrological terms.

Methods After defining climate-related flood risk in both a hydrologically sound and financially material manner, the relevant concepts are operationalized as variables. This includes a state-of-the-art global flood model is consulted, the Aqueduct Flood tool. This is applied to construct a global flood risk assessment framework that predicts flood risk in future climate change scenarios. Risk is expressed as Expected Annual Damage (EAD). Results are illustrated with the use of a representative case study: a sample of a real-estate portfolio owned by a Dutch pension fund investment manager.

Results The flood risk assessment framework is summarized into three key steps: 1. defining the model parameters, 2. collecting flood risk data, and 3. identifying flood risk. Each step is illustrated with results from the case study. Flood risk may be identified by plotting total EAD along axes of scenarios and timeframes to understand how risk develops over time. Risk hotspots are identified using maps.

Discussion The model's degree of reliability and validity primarily relates to uncertainty in datasets. Moreover, model output cannot be validated as the data exist in the future. The utility of risk assessment for global financial stability and climate adaptation remains a topic of current debate. However, the value of the tool lies in increasing firm-level resilience to climate change by exposing hotspots.

Conclusion The proposed framework may be used as a point of departure to model, understand, and manage future flood risk to real-estate. A standardized framework is expected to aid in firm resiliency to climate change and promoting global financial stability in uncertain climate futures.

Keywords: Flood risk assessment, Climate adaptation, Climate Finance, Scenario Analysis

Table of contents

1. Introduction

This section will: 1. introduce the key concepts and areas of focus discussed throughout this study, 2. motivate the scope of climate-related flood risk, 3. illuminate the gap in existing literature: a standardized flood risk modelling framework – particularly a framework quantifying climate-related flood risk for financial corporations and institutions, and finally 4. Formulate a research question as a solution to this problem, the answer of which makes firms better equipped to measure and mitigate expected future damages their physical assets and operations are exposed to.

1.1. Societal background and problem definition

June 2021 marked the warning of climate change's 'point of no return' (Al Jazeera, n.d.). Based on a recent observation of ice recession in the Arctic, it is feared that the Arctic may never have summer ice again. This indicates an irreparable tipping point of global warming may already be behind us. Rockström et al. (2009) define planetary boundaries as the biophysical threshold that must not be transgressed due to the irreversible nature of the environmental changes induced. The boundary for climatic change has been set at an atmospheric carbon dioxide concentration of 350 ppm (Rockström et al., 2009). The global average concentration in 2019 was 410 ppm (Lindsey, 2020). With catastrophic shifts like these occurring at an alarmingly frequent rate, climate change and the way we measure and account for these risks are of the utmost importance, see e.g. (Battiston, 2019). The physical effects of global climate change are evident, with widespread floods, droughts, rising sea levels, record-breaking temperatures, and heatwaves increasing in frequency and intensity (Field et al., 2014). The World Economic Forum classifies failure to act on climate change as the most likely and impactful risk the world faces today (World Economic Forum, 2020). Moreover, former governor of the Bank of England Mark Carney referred to physical and transitional climate risks as some of the greatest threats to financial stability and prosperity (Carney, 2015). This makes global climate change the most pressing issue faced by the world in general, but also financial markets. One study estimates that 1.8% of the world's financial assets may be at risk to climate change, amounting to 2.5 trillion USD (Dietz, Bowen, Dixon, & Gradwell, 2016). The importance of climate risk has also been noted by the European Union, which put forward new regulations requiring the financial sector to disclose their exposure to climate risk. The Sustainable Finance Disclosure Regulation, or SFDR, states clearly that financial organizations ought to integrate sustainability risks into risk management (European Commission, 2019).

With flood-related losses equating to around a third of all global economic costs resulting from natural disasters and extreme weather events (Winsemius, Van Beek, Jongman, Ward, & Bouwman, 2013), flooding is one of the most critical physical climate-related hazards to investigate. The ever-accelerating need for flood risk measurement, in terms of physical effects and financial deprecation, is made apparent by the 410 million people at risk due to rising sea levels (Storer, 2021).

Flooding may become one of the most damaging climate extremes, particularly to real-estate (Wobus et al., 2019). The physical nature of real-estate assets makes real-estate particularly vulnerable to flood events. Moreover, the long-term nature of real-estate assets makes it interesting for long-term risks like climate risk, as these increase over time (Baldauf, Garlappi, & Yannelis, 2020). Therefore, the risk of flooding in future climate change scenarios is pertinent to those at risk of incurring substantial losses – financial corporations and institutions (Hain, Koelbel, & Leippold, 2021). As such, this research aims to address the problem of global flood risk through the creation and implementation of a flood risk model, the framework of which will work to identify potential flood risk to real-estate assets and calculate their expected annual damage. This, in turn, helps increase business resilience to climate change (Battiston, 2019).

A particular focus has been placed on the *pension sector*. Climate risk is especially material to pension funds, as this type of financial institution has a fiduciary duty to its beneficiaries to fulfill the pension promise. For this reason, pension funds generally have a more long-term vision. This long-term vision includes foreseeing the financial effects of climate change, which makes climate risks most pertinent to pension funds (Dietz et al., 2016). Nevertheless, the framework proposed in this research may still be of use to the wider financial and private sector, as the physical effects of climate change are indiscriminate with regards to the type of company or organization.

The paper presents the results of the application of the modelling framework to a representative sample real-estate portfolio. This portfolio is operated by one of the largest fund managers in the Netherlands, PGGM, and contains real-estate properties across the globe. The case study illustrates both the capabilities and limitations of the flood risk assessment model.

1.2. Scientific background

The academic literature increasingly acknowledges the need to understand and financially measure the risk posed by climate change (Fiedler et al., 2021). The physical basis and physical effects of climate change are well understood (Stocker, T. F., Qin, D., Plattner, G. K., Tignor, M., Allen, S. K., Boschung, J., ... & Midgley, 2013). Chiefly, the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports synthesize and summarize past scientific contributions to this topic. These reports detail the changes undergone by the climate system and the wider consequences resulting from such shifts, such as damages to biodiversity and human socioeconomic systems (Allen et al., 2014). Based on climate projections, future climate-related risk modelling approaches exist. Specifically for climate-related flooding, modelling approaches are widely used, see e.g. (Ward et al., 2015). However, practical applications of these modelling techniques in the financial sector are not widely studied.

Sustainable development requires both the *mitigation* and *adaptation* of climate change (IPCC, 2014). Climate change mitigation is underpinned by GHG emission reduction, whilst adaptation focuses on management efforts introduced to minimize current and future risks (IPCC, 2014). However, an issue remains – the measurement and estimation of both future time frames and the severity of physical risks prove difficult to accurately quantify (Task Force on Climate-related Financial Disclosures, 2017). As such, guidance and regulation are needed for non-climate experts to manage their risk exposure. The Task Force on Climate-related Financial Disclosures (TCFD) aims to provide this function through its use of scenario analysis. Despite their efforts, a 2019 status report showed limited uptake to these recommendations (TCFD, 2019). Connelly, Carter, Handley, & Hincks (2018) also find that climate change adaption is not sufficiently incorporated into industrial risk management, due to a lack of a ‘common language and harmonized conceptual approach’ (Connelly et al., 2018, p. 1399).

The literature acknowledges the transformative potential of climate risk assessment approaches like the TCFD recommendations (O’Dwyer & Unerman, 2020) for climate adaptation. However, the same authors identify a lack of practice in climate-related risk assessment. This is underpinned in Farbotko’s 2019 paper, which states that “climate risk is, in short, in the process of becoming mainstreamed into the market, although the regulatory environment and disclosures themselves are embryonic” (Farbotko, 2019, p. 275). A more recent paper states that the financial literature still lacks the methodologies to successfully analyze climate-related financial risk

(Battiston, Dafermos, & Monasterolo, 2021). Moreover, a recent analysis of six different commercial providers of physical risk scores finds significant divergence in the results from the small group of climate risk assessment providers (Hain et al., 2021). This demonstrates the absence of consistent risk assessment standards and the discrepancies which arise as a result.

Therefore, this paper aims to illustrate previous attempts to bridge the gap between the scientific consideration for climate change and the financial accounting of related exposure. However, this research highlights the failure of existing literature to provide a general framework which can be applied and regulated across industry standards and widely accepted by industry practitioners.

1.3. Gap in literature

One explanation for the lack of climate change adaptation within business is that both institutional investors and reporting agents are unfamiliar with the tools needed for sustainability risk assessment, such as scenario analysis (O'Dwyer & Unerman, 2020).

Not only is scenario analysis a new and unfamiliar methodology to most industry practitioners – 42% of respondents in a TCFD survey found a lack of standardized metrics for climate risk across industries (TCFD, 2019). Furthermore, a systematic literature review on flood risk management found a lack of formal methodology in risk modelling (da Silva, Alencar, & de Almeida, 2020). This research will address the need for a formal climate risk modelling framework for industry practitioners.

General high-level guidance to measuring and disclosing future climate risks is provided by the TCFD. However, methodologies to measure and quantify these risks are often proprietary and confidential. Recently, several firms have started to offer climate risk assessment as a service. Examples include Munich RE's Location Risk Intelligence Software (Munich RE, 2020), or investment research firm MSCI's climate risk assessment (MSCI, 2020), or consultancy firm South Pole (South Pole, 2021).

Currently, firms such as these are using climate data to predict future climate-related physical risks, using inconsistent methods with inconsistent outcomes (Hain et al., 2021). Moreover, their methodologies are often not publicly disclosed, verified, or regulated. As such, current climate risk measurements produced by the financial sector are unreliable and biased. In the worst case, misuse of climate models may lead to 'maladaptation and heightened vulnerability to climate change, material misstatement of risk, or greenwashing' (Fiedler et al., 2021, p. 88).

Therefore, the gap in the literature is the lack of a standard framework, through which all firms in the industry can apply the same measurement and disclosure methods, allowing for reliable, consistently calculated, climate-related financial exposure. Such a framework would level the playing field with regards to risk disclosure and aims to bring modelling assumptions out in the open, as well as make explicit the demands of financial firms for actionable climate risk data.

1.4. Research question

The aim of the research is to provide a uniform framework for financial firms to assess the risk of flooding to their real-estate portfolio in future climate change scenarios. This leads to the research question:

How can financial institutions quantify the financial risk posed by flooding to their real-estate portfolios in future climate change scenarios?

This paper will seek to answer the research question by constructing a framework based on current literature on physical climate risk, financial risk, and modelling techniques, bridging the gap between frameworks in the literature.

A key scientific contribution made by this research is the transferability of a standardized framework. Currently, with no standard for climate-related flood risk measurements, disclosure obligations, or supervisory assistance, the data available to study firms' potential economic risk is arbitrary and unreliable. For practitioners to understand the true value at risk of one of the most significant climate-related events we face; the tools, techniques, and benchmarks used must become an industry standard. This research and proposed framework will allow firms across the financial sector and possibly the wider economy to measure potential climate-related damage to physical assets.

Using the framework, cost-benefit analyses may be carried out, allowing firms and governing administrations to accurately judge the benefit and efficiency of flood-prevention strategies, increasing firm resilience to climate change, and facilitating efficient allocation of capital (Task Force on Climate-related Financial Disclosures, 2017).

2. Theoretical background

In this section, the theoretical background to the research is discussed. This research builds upon existing theories to construct a new framework. Relevant concepts include climate risk, financial risk, and flood modelling.

First, the financial risk of climate-induced flooding is discussed. Then, the concept of risk is defined by combining a general definition of risk, climate risk, and firm-specific financial risk. The different conceptualizations of risk are combined to form a definition of climate-related flood risk. Second, current climate risk assessment is discussed in the form of TCFD recommendations and scenario analysis. Third, the flood modelling techniques are discussed that form the basis for the model framework of this research. Finally, a conceptual model is presented. This conceptual model depicts the theories that this research builds on and describes the connections and relationships between the relevant concepts.

2.1. Flood risk as financial risk to real-estate

This section elaborates on the relevance of climate-related flood risk to the financial sector. Floods mainly impact financial assets such as real-estate through physical damage to assets, but also have secondary effects (Dietz et al., 2016). The following section justifies the focus on real-estate. Finally, this chapter discusses how investors factor in flood risk information in investment decisions.

2.1.1. Flood risk affects real-estate finance

The literature agrees that flood events have historically, and will continue to cause widespread financial damage, see e.g. (Bernstein, Gustafson, & Lewis, 2019). With increasing degrees of climate change, this is expected to increase (Allen et al., 2014). Floods pose a financial risk directly through physical damage to real-estate properties (Dietz et al., 2016). This is especially true for real-estate, as buildings cannot easily be moved out of harm's way and represent a large sunken cost. In this sense, flood risk can be seen as a business risk (elaborated upon in section 2.2.2.). However, the physical damage of climate change impacts the financial system at a wider level. As secondary effects, climate risks such as floods may 'reduce […] the return on capital assets, the productivity of knowledge, and/or in labour productivity' (Dietz et al., 2016, p. 676). Hence, climate risks such as flooding do not only pose a threat to individual firms, but to the wider economic system (Dietz et al., 2016).

The Sustainability Accounting Standards Board (SASB) classifies how different climate risks affect the financial condition of organizations. To illustrate the different effects on organizations, the SASB constructed the SASB Materiality Map. This Materiality Map describes the interactions between different economic sectors and the dimensions of climate risk (Sustainability Accounting Standards Board, 2018). In the materiality map, the physical impacts of climate change are identified as a key material issue to real-estate (SASB, 2018). The materiality map identifies two dimensions in which real-estate may encounter issues: first – the environment, and second – Business Model & Innovation (SASB, 2018). The environmental category makes explicit the issue of water and water waste management for real estate's financial conditions and operational performance. Whilst the business model and innovation category discuss the sustainability issue of the physical risk of climate change for real estate, specifically mentioning the risk of properties in relation to their proximity to flood zones (SASB, 2018). Because of the financial materiality of climate risks, the SASB recommends real-estate companies and investors to disclose their exposure to the effects of climate change.

2.1.2. Pricing effects of flood risk

In current financial literature, an asset's exposure to systematic risk such as climate risk can be captured in a so-called 'factor model' that is able to predict the price of an asset. A factor model is a statistical model that describes the price of an asset as a function of different measures of risk and return (van Dijk, 2020). Such methods include the Capital Asset Pricing Model (CAPM) – which considers only one factor, and the Fama-French Three-Factor Model, which considers three dimensions. These methods are useful as they inform investment decision-making. However, empirical evidence for the validity of these methods is limited (van Dijk, 2020). Multiple studies have attempted to establish whether asset prices reflect the flood risk they are exposed to. Whether flood risk is priced in or not may determine investment strategies vis-à-vis assets at risk to flooding (van Dijk, 2020). This has further implications for financial stability and the allocation of capital (Task Force on Climate-related Financial Disclosures, 2017). The TCFD expects that appropriate pricing of climate change helps direct capital towards less at-risk assets (2017).

One study in the UK finds that houses exposed to flood risk are valued on average 1.5% less (Belanger & Bourdeau-Brien, 2018). This indicates that investors do incorporate information about flood risk into investment decisions. However, decisions are based on 1. Investors' perception, and 2. information around current climate risk. A similar finding in Finland finds that recent publication of flood maps causes a price-drop in riskier properties (Votsis & Perrels, 2016). This indicates that market actors do care about flood risk and indicates a need for financially material flood risk information.

Investors do not only account for current flood risk, but also potential future risk. One US study finds a significant pricing effect of long-term sea-level rise predictions: homes exposed to future sea-level rise sell for approximately 7% less (Bernstein et al., 2019). This study finds that especially sophisticated real-estate investors – meaning with better information – account for future risk to flooding (Bernstein et al., 2019). This suggests the importance of symmetrical information around climate-related flood risk.

A recent survey of institutional investors points out that most financial actors perceive the physical effects of climate change in general to be material. This is especially true for larger, more sustainability-oriented, and long-term investment firms (Krueger, Sautner, & Starks, 2020).

These examples in the literature find a pricing effect of flood risk. However, this is dependent on investors' attitudes towards climate change and information about flooding (Bernstein et al., 2019). That means that flood risk information may not be accurately priced, as information may not be optimal. This indicates the importance of flood risk information in preventing sudden price shocks, as proposed by the TCFD (Task Force on Climate-related Financial Disclosures, 2017). At the time of writing, climate risk assessment tools do exist at early stages of development (Fiedler et al., 2021); but these vary widely in their qualifications of physical climate-related risk (Hain et al., 2021). This points to the need for a standardized flood risk assessment model. This improves the availability of information on future flood risk, to promote financial institutions' resilience to climate change.

2.2. Defining risk

A key concept applied in this research is that of climate-related flood risk. This section elaborates on different definitions and concepts of risk. The term risk is widely used in many disciplines, such as engineering, project management, finance, and climate science. Moreover, climate-related risk is a fundamentally different risk than the risks often dealt with in business and financial markets (O'Dwyer & Unerman, 2020). Within each discipline, the definition of risk differs slightly and has different connotations and implications. Therefore, it is important to define risk unambiguously.

This section will elaborate on the different definitions and conceptualizations of risk, leading up to the most recent definition proposed by the IPCC. This last definition will form the basis for this research, as the IPCC is the leading authority on climate science. This definition will be operationalized in financial terms in the methodology to create a sensible notion of financial climate risk.

A general definition of risk exists with a high degree of consensus and use (Hillson & Hulett, 2004). One example of a risk definition is that of the International Organization for Standardization (ISO): which states risk as *the effect of uncertainty on objectives* (International Organization for Standardization, n.d.). Variations of this definition are widely applied, although they may differ in wording.

A common characteristic in all definitions of risk is that it encapsulates two dimensions: the probability of an event, and the subsequent impact or consequence if that event would occur (Hillson & Hulett, 2004), (Connelly et al., 2018), and (Holton, 2004). Referring to the ISO definition, *the effect of uncertainty on objectives*, the *effect on objectives* is the consequence or impact, and *uncertainty* can be described by probability (International Organization for Standardization, n.d.).

Connelly et al. (2018) use these dimensions to generally define risk in a formula, see Equation 1:

Equation 1: Definition of risk. Retrieved from: (Connelly et al., 2018, p. 2).

$$Risk = Probability \times Consequences$$

This research considers climate risk specifically. Therefore, it is relevant to define climate risk. The IPCC refers to these same two dimensions in their definition of risk. Their core definition of risk states: “the potential for adverse consequences” (Reisinger et al., 2020, p. 5). The *potential* refers to probability, *adverse consequences* describe the consequence. Notably, the IPCC refers specifically to adverse, or negative, consequences. A complete definition of risk used in the IPCC’s Sixth Assessment report is shown below:

> “The potential for adverse consequences for human or ecological systems, recognising the diversity of values and objectives associated with such systems. In the context of climate change, risks can arise from potential *impacts* of climate change as well as human *responses* to climate change. Relevant adverse consequences include those on lives, livelihoods, health and wellbeing, economic, social and cultural assets and investments, infrastructure, services (including ecosystem services), ecosystems and species.” (Reisinger et al., 2020, p. 4).

An important note on this revised definition of risk is that it refers specifically to both the impacts of and the human response to climate change. This is important, as it highlights that risk arises both from the physical effects of climate change, but also the possibility of human response to mitigate the adverse consequences.

2.2.1. Climate risk

Climate risk refers to the potential adverse effects of climate change. The IPCC's fifth assessment report states that the earth's climate system has been significantly altered by anthropogenic greenhouse gas (GHG) emissions (Allen et al., 2014). The results of this increase in GHG concentrations and subsequent climatic change, are unprecedented changes in temperature of the earth's oceans and atmosphere. This, in turn, has impact on all human and ecological systems. Examples of changes in ecological systems include altered hydrological systems, migration patterns, species interactions, and ocean acidification. Changes in human systems include changes in crop yields, food production, and wider impacts on livelihoods, health, and economics (Allen et al., 2014). With increasing GHG concentrations, these impacts are expected to increase and intensify.

Next to these systemic changes in human and ecological systems, extreme weather events will continue to become more frequent and severe (Allen et al., 2014). These climate-related extremes include droughts, cyclones, heat waves, wildfires, and floods. As floods are responsible for a large proportion of climate risk to business (Ward et al., 2013), this research will focus on flood risk.

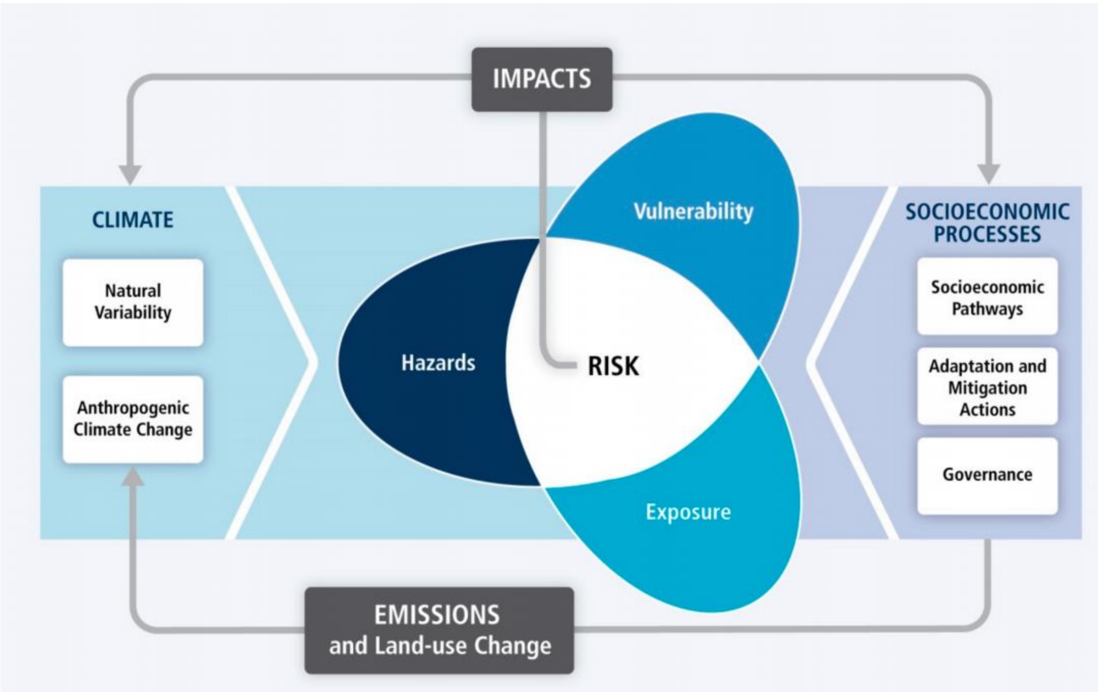


Figure 1: IPCC conceptualization of risk. Risk is conceptualized at the intersection of hazard, vulnerability, and exposure. Retrieved from: (Connelly et al., 2018), as adapted from (IPCC, 2014).

In 2012, the IPCC published a special report on managing the risk of extreme events relating to climate change. In this report, the IPCC conceptualized risk into three dimensions (Field et al., 2012), seen in Figure 1.

Hazard refers to the occurrence of an extreme climate event such as a flood, tropical cyclone, heatwave, or drought (Field et al., 2012). Hazards are dependent on natural variability, and anthropogenic climate change.

Exposure refers to where the adverse consequences occur (Field et al., 2012). As per the IPCC definition of risk, these include the presence of people, livelihoods, economic, social, and cultural assets and investments, infrastructure, services (including ecosystem services), ecosystems and species (Reisinger et al., 2020).

Finally, **Vulnerability** represents the propensity of that what is exposed to be negatively affected by the hazard.

Together, these three dimensions constitute climate risk. Risk exists where a climate-related extreme event is probable (**hazard**), creating negative consequences on people or economic, social, and cultural assets (**exposure**), where some may be more likely to be negatively affected (**vulnerability**).

The three dimensions of climate risk may be expressed as variables to operationalize, measure, and quantify risk. With this more descriptive definition and more accurate conceptualization of risk, a new equation is formulated. Incorporating the three dimensions as defined by the IPCC, Connelly et al. formulate Equation 2 below. In this equation, risk is seen as a function of the three dimensions of risk as defined by the IPCC. Namely, risk can be calculated as a function of the probability of a hazard, the exposure to that hazard, and the vulnerability of those exposed.

Equation 2: Expanded definition of risk in calculation form, retrieved from (Connelly et al., 2018, p.5)

$$Risk(R) = f(Probability\ of\ Hazard\ (p)\ \times\ Exposure\ (E)\ \times Vulnerability\ (V))$$

2.2.2. Risk in finance

While the term risk occurs both in climate science and in finance, there is a difference in definition between the two disciplines. In financial terms, risk is defined as “the chance that an outcome or investment’s actual gain will differ from an expected outcome or return. Risk includes the possibility of losing some or all of an original investment” (Chen, 2020, paragraph 1). In general definitions, including the IPCC definition, risk refers to the possibility of an adverse effect. In financial terms, however, risk is considered a neutral term. In the financial sector, risk is inextricably linked with return on investment. This is because an investor expects to be rewarded for taking on risks (Chen, 2020). Usually, lower risk will yield lower returns and vice versa. The risk or volatility of a financial product may stem from a myriad of factors. This section will elaborate on the different sources of financial risk, and how this is linked to climate risk.

Risk in financial terms is broadly distinguished into two types: systematic risk and unsystematic risk. Unsystematic risk is also sometimes referred to as idiosyncratic risk – is inherent to a specific company, portfolio, or group of assets (Chen, 2020). Systematic risk affects the overall financial system; it is therefore also referred to as market risk. Third, there is systemic risk where a firm or sector-level risk can trigger a collapse of the overall financial system through interdependencies (Schwarcz, 2008).

Next to this risk dichotomy, risk is also classified into different types depending on the source of risk (Chen, 2020). One important type of risk in a financial sense is *Business risk*. Business risk refers to the exposure of a company, organization, or portfolio to anything that threatens the achievement of financial goals (Kenton, 2020). In this sense, exposure refers to the company, organization, or investment portfolio. The hazard may stem from a wide range of sources, including climate risk.

2.2.3. Climate risk to business

In the finance and economic literature, climate change is most often described in the context of Business risk (Pattberg, 2012). Namely, it is a risk that may prevent a business from achieving its financial goals.

Climate-related risk to business is further described in the literature. The literature divides climate risk into two main categories: *1. Physical risk*; and *2. Transitional risk*. See, for example (Task Force on Climate-related Financial Disclosures, 2017), or (Pattberg, 2012), who describe the business risk of climate change. Both publications note that climate change affects business operations directly in a physical way; through damage to assets and operations, but also more indirectly through the transition to a lower-carbon economy. Transitional risk includes changes in policy, technology, and market effects that may influence a business' operations (Task Force on Climate-related Financial Disclosures, 2017). Table 1 summarizes the different climate risks.

2.2.3.1. Physical climate risk

Physical climate risk is concerned with climate change as a physical phenomenon. Physical climate risk refers to the impact of increased frequency and intensity of extreme weather events (Task Force on Climate-related Financial Disclosures, 2017). These include prolonged droughts, increasing floods, longer and more intense heatwaves, and hurricanes (IPCC, 2014). The impacts of physical climate risk include reduced production capacity, damage to physical assets, and increased insurance cost (Task Force on Climate-related Financial Disclosures, 2017).

More generally, Sussman and Freed (2008) describe the different ways in which extreme weather events resulting from climate change may pose a risk to business operations. The researchers further distinguish between the levels of business operations that are exposed to physical climate impacts.

The first level is the impact to *core operations*. This includes damage to physical assets such as real-estate, machinery, and inventory. It also includes impaired production capacity and productivity. Physical damage to property may interrupt production. Furthermore, increased ambient temperatures may negatively influence labor productivity.

The second level impacts occur on the *value chain*. On the input side, climate change may affect resource availability and production capacity of suppliers. This may impair production through the supply chain.

Third, there are climate impacts on the *broader network*. Physical damage from climate extremes may impact public utility companies such as water or electricity providers. Moreover, wider infrastructure such as roads and railroads may be negatively impacted, interrupting business operations.

2.2.3.2. Transitional climate risk

Next to the physical impacts of climate change, there are also risks involved with the transition to a lower-carbon economy. The TCFD state that changes may occur in the categories of policy and legal, technology, market, and reputation (Task Force on Climate-related Financial Disclosures, 2017).

First, policy and legislation surrounding climate change continue to evolve. Companies with a considerable contribution to GHG emissions may face repercussions from new regulations, such as emissions taxes or maximum allowed emissions. Additionally, legislation may be introduced that forces companies to act on climate risk. As discussed in the introduction, EU legislation has already passed requiring financial organizations to disclose their risk to climate change, such as the SFDR and IORP-II for pension funds. Furthermore, transition risk includes the risk of litigation and related costs. As the value loss related to climate change is expected to rise, so is the amount of litigation claims on organizations failing to act on climate change (Task Force on Climate-related Financial Disclosures, 2017). Recent examples include a court case in the Netherlands against fossil fuel giant Shell, who were ordered to reduce emissions by 45% in 2030 (Bousso, Meijer, & Nasralla, 2021). Besides policy and legal risks, climate change may pose technological risks. As new, cleaner production technology is developed, winners and losers may emerge from a paradigm shift in technological innovation. Third, market risks emerge from the complex interactions of supply chains and demand shifts in certain commodities, products, and services. A final transition risk is reputational risk. Consumer perception of a company’s contribution to climate change may become more material for a firm’s reputation. In turn, this may a shift in influence consumer demand.

Table 1: Different types of climate risk and financial impacts. Adapted from: (Task Force on Climate-related Financial Disclosures, 2017). Potential financial impacts from physical risks adapted from (Sussman & Freed, 2008).

Type of risk	**Climate-related risk**	**Potential financial impact**
Physical	Extreme weather events	*Core operations:* Physical damage to assets, business interruption *Value chain:* Supply chain disruptions *Broader network:* Disruption in infrastructure and utilities
Transition	Policy and legal	Increased operational cost due to tax or mitigation cost Litigation cost
	Technology	Reduced demand for technologies or services Technology research and development costs Costs to adopt new technology
	Market	Reduced demand Increased production cost due to increase in inputs (water, energy)
	Reputation	Reduced demand due to reputational concerns

2.2.4. Combining Financial and Flood risk: Climate-related financial flood risk

The previous sections discussed how the concept of risk is conceptualized and viewed in different academic fields. This research combines insights from multiple disciplines to construct a model framework that encapsulates both the physical, climate-related dynamics of flood risk, as well as the material financial impact of this risk. The next section summarizes the myriad of risk definitions and proposes an explicit definition of climate-related flood risk used in this paper.

As climate risk carries a different meaning from financial risk, statistical methods such as beta and R-squared may not be appropriate for measuring climate-related flood risk, as they describe different phenomena (O'Dwyer & Unerman, 2020). Climate-related financial risk in this research is conceptualized as the probability of financial damage due to climate-related extreme weather events, whereas risk in financial terms is the difference between actual return and expected return. Therefore, it is useful to use a meaningful statistical measure that describes the probability and magnitude of flooding events. The upcoming chapter 'Flood risk: Definition and Management', describes a commonly used metric of describing floods: Expected Annual Damage (EAD).

This research requires a uniform definition of risk that encapsulates all dimensions described above: it should reflect both likelihood and impact, encapsulate the three dimensions as proposed by the IPCC, and it should reflect the financial implications of risk. It should also be specific to flooding and reflect the dynamics of flooding. Therefore, the definition of **Climate-related financial flood risk** is as follows:

The combined probability and adverse financial consequence of flood events to physical assets, production, and supply chains; driven by increase climatic change.

In the methodology, this definition of risk is further elaborated upon and defined as a variable.

2.3. Climate risk assessment and management

This section will describe the different ways in which climate risk specifically can be managed. A set of general recommendations posed by the TCFD are described. An important part of these recommendations is the concept of scenario analysis.

2.3.1. TCFD recommendations

Increasing concerns that climate change might be the source of a global financial crisis have led to discussions among the G20's Financial Stability Board (FSB), one of the highest levels of economic power. The fundamental assumption is that financial stability stems from the markets 'invisible hand'. This refers to the idea that perfect information will lead to accurate pricing in the market, and prevent market shocks (Farbotko, 2019), (O'Dwyer & Unerman, 2020). This means that global financial stability requires firms to understand and disclose the risk they face to climate change. If investors understand this risk, more accurate pricing will occur, and financial crises will be averted.

To facilitate the dissemination of material climate-related financial information, the FSB have given the Taskforce for Climate-related Financial Disclosure (TCFD) the task of providing a framework that industry practitioners can use to assess and disclose their climate risk. The result of this multi-stakeholder project is a 2017 report titled 'Recommendations of the Taskforce for Climate-related Financial Disclosure', in this paper referred to as the TCFD Recommendations.

The TCFD recommendations are a set of actionable recommendations that instruct how both financial and non-financial corporations can understand, and subsequently, report on, the risks and opportunities stemming from climate change on its operations (Task Force on Climate-related Financial Disclosures, 2017).

Table 2 provides a summary of the TCFD recommendations.

Table 2: Summary of TCFD Recommendations. Retrieved from: (Task Force on Climate-related Financial Disclosures, 2017, p. 14)

Governance	Strategy	Risk Management	Metrics and Targets
Describe the board's oversight of clime-related risks and opportunities.	Describe the climate-related risks and opportunities the organization has identified over the short, medium, and long term.	Describe the organization's processes for identifying and assessing climate-related risks.	Disclose the metrics used by the organization to assess climate-related risks and opportunities in line with its strategy and risk management process.
Describe management's role in assessing and managing climate-related risks and opportunities.	Describe the impact of climate-related risk and opportunities on the organization's businesses, strategy, and financial planning.	Describe the organization's processes for managing climate-related risks.	Disclose Scope 1, Scope 2, and if appropriate, Scope 3 GHG emissions, and the related risks.
	Describe the resilience of the organization's strategy, taking into consideration different climate-related scenarios, including a 2°C or lower scenario.	Describe how processes or identifying, assessing, and managing climate-related risks are integrated into the organization's overall risk management.	Describe the targets used by the organization to manage climate-related risks and opportunities and performance against targets.

Summarized, the TCFD recommendations come down to reporting on the firm's integration of climate-related risks and opportunities to business operations. The TCFD recommends firms to incorporate climate risks on multiple levels of the organization: 1. Governance: upper management should be aware of climate risks. 2. Strategy: climate risk should be at the core of company strategy. 3. Risk management: climate risk must be incorporated into risk management;

and 4. Metrics and Targets: the company should disclose the metrics and targets they employ to do so.

The TFCD recommendations have a distinct focus on the *dependencies* of the firm to different climate change scenarios. This makes it different from other forms of sustainability reporting, as those often focus on the firm's *contribution* to climate change (O'Dwyer & Unerman, 2020). This makes the information more pertinent to investors, as climate dependencies can affect the bottom line more directly. Moreover, even the most net-zero companies with the lowest carbon footprint may be exposed to climate-related risks. This makes climate dependencies relevant for all types of firms.

2.3.2. TCFD recommendations on scenario analysis

A cornerstone of the TCFD recommendation is climate scenario analysis. Scenario analysis is 'an important and useful tool for understanding the strategic implications of climate-related risks and opportunities' (Task Force on Climate-related Financial Disclosures, 2017, p. 25). Because of the uncertain nature of both the physical and socioeconomic future, it is encouraged to predict multiple plausible scenarios.

Scenario analysis is relevant to both physical and transitional risk. The recommended approach to scenario analysis is to select at least two scenarios that present a range of both favorable and unfavorable plausible futures. It is also recommended to select multiple timeframes, such as a short-, medium-, and long-term milestone. The exact years these timeframes represent are dependent on the organization, and the projected lifespan of the company's assets and liabilities. Finally, it is recommended that firms disclose their resilience to the results of these scenarios. That is to say, what strategic plans are in place in each of these scenarios (Task Force on Climate-related Financial Disclosures, 2017).

Scenario analysis is a useful tool in dealing with uncertainties. As the degree and frequency of both coastal and riverine flooding partly depend on climatic factors (Allen et al., 2014), it is important to account for different climate scenarios when projecting flood risk. Therefore, scenario analysis is a useful tool for flood risk modelling.

2.3.3. RCP Scenarios

Scenario analysis requires the selection of scenarios. For physical climate risks, it is useful to choose scenarios that predict the physical future of climate change. For this, the Representative Concentration Pathways (RCPs), are most helpful. The RCPs represent differing degrees of climate change, from low to high greenhouse gas effects (van Vuuren et al., 2011). These pathways are the result of collaboration between climate modellers and emissions experts and are exclusively used in climate modelling. Having a uniform set of climate change assumptions allows for intercomparison and collaboration between groups of climate modellers. These scenarios are also used in the IPCC's fifth assessment report (Vuuren et al., 2011), which further validates the RCPs' value in scenario analysis.

2.4. Flood risk: Definition and Management

This paper focuses on the extreme weather event of flooding. Therefore, it is important to understand how floods occur, and how this interacts with climate change. For flood modelling and risk assessment, it is important to understand how flooding events may be described and predicted using statistical methods. To better understand how flooding affects financial assets, it is important to define flood risk.

2.4.1. What are floods and how do they occur?

A flooding event can be defined as follows:

"(1) An overflow or inundation that comes from a river or other body of water and causes or threatens damage; (2) any relatively high streamflow overtopping the natural or artificial banks in any reach of a stream; (3) a relatively high flow as measured by either gage height or discharge quantity; (4) an overflow of water onto lands that are used or usable by man and not normally covered by water. Floods have two essential characteristics: the inundation of land is temporary, and the land is adjacent to and inundated by overflow from a river, stream, lake, or ocean." (Wang & Yang, 2014, p. 823)

From this definition, the most important characteristics of a flood are an overflow or inundation of water onto used or usable land that is not normally covered by water.

A flood is a hydrological event, meaning it is related to hydrology. Hydrology is the study of the "occurrence, movement, and storage of water in the earth system" (Salas et al., 2014, p.2). Hydrology concerns itself with the physical and stochastic processes surrounding water and its different phases. An important concept relating to this definition is the *hydrological cycle*. This is the cycle that describes the movement and storage of water through its various phases and where it is stored.

The hydrological cycle, as seen in Figure 2, describes the various hydrological processes that occur within the earth system. Water is constantly moving throughout the earth system in a closed system or cycle. While this cycle is complex and involves many different processes, the most important processes are described in this paragraph. To understand flooding, it is important to understand the complex interactions between the earth's surface, the ocean, and the atmosphere.

Figure 2 schematically describes the hydrological cycle (Pallardy, 2011). The following paragraph describes the flow of water through the hydrological system, based on this image. Starting at the ocean, water evaporates into condensation, forming clouds, shown in the diagram as step 1. These clouds, containing evaporated water, move towards land and precipitate to the earth's surface, in a process called precipitation labelled 2. On land, surface water is carried by gravity towards rivers, brooks, creeks, and lakes. This process is referred to as surface runoff, labelled 3. A portion of this water is stored as rivers and lakes. Another portion of surface water continues to flow throughout the earth's surface and eventually infiltrates into the soil, labelled 4. How much water infiltrates the soil is dependent on how much water is already there, and the coarseness of the soil. Water that is contained within the soil is referred to as soil moisture. Water that infiltrates deeper into the ground is referred to as groundwater. Some of this groundwater will continue to flow down, back towards the oceans. Soil moisture is consumed by vegetation that requires water to grow. With water stored in the soil and in vegetation, water is returned to the atmosphere through transpiration and evaporation. Transpiration refers to plants transpiring moisture; evaporation is the condensation of water from the soil. Water that is stored in surface water, such as rivers and lakes, also evaporates. These processes of evaporation and transpiration are all labelled 5. Water that is still stored within the surface may flow back into the ocean either underneath or above the surface, both are labelled 6. From the transpired and evaporated water, as well as the water that has run off back into the ocean, the cycle starts anew, arriving back at evaporation labelled 1 (Pallardy, 2011).

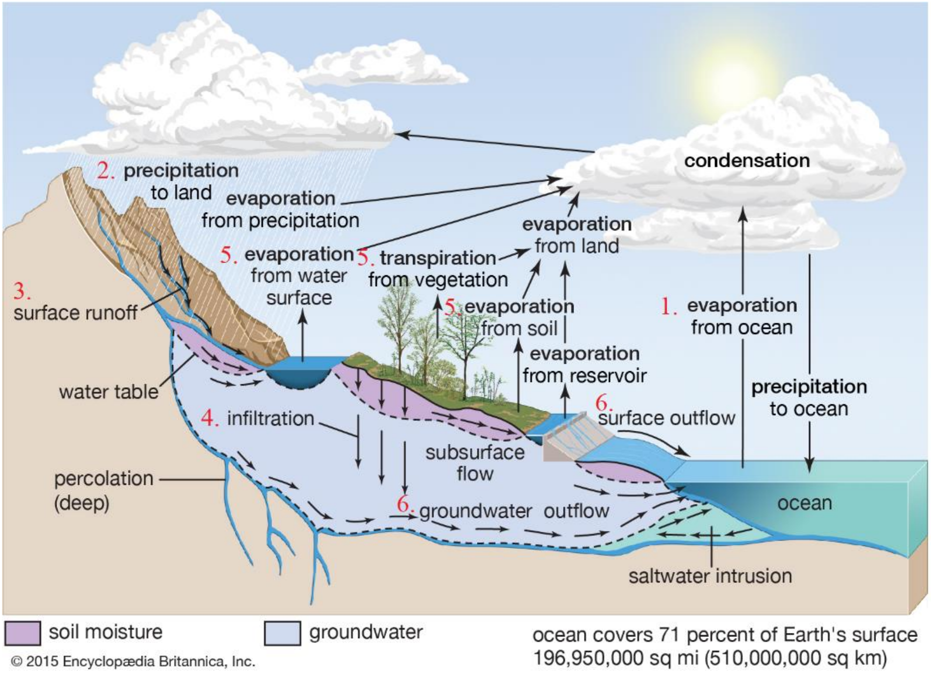


Figure 2: Diagram describing the hydrological cycle, or water cycle. Adapted from: (Pallardy, 2011).

From the definition of flooding and the hydrological cycle, it is possible to understand how a flood may occur. Flooding is an event where an excess amount of water overflows and inundates usable land that usually is not covered in water. Looking at the hydrological cycle, this may be caused by different processes. Therefore, different types of flooding are distinguished.

Flooding is often divided by practitioners into two main categories: *fluvial* or *riverine flooding*, and *coastal flooding*, see for example (Ward et al., 2020). It is useful to distinguish between different types of floods as they occur in different geographical locations and have different causes. Unsurprisingly, river floods occur near rivers while coastal floods occur along the coast.

River floods occur when the inflow of water exceeds the amount of water that can infiltrate into the soil or flow towards the ocean. Excess water must flow somewhere, and therefore may overflow the banks of the river, inundating the land next to it (Salas et al., 2014). Therefore, the main cause of river flooding is often extreme precipitation.
Coastal floods are caused by a combination of three factors: sea level, astronomical tides, and storm surges (Ward et al., 2020). First, a rise in sea level can cause water to flow onto land and cause a flood. Astronomical tides are caused by the earth's rotation, as well as gravitational

effects from the sun and moon. Tides drive wave creation, which also contributes to flooding. Storm surges refer to abnormal rising of sea-level due to a storm's wind pushing water onto shore.

Climate change drives an increase in both riverine and coastal flooding, through the increase in precipitation and rise of the global mean sea level (Allen et al., 2014). First, increased GHG emissions lead to an increase in ocean surface temperature, leading to an increase in ocean and surface water evaporation and transpiration. This will lead to an increase in precipitation, and subsequent flood frequency and severity. Second, an increase in the earth's surface temperature leads to the melting of ice sheets in polar regions, as well as expansion of the ocean water volume. This increase in total water volume leads to higher tides, as well as a rise in sea-level, which subsequently causes an increase in coastal flooding.

2.4.1.1. Describing and predicting floods

Like many hydrological processes, floods are characterized by uncertainty and randomness. Therefore, it is useful to describe these processes using statistics and probability theory. A flooding event, therefore, is a random event and can be described using a probability density function (PDF) (Salas et al., 2014). On this PDF, the y-axis shows the severity of the flood. The main ways of expressing the severity of a flood are by describing how much water is flowing, in cubic feet per second (cfs), or the resulting inundation depth in meters (m). The x-axis shows the probability of that flood, expressed as the exceedance probability (probability that a flood is greater than this severity), or return period (how many years until a flood of this magnitude occurs). The annual exceedance probability can be found by taking the inverse of the return period. In other words, a 100-year flood has a probability of 1/100 of occurring every year (Salas et al., 2014).

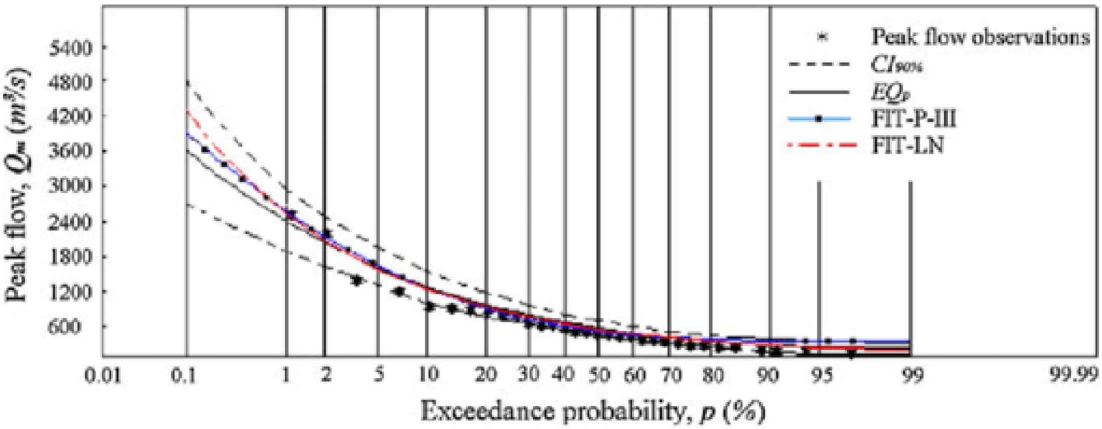


Figure 3: Example of a flood probability distribution, showing the intensity of flood on the y-axis, represented by peak flow in m^3*/s, and exceedance probability on the x-axis, as percentages. Adapted from: (Liang, Chang, & Li, 2012).*

Besides its use in expressing historical floods, probability distributions are also useful in predicting future floods. In practice, historical flood data are used to inform future flooding events. Data from past flooding events may be entered into a statistical model to predict what future floods may look like. In other words, the empirical flood distribution informs a statistical model which plots possible future distributions. One statistical distribution is referred to as a Gumbel distribution. This particular statistical distribution has the property where the maximum value of empirical data approaches the Gumbel distribution as the sample size increases (Gumbel, 1955). This property makes the model useful for predicting maximum values, such as flood events. Therefore, to predict floods, historical flood data is collected and fit to a statistical model, which in turn is used to predict flood severity in the future.

2.4.2. Flood risk management

The impact from floods may be mitigated using a range of approaches, referred to as flood risk management (FRM). The figure below gives an overview of the wide range of approaches that may be taken to mitigate the impact of flooding. These approaches range from preventing hazards at the source, to limiting exposure and increasing vulnerability. First, hazard can be limited at the source by restoring wetlands. This changes the hydrological cycle to allow for excess water to flow and decrease risk of inundation. Then, embankments and flood barriers such as dikes may be constructed to direct flow away from cities or agricultural areas, decreasing hazard. Vulnerability may be decreased through land use regulation and raising preparedness through early warning systems. Finally, financial impact may be reduced through insurance and relief funds (Most & Marchand, 2017). Flood protection standards for flood barriers are often given as a function of the degree of flooding it is meant to withstand. For example, a dyke with designed to a 100-year flood protection standard is able to protect from at most a once in 100 year flood (Scussolini et al., 2016).

Figure 4: Overview of the different approaches to flood risk management as proposed by the World Meteorological Organization. Retrieved from: (Most & Marchand, 2017)

2.4.3. Terms

- *Flood*: an overflow or inundation of water onto land that threatens to cause damage
- *Riverine flood*: flood stemming from river water. Also referred to as fluvial flood
- *Coastal flood*: flood coming from ocean water, inundating the coast
- *Exceedance probability*: the probability of a flood event greater than the given amount
- *Return period*: average time between two events of the same magnitude
- *Inundation*: the amount of water that inundates (covers) a land area

2.5. Climate-related flood modelling

This section outlines how flood events may be predicted using flood modelling. One approach to flood risk modelling is presented in detail. This approach consists of a proposed global flood risk modelling framework and forms the basis for the modelling framework this research builds on. Therefore, concepts introduced in the following sections are reflected in the methodology of the research. The operationalization of concepts introduced below is further elaborated upon in the methodology section.

Multiple methodologies exist to model flooding. Flood models use a combination of stochastic and statistical approaches to predict the magnitude of floods in different return periods. This is done by modelling a simplified version of the hydrological cycle. Using modelling techniques, it is possible to predict hydrological processes such as precipitation, river flows, and soil infiltration (Salas et al., 2014). From there, a flood model can predict flood inundation from oceans and rivers, which is in turn used for flood damage assessment.

This section elaborates upon one approach to river flood modelling, described in a paper by Ward et al. (2013). This flood modelling framework is applied in the research to quantify risk to real-estate portfolios. The proposed flood model 'cascade' consists roughly of the following steps:

1. Global hydrological-hydraulic modelling
2. Extreme value statistics
3. Inundation modelling
4. Impact modelling

1. **Global hydrological-hydraulic modelling**

First, daily precipitation and temperatures are projected in grid cells using climate models. Grid cells refer to dividing the world into millions of tiny squares, in which these calculations are performed. These temperatures and precipitation levels are used to model the global hydrological cycle. The global hydrological cycle is then simulated over multiple years, resulting in annual maximum flood volumes.

2. **Extreme value statistics**

Using extreme value statistics, the flood volumes of these simulated floods are fit to a probability distribution for each grid cell. Simulating floods and recording their statistics allows for the prediction of future flood volumes without empirical data.

3. **Inundation modelling**

Further down the model cascade, probability distributions of flood volumes are modelled together with elevation models to predict flood inundation levels. Namely, if the volume of flood water is known, it is possible to predict how much water will inundate the grid cell. This level of inundation is important to show how much damage may arise from a particular flood.

4. **Impact modelling**

In the final step, projected flood inundation distributions are converted into *impact* by combining hazard and exposure. Depending on the scope of the risk assessment, exposure may be calculated differently. Examples include impact to 1. GDP, 2. impact to population, or 3. impact to buildings (Ward et al., 2013). Damage to buildings is most relevant to this research. For this, so-called flood depth-damage curves are often used to convert inundation depth into damage (Ward et al., 2013). Flood depth-damage curves refer to the known relationship between flood depth and subsequent damage. This relationship may either be empirically found by regression of historical flood inundations and damage (Huizinga, De Moel, & Szewczyk, 2017) or constructed based on expert judgement. Using these curves, flood damages may be interpolated by plotting flood inundation depth on a depth-damage curve. Figure 5 shows an example of depth-damage curves. A two-meter flood onto an agricultural area results in 0.9 (90%) damage to the value of agriculture (Koks, de Moel, Aerts, & Bouwer, 2014).

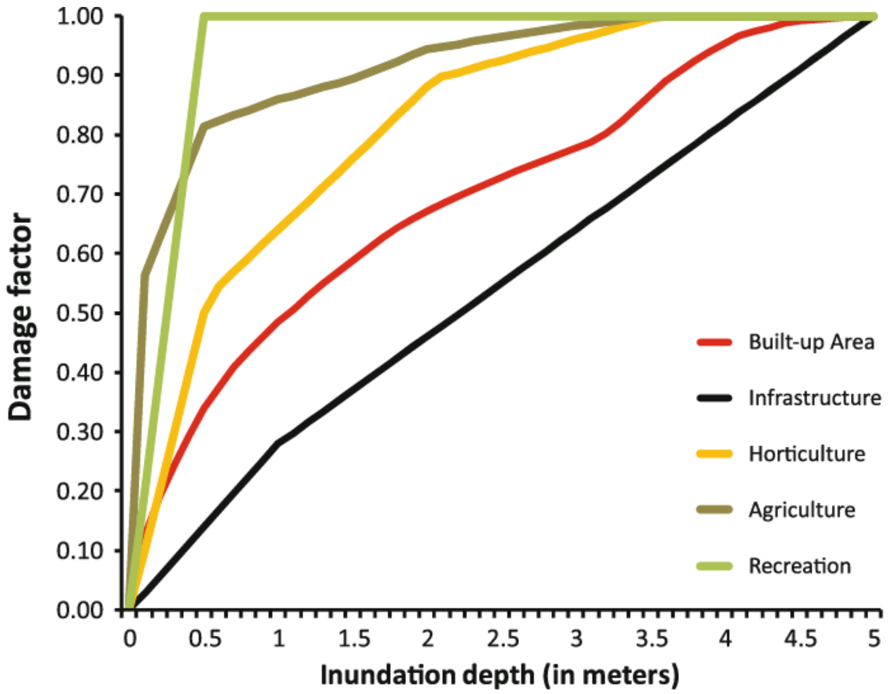


Figure 5: Example of flood depth-damage curve. This curve shows the relationship between flood depth and the subsequent recorded damage to structures. The x-axis shows flood inundation depth in m, the y-axis shows fractional damage expressed from 0 (no damage) to 1 (complete destruction). Adapted from (Koks et al., 2014)

The concept of expressing floods using a probability distribution is particularly useful in predicting flood damage. If the depth-damage curve is known, the expected value of flood damage may be calculated.

Since the distribution of flood inundation is known, and the relationship to damage is known; the probability distribution of damage is now known. If we express the probability distribution of damage as $D(p)$, where D is damage, and $D(p)$ is the damage-probability curve, then the expected damage of all possible floods may be expressed as an integral: $D_{total} = \int D(p)dp$ (Salas et al., 2014).

Here, the damage $D(p)$ of each probability p, is multiplied by that probability. This gives us an expected value. Integrating this over the entire probabilities gives the Expected Annual Damage (EAD). EAD is generally used to describe the financial damage from flooding (Wobus et al., 2019), (Winsemius et al., 2013). Therefore, this approach is applied in the methodology to calculate flood risk.

Graphically, this is shown in Figure 6 below.

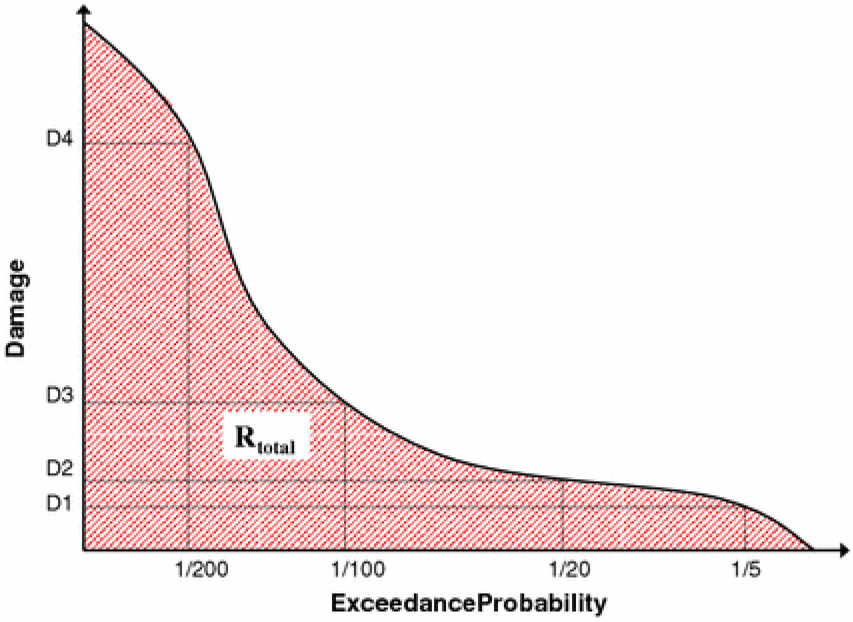


Figure 6: Flood damage probability curve. The area underneath the curve (integral), represents total risk, expressed as Expected Annual Damage (EAD). Adapted from: (Meyer, Scheuer, & Haase, 2009).

2.5.1. Aqueduct Flood model

To answer the research question, this research design leverages the state-of-the-art Aqueduct flood model. This model is the result of a collaboration between multiple researches and industry experts from the World Resources Institute, Deltares, Vrije Universiteit Amsterdam, Utrecht University, and the Netherlands Environmental Assessment Agency (PBL) (Ward et al., 2020). The Aqueduct Flood model is based on the modelling flow proposed by Ward et al. in 2013, described in the previous section. However, since 2013, further bias corrections and improvements have been added to increase the validity of the model. For example, empirically recorded historical flood data are compared to model predictions over that same period. The model is then adjusted based on the difference between historical and predicted data (Ward et al., 2020). This bias correction ensures validation of the model using real-world data.

Briefly summarized, The Aqueduct Flood model uses General Circulation Models (GCMs) to predict future climate conditions, such as precipitation and temperature. GCMs are climate models that are used to model the atmosphere and climate. Typical applications of GCMs are weather forecasting and predicting and understanding climate change. However, GCMs are also often used to predict flood occurrence (Shadmehri Toosi, Doulabian, Ghasemi Tousi, Calbimonte, & Alaghmand, 2020).

GCM predicted precipitation and temperature are then used with the PCR-GLOBWB2[1] model. This model predicts the global hydrological cycle (Sutanudjaja et al., 2018). Hydrology tools such as PCR-GLOBWB2 have been vital in understanding flooding, drought, and global sea-level change (Sutanudjaja et al., 2018).

In the Aqueduct tool, the global hydrological cycle is modelled for several years to extract flood statistics, which are applied to a statistical model that is used to predict future floods. These steps are performed for multiple RCP scenarios, to allow for scenario analysis.

In this research, flood maps from the Aqueduct Flood model are leveraged to represent hazard data in the proposed model framework.

[1] PCRaster Global Water Balance, version 2

2.5.2. Limitations of climate-related flood modelling

As indicated by the flood model cascade (Ward et al., 2013), and the presence of the Aqueduct Flood tool (Ward et al., 2020), there is no shortage of physical flood models. However, applications of such models have not yet been described in the literature. At the same time, current frameworks for assessing physical climate risk such as flooding exist but are proprietary and undisclosed in literature – hence proving to be uncritical and inconsistent. Moreover, several limitations exist for climate-related flood models, primarily due to biases and data availability.

First, as the models predict flood risk in future climate scenarios, they rely on the use of GCMs (climate models). Multiple GCMs exist, and while each model is highly scrutinized, they do vary in their predictions of future precipitation and temperature (Shadmehri Toosi et al., 2020). This introduces one bias to flood models. Second, due to the geospatial nature of flooding events, geographic coordinates are necessary for carrying out the flood risk assessment. These data are sometimes difficult or costly to obtain (Hain et al., 2021), especially for real-estate portfolios with a great number of properties. Third, flood models are highly sensitive to degrees of vulnerability (Ward et al., 2013). At the same time, this dimension is most difficult to model in climate risk metrics (Hain et al., 2021). Finally, the physical effects of anthropogenic climate change are sometimes hard to distinguish from natural variability in climate. Only with increased GHG emissions will the purely anthropogenic effects outweigh natural variability. This makes predictions before the end of the decade difficult (Fiedler et al., 2021).

2.6. Conceptual model

The goal of the research is to provide a uniform framework to quantify climate-related flood risk to companies' assets. The diagram below depicts the theoretical concepts used to provide this framework, and how they interact.

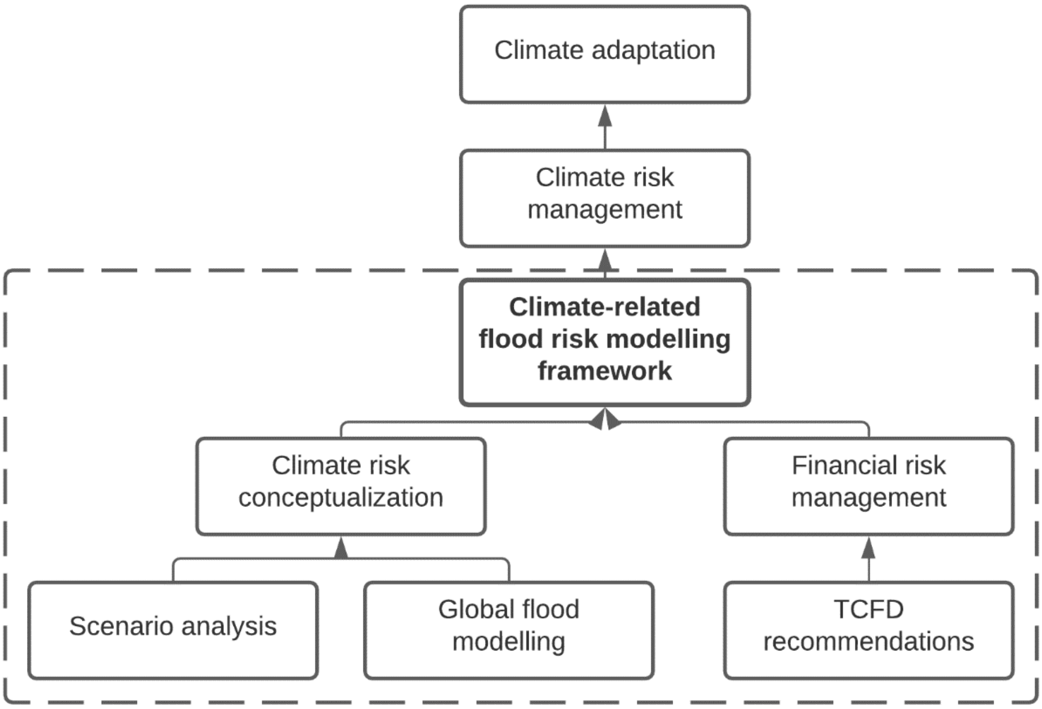


Figure 7: Conceptual model describing the relationships between theoretical frameworks used in the research. The dashed line indicates the boundary of analysis: the output of this research, a climate-related flood risk modelling framework, is used to inform climate risk management, and in turn, increase climate adaptation.

Figure 7 shows the conceptual model that describes the theoretical embedding of this research. At the center is the proposed climate-related flood risk modelling framework. This framework aims to inform climate risk management and in turn, aid in climate adaptation and increase business resiliency to climate change. The modelling framework is based on the IPCC conceptualization of climate risk, uses an established method for global flood modelling, together with scenario analysis. This is then combined with the recommendations put forward by the TCFD, to combine insights from climate science and hydrology with financial risk management. The dashed line indicates the boundary of analysis: the research focuses primarily on the quantification of climate-related flood risk. The link from flood risk assessment to risk management is explored in the discussion section but is not the primary focus of this research.

3. Methodology

In this section, the methodological choices for answering the research question are discussed. Firstly, the research design is elaborated upon. Then, the operationalization, collection, and analysis of data are explained.

3.1. Research design

To answer the research question *'how can financial institutions quantify the financial risk posed by flooding to their real-estate portfolios in future climate change scenarios?'*, a novel theoretical framework is constructed. This novel theoretical framework combines current theories of climate risk, flood modelling, and financial risk management.

To achieve this, the following research design is employed:

1. Literature review – establish the state of the art of climate risk assessment.
2. Construction of a climate risk assessment model.
3. Application of climate risk assessment model to the case study.
4. Analysis of case study results.
5. Synthesis of key steps to constructing a generalized risk assessment framework.

First, as novel theory is constructed, in which theories are explored to establish the state-of-the-art and address the limitations of existing climate risk assessments. This includes the theories seen in the previous section. To justify the choice of theory, only peer-reviewed papers are included. Pivotal papers are the flood risk assessment papers by Ward et al. and the TCFD recommendations. From this, a conceptualization of climate-related flood risk was constructed. Limitations of current climate risk assessment frameworks are identified which are addressed in this research. Limitations include a need for a standardized flood risk assessment model, as well as real-estate specific guidance.

Using current theories surrounding global climate risk, climate risk to business, and flood modelling, a novel modelling framework is constructed. This framework is based on guidance from Ward et al. (2013) and (2020), who propose a global flood risk assessment model using flood inundation as hazard and GDP as exposure. The Ward et al. paper was selected, as it produced adequate results in their sensitivity analysis (Ward et al., 2013). A second reason for selecting this paper is that the Ward et al. framework from the 2013 paper was adapted in 2020 to form the Aqueduct Flood model. The Aqueduct Flood model forms one of the main data sources for this research. However, the Aqueduct flood model does not model financial risk at the firm level, as proposed in this research. As such, this research aims to fill the literature gap of measuring financial risk due to flooding. The proposed model framework was adapted to incorporate real-estate property value as the exposure dimension, to allow for modelling the risk to real-estate at the portfolio level. This modelling framework is further elaborated upon in the data operationalization section of this chapter.

Then, this model was applied to a case study to illustrate the results the model produces, as well as to perform a sensitivity analysis. The case study selection is further described in the Case Study section. In the model application phase, the data pipeline is constructed to understand how the different concepts from the theory may be operationalized. The result of this exercise is the Data Analysis section, which shows how flood risk may be calculated – by using existing flood hazard maps, flood depth-damage curves, flood protection standards, and the value of real-estate investments.

Fourth, the results from the case study are critically analyzed. Risk hotspots are identified, and differences between scenarios and timeframes are elucidated. Results analysis includes sensitivity analysis. In this step, certain modelling parameters are varied to understand how the final output of the model varies as input parameters vary. This exposes what parameters the model is most sensitive to and gives indications of data reliability and validity.

Finally, the key steps of the modelling framework are summarized to allow for generalization of the model framework, as well as to expose modelling assumptions. This step is carried out to facilitate implementation by others to new cases. The proposed modelling framework may then be scrutinized and improved on for the benefit of constructing a standardized flood risk modelling framework to be used by practitioners.

3.2. Operationalization of data

This section makes explicit what data are used to represent the concepts discussed in the theory section.

In the theory section, risk is defined along the axes of probability and consequence; and has multiple dimensions. These have been summarized into Equation 2: which defines risk as a function of hazard, exposure, and vulnerability, seen below.

$$Risk(R) = f(Probability\ of\ Hazard\ (p)\ \times\ \ Exposure\ (E)\ \times Vulnerability\ (V))$$

Using concepts from hydrology, this general risk formula can be used to model flood risk. Based on the flood literature, flood risk is best expressed as Expected Annual Damage, which produces the following equation.

Equation 3: Equation for calculating risk, defined as expected annual damage. Adapted from (Winsemius et al., 2013).

$$EAD = \int D(p)dp$$

Flood risk is expressed as EAD, Expected Annual Damage. As an expected value, EAD reflects both the probability and consequence of uncertainty. The damage refers to damages caused by floods. The unit of damage depends on the definition of exposure. This includes damage to GDP, loss of life, biodiversity, or in the context of this research: physical damage to properties. Therefore, in this paper, the unit for EAD is euros per year.

In this equation, hazard, exposure, and vulnerability are expressed within the damage probability function $D(p)$. This is congruent with the symbolic equation for risk, which shows risk as a function of these three dimensions. In this function, p refers to the probability of each flood event, and $D(p)$ expresses the damage that may result from a certain level of flooding.

The damage probability function $D(p)$ describes how much damage results from a flood. This can be calculated by looking at flood inundation depth (the height of water that covers inundated land). The empirically known relationships between flood inundation and resulting damage are known as flood depth-damage curves (Huizinga et al., 2017). Using these depth-damage curves, projected flood inundation depths can be converted into fractional damage. A flood depth-damage curve can be described as a function $D(I(p))$, which describes fractional damage as a function of $I(p)$, inundation. Inundation, in turn is dependent on the probability.

Equation 4: EAD expressed as the integral of damage functions over each return period.

$$EAD = \int D(I(p))dp$$

In this research, flood depth-damage curves were collected from Huizinga et al., (2017). In this publication, flood-depth damage curves were constructed using regression analysis and expert judgement of global coverage historical flood damages.

The operationalization of each dimension is discussed below.

Table 3: Summary of operationalization in the research.

	Variable (unit)	**Data source**
Hazard	Flood inundation depth per return period (meters)	Ward et al., 2020
Exposure	Location and market value of real-estate investment (euros)	Case study
Vulnerability	Flood depth-damage curves (% damage per meter); Flood protection standards (return period)	Huizinga et al., 2017 Scussolini et al., 2016

Figure 8 shows a visual representation of the different variables that are used to model future flood risk, and how they interact. Table 3 above also summarizes how each of the climate risk dimensions is operationalized, along with the data source.

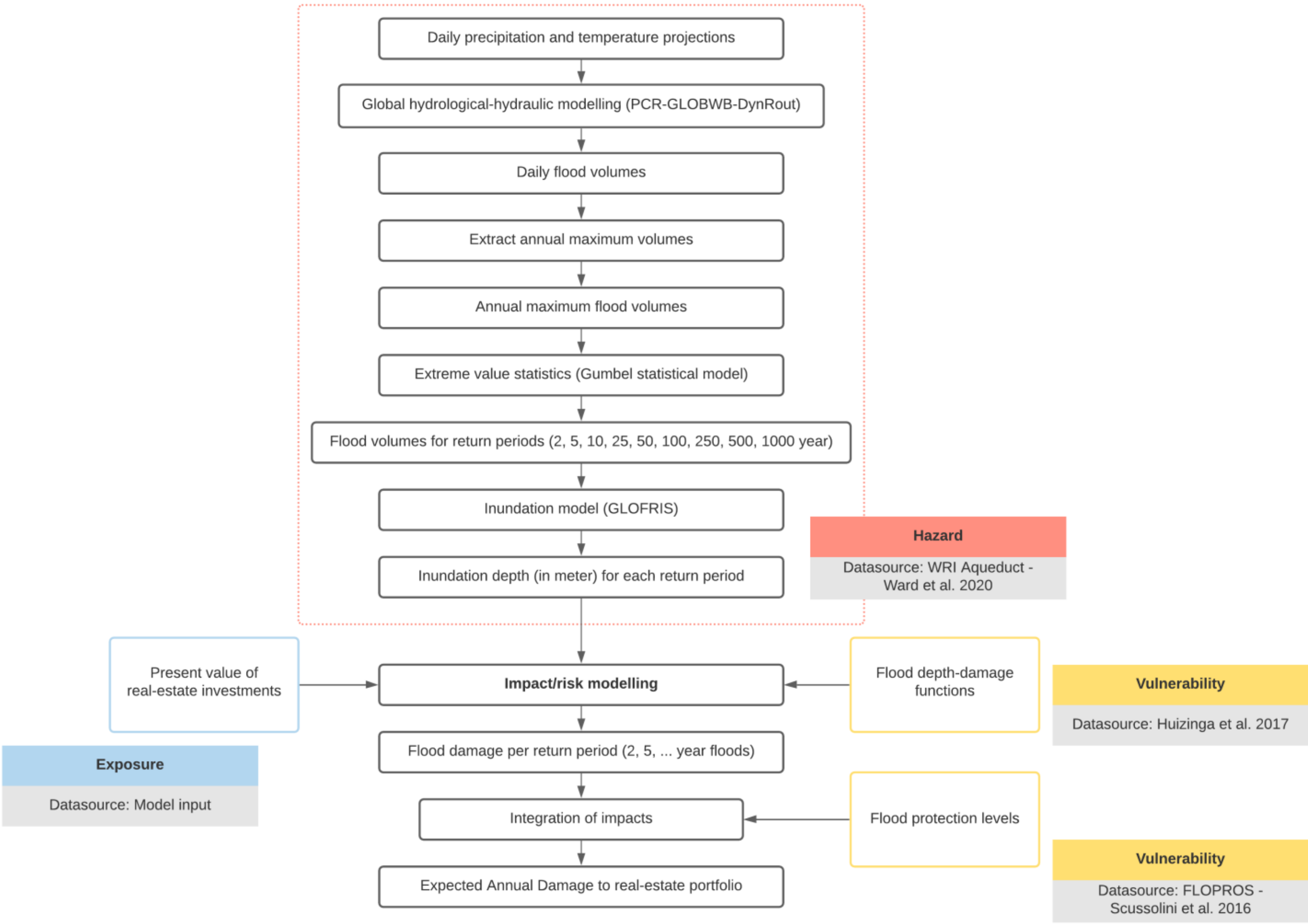


Figure 8: Graphic showing the overall flood risk modelling framework. The risk modelling consists of the three dimensions of risk: hazard, exposure, and vulnerability. In blue, exposure is represented by the present value of real-estate investments. Hazard is represented by the Aqueduct Flood model, the data pipeline of which is explained. Vulnerability is operationalized using flood depth-damage curves, derived from Huizinga et al. (2017).

3.2.1.1. Hazard

The hazard dimension is represented within the red boundary in the figure above. Hazard refers to the impact and probability of flooding events. In this research, the output from the Aqueduct flood model was used to project flood damage for different climate change scenarios, timeframes, and flood types. The output from the Aqueduct flood model is given as a global coverage map, showing flood inundation depths in meters, over 9 return periods (Ward et al., 2020). This describes the flood probability distribution as described in the theory section. More information on the methodology regarding the acquisition and use of these flood maps is found in chapter 3.3. Data analysis. The modelling steps that precede flood maps are described in the theory section.

3.2.1.2. Exposure

Exposure is shown in blue in the figure above. This research focuses on the financial risk to real-estate assets. Therefore, exposure is captured as the present value of these assets. For real-estate portfolios, there are two investment options: direct or indirect ownership of properties. With direct ownership, the portfolio holder owns and manages the property. An indirect real-estate investment refers to investing in a real-estate company that owns and manages properties. Properties are then indirectly owned. This has implications for how exposure is expressed as a variable. Exposure to direct investment is equal to the total present value of that property. However, exposure to indirect investment can be calculated by multiplying the present value of the property with the percentage share of ownership. This percentage can be found by multiplying the percentage ownership into the real-estate company, with the property value divided by the total fund size of the real-estate company. In the case study, the percentage share of ownership was assumed to be 20% for all properties, due to data availability.

3.2.1.3. Vulnerability

To capture vulnerability, shown in yellow in the figure, flood depth-damage functions were used. These describe what level of flooding causes what degree of damage. A steeper depth-damage curve means a more vulnerable asset.

Vulnerability is also expressed as a function of flood protection. For this, the FLOod PROtection Standards (FLOPROS) database is used (Scussolini et al., 2016). The FLOPROS dataset contains global coverage flood protection standards, expressed in return periods. The dataset combines information about flood protection designs, policy, and empirical information. Combining these three layers of flood protection information, a global coverage dataset containing regional level flood protection is constructed.

Flood protection standards are expressed as the flood return period that a structure (e.g. dike or levee) is designed to withstand. For example, an area with flood protection standard of 100 years is able to protect an area from up to the level of a flood that occurs every 100 years. In the model framework, these standards are incorporated as the return period from which the integral is taken under the damage probability curve. This is seen in Figure 9 below.

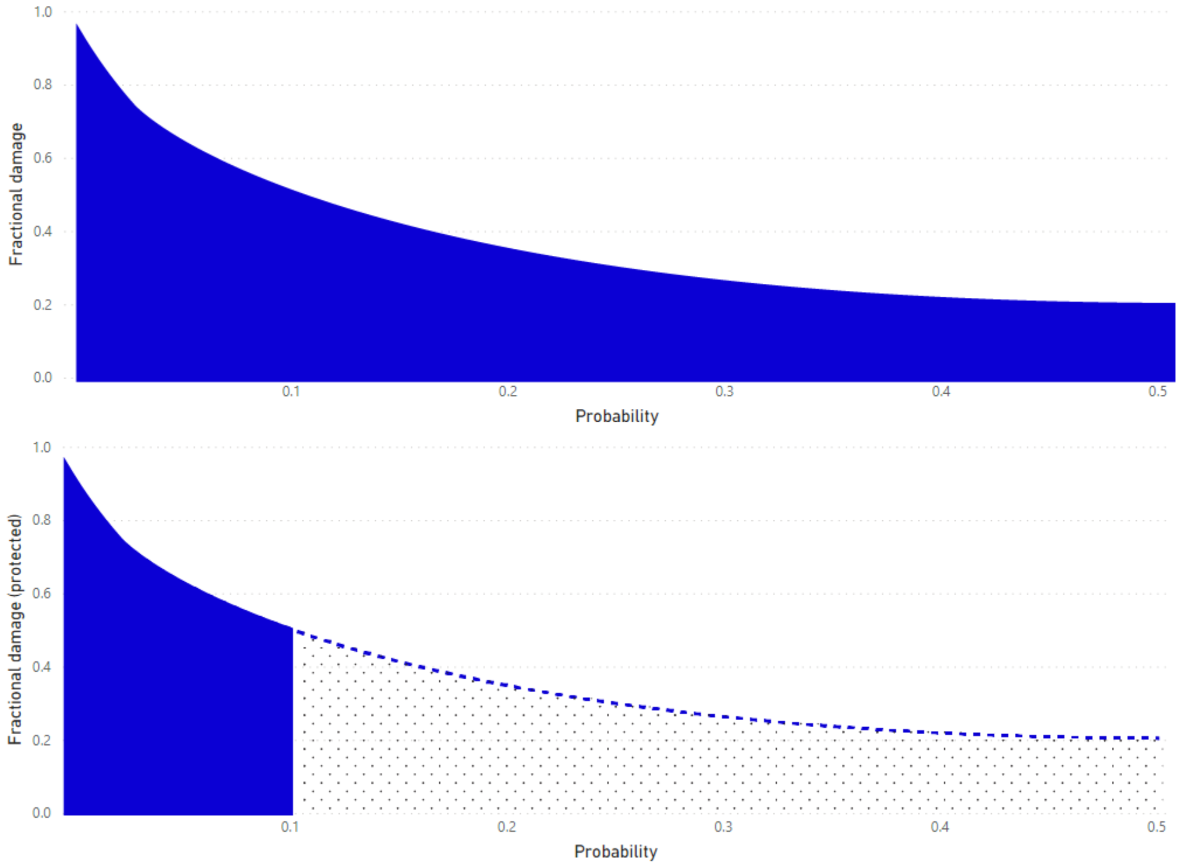


Figure 9: Operationalization of vulnerability. A flood protection standard of 10 years means the damage to the right of probability 1/10 is negated. This reduces the total risk of the above graph to only the integral in the lower graph.

3.2.1.4. Model input data

Flood hazard is dependent on the geographic location of the assets. Therefore, coordinates for each real-estate investment are used as input. Exposure is captured through the present value of the investment in that property; therefore, the input dataset includes each property's value. This is combined with the percentage of ownership of that property, as the real-estate assets are not completely owned by the case study. The input dataset further includes a column explaining the selection criteria for that object, see chapter 4. Moreover, the dataset contains columns with a unique identifier per real-estate property, along with the country and continent where it is located.

Table 4: Example of input dataset. Each row pertains to one real-estate asset. Columns contain from left to right: unique identifier, the country and continent where the property is located, type of building, value, and anonymized coordinates. These data are an example, and are not part of the case study sample.

ID	Country	Continent	Selection criteria	Sector	Value	Latitude (anonymized)	Longitude (anonymized)
1	Netherlands	Europe	Distance to coast	Industrial, commercial, or residential	€ 500.000	52	5

3.2.1.5. Model output data

Flood damage is expressed as EAD. Therefore, the model output contains EAD per property, as well as EAD as a percentage of total portfolio value, to allow for intercomparison between properties.

EAD % values are further categorized into four classes: no risk, low, medium, and high. This combats an issue expressed in the literature. Though GCMs and flood models provide high precision data, these may not necessarily be valid due to uncertainties in each modelling step (Fiedler et al., 2021). Therefore, to avoid overconfidence in numerical accuracy, EAD % figures are aggregated to a risk category (none, low, medium, high), based on quartiles. This ensures that risk hotspots can be identified but prevents overconfidence in the precise numbers.

The transformations of the input dataset to the required output are described in more detail below, in the Data analysis section.

3.3. Data analysis: from property location to flood damage

This section outlines the transformation of data to arrive at the model output. To go from model input to output, the data follow the following steps:

Input dataset → flood model → convert to damage curves → integrate damage to EAD → aggregate data → rescale to risk level (low, med, high)

Step	**Prepare input dataset**	**Predict flood statistics**	**Convert to damage curves**	**Integrate damage curve**	**Aggregate damage over region**	**Rescale risk**	**Produce results**
Explanation		Using Aqueduct flood model	Using EU Joint Research Centre data	Integration (damage times probability)	Average over region (region to be determined)	Divide into quartiles	Produce graphs that illustrate risk
Program	Excel	QGIS	R programming	R programming	Power BI	Microsoft Excel	Microsoft Power BI
Variables	Coordinates, present value	Flood inundation per return period	Flood damage per return period	Expected annual damage	Expected annual damage	Risk level	
Unit	Decimal degrees, euros	Meters, years	Percentage, years	Euros per year	Euros per year	Low, medium, high	

Predicting flood statistics

First, various flood raster maps were downloaded from the World Resources Institute database (Ward et al., 2020), available from the World Resources Institute webpage.[2]

These raster maps consist of a matrix of pixels covering the earth. Each pixel contains projected inundation depths over 9 different return periods.

[2] http://wri-projects.s3.amazonaws.com/AqueductFloodTool/download/v2/index.html.

In total, 108 raster maps were downloaded. For both riverine and coastal flooding, two climate scenarios, over three timeframes are modelled. This equals 12 sets of 9 raster maps, totaling 108. After downloading, raster maps were prepared in an open-source Geographical Information System (GIS) program called QGIS.

The figure below presents an example of these raster maps. Each pixel on this map contains projected inundation depth in meters, shown using a color gradient. In this particular color gradient, black represents 0 meters, and white represents 3 meters of flood inundation depth, respectively.

Figure 10: Example of flood statistic raster map. This section of the map shows the flood inundation from black (0 meters), to white (10 meters), of a 1000-year coastal flood. Data come from the WRI Aqueduct model (Ward et al., 2020).

To extract flood statistics data for the sample, a map layer containing points for each property was overlaid over the flood statistics maps. Using the 'Point Sampling Tool' in QGIS, flood statistics data from each scenario were extracted for each of the properties. This step was repeated a total of 12 times, twice per flood type, RCP scenario, and thrice for each timeframe. This step yields 12 comma-separated values (csv) files containing property data, and projected flood statistics for each of the modelled scenarios. Figure 11 shows an example of flood statistics data, flood inundation over different probabilities.

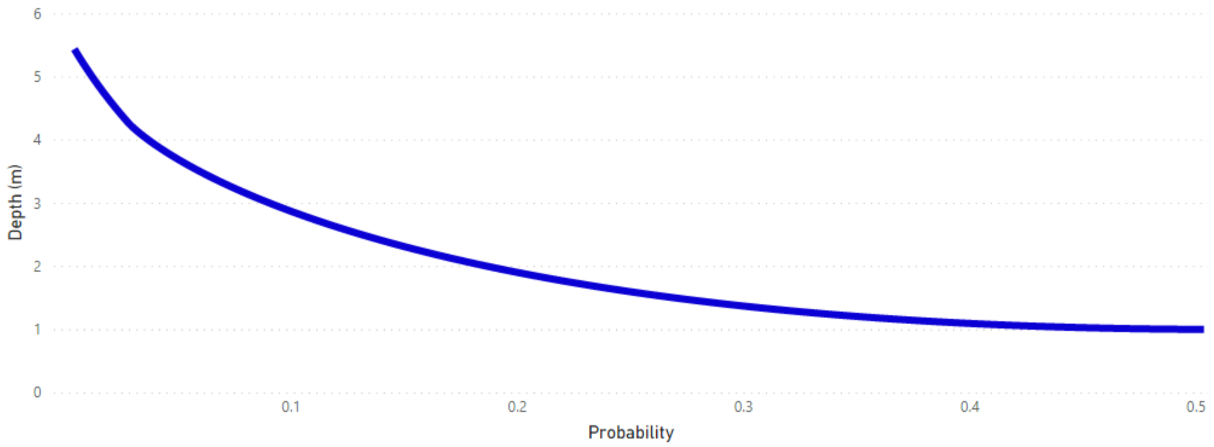


Figure 11: Illustration of hazard data, showing flood inundation depth in meters over different probabilities. The raster maps contain 9 points on this curve, for each pixel on the map.

These data show the severity of flood (expressed as inundation depth), for each of the flood return-periods. For example: a 1000-year flood inundation of 2 meters means that each year, there is a 1/1000 probability of a flood of at least 2 meters at the location of that particular property. In other words, this figure shows the flood probability distribution function for each of the sample buildings.

Conversion to damage curves

With these flood probability distributions, fractional damage was calculated for each of the 9 return periods. To do so, flood depth-damage functions were applied to each of the flood inundation numbers. Figure 12 shows the depth-damage curves that were used in approximating the damage to buildings based on flood depth. These depth-damage curves are collected from Huizinga et al., (2018).

Figure 12 shows that flood depth-damage curves differ significantly per continent. Therefore, the sample was divided into the different continents to apply approximation of damage depending on continent. Approximation was conducted by interpolating flood depth along the depth-damage curve to obtain fractional damage. After the approximation, the data were recombined to create the completed dataset. The result is a probability distribution of fractional damage to each building.

To achieve this, programming language R was used. Specifically, the library ‘stats’ was used for approximating the flood inundation along the flood depth-damage curves. The code for interpreting fractional damage from flood inundation using flood-depth damage curves is found in Appendix A.

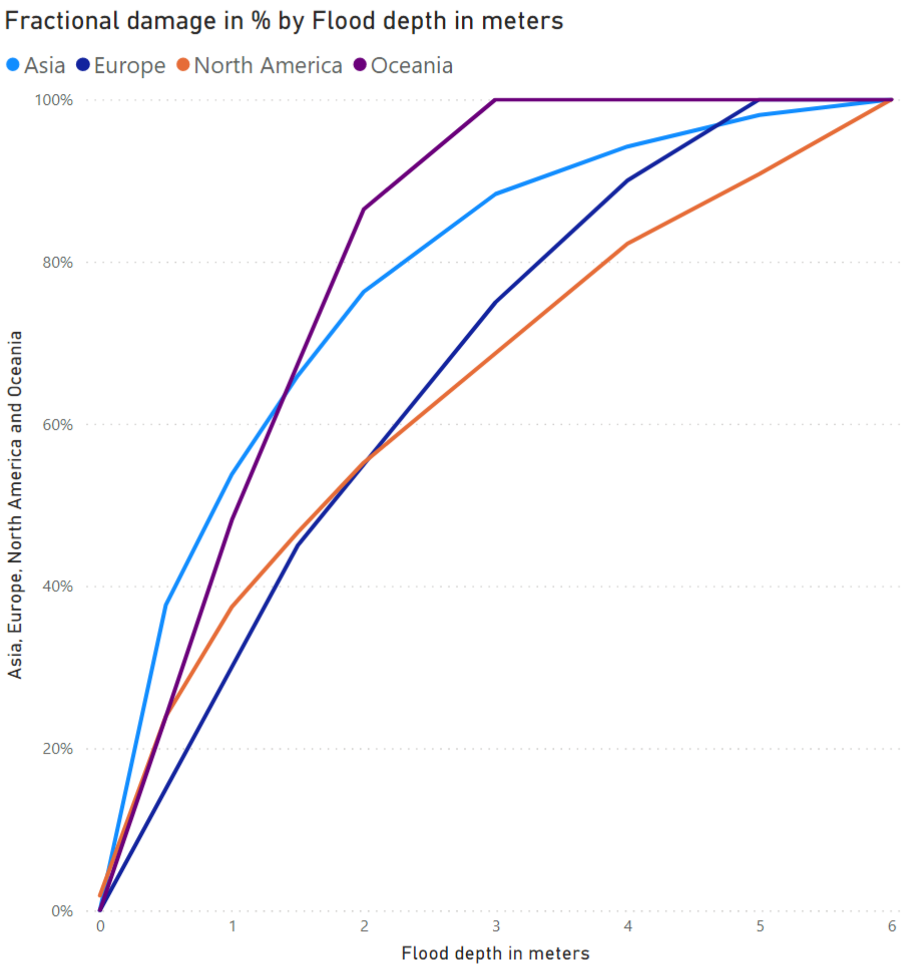


Figure 12: Flood depth-damage curve portraying fractional damage in percent as a function of flood depth in meters. Each curve corresponds to the empirical relationship between flood depth and damage to buildings in each continent that occurs in the sample: Asia, Europe, North America, Oceania. Adapted from: (Huizinga et al., 2017).

Integrate damage curve to EAD

With known probabilities of fractional damage to each of the properties, the expected value of damage can be computed. The statistic expected value is computed by multiplying the probability with the outcome. Therefore, expected damage can be found by multiplying each return period’s probability with the fractional damage, and the present value of the investment.

This statistic is referred to Expected Annual Damage. The equation below summarizes the calculation for EAD. Since the flood statistics are given as a discrete set of probabilities, instead of a continuous function; a discrete summation is used instead of an integral. This produces the following equation used to calculate the EAD for real-estate property i.

$$EAD_i = PV_i \times \sum_{p=\frac{1}{1000}, \frac{1}{500}, \frac{1}{250}, \frac{1}{100}, \frac{1}{50}, \frac{1}{25}, \frac{1}{10}, \frac{1}{5}, \frac{1}{2}} D_i(p) \times p$$

In this equation, PV_i refers to the present value of the investment into real-estate property i. Then, the fractional damage $D_i(p)$ is multiplied with the probability to produce the expected value of damage. As this expected value is fractional to the building, this is multiplied with the present value of the real-estate investment, arriving at expected annual damage to the real-estate investment.

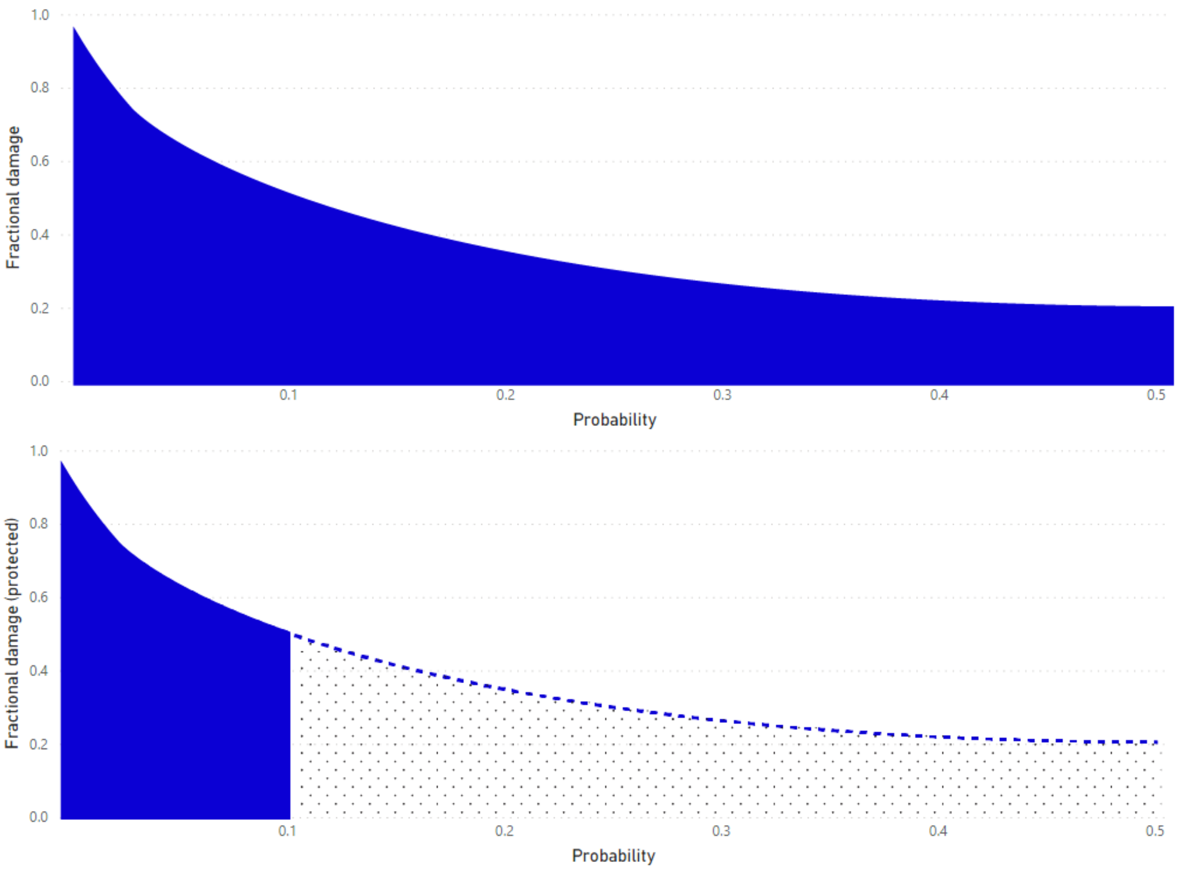


Figure 13: Illustration of EAD calculation. The area underneath the flood probability distribution represents the expected damage from the flood. Graph A (top) shows integration of the full range of floods, while graph B (bottom) represents an area protected up to a 10-year flood. This is illustrated by subtracting the expected damage from floods with probabilities over 1/10.

Vulnerability

In the previous equation for EAD, it is important to incorporate the vulnerability dimension. Namely, in many cases, flood protection measures may be in place. The global dataset FLOPROS (Scussolini et al., 2016) is consulted to extract flood protection standards for each of the properties.

Using flood protection standards from the FLOPROS, the EAD integral is cut-off at the return period of flood protection. Visually, this is seen in Figure 13, where a flood protection standard of 10 years is incorporated.

Data visualization

The EAD figures per building, for all selected model parameters, were entered into Microsoft Power BI, a dashboarding tool that allows for data visualization along different axes. This is useful, as there are three axes in which data are presented: flooding type, RCP scenario, and timeframe. The interactive dashboarding tool allows for filtering along these axes.

3.4. Model assumptions

The firm's share of ownership for a property is assumed to be all equal at 20%. This is based on the average percentage ownership of the portfolio, based on discussions with the case study company. This is likely an unfair assumption, as shares in a real-estate property are not equal in practice. The share in each property widely varies in the case study. Future applications of the modelling framework may benefit from using specific values of ownership share.

To separate financial devaluation such as discount effects and cost of capital, from the physical impact of climate change, present value of real-estate properties is assumed to remain constant throughout timeframes and scenarios. These values are likely to change in the future, due to depreciation and degradation of value and physical assets. Moreover, the market value may be different in different climate change scenarios, as climate risks may be priced differently in different climate change scenarios. Furthermore, present values are not inflation-adjusted.

Moreover, the flood protection standards data used may be outdated and incomplete (Ward et al., 2020). First, there are limitations to the resolution of flood protection data (Scussolini et al., 2016). The flood protection for an individual property may be different from the wider geographic location it is in. This is unaccounted for in the model.

Second, flood protection databases can become outdated, as they are different across different climate scenarios. Flood protection standards are recorded by return period. Flood protection measures such as dikes are rated by what probability of floods it is designed to withstand: a dike that is rated as a 50-year dike can withstand floods up to and including a flood that occurs on average every 50 years. However, with changing climate conditions, flood intensity is expected to increase (Allen et al., 2014). A 50-year flood protection level in 2010 may only protect from a 25-year flood in the future (Ward et al., 2020). Therefore, flood protection levels now are not the same as flood protection levels in 2050 or 2080. This assumption is covered in the sensitivity analysis, where flood protection standards are varied to observe the response of the model output.

4. PGGM Real-estate case study

To illustrate the proposed model framework and the results it produces, a case study was employed. The methodology for model construction was applied to assess the flood risk of a sample real-estate portfolio. The selected sample real-estate portfolio is provided by PGGM Investments.

4.1. Background PGGM Real-estate

PGGM Investments (Pensioenfonds voor Gezondsheidszorg, Geestelijke, en Maatschappelijke belangen), is the Netherlands' second-largest pension investment company, managing over 260 billion euros as of end 2020 (PGGM, 2021). Since the 1980s, PGGM has aimed to invest responsibly, valuing not only financial return but also a positive societal impact (Lindeijer, van Dam, Kramer, & Op 't Veld, 2019). As part of sustainability strategy, the fund actively gathers data on climate risk to its portfolio (Jansen, 2019). This includes both physical and transitional risk. As of 2019, PGGM Investments has a stake in around 4000 properties globally. These properties altogether are valued at € 160 billion in 2019. Of this amount, PGGM has a stake of € 14 billion (Verbraeken, 2019). With global coverage, the long investment horizon of real-estate, and the size of the portfolio, future climate shocks are relevant to the fund.

As the effects of climate change are expected to exacerbate with higher GHG emissions in the future, climate risks are especially relevant in the long-term. This means that climate risks are particularly salient to pension funds, as these have a fiduciary responsibility to pay out members' pensions (van Dijk, 2020), (Dietz et al., 2016). For physical risk assessment, models by reinsurer Munich RE have been employed (Munich RE, 2020). As of 2019, PGGM is the only institutional real-estate investor using a climate risk instrument (Verbraeken, 2019). This indicates both the relevance of climate risk to financial institutions, as well as the proprietary and confidential nature of such assessments.

4.2. Sampling strategy

Given the fund's size, focus on sustainability, and global coverage of portfolio, it presents an interesting case study for applying the proposed model framework. Based on a prior flood risk assessment by Munich RE, a sample of real-estate properties was selected.

The sampling strategy was as follows: for three regions, Asia-Pacific (APAC), United States (US), and Europe, Middle-East and Africa (EMEA), several properties were selected. Namely, from each of the three regions, 50 properties closest and furthest from the coast have been selected, as well as the 50 properties with the highest and 50 properties with the lowest riverine flood risk. This totals to 600 properties. This sampling strategy allows for an illustrative case study, consisting of both high and low exposure to flood risk. This also allows for near-global coverage. However, this strategy does introduce a bias to the sample prior to assessment, as it may not necessarily be representative of other pension fund real-estate portfolios.

Furthermore, to protect the pension fund's interest, the sample data have been anonymized to a certain degree. First, an error margin has been introduced to the exact latitude and longitude of each property. This ensures anonymity of the exact locations of properties. Furthermore, exact present values of the properties have been obscured and instead grouped into 12 value classes, ranging from 50,000 € to 4,500,000,000 €. This ensures anonymity of the fund's sensitive financial information.

Table 5: Statistics of sample portfolio data.

	N	**Avg Present Value (PV)**	**Standard deviation PV**
Asia	103	€ 35,471,845	€ 50,205,977
Europe	200	€ 6,097,550	€ 7,661,505
North America	198	€ 14,136,869	€ 20,225,971
Oceania	97	€ 43,645,361	€ 55,833,872
Total	**598**	**€ 19,867,183**	**€ 36,043,655**

Disclaimer: Since exact locations and market values have been anonymized, the results presented for the sample case study are not representative of PGGM Investments' actual real-estate portfolio.

5. Results

This section describes the results of constructing a global climate-related flood risk assessment framework, illustrated with results from the case study. Based on the literature review, construction, and application of a novel flood risk model, a flood risk assessment framework is proposed consisting of three steps: 1. Define model parameters, 2. Collect flood model data, and 3. Identify flood risk using the model framework. Each of the steps is elaborated upon, justified, and illustrated with results from the case study. Comparing percentual damage to the sample real-estate portfolio to percentual damage to GDP in other studies, it was found that the results are in the same order of magnitude. Furthermore, the case study was found to be most at risk to coastal flooding, in worst-case RCP8.5, in 2080. Risk hotspots are identified in a map.

5.1. Climate-related flood risk assessment framework

Based on the literature review and the carried-out case study, the following risk assessment framework may be carried out to quantify financial risk to flooding. Figure 14 summarizes the key steps a firm may take to assess flood risk to real-estate assets. In the following section, each step of the modelling framework is elaborated upon, and illustrated with results from the case study.

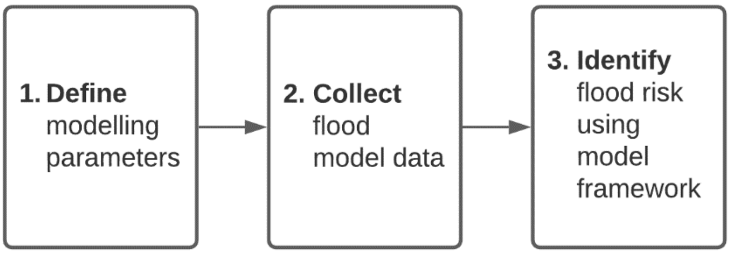


Figure 14: Climate-related flood risk assessment framework consisting of four steps.

1. Define modelling parameters

First, the model parameters are selected. In this step, the goal and scope of the risk assessment are defined. Parameters that determine scope include the selection of climate scenarios and timeframes. Since flooding events are expected to take place in the future, it is relevant to define how far into the future assessments are relevant. It is useful to define short-, medium-, and long-term timeframes. Such timeframes depend on the firm's investment horizon, or the time an investor expects to hold a security or asset. Flood risk to a building in 2080 may not be relevant to an asset owner, if it is expected to be sold before then. Moreover, since the future is uncertain, it is helpful to define a range of scenarios. Based on the literature, and its wide use in climate modelling, the RCP scenarios are particularly helpful (Vuuren et al., 2011). Namely, RCP scenarios describe the physical trajectory of climate change, and are widely adopted in modelling which is helpful for data availability. The use of scenarios allows the user to assess risk in a case where global GHG emissions are strongly reduced or continue to increase. RCP scenarios are given based on the strength of the greenhouse effect, ranging from 2.6 to 8.5, where 8.5 is the most extreme degree of climate change. These scenarios are predictions of global GHG emissions per year, which are agreed upon between climate modelers (Vuuren et al., 2011). Generally used RCP scenarios are RCP2.6 (optimistic, high mitigation), RCP4.5, RCP6.0, and RCP8.5 (pessimistic, business-as-usual).

Case study parameters

In the case study climate scenarios RCP4.5 and RCP8.5 were selected, as these represent a realistic spread of future climate scenarios. Namely, RCP8.5 most closely resembles current GHG emissions patterns (Schwalm, Glendon, & Duffy, 2020). Conversely, the same researchers found that RCP2.6 overestimates actual mitigation efforts. In other words, the research suggests that current global GHG concentrations are more likely to be on an RCP8.5 track than RCP2.6. RCP4.5 then represents a realistic lower emissions scenario. Hence, motivating the selection of scenarios.

For timeframes, the years 2030, 2050, and 2080 were selected. These represent the short-term, medium-term, and the long-term timeframes. The specific years were chosen partly because of data availability of the Aqueduct Flood model, and to present a good overview of how flood risk develops over time. The model is projected far into the future, as pension funds generally require a longer-term vision to ensure stability of returns to meet its fiduciary duty (Clark & Urwin, 2008).

2. Collecting flood model data

After defining the goal and scope of the risk assessment, flood risk data is collected. This includes the input data that the model requires, along with the data sources for flood hazard, depth-damage curves, and flood protection standards. First, the input dataset includes the geographical location and value of the investments. Second, flood hazard data sources consist of flood hazard maps, as described in the methodology. Depending on the selection of parameters, different maps may be used. For example, flood hazard outputs are highly dependent on climate scenario and timeframe. Furthermore, the geographical distribution of the unit of exposure defines the required data. A global portfolio requires global coverage hazard maps. Finally, depth-damage curves may be collected either from prior empirical studies, or by making assumptions about how flood depth causes damage.

Case study data collection

For the case study, Aqueduct Flood hazard maps were used to predict flood hazard along the two defined scenarios, in short-, medium-, and long-term timeframes. This data source was further selected for its global data coverage (Ward et al., 2020). Moreover, the FLOPROS dataset was used to collect global flood protection levels to cover the vulnerability dimension (Scussolini et al., 2016). Finally, depth-damage curves were collected from Huizinga et al. (2017).

3. Identifying flood risk

The third step of climate risk assessment is the quantification of flood risk. This is done by applying the flood risk modelling framework proposed in Figure 15. The application of this framework is further discussed in the data analysis section of the methodology.

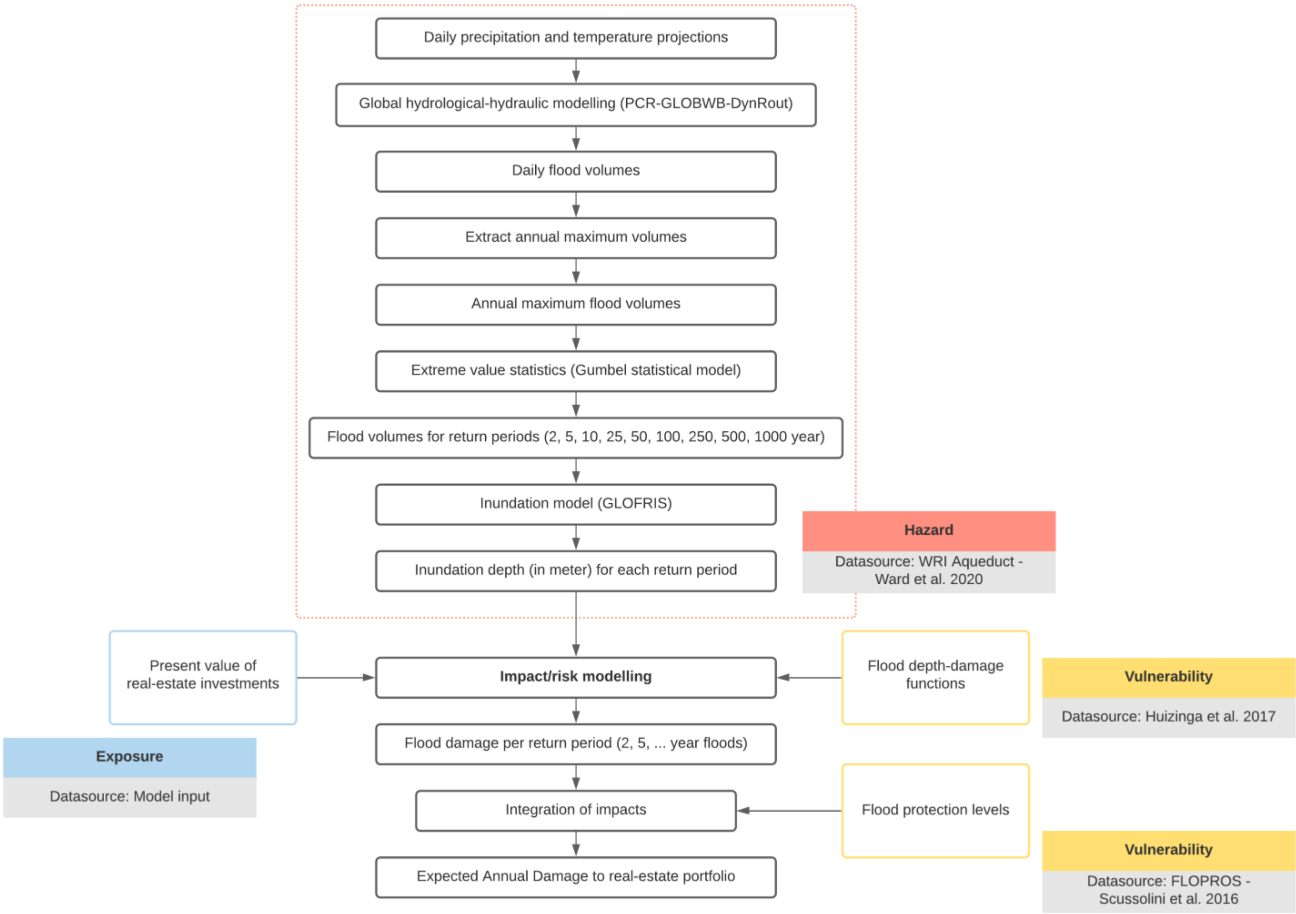


Figure 15: Flood risk modelling framework, illustrating the flow of data to arrive at risk to flooding in future climate scenarios. Here, the three dimensions of risk are illustrated by different datasets.

Case study risk identification

The framework is applied to the case study sample portfolio, consisting of 600 properties with an average investment value of €19,9 million, totaling €11.9 billion. Note that these do not reflect PGGM Investments' real-estate portfolio. Rather, they represent a sample portfolio that is meant to illustrate the functionality of the model.

The results are presented in the following section. This section illustrates what results can be expected when carrying out the risk assessment framework. The following results do not represent the climate risk faced by PGGM Investments.

First, overall risk is shown as EAD %: percentage Expected Annual Damage (EAD), representing damage as a percentage of the total sample portfolio value. The results are shown along the dimensions of climate scenario, as well as timeframe. That the following results are forward-looking and are therefore difficult to validate or test. However, the results will be compared with similar risk assessment studies to regional GDP, in a first attempt at validation.

As EAD is an expected value, it is calculated by multiplying probability with impact. The present value of real-estate investments are expected to remain constant. Therefore, increases in EAD can be directly attributed to the increase of probability of flood damage to real-estate.

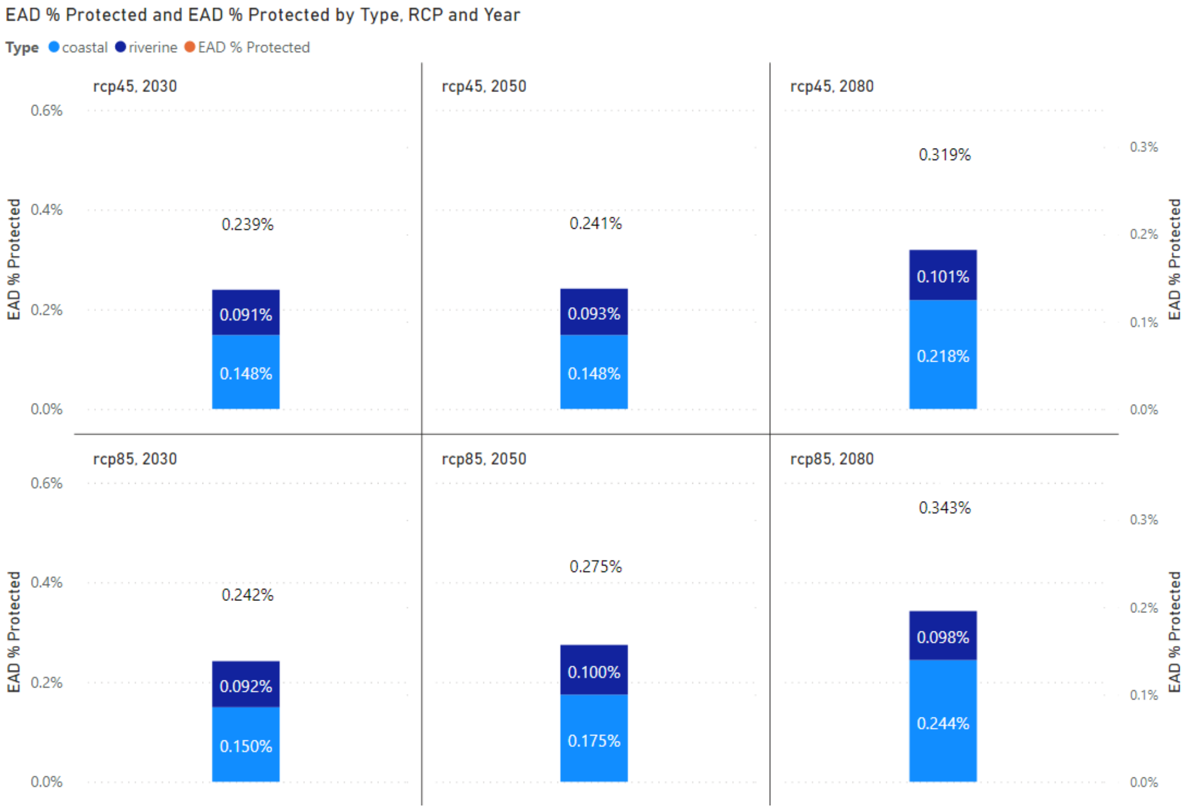


Figure 16: Bar chart of total EAD as a percentage of the sample portfolio, arranged by flooding type, RCP scenario, and timeframe.

Figure 16 shows EAD to the sample portfolio as a percentage of the total value of the portfolio. Charts are organized by flood type, RCP, and timeframe. The top row shows the three timeframes in RCP4.5, the bottom row shows the same timeframes in RCP8.5. Light blue signifies coastal flooding, dark blue signifies riverine flooding. The total percentual EAD is shown on the top of the bar. Figure 17 also shows percentage EAD, but data are grouped per continent on the x-axis.

These figures show that in this model, the case study is generally exposed to greater risk from coastal flooding (light blue) than riverine flooding (dark blue). Depending on the scenario and timeframe, flooding is predicted to present from 0.24% to 0.34% damage to the portfolio per year. Furthermore, expected damage is expected to be significantly higher in RCP8.5 than in RCP4.5, for each of the timeframes. This is congruent with the assumption that higher GHG emissions lead to more severe flooding events. The difference between RCP scenarios becomes most clear in 2080, where the EAD starts to diverge between scenarios.

As expected, damages are expected to be highest in scenario RCP8.5 in 2080. This is because in higher emission scenarios, further into the future, the results from the greenhouse gas effect are predicted to be higher, including the severity of flood events (Stocker et al., 2013). This holds for both coastal and riverine flooding.

Comparing results with previous studies

Despite validation difficulties, results can be compared with other predictions. Calculating EAD relative to total GDP of the European Union, Alfieri et al. find a percentual EAD between 0.2 and 0.4% of GDP per year in 2050, and between 0.3 and 0.9% in 2080 (Alfieri, Feyen, Dottori, & Bianchi, 2015). See Appendix B for the precise calculation. In an American study, Wobus et al. predict EAD due to flooding of 154 million USD to the Houston metropolitan area (2019). Dividing this by the 2019 GDP of the metropolitan area (512.2 billion USD) (Jankowski & Duran, 2021) – gives a relative EAD equal to 0.03% of GDP. These back-of-the-envelope calculations do not fully validate the model as they compare singular regions with a global real-estate portfolio. However, these estimates do put the model's results within the same order of magnitude (most model estimates are tenths of percentage points to total value) – partially validating their results.

Regional differences in flood risk

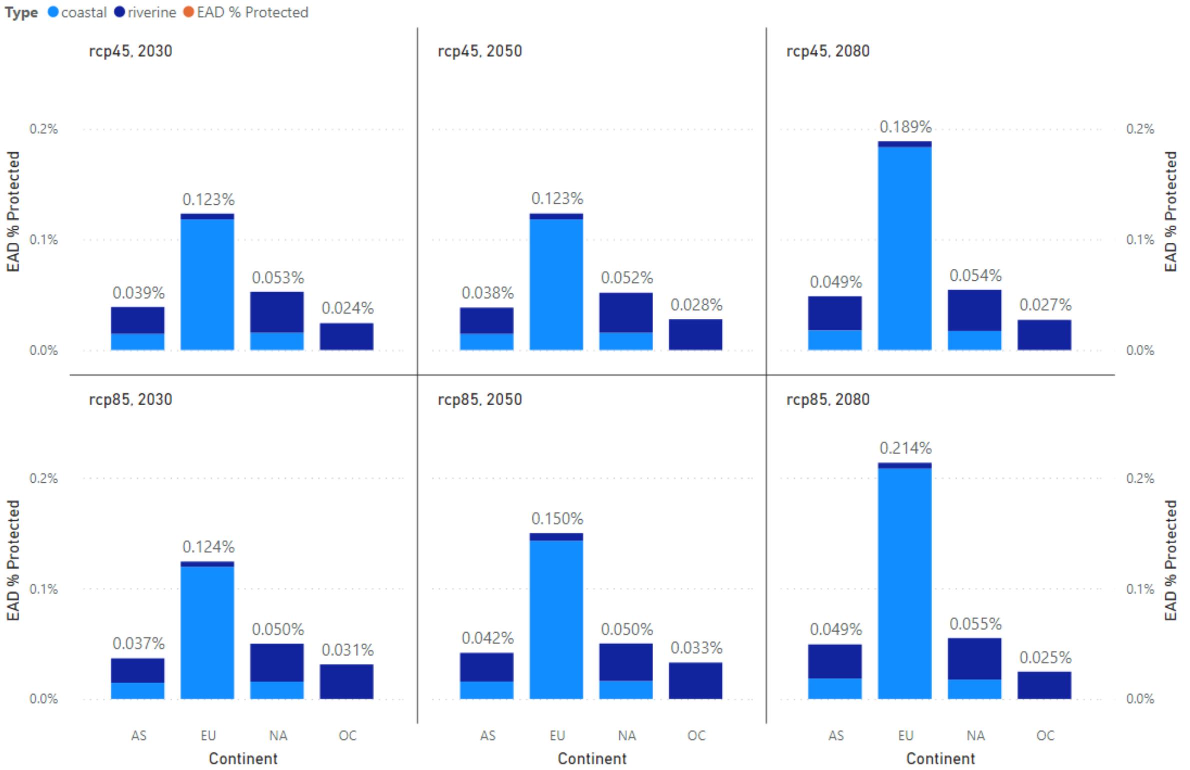


Figure 17: Bar chart per continent, of total EAD as a percentage of sample portfolio value. Arranged by flooding type (light blue is coastal, dark blue is riverine), RCP scenario (top and bottom row), and timeframe (columns). AS = Asia, EU = Europe, NA = North America, OC = Oceania.

In Figure 17, it is evident that throughout scenarios and timeframes, Europe is most at risk to flooding in the model. This is mostly due to coastal flooding. One explanation for this is the high concentration of buildings in the Netherlands, where there are high damage, low-probability risks to coastal flooding. Europe is exposed to nearly no riverine floods but is moderately to highly at risk to coastal flooding depending on scenarios and timeframe. Oceania is slightly at risk to riverine flooding, but not at all to coastal flooding. This is an unexpected result, as most Australian properties are located along the coast. North America is moderately at risk to both riverine and coastal flooding.

Figure 18 and Figure 19 show relative risk hotspots of the portfolio, to coastal and riverine flooding, respectively. Note that legend for size and color is different between the figures and is dramatized to show relative risk. The figures show that for coastal flooding, some properties in Europe, Japan, and China are most at risk. For riverine risk, the US is most at risk, along with buildings in Australia and, again, coastal China.

Figure 18: Global risk hotspots to Coastal flooding in RCP8.5, year 2080. Size and color are scaled with EAD % (percentual expected annual damage). Note that these are different between the two figures.

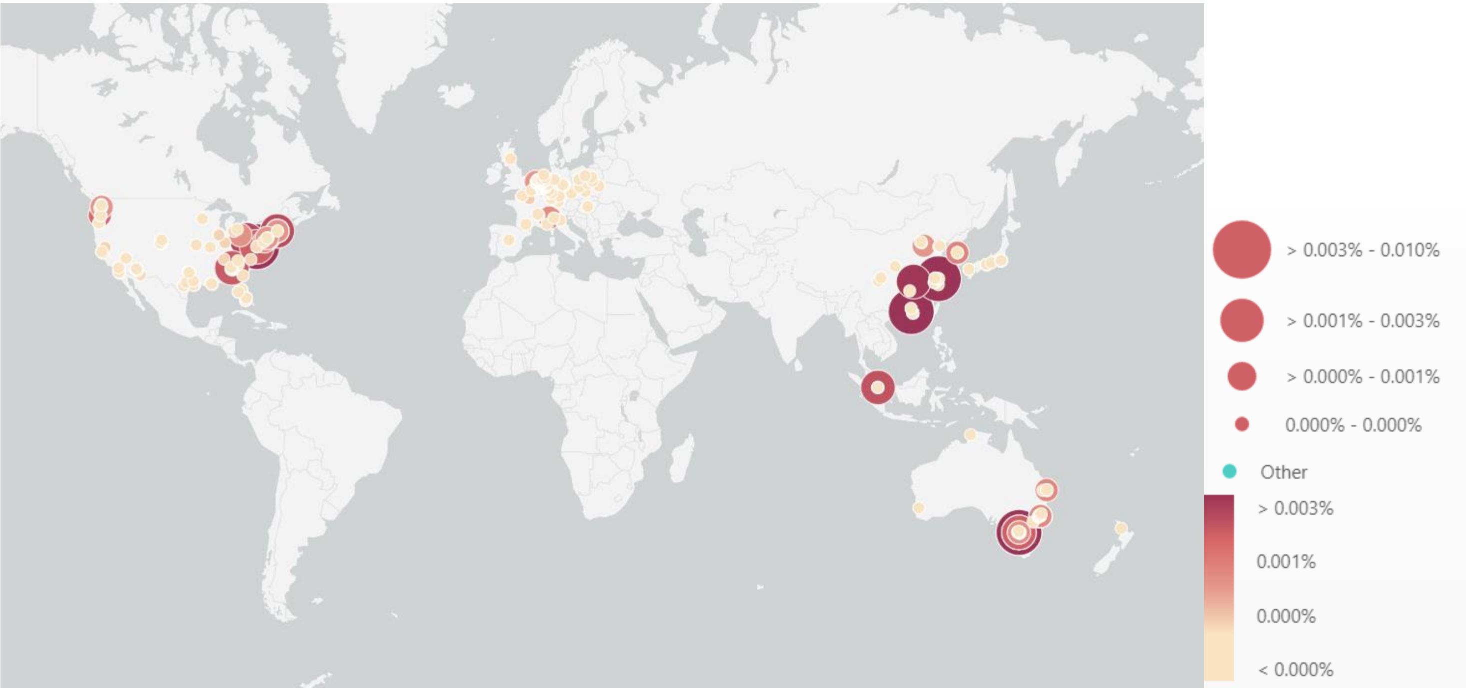


Figure 19: Global risk hotspots to Riverine flooding, RCP8.5, 2080. Size and color are scaled with EAD % (percentual expected annual damage). Note that the legends are different between the two figures.

The above results illustrate the precision of the flood risk model and may be integrated into the firm's wider risk assessment strategy. It allows the user to start to understand risk to flooding in future climate change scenarios, as well as illustrate hotspots. While prudence must be exercised in relying on the actual numbers, the results are best interpreted through intercomparison between scenarios and properties.

Risk assessment as proposed in this research may be best used as a first step towards deeper risk analysis. Risk assessment as proposed should trigger more in-depth discussions and analyses into the risks faced by the company and the financial and moral dilemmas associated with these (O'Dwyer & Unerman, 2020). For example, cost-benefit analyses may be applied: comparing the cost of flood protection to the benefit of reduced risk may inform risk management decisions (Ward et al., 2020).

5.2. Sensitivity analysis

Sensitivity analysis was performed to illustrate what model parameters influence the model output most. From sensitivity analysis, it was found that the variable for flood protection standards influences the EAD variable most. Comparing results in the absence of flood protection with the FLOPROS dataset, it was found that risk was on average 16 times higher without flood protection, see Table 8 in Appendix B.

This indicates that the flood model is highly sensitive to the levels of flood protection. This is an important finding that corresponds to the literature. Flood protection data are extremely important, as most flood assessments assume no protection. Flood risk expressed as EAD is found by integrating over both low and high probability events. This means the EAD risk measure is sensitive to the damage of high probability events, while these may be often protected against (Scussolini et al., 2016). For example, including only a 5-year protection standard can decrease flood protection by 40% (Scussolini et al., 2016).

6. Discussion

6.1. Implications for theory

The presented modelling framework addresses the need for a standardized flood risk assessment methodology. Future research may build on this framework and adapt it to assess flood risk to different asset classes or types of firms. For example, as the model addresses the physical damage to buildings and their operations, the proposed framework may be interesting for other sectors reliant on real-estate facilities for production or distribution (Weinhofer & Busch, 2013). These include manufacturing, distribution, transportation, or retail. Consequently, if these risks are known, they may be disclosed to investors to allow these firms to assess risk. Future efforts may also be directed at supplementing the framework with additional bias corrections and measures to increase validity.

6.1.1. Does climate-related flood risk assessment lead to climate adaptation?

The recommendations set forward by the TCFD operate on the assumption that climate risk disclosure will lead to accurate pricing and therefore efficient allocation of capital. However, the effectiveness of disclosure is questioned by some articles. Pattberg refers to institutional investor interest in climate change as “investor environmentalism”, and claims there is insufficient evidence that the disclosure of climate risk creates financial incentives towards climate change mitigation (Pattberg, 2012, p. 623).

Other critiques on climate-related risk disclosure include considerations of whether climate risks to the financial system can be accurately perceived, or whether investors have the knowledge and willingness to act on this information (Farbotko, 2019). Risk, with its many definitions, has been distinguished from ‘uncertainty’, by Knight in 1921. The difference between uncertainty and ‘Knightian risk’, is that uncertainty is randomness with unknowable probability, where risk is randomness with knowable probability (Knight, 1921). It is the ‘Knightian risk’ that can be managed. There are critiques that climate change is not a Knightian risk, as it is a phenomenon that has never occurred (Christophers, 2017). For this reason, risk disclosure is ineffective at securing global financial stability. Moreover, the author argues that the financial players with the most ‘market-making power’ can transfer risk to those with less information. This implies individual investors may gain at the expense of the rest of the market (Christophers, 2017). Moreover, Christophers argues that herd behavior is all too common, and climate risk pricing may follow the same fate as the dot-com bubble, where market participants followed the same strategy and massively overpriced internet companies – with market shocks as a result (2017). The author’s fear is that market actors will collectively act irrationally and underestimate climate risk, leading to market shocks when climate-related extreme weather events take place (Christophers, 2017).

Despite concerns about the effectiveness of climate risk disclosure at attaining global financial stability, climate risk assessment in business does increase market actors’ engagement with climate change (Pattberg, 2012). Therefore, climate-related risk assessment – flood risk included – is a helpful tool; if not at system level but at firm-level adaptation to climate change.

Another limitation of the study is the focus on the financial interests of asset owners. However, regional stakeholders may also be important in investment decisions. Identification of risk hotspots may lead to divestment of risky properties. Divestment from a region may lead to loss of welfare in that region (Husby, Mechler, & Jongman, 2016). One study into the Rotterdam area found that divestment due to flood risk may have detrimental effects. In their macroeconomic model, divestment was found to decrease labor opportunities and economic production, while increasing unemployment (Husby et al., 2016). Divestment due to increased adoption of risk assessment approaches may cause similar effects globally. However, risk assessment may be used for cost-benefit analysis of flood protection (Ward et al., 2020). These may favor investing into adaptation instead of divestment, such as constructing dykes.

6.2. Limitations of the research

The limitations of the research are discussed in the following section. This includes limitations concerning validity and reliability from both the model framework as well as the case study.

6.2.1. Validity and reliability

The validity and reliability of this research exist on two levels: Firstly, the validity and reliability of the risk assessment framework. Secondly, the validity of the case study as an example of pension fund real-estate portfolios.

6.2.1.1. Flood risk model validity and reliability

Flood depth-damage curves

There are questions of reliability with the use of flood depth-damage functions. Namely, the flood depth-damage functions were used from one particular study's empirical findings: (Huizinga et al., 2017). Depth-damage functions curves may differ if these are found using different data sources.

Moreover, there may be questions of validity due to data resolution. Flood depth-damage curves were assumed constant across the continent level. However, the depth-damage relationship may differ on a more regional level. Therefore, there may be more variance in flood risk between countries within the same continent than captured in the model. Further data limitations stem from the data resolution of the flood depth-damage data. The fractional damage of floods is given at a resolution of 50 cm intervals, whereas the data that was plotted along these curves has a resolution of one tenth of a millimeter. This leads to a loss of precision in the data, as damage data was linearly interpolated between each 50 cm interval.

Expected value

A final point of validity is the use of expected annual damage to represent overall risk. Namely, a single number containing the expected value (probability times outcome) obscures the wide range of probabilities. This is especially salient as most climate risk occurs at the tail-end of probability distributions (Dietz et al., 2016). However, the expected value still is a valuable tool in differentiating between risk hotspots, as it allows for easy intercomparison.

Sensitivity analysis

An important step in ensuring validity and reliability of results is the execution of sensitivity analysis. This helps expose the sources of uncertainty within the model. The model is most sensitive to levels of flood protection. This is consistent with the literature, who report that flood protection is responsible for around 90% risk reduction (Ward et al., 2017). The model is less sensitive to climate scenario and timeframe. While these do cause variance in model output, flood protection standards are significantly more important.

Validation issues

One of the main drawbacks of the model is the inability to verify or validate the results from the model. The reason for this is that the model projects annual damage in the future. Because of the uncertainty in the future, and the impossibility to collect data that exists in the future, unverifiable assumptions must be made. This makes it is difficult to verify or validate results. This problematizes measures of assurance and validity. However, given the validity of the Ward et al. 2013 model, which compared historical simulations to empirical data and found robust results, it is expected that the Aqueduct Flood model data is valid.

6.2.1.2. Case study validity and reliability

In the case study, there is an existing sample bias. Namely, as stated in the case study sampling section, the used sample contains real-estate properties that have already been found to be at risk to floods. Moreover, there is an additional bias resulting from the prior assessment that formed the basis for that sample. Since the methodology of the prior assessment by Munich RE is confidential, it is unknown what bias exists in this model. Subsequently, it is unknown to what extent the case study is representative of real-estate portfolios.

6.2.1. Compound flooding

This research studied the occurrence of coastal flooding and riverine flooding separately. However, an understudied dimension of climate risk is the compounding of different climate risks. Particularly, compound flooding: the compound effect of coastal and riverine flooding (Zscheischler et al., 2018). High sea-level situations or storm surges could co-occur with riverine flooding events and exacerbate one another. However, because of the complex interactions between the two, as well as the uncertain timing of both events, it is not as simple as adding together the EAD values. Instead, one study suggests using a dimensionless "Compound Hazard Ratio", which is multiplied with the flood inundation of riverine flooding to account for the increased flood risk (Ganguli & Merz, 2019). Future research may benefit from investigating the validity of such a ratio in a wider flood risk model.

7. Conclusion

This research sought to answer the question *How can financial institutions quantify the financial risk posed by flooding to their real-estate portfolios in future climate change scenarios?*
To answer this question, current literature was consulted on the topics of climate change adaptation in the financial sector, concepts of climate risk, financial risk, as well as current global flood modelling techniques. Applying concepts from the literature, a modelling framework was proposed that converts geospatial data to expected annual damage to a real-estate portfolio. This model was applied to a sample real-estate portfolio of a Dutch pension fund investment manager, which illustrated the model output. Sensitivity analysis was applied to the model. Summarizing the key steps in flood modelling, a three-step modelling framework was proposed. In conclusion, financial institutions may quantify the financial risk to real-estate portfolios to flooding by applying the proposed modelling framework. The model output may then be used to inform risk management decision-making.

The proposed modelling framework may be built upon and further validated to help increase financial resilience to climate change by capital market participants. Suggested areas for improvement are increasing the availability of data on vulnerability. Financial institutions with investments in real-estate are advised to leverage publicly available flood data to gain an understanding of their exposure to risk in future climate change scenarios. The academic community is invited to scrutinize and improve upon the model framework to increase its validity.

As human-induced greenhouse gas emissions continue to rise, the planet's climatic system is being altered perhaps irreversibly. The result is more frequent extreme weather events, which makes understanding the physical and financial risk of climate-related events more important than ever. Preservation of the ecological, sociological, and economic system is of critical concern. The lack of sufficient tools and regulations risk measurement leaves us vulnerable to significant and preventable losses. Particularly for financial institutions which underpin the global financial network. The application of this paper's proposed risk assessment framework not only allows for increased resilience to climate-related flooding but also aims to promote global financial stability.

8. Acknowledgements

Firstly, I’d like to thank prof. dr. Kees Koedijk for the supervision, guidance, and mentorship throughout this research project. A huge thanks to dr. Jeroen Derwall for his helpful feedback at the eleventh hour. A special thanks to dr. Maarten Jennen for providing me with a very interesting case study, along with helpful advice and insight into the application of climate analytics. My appreciation goes out to Max Tesselaar, Timothy Tiggeloven, and Eric Mortensen at the Vrije Universiteit Amsterdam, who provided valuable assistance with flood modelling and directed me towards the correct databases. Finally, I’d like to thank my family, friends, and girlfriend for the moral support throughout the research.

9. References

Alfieri, L., Feyen, L., Dottori, F., & Bianchi, A. (2015). Ensemble flood risk assessment in Europe under high end climate scenarios. *Global Environmental Change*, *35*, 199–212. https://doi.org/10.1016/J.GLOENVCHA.2015.09.004

Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Church, J. A., … Yohe, G. (2014). *IPCC fifth assessment synthesis report - Climate Change 2014 synthesis report* (P. Aldunce, T. Downing, S. Joussaume, Z. Kundzewicz, J. Palutikof, J. Skea, … Z. Xiao-Ye, Eds.). Retrieved from http://www.ipcc.ch/pdf/assessment-report/ar5/syr/SYR_AR5_LONGERREPORT.pdf

Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does Climate Change Affect Real Estate Prices? Only If You Believe In It. *The Review of Financial Studies*, *33*(3), 1256–1295. https://doi.org/10.1093/RFS/HHZ073

Battiston, S. (2019). The importance of being forward-looking: managing financial stability in the face of climate risk. *Financial Stability Review*, (23), 39–48. Retrieved from https://econpapers.repec.org/RePEc:bfr:fisrev:2019:23:5

Battiston, S., Dafermos, Y., & Monasterolo, I. (2021, June 1). Climate risks and financial stability. *Journal of Financial Stability*, Vol. 54, p. 100867. https://doi.org/10.1016/j.jfs.2021.100867

Belanger, P., & Bourdeau-Brien, M. (2018). The impact of flood risk on the price of residential properties: the case of England. *Housing Studies*, *33*(6), 876–901. https://doi.org/10.1080/02673037.2017.1408781

Bernstein, A., Gustafson, M. T., & Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, *134*(2), 253–272. https://doi.org/10.1016/j.jfineco.2019.03.013

Bousso, R., Meijer, B., & Nasralla, N. (2021). Shell ordered to deepen carbon cuts in landmark Dutch climate case. Retrieved June 25, 2021, from Reuters website: https://www.reuters.com/business/sustainable-business/dutch-court-orders-shell-set-tougher-climate-targets-2021-05-26/

Carney, M. (2015). *BIS central bankers' speeches Mark Carney: Breaking the tragedy of the horizon-climate change and financial stability*. (September), 1–12. Retrieved from www.pwc.com/gx/en/ceo-agenda/ceo-survey.html

Chen, J. (2020). Risk Definition. Retrieved May 22, 2021, from https://www.investopedia.com/terms/r/risk.asp

Christophers, B. (2017). Climate Change and Financial Instability: Risk Disclosure and the Problematics of Neoliberal Governance. *Annals of the American Association of Geographers*, *107*(5), 1108–1127. https://doi.org/10.1080/24694452.2017.1293502

Clark, G. L., & Urwin, R. (2008). Best-practice pension fund governance. *Journal of Asset Management*, *9*(1), 2–21. https://doi.org/10.1057/jam.2008.1

Connelly, A., Carter, J., Handley, J., & Hincks, S. (2018). Enhancing the practical utility of risk assessments in climate change adaptation. *Sustainability*, *10*(5), 1399. https://doi.org/10.3390/su10051399

da Silva, L. B. L., Alencar, M. H., & de Almeida, A. T. (2020, November 1). Multidimensional flood risk management under climate changes: Bibliometric analysis, trends and strategic guidelines for decision-making in urban dynamics. *International Journal of Disaster Risk Reduction*, Vol. 50, p. 101865. https://doi.org/10.1016/j.ijdrr.2020.101865

Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). Climate value at risk' of global financial assets. *Nature Climate Change*, *6*(7), 676–679. https://doi.org/10.1038/nclimate2972

European Commission. (2019). Regulation (EU) 2019/2144 of the European Parliament and of the Council of 27 November 2019. *Official Journal of the European Union*, *62*. Retrieved from https://eur-lex.europa.eu/eli/reg/2019/2088/oj

Farbotko, C. (2019). Global financial stability, rapid transition to a low-carbon economy and social justice: can climate-related financial risk disclosure do it all? *Australian Geographer*, *50*(3), 273–278. https://doi.org/10.1080/00049182.2018.1519874

Fiedler, T., Pitman, A. J., Mackenzie, K., Wood, N., Jakob, C., & Perkins-Kirkpatrick, S. E. (2021). Business risk and the emergence of climate analytics. *Nature Climate Change*, *11*(2), 87–94. https://doi.org/10.1038/s41558-020-00984-6

Field, C. B., Barros, V., Stocker, T. F., Dahe, Q., Jon Dokken, D., Ebi, K. L., … Midgley, P. M. (2012). Managing the risks of extreme events and disasters to advance climate change adaptation: Special report of the intergovernmental panel on climate change. In *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change* (Vol. 9781107025). https://doi.org/10.1017/CBO9781139177245

Field, C. B., Van Aalst, M., Adger, W. N., Arent, D., Barnett, J., Betts, R., … others. (2014). Part A: Global and Sectoral Aspects: Volume 1, Global and Sectoral Aspects: Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In *Climate change 2014: impacts, adaptation, and vulnerability* (pp. 1–1101). IPCC.

Ganguli, P., & Merz, B. (2019). Extreme Coastal Water Levels Exacerbate Fluvial Flood Hazards in Northwestern Europe. *Scientific Reports*, *9*(1), 1–14. https://doi.org/10.1038/s41598-019-49822-6

Global warming may have already passed irreversible tipping point | Climate News | Al Jazeera. (n.d.). Retrieved July 4, 2021, from Al Jazeera website: https://www.aljazeera.com/news/2021/6/15/global-warming-may-have-already-passed-irreversible-tipping-point

Gumbel, E. J. (1955). Statistical Theory of Extreme Values and Some Practical Applications. *The Mathematical Gazette*, *39*(330), 341. https://doi.org/10.2307/3608620

Hain, L. I., Koelbel, J., & Leippold, M. (2021). Let's get physical: Comparing metrics of physical climate risk. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3829831

Hillson, D. a., & Hulett, D. T. (2004). Assessing risk probability: alternative approaches. *2004 PMI Global Congress*, (Collins 1979), 1–7. Retrieved from https://www.pmi.org/learning/library/assessing-risk-probability-impact-alternative-approaches-8444

Holton, G. A. (2004). Defining risk. *Financial Analysts Journal*, *60*(6), 19–25. https://doi.org/10.2469/faj.v60.n6.2669

Huizinga, J., De Moel, H., & Szewczyk, W. (2017). *Global flood depth-damage functions: Methodology and the database with guidelines*. https://doi.org/doi:10.2760/16510

Husby, T. G., Mechler, R., & Jongman, B. (2016). What if Dutch investors started worrying about flood risk? Implications for disaster risk reduction. *Regional Environmental Change*, *16*(2), 565–574. https://doi.org/10.1007/s10113-015-0769-2

International Organization for Standardization. (n.d.). *Risk Management (ISO 31000)*.

IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution. In *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Retrieved from http://www.ipcc.ch.

Jankowski, P., & Duran, H. (2021). Annual Update: Gross Domestic Product. Retrieved July 9, 2021, from Houston.org website: https://www.houston.org/houston-data/annual-update-gross-domestic-product

Jansen, L. (2019). Klimaatverandering als financieel risico. Retrieved June 4, 2021, from PGGM website: https://www.pggm.nl/blogs/klimaatverandering-als-financieel-risico/

Kenton, W. (2020). Business Risk Definition. Retrieved May 22, 2021, from https://www.investopedia.com/terms/b/businessrisk.asp

Knight, F. H. (1921). *Risk, uncertainty and profit* (31st ed.). Houghton Mifflin.

Koks, E. E., de Moel, H., Aerts, J. C. J. H., & Bouwer, L. M. (2014). Effect of spatial adaptation measures on flood risk: Study of coastal floods in Belgium. *Regional Environmental Change*, *14*(1), 413–425. https://doi.org/10.1007/s10113-013-0514-7

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *Review of Financial Studies*, *33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Liang, Z., Chang, W., & Li, B. (2012). Bayesian flood frequency analysis in the light of model and parameter uncertainties. *Stochastic Environmental Research and Risk Assessment*, *26*(5), 721–730. https://doi.org/10.1007/s00477-011-0552-y

Lindeijer, E., van Dam, J., Kramer, B., & Op ’t Veld, H. (2019). PGGM: a pension investor’s perspective on accelerating sustainable finance. *Financial Stability Review*, (23), 69–75. Retrieved from https://ideas.repec.org/a/bfr/fisrev/2019238.html

Lindsey, R. (2020). Climate Change: Atmospheric Carbon Dioxide | NOAA Climate.gov. Retrieved February 19, 2021, from Climate.gov website: https://www.climate.gov/news-features/understanding-climate/climate-change-atmospheric-carbon-dioxide

Meyer, V., Scheuer, S., & Haase, D. (2009). A multicriteria approach for flood risk mapping exemplified at the Mulde river, Germany. *Natural Hazards*, *48*(1), 17–39. https://doi.org/10.1007/s11069-008-9244-4

Most, H. van der, & Marchand, M. (2017). *Selecting measures and designing strategies for Integrated Flood Management - a guidance document*. (April), 46. Retrieved from www.gwp.org

MSCI. (2020). *MSCI ESG Climate Risk Reporting*. Retrieved from www.msci.com.

Munich RE. (2020). *Munich Re’s Location Risk Intelligence Climate Change Edition*.

O’Dwyer, B., & Unerman, J. (2020). Shifting the focus of sustainability accounting from impacts to risks and dependencies: researching the transformative potential of TCFD reporting. *Accounting, Auditing & Accountability Journal*, *33*(5), 1113–1141. https://doi.org/10.1108/AAAJ-02-2020-4445

Pallardy, R. (2011). Water cycle. In *Encyclopedia Britannica*. Retrieved from https://www.britannica.com/science/water-cycle

Pattberg, P. (2012). How climate change became a business risk: Analyzing nonstate agency in global climate politics. *Environment and Planning C: Government and Policy*, *30*(4), 613–626. https://doi.org/10.1068/c1179

PGGM. (2021). PGGM - Integrated report 2020. Retrieved June 14, 2021, from https://www.pggminvestments.nl/about-us

Reisinger, A., Howden, M., Vera, C., Garschagen, M., Hurlbert, M., Kreibiehl, S., … Ranasinghe, R. (2020). *The concept of risk in the IPCC Sixth Assessment Report: a summary of cross-working group discussions*. (September), 15.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., … Foley, J. A. (2009, September 24). A safe operating space for humanity. *Nature*, Vol. 461, pp. 472–475. https://doi.org/10.1038/461472a

Salas, J. D., Govindaraju, R. S., Anderson, M., Arabi, M., Francés, F., Suarez, W., … Green, T. R. (2014, January 1). Introduction to hydrology. *Modern Water Resources Engineering*, pp. 1–126. https://doi.org/10.1007/978-1-62703-595-8_1

Schwalm, C. R., Glendon, S., & Duffy, P. B. (2020). RCP8.5 tracks cumulative CO2 emissions. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(33), 19656–19657. https://doi.org/10.1073/PNAS.2007117117

Schwarcz, S. L. (2008). Systemic Risk. *SSRN Electronic Journal*. Retrieved from http://ssrn.com/abstract=1008326Electroniccopyavailableat:http://ssrn.com/abstract=1008326http://ssrn.com/abstract=1008326Electroniccopyavailableat:https://ssrn.com/abstract=1008326Electroniccopyavailableat:http://ssrn.com/abstract=1008326

Scussolini, P., Aerts, J. C. J. H., Jongman, B., Bouwer, L. M., Winsemius, H. C., De Moel, H., & Ward, P. J. (2016). FLOPROS: an evolving global database of flood protection standards. *Natural Hazards and Earth System Sciences*, *16*(5), 1049–1061. https://doi.org/10.5194/nhess-16-1049-2016

Segal, T. (2020). Common Methods for Measuring Risk in Investments. Retrieved June 25, 2021, from Investopedia website: https://www.investopedia.com/ask/answers/041415/what-are-some-common-measures-risk-used-risk-management.asp

Shadmehri Toosi, A., Doulabian, S., Ghasemi Tousi, E., Calbimonte, G. H., & Alaghmand, S. (2020). Large-scale flood hazard assessment under climate change: A case study. *Ecological Engineering*, *147*, 105765. https://doi.org/10.1016/j.ecoleng.2020.105765

South Pole. (2021). Geospatial Solutions - Sustainability Solutions - What We do - South Pole. Retrieved June 26, 2021, from https://www.southpole.com/sustainability-solutions/geospatial-solutions

Stocker, T. F., Qin, D., Plattner, G. K., Tignor, M., Allen, S. K., Boschung, J., ... & Midgley, P. M. (2013). *Climate Change 2013: The Physical Science Basis, Working Group 1 (WG1) Contribution to the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report (AR5)*. Cambridge, United Kingdom and New York, USA: Cambridge University Press.

Stocker, T. F., Qin, D., Plattner, G. K., Tignor, M. M. B., Allen, S. K., Boschung, J., … Midgley, P. M. (2013). Climate change 2013 The Physical Science Basis: Working Group I contribution to the fifth assessment report of the intergovernmental panel on climate change. In *Climate Change 2013 the Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Vol. 9781107057). https://doi.org/10.1017/CBO9781107415324

Storer, R. (2021). Up to 410 million people at risk from sea level rises – study | Sea level | The Guardian. Retrieved July 3, 2021, from The Guardian website: https://www.theguardian.com/environment/2021/jun/29/risk-from-sea-level-rises-unless-emissions-reduced

Sussman, F. G., & Freed, J. R. (2008). *Adapting to Climate: Business Approach*.

Sustainability Accounting Standards Board. (2018). Materiality Map. *Sustainability Accounting Standards Board*. Retrieved from https://www.sasb.org/standards/materiality-map/

Sutanudjaja, E. H., Van Beek, R., Wanders, N., Wada, Y., Bosmans, J. H. C., Drost, N., … Bierkens, M. F. P. (2018). PCR-GLOBWB 2: A 5 arcmin global hydrological and water resources model. *Geoscientific Model Development, 11*(6), 2429–2453. https://doi.org/10.5194/gmd-11-2429-2018

Task Force on Climate-related Financial Disclosures. (2017). *Recommendations of the Task Force on Climate-related Financial Disclosures*. (December), 1–6. Retrieved from https://www.fsb-tcfd.org/wp-content/uploads/2017/06/FINAL-2017-TCFD-Report-11052018.pdf

TCFD. (2019). *Task Force on Climate-Related Financial Disclosures Status Report*. Retrieved from https://assets.bbhub.io/company/sites/60/2020/10/2019-TCFD-Status-Report-FINAL-0531191.pdf

van Dijk, M. A. (2020). *Assessing Climate risk for Investment Portfolios: an Overview for Dutch Pension Funds*. Retrieved from https://climateactiontracker.org/global/temperatures/,

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., … Rose, S. K. (2011). The representative concentration pathways: An overview. *Climatic Change*, *109*(1), 5–31. https://doi.org/10.1007/s10584-011-0148-z

Verbraeken, H. (2019). Risico op klimaatschade bij vastgoed nu veel preciezer te bepalen. *Financieel Dagblad*. Retrieved from https://fd.nl/ondernemen/1317209/risico-op-klimaatschade-bij-vastgoed-nu-veel-preciezer-te-bepalen

Votsis, A., & Perrels, A. (2016). Housing Prices and the Public Disclosure of Flood Risk: A Difference-in-Differences Analysis in Finland. *Journal of Real Estate Finance and Economics, 53*(4), 450–471. https://doi.org/10.1007/s11146-015-9530-3

Vuuren, D. P. van, Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., … Rose, S. K. (2011). The representative concentration pathways: an overview. *Climatic Change 2011 109:1*, *109*(1), 5–31. https://doi.org/10.1007/S10584-011-0148-Z

Wang, L. K., & Yang, C. T. (2014). *Modern water resources engineering*. Humana Press Inc.

Ward, P. J., Jongman, B., Aerts, J. C. J. H., Bates, P. D., Botzen, W. J. W., DIaz Loaiza, A., … Winsemius, H. C. (2017). A global framework for future costs and benefits of river-flood protection in urban areas. *Nature Climate Change, 7*(9), 642–646. https://doi.org/10.1038/nclimate3350

Ward, P. J., Jongman, B., Salamon, P., Simpson, A., Bates, P., De Groeve, T., … Winsemius, H. C. (2015). Usefulness and limitations of global flood risk models. *Nature Publishing Group*. https://doi.org/10.1596/978-0-8213-9561-5

Ward, P. J., Jongman, B., Weiland, F. S., Bouwman, A., Van Beek, R., Bierkens, M. F. P., …

Winsemius, H. C. (2013). Assessing flood risk at the global scale: Model setup, results, and sensitivity. *Environmental Research Letters*, *8*(4), 044019. https://doi.org/10.1088/1748-9326/8/4/044019
Ward, P. J., Winsemius, H. C., Kuzma, S., Bierkens, M. F. P., Bouwman, A., Moel, H. DE, … Luo, T. (2020). Aqueduct Floods Methodology. *World Resources Institute*, (January), 1–28. Retrieved from www.wri.org/publication/aqueduct-floods-methodology.
Weinhofer, G., & Busch, T. (2013). Corporate Strategies for Managing Climate Risks. *Business Strategy and the Environment*, *22*(2), 121–144. https://doi.org/10.1002/BSE.1744
Winsemius, H. C., Van Beek, L. P. H., Jongman, B., Ward, P. J., & Bouwman, A. (2013). A framework for global river flood risk assessments. *Hydrology and Earth System Sciences*, *17*(5), 1871–1892. https://doi.org/10.5194/hess-17-1871-2013
Wobus, C., Zheng, P., Stein, J., Lay, C., Mahoney, H., Lorie, M., … Martinich, J. (2019). Projecting Changes in Expected Annual Damages From Riverine Flooding in the United States. *Earth's Future*, *7*(5), 516–527. https://doi.org/10.1029/2018EF001119
World Bank. (n.d.). GDP (current US$) - European Union. Retrieved July 11, 2021, from https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=EU
World Economic Forum. (2020). *The Global Risks Report 2020*. Retrieved from http://www3.weforum.org/docs/WEF_Global_Risk_Report_2020.pdf
Zscheischler, J., Westra, S., Van Den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., … Zhang, X. (2018, June 1). Future climate risk from compound events. *Nature Climate Change*, Vol. 8, pp. 469–477. https://doi.org/10.1038/s41558-018-0156-3

10. Appendix A

Code used in R to convert flood depth into flood damage using depth-damage curves.

```
#Set up workspace
setwd("C:/Users/jornk/Documents/SBI2019/Year 2/Master thesis/Data collection/R")
library(dplyr)
library(stats)

#---- Load in depth-damage functions from JRC ----
#Damage curves are saved
dmg <- readRDS("dmg.rds")

#Data containing flood depths is imported from Excel
library(readxl)
rsample <- read_excel("~/SBI2019/Year 2/Master thesis/Case study/PGGM rcp85 coast 2050.xlsx",
                      na = "#NA")

#This will be grouped and split by continent

#Combining the different continents into one vector
regions <- c("AF", "AN", "AS", "EU", "NA", "OC", "SA")

#Create a new dataframe for each continent
#This tells the code to create a new dataframe for each of the continents
for (region in regions) {
  nam <- paste("rsample", region, sep = "")
  assign(nam, filter(rsample, REGION == region))
}

#---- Split damage functions per continent----
#Damage curves were also split based on continent
dmgAS <- dmg %>%
  filter(region == "asia")
dmgEU <- dmg %>%
  filter(region == "europe")
dmgNA <- dmg %>%
  filter(region == "north_america")
dmgOC <- dmg %>%
  filter(region == "oceania")

#Here, the approximation function is applied to each of the return periods,
#which are split up into the four continents

#For each continent dataset: unlist, approximate, create matrix, and cbind to combine output with input
sampleoutAS <- data.frame(matrix(unlist(approx(dmgAS$flood_depth, dmgAS$damage, as.matrix(rsampleAS[,12:20]),
   rule = 2)[2]), nrow = nrow(rsampleAS), byrow = F))
outAS <- cbind(rsampleAS, sampleoutAS)

sampleoutEU <- data.frame(matrix(unlist(approx(dmgEU$flood_depth, dmgEU$damage, as.matrix(rsampleEU[,12:20]),
   rule = 2)[2]), nrow = nrow(rsampleEU), byrow = F))
outEU <- cbind(rsampleEU, sampleoutEU)

sampleoutNA <- data.frame(matrix(unlist(approx(dmgNA$flood_depth, dmgNA$damage, as.matrix(rsampleNA[,12:20]),
   rule = 2)[2]), nrow = nrow(rsampleNA), byrow = F))
outNA <- cbind(rsampleNA, sampleoutNA)

sampleoutOC <- data.frame(matrix(unlist(approx(dmgOC$flood_depth, dmgOC$damage, as.matrix(rsampleOC[,12:20]),
   rule = 2)[2]), nrow = nrow(rsampleOC), byrow = F))
outOC <- cbind(rsampleOC, sampleoutOC)


#All the output datasets containing damage are recombined
casestudyout <- rbind(outAS, outEU, outNA, outOC)

#A new Excel file is written to save the output of the above code
write.csv(casestudyout, "PGGM output rcp85 coast 2050.csv")```
```

11. Appendix B

Additional figures and tables.

Table 6: List summarizing the different definitions and conceptualizations of risk; including a general definition of risk, climate risk, risk in financial terms, and the definition of risk used in this research.

Discipline	Definition	Conceptualization	Source of hazard
General	Probability of adverse consequences	Risk = likelihood times impact	Widely varied
Climate risk definition	See section Defining risk for full definition	Risk = hazard times exposure times vulnerability	Climate-induced weather extremes: droughts, cyclones, heat waves, wildfires, and floods
Financial risk definition	The likelihood of lower investment returns or outcomes	Standard deviation, VaR, R-squared, beta, Sharpe ratio	Business, Default, Foreign-Exchange, Interest rate, Political, Counterparty, or Liquidity

Table 7: Table converting EAD projections of Alfieri et al. (2015) to comparable measures to validate the model.

EAD projection in 2007 GDP (Alfieri et al., 2015)	GDP EU 2007	Total GDP EU 2007 (World Bank, n.d.)	EAD projection as a percentage of total GDP
5.3 billion euro	14.69 trillion USD	11.13 trillion euro	0.05%
20 to 40 billion euro	14.69 trillion USD	11.13 trillion euro	0.18% 0.36%
30 to 100 billion euro	14.69 trillion USD	11.13 trillion euro	0.27% 0.90%

Table 8: Results from sensitivity analysis of vulnerability. No protection refers to full damage, 10y protection is 10-year protection standard across the whole sample. The same is true for 25y protection. FLOPROS refers to data collected from the FLOPROS dataset, and is used in the study. Results are given in EAD %, Expected Annual Damage as a percentage of total portfolio value of the sample.

	EAD %					
RCP	*RCP45*	*RCP45*	*RCP45*	*RCP85*	*RCP85*	*RCP85*
Timeframe	*2030*	*2050*	*2080*	*2030*	*2050*	*2080*
No protection	3.73%	3.68%	4.91%	3.76%	5.27%	5.3%
10y protection	0.58%	0.57%	0.75%	0.6%	0.72%	0.79%
25y protection	0.31%	0.3%	0.4%	0.32%	0.37%	0.41%
FLOPROS	0.24%	0.24%	0.32%	0.24%	0.28%	0.34%

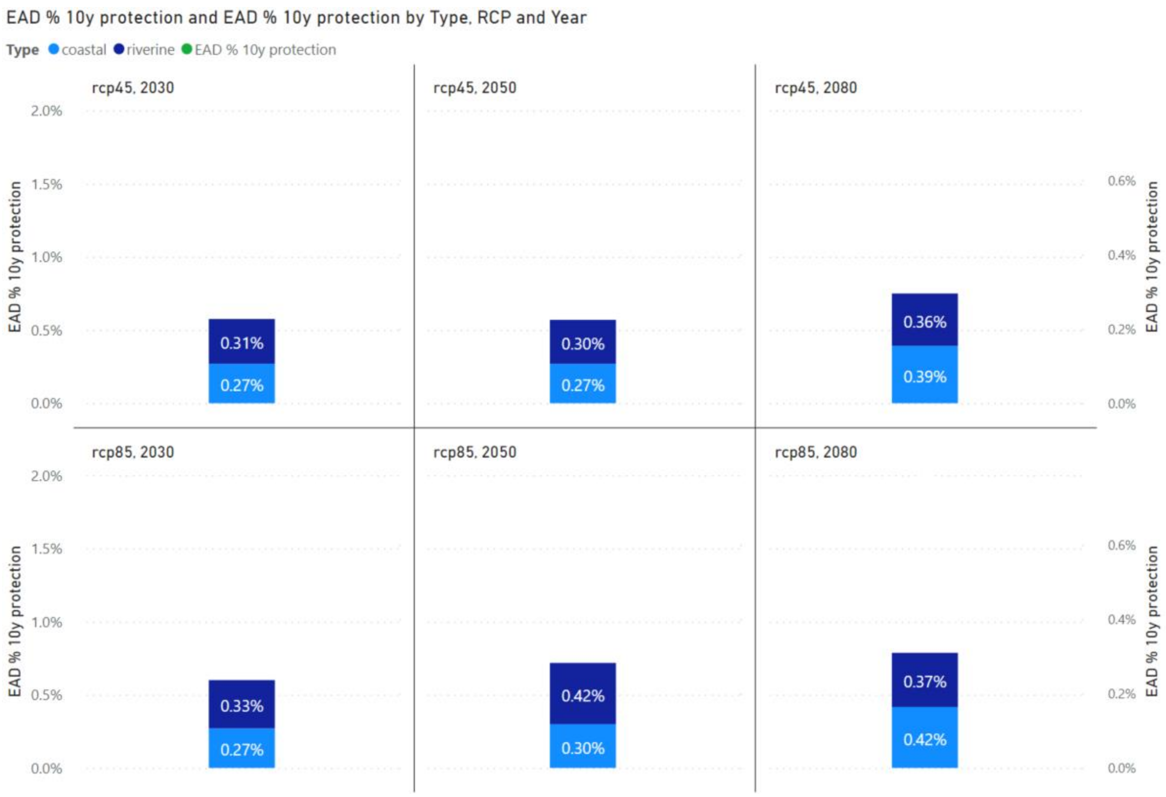


Figure 20: Results from sensitivity analysis. Assuming 10-year flood protection standards across the portfolio.

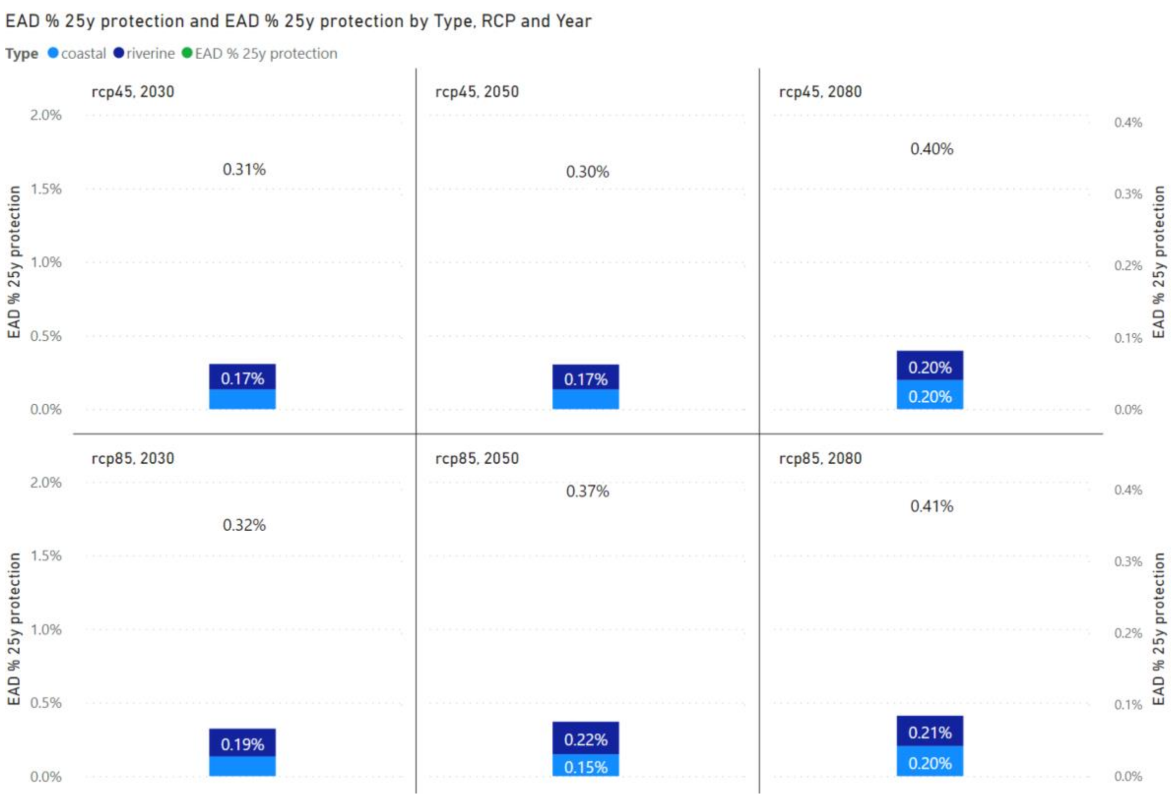


Figure 21: Results from sensitivity analysis. Assuming 25-year flood protection standards across the portfolio.