Financial Modeling of Extreme Flood Events on Corporate Property Damage and Business Interruption Loss: A Geospatially-Informed Facility Portfolio Approach

by

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Dedication

To my wife, older daughter, and younger daughter who will be born this summer.

"Believe you can and you're halfway there."

—Theodore Roosevelt

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Abstract

To build a society that is adaptive to climate change, it is essential that not only public institutions but also the private sector take appropriate action. In 2015, the Paris Agreement reinforced a shared global understanding regarding both the mitigation of and adaptation to climate change. In 2017, the Task Force on Climate-related Financial Disclosures (TCFD) released its guidelines, recommending that companies recognize and disclose the financial risks they face from climate exposures, including from the increasing probability of floods. Understanding corporate financial risks from flooding facilitates strategic decision-making for making prudent investments in risk mitigation and climate transition.

This dissertation proposes an approach that integrates datasets derived from hydrological models with those from corporate financial records. A new financial model for corporate flood risk assessment is constructed based on hydrological and financial data, as well as geospatial information that captures corporate risk from the perspective of individual facilities to the listed equity holding. Using flood damage algorithms, the model quantifies both direct impacts on property damage (PD) and indirect impacts such as business interruption losses (BIL). Capital stock losses are derived from the valuation of capital investments in fixed assets, information available as Plant, Property and Equipment (PP&E) on the balance sheet. The approach was first tested using publicly available corporate records from four Japanese companies to identify the extent of modeled underestimation or overestimation relative to public disclosures and to reveal sources of uncertainty. The results of Expected Annual Damage (EAD) assessments at both the

facility and corporate levels provide insights that support strategic investment decisions aimed at mitigating flood risk.

Next, I sought to apply the proposed financial model approach to all 225 companies and 11 industry sectors comprising the Nikkei 225 Index. Based on analysis of 18,000+ facilities across global regions, regional and sectoral risk attributes, as well as contributions from PD and BIL were estimated. The total EAD for all 225 companies is 7 billion USD per year, with approximately 60% resulting from facilities in Asia, based on three time points (2030, 2050 and 2080). The median and outlier values of EAD as percent of net income generally fall within a 5-15% range, seen as a trigger value for implementation of corporate financial risk mitigation.

Lastly, this study addressed the challenge of insufficiently granular temporal resolution of corporate flood prediction to make strategic investment decisions. To address this issue, hydrological calculations from global climate projection data using the RCP 8.5 scenario from the MIROC-ESM-CHEM model combined with the Ca-Ma flood model enabled the estimation of EAD on an annual basis by region and industry. On average across all regions, the EAD value in 2089 is projected to increase by approximately 10% due to property damage, and by a few percent due to BIL, when compared to 2020. In terms of industry, the EAD of the energy sector due to property damage peaks in 2041, and the EAD in 2089 was estimated to increase by more than 20% compared to 2020.

Overall, this dissertation quantified corporate financial flood risks through two channels, and demonstrated that, given key underlying assumptions and limitations, the model is scalable to all industry sectors, while considering global distribution of corporate facilities of firms. The findings of this study provide essential insights for the financial flood risk management by the private sector.

Chapter 1 Introduction

This chapter introduces how my research at the intersection of climate-related risks and finance is grounded and why it relates to the broader field of environmental engineering.

1.1 Climate Change Impacts on the Economic and Financial System

Climate change research and its many derivative attributes have found widespread emphasis in the environmental engineering discipline including a focus on modeling anthropogenic carbon emissions and their impact on the land-air-water interface through the increasing frequency of floods, droughts, and other natural disasters such as heat waves, storms and hurricanes (Hirabayashi et al., 2013; Willner et al., 2018). Receiving less attention in the field is how climate change and its impact on extreme events affects society's economic structures and the global financial system that depends on it in a bi-directional flow of capital. This physical-financial interconnect urgently requires better quantitative understanding to help inform future decision-making for public and private investments in adaptation to climate change.

The basic tenets of the interconnect find its origins in the International Panel on Climate Change (IPCC), established in 1988 by the World Meteorological Organization (WMO) and the United Nations of Environmental Program (UNEP) to provide policymakers with scientific data. The Annual Report (AR) 5 in 2014 stressed *"It is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century"* (IPCC, 2014). Furthermore, the AR 6 in 2023 emphasizes *"It is unequivocal that human influence has warmed*

the atmosphere, ocean and land" (IPCC, 2023). It is crucial to assess the effects of climate change on our worldwide system based on scientific analyses under climate change scenarios.

Various climate change projections have, for example, quantitatively evaluated that the occurrence of heavy precipitation will likely escalate (Thackeray et al., 2022). Climate change scenarios, stemming from human activities as a cause of greenhouse gas production and accelerated increases, lead to an intensification of extreme precipitation and floods events over various climatic zones (Tabari, 2020). The Emergency Events Database (EM-DAT) provided by the Centre for Research on the Epidemiology of Disasters (CRED) reported that the economic losses from floods and storms were more pronounced than those of other natural disasters in 2021, and the economic losses incurred that year were at least 1.7 times greater than the average damages calculated between 2001 and 2020 shown in Figure 1.1 (CRED, 2022). Furthermore, the implications of climate change on excessive riverine inundation flooding events were shown to negatively affect global supply chains and broader economic productivity.

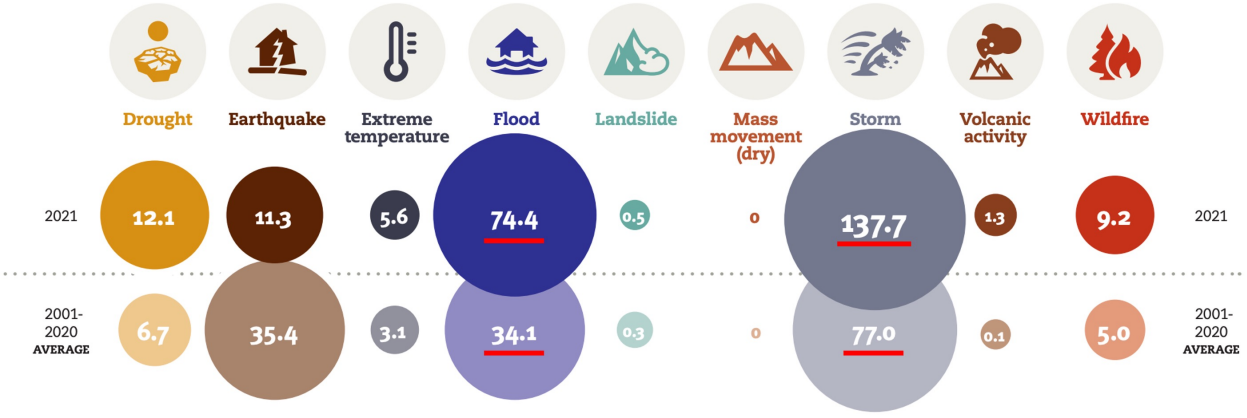


Figure 1.1 Economic losses (unit: billion USD) by disaster type (Source: CRED, 2022, p.7, edited)

Based on scientific data, the socio-economic discourse among governmental policy makers led to strategies to alleviate and adapt to the challenges of climate change among governmental policy makers. The Sendai Framework for Disaster Risk Reduction 2015-2030, adopted by the United Nations (UN) at the Third UN World Conference on Disaster Risk Reduction, and coordinated by the United Nations Disaster Risk Reduction (UNDRR), highlighted the importance of reducing risks prior to disasters and created a framework that encompasses the timeframe from 2015 to 2030. The concept of Build Back Better promotes the idea of not only rebuilding structural defenses, but also making them more robust than they were prior to past disasters (UN, 2015; Birkmann et al., 2023). The critical role of adopting non-structural measures, including disaster insurance, was also emphasized (UN, 2015). In addition, the Paris Agreement, signed in 2015, involved a commitment from member nations to implement strategies and investments using public, private and blended finance structures aimed at limiting the global temperature increase below 2°C by the end of the 21st century (UNFCCC, 2015). Advancing national climate adaptation under the Paris Agreement is critical not only to reduce risk, but also to facilitating a nation's development (Fuldauer et al., 2022).

Aside from addressing physical impacts of climate change, the extant literature has focused on evaluating the macroeconomic effects of climate impacts such as flooding by using socio-economic indicators, including Gross Domestic Product (GDP), population density, and land use data. Existing studies assessed the risk of river flooding, focusing on the estimation of GDP loss by considering land use data (Winsemius et al., 2013; Englhardt et al., 2019). The financial costs and benefits related to the protection against river flooding were analyzed using the results from hydrological models along with relevant socio-economic impact data (Ward et al., 2017). Jonkman et al. (2008) conducted their estimations using land use metrics, economic

data including maximum direct damage amounts, and flood damage functions. Furthermore, various studies have focused on the spatial economic impacts of floods using demographic distribution (Hirabayashi et al., 2013; Arnell and Gosling, 2016) and GDP (Ward et al., 2013; Ward et al., 2014; Jongman et al., 2015; Winsemius et al., 2016).

Aside from societal economic impact, it was recognized that climate change was starting to affect and destabilize the financial system as well (Furukawa et al., 2020), including financial institutions such as insurance companies, stock exchanges, investment banks and pension funds, where capital is exchanged and transferred from one place to another (Monasterolo, 2020). As a result, there is a growing awareness that achieving the global climate and sustainability targets requires aligning financial institutions such as banks and securities regulators with sustainable corporate operations and activities. For example, a well-coordinated and timely reduction or risk adjustment of banking loans to the fossil fuel industry is necessary if Paris climate targets are to remain achievable (Rickman et al., 2024).

However, to date, investments are still largely allocated into economic activities that are not aligned with climate targets and their derivative effects on operations such as those from water scarcity (Tian and Adriaens, 2025), flooding (Abe and Adriaens, 2025), or carbon emissions and, hence, are at odds with the definition of sustainable finance. For example, a climate stress-test of the financial system showed that investors in the Eurozone and the United States are considerably exposed to financial contracts and securities issued by companies whose revenues are directly or indirectly (because of exposure to floods or droughts) related to fossil fuels' extraction and combustion (Battiston et al. 2017). It has been estimated that pension funds and investment funds are exposed for about 30% of their equity portfolios, estimated by industry white papers at $7 trillion (Díaz, 2021), to assets that could become stranded during transition to

a low-carbon economy. In addition, interlinkages among financial institutions can amplify shocks (both positive and negative) via reverberation of losses in the broader financial system supporting banking, investments, and corporate or public economic growth.

It is also increasingly recognized that investors and financial markets are not yet pricing climate-related risks (and opportunities) in the value of financial contracts (Morana and Sbrana 2019). Hence, investors may be exposed to risks they are not fully aware of and are uncertain about opportunities for returns from sustainable investment strategies (Monasterolo and de Angelis, 2020). Mispricing of climate risks could lead to asset price volatility and affect financial stability if large and correlated financial assets are involved, with potential implications for broader systemic risk that cannot be diversified away from (Campiglio et al., 2023; Bua et al., 2024). The impact on stability of the financial system central banks and regulators has resulted in recommendations to investors and financial institutions to assess and quantify their exposure to climate-related financial risks. Financial regulators have started to design scenarios for climate stress tests to assess how vulnerable the financial system is to climate change. Nevertheless, the financial community falls short of methodologies that allow for the successful analysis of the risks that climate change poses to financial stability. Indeed, the characteristics of climate risks (i.e., geospatial correlation, deep uncertainty in expected trends and impacts, non-linearity of effects and endogeneity) challenge traditional approaches to macroeconomic and financial risk analysis, and indicate an increasing need for more granular bottom-up (corporate) data to supplement top-down (fund or bank-level) financial disclosures (Battiston et al., 2021).

1.2 Corporate Financial Climate and Flood Risk Disclosure

The elevated global understanding of climate challenges has driven the introduction of financial legislation to either institute voluntary or mandated requirements for companies to disclose their climate-related risks. Corporations are facing increased demands for their business operations to be more transparent about climate-related strategies, their financial exposure to climate change, and the risk management practices they deploy to mitigate these risks (Kim et al., 2023). To address this issue, the Financial Stability Board (FSB), an international body that monitors and makes recommendations about the global financial system, established the Task Force on Climate-related Financial Disclosures (TCFD) in 2017 in light of a request from the Group of 20 Finance Ministers and Central Bank Governors (O'Dwyer and Unerman, 2020; Di Marco et al., 2023). The premise of TCFD was to make it easier for investors, lenders, and insurance underwriters to assess and price climate-related risks and opportunities in global securities that underpin pension funds, banking and international trade. It promoted disclosure of these risks by corporations (Ding et al., 2023), asset managers (Greenwood and Warren, 2022) and banks (Friedrich et al., 2023), aiming to improve transparency and support informed investment decisions. An example is presented in Table 1.1, which shows the number of corporations that disclose their climate-related risks through the Carbon Disclosure Project (CDP). The data show that the number of companies that disclose their climate-related risks in 2023 has increased by 2.4 times when compared to the data from 2020, in part because of growing demand by investors and governments seeking to stabilize financial risk exposures and avoid blind spots that may cause unexpected cascading failure effects.

The increasing urgency of climate risks encouraged governments to require corporations to report their sustainability information, such as physical and financial impacts from natural disasters, including floods, on their global business operations. In 2022, the United Kingdom

implemented an amendment to the Companies Act 2006, requiring corporations to disclose the risks associated with climate change as a mandatory requirement. The European Union issued the Accounting Directive (2013/34EU 1) in 2022, amended by the Corporate Sustainability Reporting Directive (CSRD - 2022/2464 2) requiring companies to report information to indicate how sustainability issues affect their growth, performance and corporate status. In 2023, Japan introduced a new section in its securities reports for public companies to disclose sustainability information, following the TCFD recommendations. In 2024, the Securities and Exchange Commission (SEC) of the United States, the Federal Reserve and the US Treasury also mandated financial risk disclosures associated with climate change by public companies, fund managers and banks. This rule has recently been frozen by the current Administration, effectively not requiring companies and financial institutions to disclose climate-related financial risk exposures. However, US companies and funds conducting business or investments in the EU, or co-listed outside of the US, still have the disclosure requirement.

Table 1.1 Number of Corporations which Disclose their Climate-related Risks via CDP (CDP, 2025)

	2020	2021	2022	2023	2023/2020
Climate	9,526	13,126	18,636	23,202	2.4
Water	2,934	3,368	3,908	4,815	1.6
Forests	687	864	1,048	1,152	1.7

1.3 Dissertation Structure

This dissertation, taking into account the need to bridge physical and financial risks from climate change, primarily aims to analyze the corporate financial flood risks resulting from extreme events. The scope of this study is shown in Figure 1.2 by using the TCFD framework as

context (TCFD, 2017). Based on this figure, climate-related risks are classified into two distinct types: 1) Transition risks that arise from the transition to a low-carbon economy, and 2) Physical risks that involve the physical impacts of climate change. The transition risks are segmented into four key categories, illustrating how different societal shifts during the transition, such as policy and legal, technology, market, and reputation, can impact business activities. The physical risks are classified into chronic changes, such as droughts resulting from higher average temperatures, and acute events, such as floods that occur due to extreme weather conditions. In terms of opportunities, the TCFD specifies five categories that organizations can adopt in response to climate change: Implementation of resource efficiency measures, diversification of energy sourcing, shifts in products and services, accessing different markets, and strategic investment in resilience.

My dissertation highlights floods as an acute physical risk factor, while excluding chronic physical hazards such as the effects of droughts. Transition risks, such as policy and legal, technological innovations and reputational risks, are not addressed within the focus of this study. My emphasis is to explore and quantify or estimate corporate financial impacts of floods in their income statement and balance sheet reports, specifically through metrics such as revenue, operating profit and investment in property, plant and equipment (PP&E) assets.

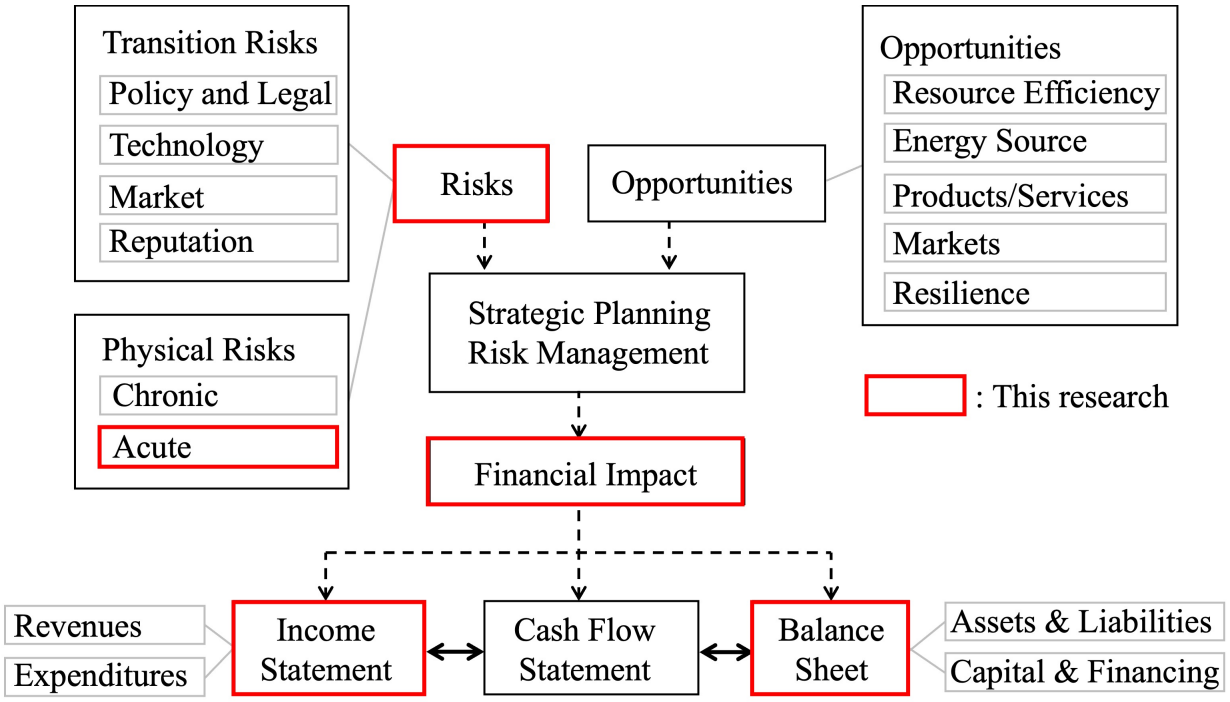


Figure 1.2: Scope of this research and illustration of the TCFD framework adapted from the TCFD guideline (Source: TCFD, 2017, p.8, edited)

Based on this context, my research identifies the following three challenges that corporations confront in disclosing financial flood risk exposures associated with flood hazards, aligned with the TCFD recommendations, as part of their climate change adaptation efforts.

1. A significant obstacle for financial risk disclosure is that the indicators and benchmarks for climate-related financial risks and the methodologies for their derivation have not been formally established or broadly agreed on (Binger et al., 2022). To date, the focus of flood risk-related research has been on macroeconomic risk analyses using data sources such as Gross Domestic Product (GDP) and the distribution of the population (Burke et al., 2015; Huang et al., 2018; Koks et al., 2019). In studies conducted at the facility level, models such as Hazards United States (HAZUS) are often acknowledged; however, this model is specifically

constructed for the United States and has not been extended to a global scale (Scawthorn et al., 2006; Haque et al., 2022). Kusuma et al. (2024) pointed out that corporations need to improve their level of transparency and comprehensiveness in preparing financially-informed sustainability reports according to more detailed standards.

2. A key challenge to understanding how flood risks differentially impact corporate financial performance is to gain insights in the regional and financial attributes at the facility and the industry sector scales. In the realm of industry-scale analyses, Input-Output (I-O) analysis and Computable General Equilibrium (CGE) analysis have been utilized, both of which have been applied to evaluate the economic impacts of flooding (Carrera et al., 2015; Dormady et al., 2022). Hu et al. (2019) addressed flood risk at the more granular municipal level and recognized that techniques for integration at larger scales are a significant obstacle. (Campiglio et al., 2023). For example, at the facility scale, regional climate event correlation on the risk map may impact multiple facilities and thus risks should not be quantified as being independent. Hence, the translation of physical flood risks to financial risks is subject to an as yet unquantified propagation of uncertainty at multiple levels.
3. Typical flood prediction models operate at aggregate (decadal) timescales, yet corporate financial disclosures are reported at the quarterly or annual level. Hence, the temporal granularity of flood prediction and financial reporting for improved corporate risk management and investment decision-making requires better integration. Carè (2023) highlights that while the gradual progression of climate change occurs over decades, climate stress evaluations are often carried out over

shorter periods, potentially leading to a failure in an incomplete evaluation of the long-term consequences for financial stability. Climate risk assessment requires not only an understanding of hazards across multiple spatial and temporal scales, but also a grasp of exposures (such as the geographical distribution of assets and value chains), and their vulnerabilities (Arribas et al., 2022).

1.3.1 Question 1: Determine the feasibility to quantify corporate financial flood risks by integration of financial disclosures and hydrological model outputs.

The importance of this first question stems from the necessity to assess the financial risks associated with flooding on corporations, in accordance with the TCFD framework. The level of transparency exhibited by different companies is increasingly significant, and there is a rising expectation for more comprehensive and financially-oriented disclosures (Kusuma et al., 2024). One of the primary difficulties lies in the lack of defined indicators and approaches for estimating corporate financial flood risks (Binger et al., 2022). To address this challenge, it is essential to conduct research that seeks to clarify a systematic approach applicable across companies and sectors, while acknowledging model uncertainties and limitations.

The first inquiry holds relevance for institutional investors as well. Krueger et al. (2020) emphasized that institutional investors are aware that climate-related risks carry financial implications for the corporations in their portfolios, and they recognized that, particularly in terms of regulatory risks, the effects have begun to emerge in terms of both volatility and asset valuation risks. In other words, the assessment of the corporate financial flood risk can serve as a catalyst for the reevaluation of portfolios managed by institutional investors.

Additionally, this initial question is also vital for financial institutions, including the banking sector. Huang et al. (2022) stressed that the evaluation of corporate physical risks associated with climate change can lead to unfavorable lending conditions from financial institutions, such as escalated interest rates and more restrictive contract terms. These impacts were based on corporate executive opinions and the degree of climate-related risk exposure.

This chapter introduces a method for quantifying corporate financial flood risks on corporate facilities by using information derived from a business database, outputs of a hydrological product, and flood damage parameters. It also compares the estimated financial impacts with values reported in the published statements of the companies in their annual reports and TCFD disclosures. Importantly, the analysis of data was done in an uncertainty context, by acknowledging the impact of various metrics used to benchmark financial risk, the limitations of simplifying financial risk to capital asset investments and revenue, and explicitly stating that no autocorrelation of climate events impacting multiple facilities in a target region was assumed. The work in this chapter has been published as a manuscript in the International Journal of Disaster Risk Science, as referenced below:

> **Abe Masahiro**, and Adriaens Peter. (2025). Assessment of Corporate Financial Flood Risks Due to Property Damage and Business Interruption Loss. *International Journal of Disaster Risk Science* 16(2). https://doi.org/10.1007/s13753-025-00638-1

1.3.2 Question 2: Identify and quantify regional and industry-sector attributes of corporate financial flood risk at a portfolio level

The second question is essential as it facilitates an understanding of systemic risk in portfolios and triggers that can lead to a major financial loss impact across industry sectors. Li et

al. (2021) pointed out that analyzing the financial implications of flood risk is a proxy to comprehending systemic risk. This inquiry is important, as it enhances our understanding of the factors that influence the evaluation of corporate creditworthiness in relation to both bank financing and the issuance of corporate bonds (Capasso et al., 2020). In other words, financial institutions take into account a corporation's creditworthiness based on its responses to climate risks and the trends identified among similar enterprises.

In addition, this second question may serve as a potential reference point for the insurance industry in determining premiums associated with disaster-related property coverage for businesses. Kunreuther (2008) asserts the principle that insurance premiums should be reflective of risk levels, and hence risk reduction can serve as a factor to facilitate lower premiums. As a means to formulate a transparent incentive system for reducing flood risks in flood insurance, concepts such as risk-based premium determination, where insurance rates are set in accordance with flood risk levels in particular areas have been considered (Surminski et al., 2017).

In this chapter, the techniques introduced in Chapter 2 are applied to evaluate the financial risks from floods to the 225 firms listed in the Nikkei 225 index, based on sector-specific classification using the Global Industry Classification Standard (GICS). By analyzing the financial risk outcomes associated with industry sectors and their constituent corporate business operations, the study aims to identify and quantify the impact of geographical and sectoral attributes at the facility level. Again, it should be noted that uncertainties associated with inferred facility financial data and spatial autocorrelation of event impacts on flood risk to facilities were not explicitly quantified or addressed, given my focus on financial method development and testing for sector and regional comparison purposes, while the spatial

dependence can affect results particularly for *"tail dependence in national and continental risk assessments"* (Nguyen et al., 2020). These authors indicate that it's important to demonstrate the spatial dependence of flood peaks to minimize the misestimation which tends to increase with increasing spatial scale. This limitation may be particularly significant for my calculations, as quantifying the potential for flood risk across sectors and regions is of *"considerable importance in view of the natural and strong spatial dependence of this particular natural peril"* (Albrecher et al., 2020).

1.3.3 Question 3: Does the use of temporally-discrete hydrological models improve time-series granularity of corporate financial flood risk exposure?

The third question plays a crucial role in improving granularity of outputs proposed in the previous chapter and facilitating greater transparency of corporate financial flood risk exposure by increasing the reliability of the results produced through multiple hydrological models, as used in the Aqueduct Floods database (Ward et al, 2020; Abe and Adriaens, 2025). The information disclosed by corporations regarding their risk evaluation processes, for example, is incomplete, resulting in few firms being recognized for their high level of transparency, which remains an obstacle (Kusuma et al., 2024). If financial regulatory compliance requirements extend beyond the current levels of transparency, including the disclosure of underlying assumptions, the importance of this question will become even more pronounced.

In addition, the third inquiry is important to understand the extent of uncertainty that is embedded within processes using hydrological models (Hu et al., 2019). Since the current work requires global predictive outputs to capture the impact on regional distribution of corporate facilities, this chapter explores the level of uncertainty present in hydrological models by

comparing the outcomes of corporate financial flood risks carried out with temporally-granular SiBUC and CaMa-Flood models compared to projections based on Aqueduct Floods (Abe and Adriaens, 2025).

In summary, the structure of the dissertation is as follows (Table 1.2). Chapter 2 focuses on building and testing a financial model that links acute physical risks from floods to financial risk exposures from business interruption and property damage, by aggregating financial risk to the corporate level. Chapter 3 presents an industry sector level analysis of companies listed on the Nikkei 225, thus exploring the impact of regional and sector-specific attributes on financial risks, and informing opportunities to adjust component allocation in investment portfolios with minimal flood risk exposures. While previous chapters used long-term flood predictions on financial risk exposures, Chapter 4 introduces the impact of temporal granularity on annual financial risk from flood-related business interruption and property damage.

Table 1.2 Research questions and corresponding chapters

Topics	***Focus***	***Corresponding Chapter***
Corporate Financial Flood Risk Model	Development and validation of a financial model that integrates flood risk to corporate facilities with business interruption and property damage, and aggregates this risk at corporate level	Chapter 2
Application of Corporate Financial Flood Risk Model at the Index Level (Nikkei 225)	Financial indexes are represented by corporate constituents across many industries and climate regions. This chapter quantifies the impact of regional and sector-specific attributes at the index scale.	Chapter 3
Temporal Impacts of Flood Risk Prediction on Corporate Financial Risk Exposures	As companies need to make time-dependent decisions on investment strategies to mitigate flood risks. This chapter expands on Chapter 3 to explore the impact of temporal granularity of flood predictions on financial risk.	Chapter 4

1.4 Computational Assumptions and Limitations

In the current study, various assumptions were made to simplify the financial risk calculation, while acknowledging the multiple sources of uncertainty in the input data and computational processes. This section describes six main assumptions and their associated limitations: (1) Spatial independence in facility-based modeling, (2) Mutual independence of property damage and business interruption loss, (3) Use of 10-year averaged corporate data, such as sales and PP&E, (4) No temporal change or capacity redundancy in the corporate global facility portfolio, (5) Application of grid scale of hydrological models (~1km) as a proxy for facility footprint, and (6) Use of Japanese public surveys on business interruption from floods for all facilities in all regions.

First, the current study assumes spatial independence for evaluating financial corporate flood risk at the facility-level. It is essential to recognize that this major assumption can significantly distort results, especially in the tail of the distribution where extreme events occur. Nguyen et al. (2020) emphasized the importance of including the spatial dependence of flood peaks and particularly of tail dependence in national and continental flood risk assessments. Duha et al. (2020) identified the role of spatial dependence for large-scale flood risk estimation by investigating how assumptions about the spatial dependence affect risk estimates, and demonstrates the importance of representing the spatial dependence of flood peaks and damage for risk assessments. Falter et al. (2015) demonstrated that in contrast to traditional flood risk assessments, where homogenous return periods are assumed for the entire catchment, their approach delivered spatially heterogeneous patterns of hydrological calculations which respect the spatial correlations of the different processes and their spatial interactions. Future work may

include the integration of spatial dependences of inundation depths for each grid cell impacting regional proximity of facilities, since spatial dependence of extreme hazards on different facilities was observed in flood risk analysis (Brunner et al., 2019; Quinn et al., 2019; Koh et al. 2025).

Second, the study assumes that the calculations of Property Damage and Business Interruption Loss (BIL) are mutually independent (Koks et al., 2015; Kabirzad et al., 2024). In other words, the results of Property Damage do not affect BIL, and vice versa, although in reality Property Damage can influence BIL. For example, if a facility suffers significant Property Damage, it may not be able to operate at full capacity even after restoration for extended time periods. The recovery process following a disaster has been studied using probabilistic approaches in various publications, such as Yang et al. (2015). Furthermore, BIL between facilities is not necessarily independent and can be mutually influential. For instance, in the manufacturing industry, if one facility is flooded and production halts, another facility that is not flooded may face a shortage of materials and also be unable to continue production; this is a typical example of supply chain risk. Countermeasures such as inventory buffers and mirror facilities have been discussed as possible responses to implement capacity/production redundancy (Umar and Wilson, 2024).

Third, in this study, each company's performance indicators (e.g., revenue, property, plant, and equipment) are fixed by using 10-year average values. In other words, in calculations that assume future scenarios, changes in company revenue growth or the value of property, plant, and equipment (PP&E) are disregarded. This assumption is applied to facilitate/isolate analysis of the direct impacts of climate change (Hsiang et al., 2017; Bressan et al., 2024; Orlov et al., 2024). This is similar to approaches where, when discount rates and other factors required to

calculate present value are incorporated, the elements that drive changes in value tend to be concealed. These constraints and assumptions are also used in Hirabayashi et al. (2013), where the population is fixed at 2005 levels to analyze the impacts of climate change. Likewise, Alfieri et al. (2015) assumes a constant estimated population in their analysis.

Fourth, it was assumed that the corporate global facility portfolio remains constant over time. In other words, the number and size of facilities, as well as their spatial distribution, are assumed not to change in the future. However, in reality, if a facility is affected by flooding, some companies may choose to depreciate the value, invest in hardening, or relocate it to an area with lower flood risk. In this study, changes in facility locations are not considered due to a lack of information and the difficulty of predicting future facility placements.

Fifth, in this study, flood depth from hydrological models is represented at a spatial resolution of 30 arc-seconds (~1 km) derived from Aqueduct Floods (Ward et al., 2020) in Chapters 2 and 3, and 1 arc-minute (~2 km) based on SiBUC (Tanaka, 2004; Kotsuki et al., 2013) and CaMa-Flood (Yamazaki et al., 2011) in Chapter 4. These grid-based values are used as a proxy to estimate flood impacts at the facility footprint level. The meteorological input data used in the hydrological models, Aqueduct Floods, SiBUC, and CaMa-Flood, are based on Global Climate Models (GCMs) derived from CMIP5 and linearly interpolated to a spatial resolution of 0.5 degree (~56km). In contrast, analyzing cyclones typically requires a spatial resolution of around 20 km (Hong et al., 2021; Murakami and Wang, 2022), and analyzing thunderstorms requires resolutions of a few kilometers. Therefore, it is important to recognize that the flood risk analysis in this study is based on assumptions of frontal rainfall events.

Sixth, the impact function for Business Interruption Loss (BIL) due to flooding is assumed to be applicable outside Japan, even though it is based on survey data from Japanese

companies (MLIT, 2023). The Japanese survey data were used to derive an average value of disruption days based on approximately 25 years of flood events in Japan. Additionally, it is assumed that during the period of disruption, operations are completely halted; a 100% cessation of activity is assumed.

Chapter 2 Assessment of Corporate Financial Flood Risks due to Property Damage and Business Interruption Loss

This section introduces the development and testing of a corporate financial loss model from flood risks at the facility level, by integrating financial disclosures and hydrological model outputs.

2.1 Introduction

Projections regarding the impact of global warming on society, the economy, and the worldwide financial system, are quite alarming. Numerical analysis across various climate change scenarios demonstrates that heavy precipitation will occur more frequently (Thackeray et al. 2022). The increase in potential flood risk on a global scale is primarily attributed to amplified vulnerability in regions, specifically Asia and Africa, where the frequency of floods is projected to rise (Hirabayashi et al. 2021). Without extensive structural adjustments, it is anticipated that global fluvial flood-related economic damages may surge by 17% in the next 20 years, despite partial compensation through market adjustments within the global trade network (Willner et al. 2018). The impacts of climate change on excessive riverine inundation are already causing negative effects on overall economic productivity at a global scale. The amplified global acknowledgment of climate risks has led business sectors to disclose their climate-related risks. However, Fiedler et al. (2021) stressed that the conceptual gap between the requirements of the business sector and the principles of and advances in climate science is notably extensive. For the financial sector and its regulators, it is essential that climate projections are formulated, implemented, and provided with the same level of expertise as that found in weather forecasting

services, to understand the impact of corporate risks on the financial system. To address this knowledge gap, the current research proposes an integrative model to link hydrological datasets, corporate financial information, and flood depth functions to quantify the financial impact of floods. Moreover, the regional disparity in climate regimes and flood risks necessitates that analyses are conducted at the facility, rather than the corporate scale.

2.2 Climate-Related Financial Legislation and Theoretical Approaches

The rising global understanding of climate risks has resulted in the implementation of financial legislation to force companies to disclose their climate-related risks. Organizations, especially public companies and their institutional investors, are increasingly required to be more transparent about their financial exposure to climate change, their climate-related strategies, and the risk management practices that mitigate such risks (Greenwood and Warren 2022; Ding et al. 2023). To address this significant challenge, the Financial Stability Board established the Task Force on Climate-related Financial Disclosures (TCFD) in response to a request from the Group of 20 Finance Ministers and Central Bank Governors. Since climate-related risks are a source of financial risk, impacting revenues and capital structuring of companies and instability in the capital markets, it is within the mandates of central banks and supervisors to ensure the financial system's resilience to such risks (Steuer and Tröger 2022; Bowman 2024).

While much progress has been made in geospatial hydrological modeling of flood risks, the extant literature on financial risk assessment in support of this regulation is sparse. Various numerical models have been developed and applied for calculating flood impacts based on hydrological processes (Yamazaki et al. 2011; Alfieri et al. 2013; Winsemius et al. 2013; Ward et al. 2020). The financial consequences of natural hazard-related disasters in the public or

private sphere have been studied in the extant literature, but are mainly focused on macroeconomics (Burke et al. 2015; Huang et al. 2018), with less attention to microeconomic impacts (Pan and Qiu 2022). Some cases demonstrate the application of input-output (I-O) analysis (Leontief 1936) to analyze the interconnectedness of economic activities and to measure the propagation effects of flood events (Van der Veen and Logtmeijer 2005; Hallegatte 2008; Jonkman et al. 2008). However, these frameworks reflect and are informed by a fragmented economic value system based on supply chain relationships established between producers and consumers, while lacking links between income and consumption (Gao et al. 2020).

Computable general equilibrium (CGE) modeling is an economic technique that employs a system of equations to illustrate consumer demand for goods and the supply generated by producers, and has been used to explore the impacts of flooding on economic activity. Equilibrium constraints are utilized to resolve the demand and supply requirements, after which the stability point is analyzed. For example, Carrera et al. (2015) focused on assessing direct and indirect economic impacts of flooding that occurred in the Po River region of Italy in 2000. Dormady et al. (2022) investigated production theory relationships, identifying the cost-effectiveness of a full range of explicit resilience tactics, particularly through the analysis of Hurricane Sandy in 2013 and Hurricane Harvey in 2017 in the United States. A significant limitation of CGE models lies in the assumption that entities make optimal decisions and that the economy is always in equilibrium. Hence, CGE models may be more appropriate for evaluating long-term (chronic) scenarios (Rose and Liao 2005) than for acute storm and flood events as envisioned under financial risk exposures.

The socioeconomic data approach connects flooded area information and socioeconomic data, such as gross domestic product (GDP), population density, and land use. Winsemius et al.

(2013) proposed a framework for global flood risk assessment for river floods, by estimating affected GDP based on population or land use. The costs and benefits associated with river flood defenses were estimated by utilizing the results from the outputs of hydrological models and relevant socioeconomic data (Ward et al. 2017). Further research has emphasized hydrological and financial risk impact analysis from floods on the spatial distribution of population (Hirabayashi et al. 2013; Arnell and Gosling 2016) and GDP (Ward et al. 2013; Ward et al. 2014; Jongman et al. 2015; Winsemius et al. 2016) exposed to riverine flooding, as well as the financial impacts caused by these events. Few studies have focused on the cost of direct flood losses at a global scale under varying scenarios of warming (Dottori et al. 2018).

The impact of floods on direct corporate property damage has generally been quantified using damage assessment of financial risk related to structural vulnerability (Pistrika and Jonkman 2010; Englhardt et al. 2019). Damage curves of a building, which relate the depth of flooding to the financial loss impact, are subject to the influence of structural attributes such as building material, archetype, and layout (Suppasri et al. 2013; Huizinga et al. 2017; Masoomi et al. 2019; Postacchini et al. 2019; Jansen et al. 2020). On a global scale, the Joint Research Centre in the European Commission created flood damage ratios from various types of information across continents (Huizinga et al. 2017). Pan and Qiu (2022), using panel regression analysis as a function of global corporate headquarter location, inferred that the impact is more pronounced for firms with, among others, more tangible asset investment (property, plant, and equipment, PP&E), tight financial constraints (for example, cash holdings), and low geographic diversification in their facilities.

It is essential for companies to identify flood risks on their business in terms of damage and business interruption by utilizing knowledge of climate science trends and causal

relationships, and translating this into leading financial indicators for reporting purposes. Business interruption from floods has been explored in a wide range of academic studies (Tanoue et al. 2020; Taguchi et al. 2022), using either survey data (Dormady et al. 2022) or resilience characteristics of each industry sector (Yang et al. 2016). Yang et al. (2015) proposed a methodology for estimating business interruption loss from floods in Japan based on economic census data and surveyed information. The estimation employed functional fragility curves and accelerated failure time models to quantify the extent of damage to production capacity and the time required for production recovery.

Alterations in socioeconomic consequences of floods due to climate change have been analyzed, employing hydrological models in conjunction with demographic data (Hirabayashi et al. 2021). For example, Tanoue et al. (2020) estimated business interruption loss (BIL) utilizing daily production value and number of days of flood inundation and recovery period under the assumption that the recovery phase on a global scale lasts twice as long as the inundation period based on information provided by the Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT 2005). Taguchi et al. (2022) assessed flood impacts based on a gridded GDP ratio with the assumption that building height within each grid was proportional to GDP per capita, and calculated BIL based on annual production of secondary and tertiary industries with the grid. Lastly, Koks et al. (2019) elaborated on business activity disruption and critical infrastructure asset failure by modeling a framework to value the economic losses due to floods and electricity failures. These approaches depend on aggregated data inputs and do not have the granularity to identify financial flood risks associated with corporate facilities, which may be geographically widely distributed, with differential exposure based on their climate regimes, and exhibit their own unique financial characteristics.

2.3 Data Sources and Analysis

2.3.1 Flood-Hazard Maps

Flood hazard maps have been developed to assess flood risks both at the local and global scales. Local scale flood hazard maps have been developed based on historical observed data and hydrological models. For example, Wing et al. (2022) calculated average annual losses and projected the possibility of flood risk increases resulting from population change in the United States. Bates et al. (2023) estimated expected annual damage (EAD) from fluvial and coastal flood risks at 1 arcsec spatial resolution (~ 30 m at the equator) over the whole United Kingdom. In terms of large-scale flood hazard analysis, flood maps have been created by Fathom (Sampson et al. 2015), Aqueduct Floods (Ward et al. 2020), and Kimura et al. (2023).

In the current study, hydrological data are based on the Aqueduct Floods database produced by the World Resources Institute, Washington, DC, with the assumptions and limitations implied therein. One of its modules, Aqueduct Floods, comprises simulated global flood depth data based on a range of global climate models and climate change scenarios from the Intergovernmental Panel on Climate Change (IPCC) (Ward et al. 2020). The Aqueduct Floods tool is based on the Global Flood Risk with IMAGE Scenarios (GLOFRIS) modeling to simulate flood depth for 30 arcsec spatial resolution (~ 1 km at the equator) globally, developed by Ward et al. (2013) and Winsemius et al. (2013). Outputs from hydrological modeling are then projected under two greenhouse gas concentration scenarios, Representative Concentration Pathway (RCP) 4.5 and RCP8.5, five types of global climate models (GCMs; NorESM1-M, GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC-ESM-CHEM), a mode of river floods, and three time horizons (2030, 2050, and 2080) (Ward et al. 2020). The spatial resolution

of these GCMs is not sufficient for the analysis of localized intense rainfall events caused by cyclones or thunderstorms; therefore, the current research should be interpreted as applicable to river flooding that occurs as a result of frontal rainfall. This data set has been used as the basis for extant academic research (Adshead et al. 2024; Assab 2024). Zhang et al. (2023) estimated flood damage by calculating average annual loss with Aqueduct Floods and their flood probabilities. Ye et al. (2024) evaluated EAD using Aqueduct Floods to assess risk from tropical cyclones and floods on power grids in Southeast Asia and East Asia.

Table 2.1 shows the summary statistics of the dataset extracted from Aqueduct Floods used in this study, using three time horizons for a 100-year storm under RCP8.5, which predicts a temperature increase of about 4˚C by 2100, relative to pre-industrial temperatures. It also predicts more rapid warming and more pronounced changes in indicators like river flow, water temperature, and precipitation. The areas and their proportions at various depth levels represent the calculated flooded areas to reach specific depths in the event of 100-year floods for each grid of Aqueduct Floods data. If a company's facility is located in these areas, it is expected that property damage or business interruption loss (BIL) could occur due to flooding.

Table 2.1 Summary statistics of Aqueduct Floods data for conditions used in this study (Scenario: RCP 8.5, 5 GCMs; Return Period: 100-year; Type: River Flood Region: Global)

Flood depth (m)	2030						2050						2080					
	Max		Min		Ave		Max		Min		Ave		Max		Min		Ave	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
0<d<1	8,073,998	6.20	7,885,339	6.05	7,976,705	6.12	8,020,646	6.16	7,802,288	5.99	7,899,718	6.06	7,886,688	6.05	7,625,703	5.85	7,739,258	5.94
1≤d<2	867,529	0.67	753,349	0.58	836,621	0.64	947,383	0.73	811,433	0.62	889,691	0.68	1,030,202	0.79	902,911	0.69	977,848	0.75
2≤d<3	351,246	0.27	278,905	0.21	320,310	0.25	376,558	0.29	303,800	0.23	353,096	0.27	437,476	0.34	350,393	0.27	405,812	0.31
3≤d<4	168,671	0.13	125,929	0.10	153,987	0.12	188,638	0.15	138,835	0.11	171,405	0.13	242,127	0.19	169,664	0.13	214,239	0.16
4≤d<5	101,415	0.08	70,215	0.05	86,164	0.07	119,846	0.09	81,548	0.06	97,717	0.08	151,066	0.12	102,700	0.08	132,306	0.10
5≤d<6	61,693	0.05	38,848	0.03	51,469	0.04	75,124	0.06	49,425	0.04	61,559	0.05	102,674	0.08	63,110	0.05	83,509	0.06
6≤d	126,581	0.10	66,800	0.05	97,182	0.07	166,055	0.13	92,717	0.07	123,832	0.09	258,049	0.20	128,779	0.10	184,466	0.14

2.3.2 Financial Database Information

For corporate financial information, such as investment in fixed assets (PP&E), sales, operating profits, location and number of employees for subsidiaries, the data are derived from Orbis, a database which was formerly a Bureau van Dijk solution and is currently provided by Moody's (Moody's 2025). This database has been used for studies focused on global supply-chain networks in relation to specific degrees of physical climate exposure (Pankratz and Schiller 2024). Bassetti et al. (2024) used Orbis to examine the relationship between physical climate risk exposure among Italian firms and the possibility of incurring additional borrowing costs due to spatial spillovers. In the current study, the average PP&E and sales from 2012 to 2021 were used, given the importance of fixed assets as a predictor (Pan and Qiu 2022) and the relationship between business interruption and sales (Dormady et al. 2022). Four Japan-headquartered companies—Asahi Group Holdings, Ltd., Japan Tobacco Inc., DENSO Corporation, and Kyocera Corporation—were selected to test the financial model proposed in this study, based on the following rationale.

1. Japanese government survey information focuses on business interruption from floods.
2. These companies disclose the financial impact of flood risks in their TCFD reports.
3. Representative companies of multiple industry sectors (food and beverage, tobacco, manufacturing) that have corporate financial flood risk identified by the proposed method are reflecting a wide range of fixed asset investments and revenues.
4. The inclusion of a range of global distribution of facilities and subsidiaries is compatible with the Aqueduct flood maps and geospatial flood damage curves (see Section 2.3.3). Information on facilities' size and geospatial distribution is shown in Table 2.2.

Table 2.2 Summary statistics on geospatial distribution for study corporate facilities

Region	Asahi Group Holdings, Ltd.			Japan Tobacco Inc.			DENSO Corporation			Kyocera Corporation		
	Facilities (%)	Weighted PP&E (Billion USD)	Weighted Sales (Billion USD)	Facilities (%)	Weighted PP&E (Billion USD)	Weighted Sales (Billion USD)	Facilities (%)	Weighted PP&E (Billion USD)	Weighted Sales (Billion USD)	Facilities (%)	Weighted PP&E (Billion USD)	Weighted Sales (Billion USD)
Europe	10.57	1.08	3.09	16.87	4.41	13.22	7.03	0.29	0.92	16.99	0.35	1.62
North America	2.44	0.002	0.005	8.43	0.03	0.08	11.72	0.02	0.05	48.37	0.77	3.61
Central and South America	0	0	0	7.23	0.06	0.19	7.03	0.03	0.10	3.27	0.01	0.05
Asia	43.90	3.88	11.09	56.63	1.86	5.57	73.44	12.78	41.02	30.07	1.83	8.57
Africa	0	0	0	10.84	0.50	1.51	0	0	0	0.65	0.003	0.01
Oceania	43.09	1.39	3.96	0	0	0	0.78	0.01	0.02	0.65	0.003	0.01
Total	100	6.35	18.16	100	6.86	20.57	100	13.12	42.11	100	2.96	13.87

Note: PP&E = Property, plant, and equipment.

The summary data on corporate facilities of the companies indicate significant differences in distribution between Asia, North America, and Europe, reflecting major variation in exposure to flood risk based on Aqueduct Floods data, and thus implied financial risk on assets and business interruption. The distribution of PP&E and sales weighted by the number of employees derived from Orbis across facilities and subsidiaries is shown in Table 2.2. The data show that Asahi Group Holdings, Ltd., DENSO Corporation, and Kyocera Corporation have weighted PP&E and sales concentrated in Asia, while Japan Tobacco Inc. has most of its production facilities situated in Asia, but its weighted PP&E and sales values are concentrated in Europe.

2.3.3 Flood Damage Curves

Estimates of flood risk to corporate fixed assets were based on the flood depth-damage ratio functions created by the Joint Research Centre of the European Commission (Huizinga et al. 2017). The flood damage functions are based on an extensive review of information from multilingual websites, and evaluated in light of land use, building structural characteristics, and

construction details. Since facilities of the selected global companies in this study span all six regions (Asia, Africa, North America, Central and South America, and Oceania), it is essential to use flood damage curves that are differentiated by region. The damage curves for industrial buildings were used in this research to estimate property damage from floods. Due to the absence of its damage curves specific to Oceania, I adopted the global damage curve for facilities in this region. While other flood damage functions exist for targeted regions such as the US, the Huizinga et al. (2017) dataset allowed me to quantify uncertainties in PD predictions when considering the impact of regional conversion assumptions.

To estimate BIL from floods, this research employed estimated business interruption data based on survey data (MLIT 2023). This updated dataset replaces a former version (MLIT 2005) and the former report has been widely applied in a range of academic studies (Tanoue et al. 2020; AL-Hussein et al. 2022; Nihei et al. 2023). The updated MLIT (Ministry of Land, Infrastructure, Transport and Tourism) dataset in 2023 was used for estimating BIL, and the former version was used to conduct a sensitivity analysis around the estimates. Alternatively, Taguchi et al. (2022) estimated BIL based on inundation periods calculated by hydrological models and the gridded GDP associated with building height in each grid. Yang et al. (2016) considered resilience characteristics of each industry sector, as well as probabilistic distribution of business interruption losses, for the case of urban flood disasters. In addition, Koks et al. (2019) elaborated on business activity disruption and critical infrastructure asset failure by modeling a framework for business interruption caused by both business operations disruption and critical infrastructure system disruption to value the economic losses due to floods and electricity failures. Due to the lack of various regional datasets for BIL functions, I used the 2023 MLIT dataset as a proxy for disruption in other flood exposed regions, assuming that facilities

and subsidiaries confront similar challenges as a function of flood depth.

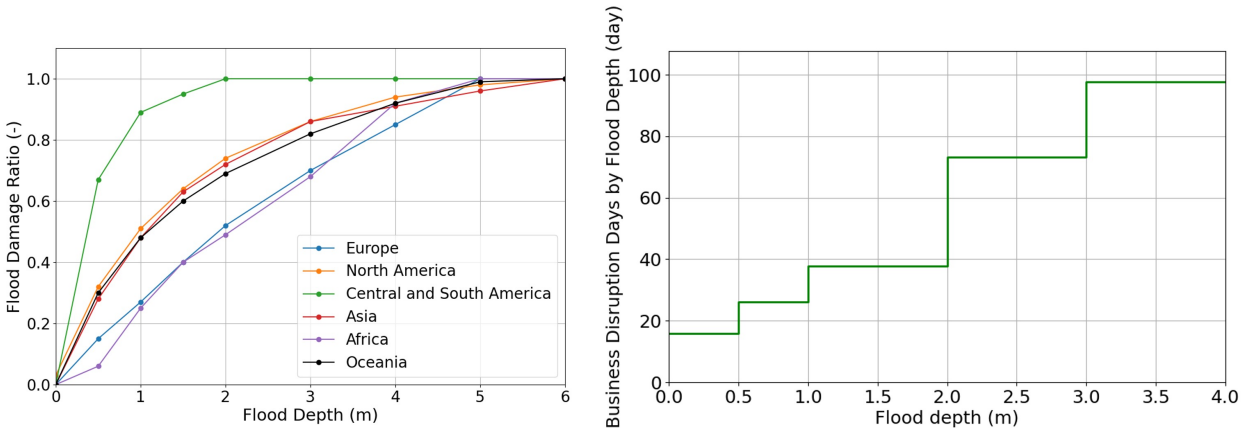


Figure 2.1: Relationship between flood depth and impacts on property and business (Left: Flood depth damage curves (Huizinga et al., 2017); Right: surveyed business disruption (MLIT, 2023))

2.4 Methodological and Algorithmic Approach

2.4.1 Facility-Level Flood Risk Analysis

To assess facility-specific financial impacts from flood risks, previously published approaches are insufficient. Hence, I propose to integrate the results from previous studies into a geospatial flood-informed model that employs facility-specific financial input data. Existing models include the HAZUS model, developed by the U.S. Federal Emergency Management Agency, to evaluate flood hazards at the level of individual facilities and to represent these risks using geographical information system (Cochrane 2004; Scawthorn et al. 2006). HAZUS also conducts a quantitative analysis of the reduction of future flood losses and damages (Haque et al. 2022). However, the model has not been applied to estimate corporate financial flood risks for public companies with facilities located across the globe. The current study combines

hydrological and financial datasets with flood damage conversion functions to estimate corporate financial flood risks globally.

Due to difficulties of the HAZUS model in quantifying and integrating flood risks at individual sites across corporate facilities in different climate regimes, I aimed to design and test an analytical approach that captures both aggregated corporate financial risk metrics resulting from public disclosures and climate data, and facility-level risk based on geographical distribution of facilities across different climate regimes. Hence, this research linked corporate financial information at a facility level and geospatial facility locations through the utilization of hydrological models with corporate exposure across its facility portfolio.

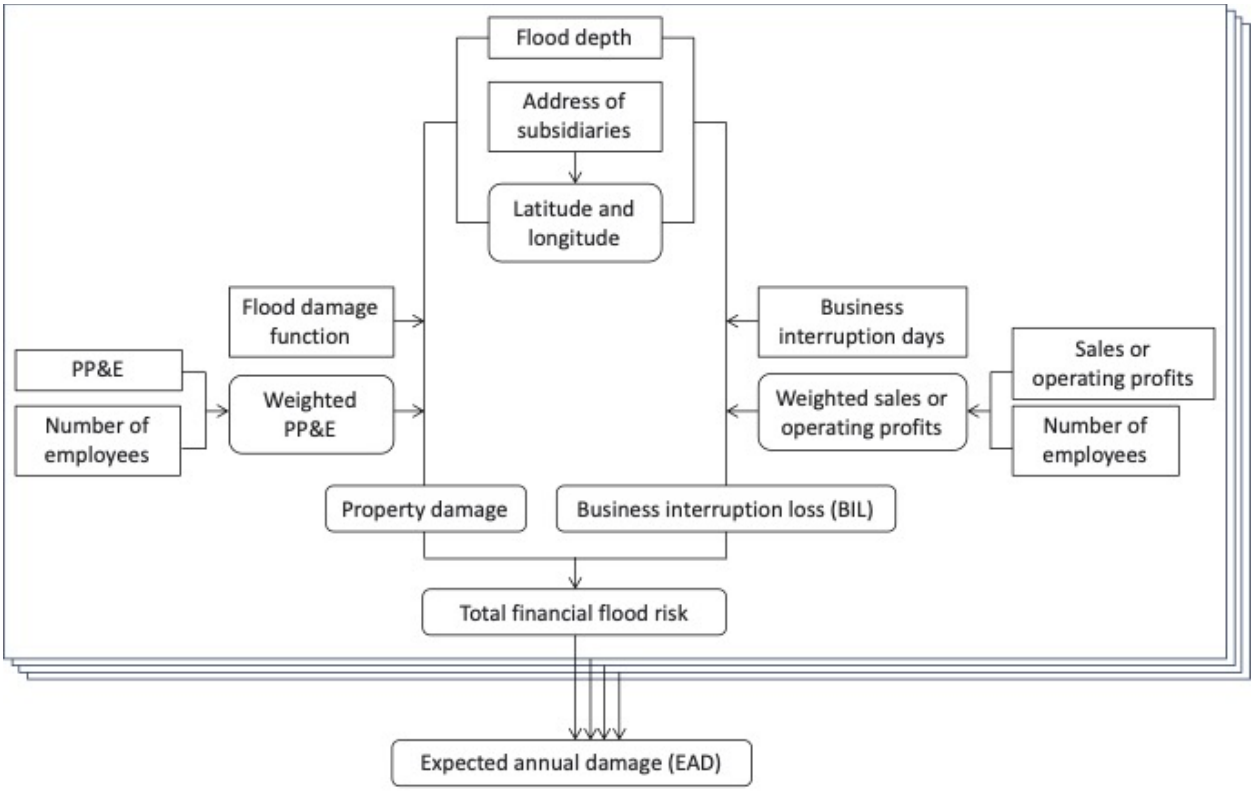


Figure 2.2: Information flow for the assessment of corporate financial flood impacts. PP&E = Property, plant, and equipment. No propagation of uncertainty is implied. All input data are assumed independent.

As shown in Figure 2.2, the methodology employs multiple data imputation, aggregation and fusion techniques. This data fusion approach is based on the integration of individual datasets to compute flood impacts on physical damage to property and business interruption at the facility level and consolidation at corporate level. This is similar to the approach taken by Koks et al. (2015) and Dormady et al. (2022) who categorized risks into both direct impacts and indirect critical infrastructure components. The rationale for utilizing PP&E is based on findings by Pan and Qiu (2022) that fixed assets are a significant driver for corporate financial flood risk given business investments for acquisition of new equipment, land, and assets and the construction/upgrades of properties. Operational risks from flooding resulting from business interruption are accounted for by incorporating reduced net sales as an opportunity cost, as inferred by Taguchi et al. (2022) in their model linking flood risk and operational efficiency.

$$R = \sum_i d_i S_i + \sum_i r_i P_i \tag{2.1}$$

where R is total risks from floods for a company, d_i is business disruption for facility i, S_i is daily sales for facility i, r_i is flood damage ratio on fixed asset for facility i, P_i is PP&E for facility i.

2.4.2 Quantification of Expected Annual Damage (EAD)

Rather than losses per event with return-period, EAD is a metric required for corporations to consider their investment in flood mitigation across their facility portfolios. Risk curves are commonly used for estimating EAD from floods. The relationship between EAD and exceedance

probability from floods is shown by the integral under the curve (National Research Council 2000). An approximation of the area can be expressed as follows and applied to flood risk assessment (Meyer et al. 2009).

$$EAD = \sum_{i} D[i] \times \Delta P_i \tag{2.2}$$

$$D[i] = \frac{D(P_{i-1}) + D(P_i)}{2} \tag{2.3}$$

$$\Delta P_i = |P_i - P_{i-1}| \tag{2.4}$$

where $D[i]$ is the mean damage of two known points of the curve, and ΔP_i is the probability of the interval between those points. In this study, various return periods were used (2, 5, 10, 25, 50, 100, 250, 500, and 1,000-year floods) for projected timepoints 2030, 2050, and 2080. Also, the outputs based on five different types of GCMs for the RCP8.5 scenario were used to mitigate uncertainties associated with climate model inputs. The EAD estimates the total damages in the future with predicted financial risks in each year. Velasco et al. (2018) analyzed direct tangible damages using depth-damage curves and calculated the EAD by weighting the damages of each event with its probability. Zeng et al. (2023) conducted a cost-benefit analysis with EAD, considering the effects of flood risk reduction. Ye et al. (2024) studied risk estimation of tropical cyclone induced winds and coastal floods by using EAD. Outcomes resulting from the analysis with EAD have the potential to inform corporations to make informed decisions regarding their investments on flood risk mitigation measures for their facility portfolio.

2.4.3 Uncertainty Propagation

It is important to recognize that various forms of uncertainty propagation may occur, and understanding these uncertainties is crucial for interpreting the results (Figure 2.2). While uncertainty propagation of model inputs was not explicitly considered, the results were interpreted in a limited uncertainty context, acknowledged here. First, there is inherent uncertainty in the input data from Aqueduct Floods (Ward et al., 2020). The current study uses the results from five different GCMs as inputs derived from the Aqueduct Floods, and quantifies the variability in results due to differences among GCMs and the uncertainties stemming from the hydrological models' uncertainty. The spatial modeling of extreme events has obvious applications for evaluating the impacts of catastrophic events (Davison et al., 2013). Indeed, spatial dependence of extreme hazards on different facilities, auto-correlation, was observed from not only flood risk analysis (Brunner et al., 2019; Quinn et al., 2019; Koh et al. 2025) but also seismic risk analysis (Davison and Gholamrezaee, 2012). Although spatial autocorrelation was not addressed in the present study, it may influence the results particularly in the distribution's tail (Nguyen et al., 2020). While I implemented sensitivity analysis on the input parameters of my model, I did not conduct any uncertainty analysis regarding autocorrelation on extreme climate events. This limitation is acknowledged, and addressing it is recommended as a direction for future research.

Additionally, business databases such as Orbis datasets can contain mixed levels of uncertainty across financial and ancillary datasets. While values like sales and PP&E are based on annual report data and are considered relatively reliable, information such as facility locations and employee counts involve higher uncertainty and should be interpreted with caution. Since

PP&E and sales data were interpolated from corporate disclosures and informed by more sparsely available facility-level data, uncertainty is associated with facility-level financials.

Furthermore, there is significant uncertainty in the use of flood damage ratios (Huizinga et al., 2017) and business interruption days (MLIT, 2023). These are based on average values derived and aggregated from various sources, and it is important to understand that they represent general relationships rather than precise estimates. To reduce uncertainty, one possible approach is to integrate place and regionally-specific literature and consider the variability across studies (Xu et al., 2023), but the range of damage curve data in the Huizinga et al. (2017) was considered sufficient to capture uncertainty in prediction in the current study. Finally, the definition of total financial flood risk as the sum of Property Damage and Business Interruption Loss also involves uncertainty (Koks et al., 2015; Dormady et al., 2022). While this is a simplified framework to analyze the financial impacts of flooding on companies, in reality, other types of risks—such as supply chain disruptions—may also arise. Thus, it is essential to recognize that this definition itself carries inherent limitations and uncertainties.

2.4.4 Model Verification

2.4.4.1 Corporations and Facilities

I selected four corporations (Table 2.2) to test and verify the methodology as application cases, based on the criteria described earlier. They were selected also because their corporate financial flood risk estimates are based on principles and accounting metrics embedded in the proposed method and their corporate reports or websites disclose quantitative results for their financial flood risks. The disclosed information is shown in Table 2.3. Asahi Group Holdings, Ltd. and DENSO Corporation estimated their financial flood risks based on sales data, which are

nominal aggregated values of production prices. Instead, Japan Tobacco Inc. and Kyocera Corporation calculated their financial flood risks based on operating profits, which are values obtained by subtracting expenses such as the cost of goods sold (COGS) and general administrative expenses (SG&A) from revenue, such as salaries, rent, and utilities. In this study, I estimated financial flood risks based on sales for Asahi Group Holdings and DENSO Corporation and on operating profits for Japan Tobacco Inc. and Kyocera Corporation by using the ratio between sales and operating profits obtained from Orbis.

Table 2.3 Reported Financial Flood Risk for Corporations Used in this Study

Company	Expected year	Scenario	Flood year	Assessed risk	Financial flood risk	Data source	Reference
Asahi Group Holdings, Ltd.	2050	RCP8.5	100-year	BIL on sales	6.6-6.72 billions of JPY	[1] ASAHI GROUP Sustainability Data Book (2022), [2] ASAHI GROUP Sustainability Report (2023)	[1] Available online: https://s3-ap-northeast-1.amazonaws.com/asahigroup-doc/company/policies-and-report/pdf/en/databook_en.pdf. Accessed 16 December, 2024. [2] Available online: https://s3-ap-northeast-1.amazonaws.com/asahigroup-doc/company/policies-and-report/pdf/en/sustainabilityreport_en.pdf. Accessed 16 December, 2024.
Japan Tobacco Inc.	-	RCP2.6, RCP8.5	-	BIL on operational profits	RCP2.6: 7.1 billions of JPY, RCP8.5: 18.8 billions of JPY	Integrated Report 2023	Available online: https://www.jt.com/investors/results/integrated_report/pdf/2023/integrated2023_E_all.pdf. Accessed 16 December, 2024.
DENSO Corporation	2035	-	-	BIL on sales	100 billions of JPY	Integrated Report 2022	Available online: https://www.denso.com/global/en/-/media/global/about-us/investors/annual-report/2022/annual-report-doc-2022-viewing-en.pdf. Accessed 16 December, 2024.
Kyocera Corporation	2030	SSP1, SSP2	-	BIL on operational profits	SSP1: 2-3 billions of JPY, SSP2: 3-7 billions of JPY	[1] Integrated Report 2023, [2] Official website	[1] Available online: https://global.kyocera.com/sustainability/catalog/pdf/2023/all_light.pdf. Accessed 16 December, 2024. [2] Available online: https://global.kyocera.com/sustainability/eco/tcfd.html. Accessed 16 December, 2024.

Note: RCP = Representative concentration pathway, SSP = Shared socio-economic pathway, BIL = Business interruption loss.

2.4.4.2 Process Application

I used 10-year averaged PP&E and sales from 2012 to 2021 derived from Orbis to normalize the dataset for particularly extreme effects, such as COVID-19 and I rescaled annual values to the average daily values. Facility-level locations were collected from Orbis by using information on global ultimate owner (GUO) 50, ultimate owner (C1), direct owner (C2), and legal form (LF) categories (Moody's 2025), and I geocoded city, street names using the Google Map Application Process Interface (API). Pankratz and Schiller (2024) geocoded facility-level locations using Bing Maps, hence, alternative but similar methods for geocoding are appropriate. Weighted values for PP&E and sales for each facility were based on their number of employees derived from Orbis (Table 2.2). Due to the database being incomplete, I used the difference between available facility-level aggregates and corporate total divided by the remaining number of facilities to estimate the number of employees for the other facilities, if the total number of facilities' employees is less than the total number of employees of the corporation. Flood depth values were analyzed over nine return periods for 5 GCMs based on facility location and were used to calculate financial impacts from flood risks on property damage and BIL by using the weighted PP&E and sales with flood damage curves and the MLIT survey on business disruption. Finally, results from this method and corporate reported values were quantitatively compared to justify this method.

2.4.4.3 Justification for the Financial Loss Estimation Model of Corporate Flood Risks

Comparisons between outputs from the proposed methodology and reported corporate values were conducted to provide justification for the method introduced in this study. It should be noted that two different datasets were employed to compare my calculated losses: Publicly

disclosed information from corporate reports such as TCFD/sustainability reports, and private information provided under non-disclosure protection (Figure 2.3). In my calculations, five correction steps were taken. First, if the conditions of the reported value, such as the return period or the GCM used, are unknown, the financial flood risk was estimated using the flooded depth values for 100-year to 1,000-year floods across 5 GCMs provided by Aqueduct Floods, and the maximum and minimum values are shown as error bars. Second, I collected corporate reported values in multiple years and the maximum and minimum values are shown as error bars. Third, I calculated the unit of simulated values using 10-year averaged PP&E and sales data from 2012 to 2021, converted into million USD by using the currency exchange rate between U.S. dollar (USD) and Japanese yen (JPY) of each respective year. Finally, a 45-degree line is added to compare the calculated values with the reported values (Figure 2.3).

Regarding Asahi Group Holdings, the reported BIL value is USD 49.7 million, while the average calculated BIL result is USD 166.8 million, indicating that the calculated value is higher. For DENSO Corporation, the reported BIL value is USD 760.5 million, compared to an average calculated value of USD 114.6 million, showing a lower calculated result. In the case of Japan Tobacco, the reported BIL value is USD 137.5 million, while the average calculated value is USD 120.2 million. Although the calculated value is slightly lower, it remains within 13% of the reported value. For Kyocera Corporation, the reported BIL value stands at USD 37.3 million, whereas the average calculated value is underestimated at USD 2.8 million.

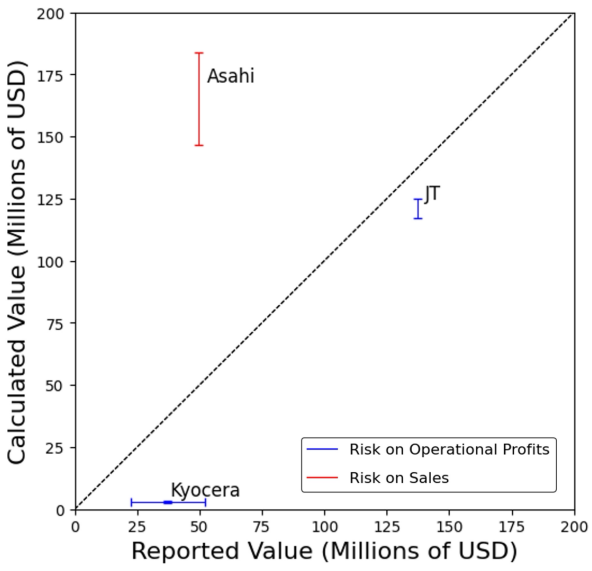
A potential explanation for overestimation as compared to the reported values, such as for Asahi Group Holdings, is that the current method does not explicitly account for corporate capacity redundancy against flood events. Companies with advanced supply chain risk management may mitigate the adverse effects by sourcing inventory from different sites,

effectively reducing the cumulative damage sustained (Umar and Wilson 2024). Similarly, subsidiaries or facilities often plan to build up inventory or take on business interruption insurance, resulting in lower realized losses than may otherwise be predicted (Altay and Ramirez 2010; Dong et al., 2018). Hence, the estimate from the model should be interpreted as a worst-case scenario for opportunity cost resulting from floods.

Additional potential reasons for underestimation may result from the choice of damage function, which may not be suitable to the particular asset being analyzed, as seen for assets of Japan Tobacco, DENSO Corporation, and Kyocera Corporation. Inaccurate assumptions regarding application of the MLIT information on business interruption globally may affect the results as well. For example, Sultana et al. (2018) investigated the relationships between flood depth, the duration of business interruptions, and the incurred costs, using data gathered from their survey responses in Germany. They noted that, even under equivalent flood depth, the duration of business interruption ranged from single digit to as long as about 400 days. In other words, the parameters governing the BIL could result in a lower assessment than the risk metrics determined by the organization. If a corporation (or facility) has a history of long-term business suspensions due to flooding, it can refine the accuracy of its risk analysis by leveraging insights from its past experiences. Relying on specific corporate experiences to evaluate BIL likely results in a substantial underestimation in this analysis, which is based on the surveyed average number of interruption days in Japan.

Regarding property damage, the companies considered here do not explicitly disclose quantitative metrics as “property damage” for comparison purposes. Figure 2.4 illustrates the regional calculation results of property damage for each corporation. It should be noted that these results illustrate the total property damage if a 100-year flood were to occur in each grid of

Aqueduct Floods, and they do not represent the property damage expected to occur once every 100 years. A review produced by a Japanese insurance agency based on press releases from various companies provides some indicators of actual losses sustained (Sompo Risk Management Inc. 2022). For example, during the heavy rains of 2018, a general food wholesale company reported property damage totaling approximately USD 5 million, primarily due to flooding of stores and production centers across multiple prefectures. In the manufacturing industry, one firm reported approximately USD 76 million in damages, mainly caused by factory and logistics hub closures, as well as costs related to relocating and recovering operations at its affected sites. During the typhoon of 2019, a transportation company disclosed losses of nearly USD 261 million, primarily due to the retirement of railway vehicles and the detrimental impact of water damage or contamination of tracks and stations caused by breaches in river embankments. The damage estimates may take into account variables that are not limited to direct facility damage, rendering direct comparison challenging beyond order of magnitude assessments that are in the range of the estimates.



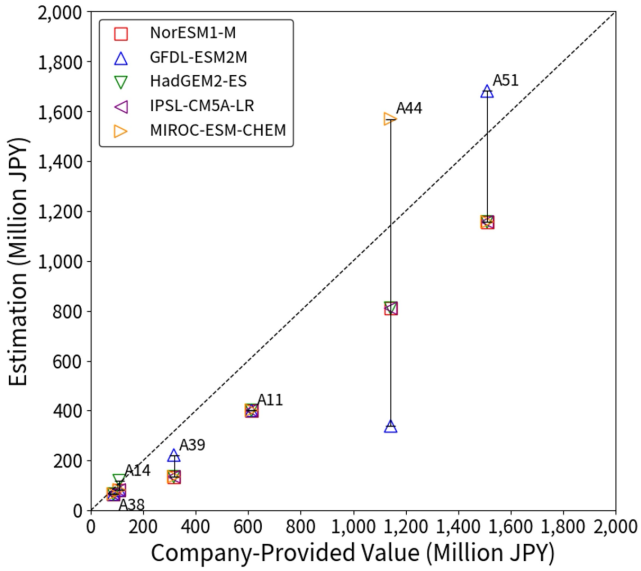


Figure 2.3: Comparison of reported and calculated business interruption loss (BIL). Left: The used data is based on publicly available data; Asashi: Asahi Group Holdings, Ltd.; JT: Japan Tobacco Inc.; Kyocera: Kyocera Corporation. Right: The used data is based on proprietary datasets. Flood scale is 1,000-year flood for each grid; under RCP8.5, using 5 GCMs, and estimated year is 2030. This comparison was conducted for the facilities at risk in both cases.

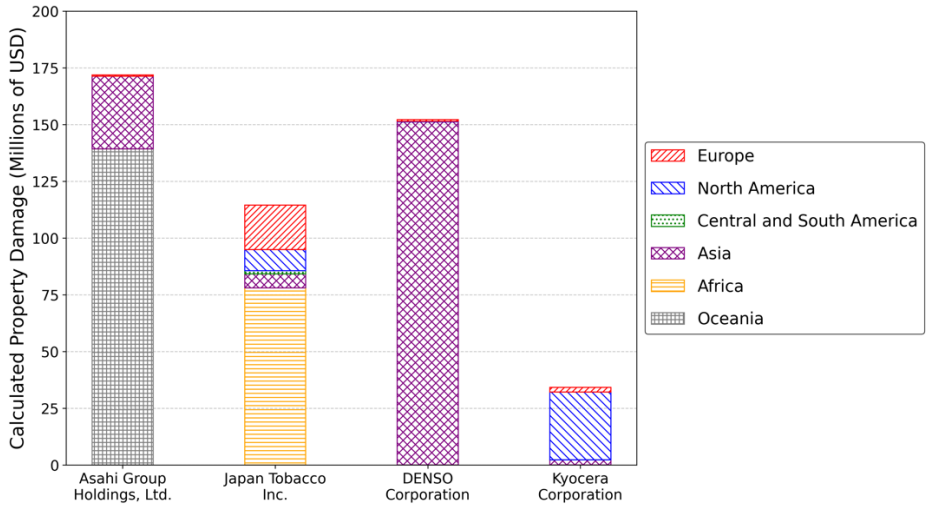


Figure 2.4: Calculated property damage at the corporate level. Flood scale is 100-year flood for each grid; under RCP8.5, using 5 GCMs, and estimated year is 2030.

2.5 Results

2.5.1 Property Damage and BIL Risk at Facility-level

The financial risk trends associated with flooding for each facility under 100-year probability scales of flooding are shown in Figure 2.5. These values correspond to "Property damage" and "Business interruption loss (BIL)" as illustrated in the flowchart presented in Fig. 1. It is important to highlight that these graphs indicate the financial risks to each facility under different probabilities of flooding. Nevertheless, these statistics do not imply that the same scale of flooding occurs simultaneously across all facilities. The calculations used the inundation depth data from Aqueduct Floods for river flooding in 2030, based on the RCP8.5 scenario of five GCMs. The error bars show maximum and minimum values among the outputs using different

GCMs, which indicate the uncertainty associated with the financial risk values due to the differences in GCMs for each company. Although this ratio is subject to the binning method of the histogram, it remains within a range of ±11.43% in this case. Moreover, manufacturing companies such as DENSO Corporation and Kyocera Corporation demonstrate a more pronounced decline in the histogram in comparison to consumer goods firms such as Asahi Group Holdings and Japan Tobacco Inc. This suggests that the variation of flood risk levels among facilities is more significant for manufacturing companies.

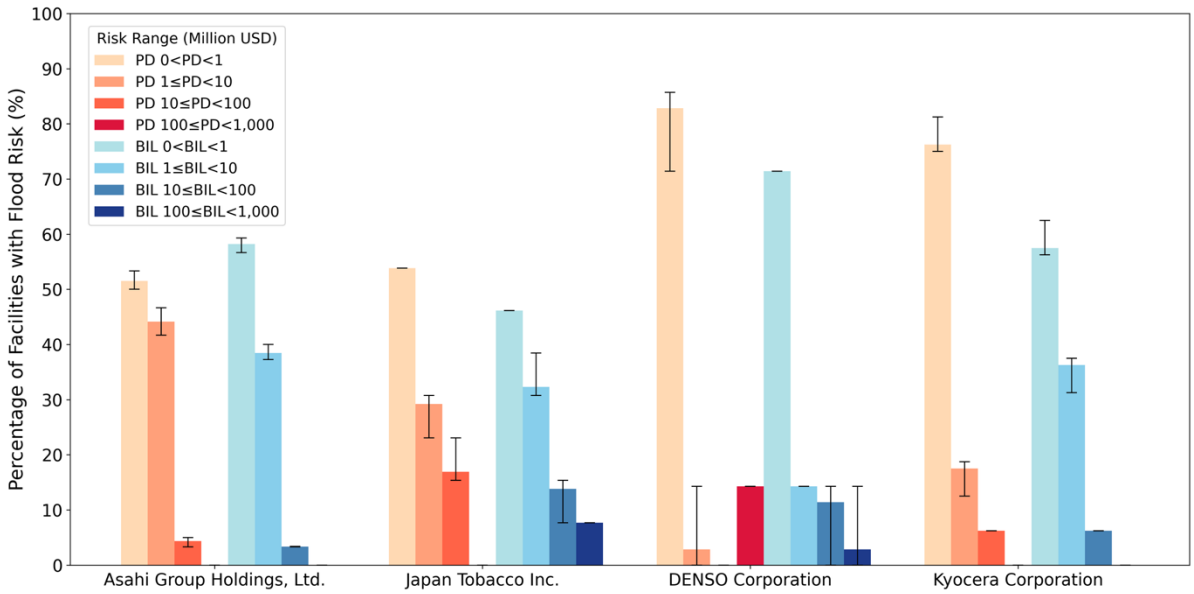


Figure 2.5 Histograms for property damage (PD) and business interruption loss (BIL) at the facility level from 100-year flood, under RCP8.5, estimated year is 2030, and using 5GCMs

2.5.2 Implied Expected Annual Damages

Expected annual damages at the facility level helps decision makers to understand appropriate degrees of investment in flood risk reduction for facilities. The averaged values across five EAD estimates from five GCMs in 2030, 2050, and 2080 are plotted in Figure 2.6.

The PP&E and sales of each company are based on the 10-year average from 2012 to 2021, with no additional adjustments made for projected growth for forthcoming years. This is because the inclusion of corporate growth rates and discount rates introduces more uncertainties in the assessment of the impacts of future fluctuations in flood risk. Based on this rationale, the number of facilities affiliated with Asahi Group Holdings, Ltd. that carry financial flood risk is 60. The facility with the highest risk value located in Australia shows a decline in EAD from 2050 to 2080 due to the reduction in projected flood depths from 2050 to 2080. The Kyocera Corporation's facility in Mexico, estimated as having the highest risk value, shows a slight reduction in EAD from 2050 to 2080. It is plausible that the fluctuations in risk values are driven by the effects of climate change as indicated by the GCMs. The density of values is visualized using kernel density estimation (KDE). Figure 2.6 shows that most facilities fall within the financial flood risk range of USD 0 to 1 million, followed by a considerable number of facilities with approximately USD 4 million in financial flood risk. Among the other three companies, there is one facility with a significantly high flood risk, but the others have relatively small values. Table 2.4 illustrates the regional distribution of facility-level analysis results for each company. These specified regions align with the regional classification used in the function for calculating property damage (Huizinga et al., 2017). Asahi Group Holdings, Ltd. facility risk profile shows that approximately 83.33% of its facilities exposed to risk are in the Oceania region, with Asia representing 11.67%. A similar trend can be identified in relation to EAD. However, in the analysis of the values projected between 2030 and 2080, the risk share in the Asia region increases, while the Oceania regional share decreases, and the risk share in Europe remains stable.

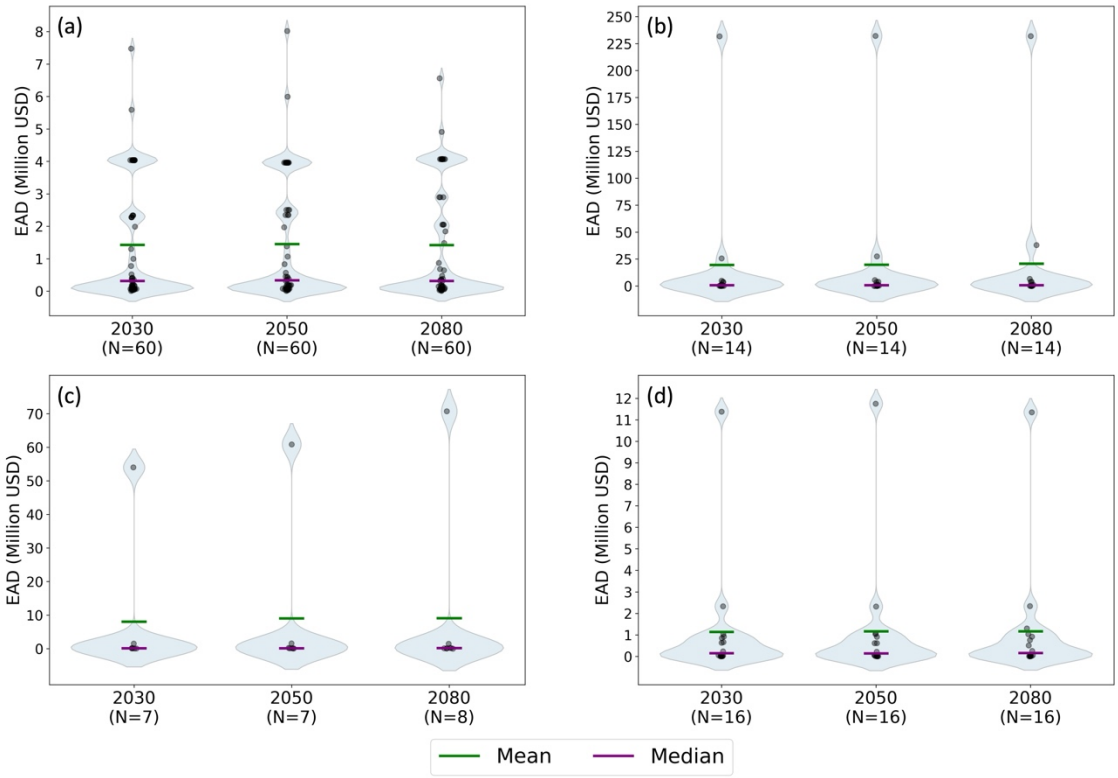


Figure 2.6 Implied expected annual damages (EAD) at the facility level. (a) Asahi Group Holdings, Ltd.; (b) Japan Tobacco Inc.; (c) DENSO Corporation; (d) Kyocera Corporation, under RCP8.5 and using 5 GCMs.

For Japan Tobacco Inc., 35.71% of its facilities at risk are located in the Asia region, followed by Europe at 28.57%. Nevertheless, in terms of EAD related to property damage, Africa accounts for the majority, with 69.57% in 2030 and 73.01% in 2080. With respect to EAD for business interruption losses, facilities in Europe dominate with 91.37% in 2030 and 89.72% in 2080. For DENSO Corporation, 50.00% of its facilities with flood risk are based in the Asia region. Regarding the EAD values for property damage, Asia has an overwhelmingly high share of 99.37% in 2030 and 99.52% in 2080. Similarly, the EAD for BIL indicates high percentages with 94.40% in 2030 and 95.45% in 2080. Finally, for Kyocera Corporation, 75.00% of its facilities with flood risk are positioned in North America. The EAD for property damage also

presents North America as the dominant region, with 87.25% in 2030 and 81.08% in 2080. Correspondingly, for EAD for BIL, North America accounts for the majority with 65.19% in 2030 and 65.46% in 2080.

Table 2.4 Regional distribution of expected annual damages (EAD) for property damage (PD) and business interruption loss (BIL) between 2030 and 2080, under RCP8.5 and using 5 GCMs

Region	Asahi Group Holdings, Ltd.									
	Number of Facilities with Risk	%	EAD (PD), 2030, RCP8.5	%	EAD (PD), 2080, RCP8.5	%	EAD (BIL), 2030, RCP8.5	%	EAD (BIL), 2080, RCP8.5	%
Europe	3	5.00	0.09	0.37	0.10	0.36	0.43	0.72	0.43	0.75
North America	0	0	0	0	0	0	0	0	0	0
Central and South America	0	0	0	0	0	0	0	0	0	0
Asia	7	11.67	3.42	13.27	5.40	19.67	5.95	9.90	6.28	10.86
Africa	0	0	0	0	0	0	0	0	0	0
Oceania	50	83.33	22.22	86.36	21.95	79.97	53.66	89.38	51.09	88.40
Region	Japan Tobacco Inc.									
	Number of Facilities with Risk	%	EAD (PD), 2030, RCP8.5	%	EAD (PD), 2080, RCP8.5	%	EAD (BIL), 2030, RCP8.5	%	EAD (BIL), 2080, RCP8.5	%
Europe	4	28.57	3.22	17.89	3.55	12.55	233.54	91.37	233.54	89.72
North America	2	14.29	0.91	5.05	1.01	3.56	0.77	0.30	0.78	0.30
Central and South America	1	7.14	0.28	1.57	0.31	1.10	0.18	0.07	0.18	0.07
Asia	5	35.71	1.07	5.93	2.76	9.78	4.37	1.71	4.42	1.70
Africa	2	14.29	12.54	69.57	20.64	73.01	16.76	6.56	21.38	8.21
Oceania	0	0	0	0	0	0	0	0	0	0
Region	DENSO Corporation									
	Number of Facilities with Risk	%	EAD (PD), 2030, RCP8.5	%	EAD (PD), 2080, RCP8.5	%	EAD (BIL), 2030, RCP8.5	%	EAD (BIL), 2080, RCP8.5	%
Europe	1	12.50	0.13	0.46	0.15	0.36	1.39	5.13	1.31	4.17
North America	3	37.50	0.05	0.17	0.05	0.13	0.13	0.48	0.12	0.39
Central and South America	0	0	0	0	0	0	0	0	0	0
Asia	4	50.00	28.66	99.37	41.07	99.52	25.65	94.40	30.00	95.45
Africa	0	0	0	0	0	0	0	0	0	0
Oceania	0	0	0	0	0	0	0	0	0	0
Region	Kyocera Corporation									
	Number of Facilities with Risk	%	EAD (PD), 2030, RCP8.5	%	EAD (PD), 2080, RCP8.5	%	EAD (BIL), 2030, RCP8.5	%	EAD (BIL), 2080, RCP8.5	%
Europe	3	18.75	0.40	7.21	0.42	7.72	3.89	30.53	3.89	29.31
North America	12	75.00	4.84	87.25	4.41	81.08	8.30	65.19	8.68	65.46
Central and South America	0	0	0	0	0	0	0	0	0	0
Asia	1	6.25	0.31	5.54	0.61	11.19	0.54	4.28	0.69	5.23
Africa	0	0	0	0	0	0	0	0	0	0
Oceania	0	0	0	0	0	0	0	0	0	0

2.5.3 Model Robustness and Sensitivity to Input Parameters

The purpose of sensitivity analysis is to quantitatively evaluate the relative importance of the model's parameters by analyzing the degree of change in results that occurs when these

parameters are altered. To determine the level of confidence in the risk assessment results, the extent of variability in the results due to changes in the parameters was calculated.

A sensitivity analysis on the rate of change in total corporate financial flood risk was conducted using fixed flood damage functions, comparing results across regions to those specifically adapted for each region (Figure 2.7). The averaged values across five EAD estimates from five GCMs are used in a manner consistent with that depicted in Figure 2.6. For each company, a total of 12 analytical plots were generated, combining six types of flood damage functions for facilities (Europe, North America, Central and South America, Asia, Africa, and Oceania) and two types of damage relationship values for BIL (MLIT 2005 and MLIT 2023). Although the boundary between sub-floor flooding and above-floor flooding is not explicitly stated in the flood damage relationship values provided by Japanese MLIT for 2005, I applied the value for sub-floor flooding for depths less than 0.35 m based on Japanese architectural standards. The statistical results of this analysis are shown in Table 2.5. Across all companies analyzed, the maximum variation was 66.82% (DENSO Corporation), while the minimum change was -65.89% (Asahi Group Holdings, Ltd). Hence, changes in parametric criteria for property damage and BIL will affect financial impact within this range.

By comparing the difference in flood damage parameters for the mean change between the MLIT survey results in 2005 and 2023, the principal EAD risk factors can be determined. For Asahi Group Holdings, Ltd. and DENSO Corporation, the variations in property damage criteria demonstrate greater values, implying that these criteria are more important in determining the financial flood risks. On the other hand, for Japan Tobacco Inc., the mean changes in BIL parameters show greater values, indicating that BIL parameters play a more critical role in determining its financial flood risk. As for Kyocera Corporation, the similarity in the values

between both parameters leaves the interpretation of business interruption versus capital stock losses from floods more difficult to make.

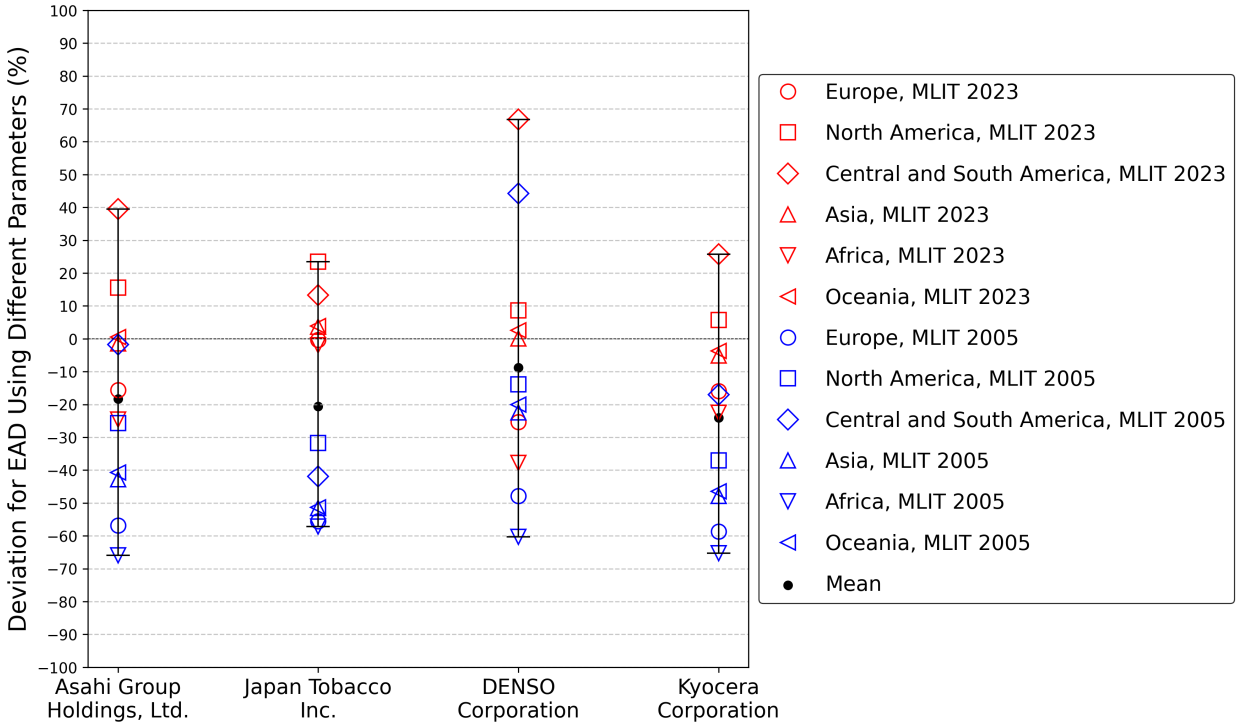


Figure 2.7: Sensitivity analysis for expected annual damages (EAD) using survey and fixed asset parameters, under RCP8.5, using 5 GCMs, and the estimated year is 2080. The zero mark in the y axis indicates EAD losses based using facility property damage based on the flood damage curve from the actual region where they are located and BIL based on the MLIT 2023 data. Any deviation is based on different assumptions of damage curve use and comparison with the MLIT 2005 BIL data.

Table 2.5 Descriptive statistics for overall expected annual damage (EAD) impacts on business interruption loss (BIL) and property damage (PD) using different parameters, under RCP8.5, using 5 GCMs, and the estimated year is 2080

	Asahi Group Holdings, Ltd.	Japan Tobacco Inc.	DENSO Corporation	Kyocera Corporation	Total
Maximum	39.55	23.66	66.82	25.63	66.82
Mean	-18.31	-20.58	-8.74	-24.09	-17.93
Minimum	-65.89	-57.03	-60.26	-65.36	-65.89
% Difference in PD Parameters for MLIT 2023	64.18	25.26	104.59	48.20	60.56
% Difference in PD Parameters for MLIT 2005	64.18	25.26	104.57	48.20	60.55
% Mean Change between MLIT 2023 and MLIT 2005	41.26	55.43	22.50	42.78	40.49

2.6 Discussion

I demonstrated the results of flood depth projections on property damage and BIL at the facility level, calculated the implied EAD, and tested variability using sensitivity analysis (see Sect 5). Integrating datasets derived from hydrological models and corporate financial records allowed us to estimate property damage and BIL at the facility level. However, the estimation of weighted investment in fixed assets and sales data for individual facilities relies on proxy assumptions such as number of employees at each facility, indicating that facility-level financial data need to be verified based on private disclosures not available to the authors. Additionally, this study did not account for monthly variations in sales used for BIL, highlighting a limitation in the temporal granularity of the estimates.

The comparison between the reported values and the estimated values illustrated support for this approach, while also emphasizing the importance of thoroughly addressing the uncertainties associated with flood damage functions (Figure 2.3). This comparative analysis focused mainly on BIL, since the lack of information regarding the precision of financial flood risk assessment for property damage does not allow for a robust quantifiable verification. Furthermore, it should be assumed that this approach reflects a worst-case scenario where corporations have not implemented any supply chain or inventory risk mitigation measures against flood risk. In reality, multiple measures are undertaken by corporations to build resilience to flood and other climate risks, but these are not reflected in the current study given their bespoke nature (Umar and Wilson 2024).

The uncertainties in the flood damage functions were quantified through sensitivity analysis focusing on survey and fixed asset parameters (Figure 2.7). The results revealed that

dominant parameters vary by corporations (see Section 2.5.3). Moreover, the surveys on business interruption days used to calculate BIL are based on flood events in Japan and applied to overseas facilities under the assumption that such estimates are transferable, though geographical differences may exist. Similarly, the fixed asset parameters used to estimate property damage rely on average data from existing studies and do not account for facility-specific structural factors, such as critical manufacturing operations situated on specific floors or underground production processes, which constrain the accuracy of these estimates.

2.7 Conclusions

This study sought to quantify the financial impact of floods due to corporate property damage and BIL by integrating facility-level business databases, parameters related to property damage and BIL caused by floods, and outputs from hydrological analyses. The models proposed here, and tested on four Japanese companies, addressed the research need for integrating data at the facility level (Rose and Huyck 2016), and relating flood risks to financial metrics. While the necessity for data collection remains vital, the use of facility-level business databases enabled the approach to provide more facility-specific results for property damage and BIL compared to previous studies (Dormady et al., 2022; Taguchi et al., 2022).

Despite these limitations discussed in the previous section (see Sect. 6), the findings of this analysis could provide crucial support for organizations in benchmarking their specific climate-related financial risks. This information is critical for corporations to make informed investment decisions regarding risk management strategies, such as constructing flood barriers for facilities, elevating critical equipment like power systems or acquiring flood insurance. Insurers may utilize their financial assessments of flood risk to determine premiums reflecting

regional differences. Furthermore, in the context of the TCFD disclosures, and more recently its integration in required corporate accounting under International Financial Reporting Standard—Sustainability 2 (IFRS-S2), governmental organizations and global institutions are urged to facilitate the practice of climate risk disclosure among businesses. This process can be promoted by supplying valuable information that alleviate assessment uncertainties and by broadly showcasing companies that have successfully navigated climate risk analysis through various means.

Chapter 3 Industry Sector Application of Financial Risk Models using the Nikkei 225 Index

This chapter explores how the methodology introduced in Chapter 2 can be applied to the 225 companies listed in the benchmark Japan Nikkei 225 Index to understand sector-specific financial property damage and business interruption risks from geographic distribution of corporate facilities.

3.1 Introduction

There has been an increasing worldwide interest in implementing strategies for adaptation to climate change, including not only public institutions but also private sector firms. Following the consensus on the 2°C target established in the 2015 Paris Agreement, there is a notable surge in the interest of stakeholders regarding carbon neutrality, the effects of climate-related risks, and business strategies related to Environmental, Social and Governance (ESG) investments. After establishment of the Task Force on Climate-related Financial Disclosures (TCFD) in response to a request from the Group of 20 Finance Ministers and Central Bank Governors, governmental entities, such as EU, Japan, UK and US, have updated the regulations and required corporations to disclose their sustainability-related information associated with their business activities. (Steuer and Tröger, 2022; Bowman, 2024). Although there is a high-level global dialogue regarding corporate disclosure requirements, Fiedler et al. (2021) emphasized that the conceptual gap between the requirements of the business sector and the advances in climate science is substantial. The International Sustainability Standards Board (ISSB) standards issued in 2023 are built on the concepts that support the International Financial Regulatory

Standard (IFRS) Accounting Standards, which are required by more than 140 jurisdictions (ISSB, 2023). Despite these promulgations, there is no common standard of how to assess financial risks from climate impacts such as floods impacting global corporate facilities.

This study analyzes the financial impacts from flood risk exposure to all 225 corporations listed in the Nikkei 225 index and quantifies business interruption and property damage components across industries and regions, by integrating flood risk projections with corporate financial metrics (Abe and Adriaens, 2025). Despite the extensive research conducted on the economic consequences of climate risks, there is a dearth of extant literature on how flood risk influences and scales corporate financial performance from facility to index scale. The objective of the current study is to enhance understanding of corporate financial risks by assessing the impact of flooding to industry components in an index, while at the same accounting for the geospatial impact of climate regimes on global corporate facilities.

3.2 Background

3.2.1 TCFD and the Impact of Climate Risk on Investment Portfolios

From the perspective of investors, physical risk from climate implies significant financial risk for investment portfolios, as it materializes over a long period of time and is thus of particular concern for pension funds, investment banks, insurance funds, and sovereign wealth funds. Climate risk is often considered to be systematic (affects all companies and sectors), given the pervasive nature of the effects of climate change worldwide (Li et al., 2021). These systemic risks to the financial sector include flood risk (Mandel et al., 2021), as banks are exposed to corporate bonds and loans from companies used to finance operations, supply chains and expansion. It is important to understand relations between geospatially-exposed assets such as

corporate facilities to floods and the distribution of these financial impacts. At the microeconomic (corporate) level, not all facilities are equally exposed to financial flood risks, given their physical location in different climate regimes, wide range of size (investment in fixed assets, revenue), and type of operations (production, R&D, administrative).

At the macroeconomic (fund) level, Roncoroni et al. (2021) applied climate-related shocks to banks and investment funds and demonstrated how investment funds sustain losses and transmit impacts to other financial market participants. Focusing on European investment portfolios, Amzallag (2022) shows that systemic vulnerabilities remain and many fund portfolio diversification approaches do not yet adequately incorporate and adjust for climate risk. Part of the challenge is that systematic climate-related risks are distinct from other systematic sources of risk that investors are used to analyze (such as market, credit, and liquidity risk) and are characterized by significant uncertainty in the use of relevant metrics that should be used (Bingler et al., 2022). The extant literature evaluates climate financial risks in the context of corporate production, and potential impact on default or credit risks on corporate bonds and impact on financial institutions holding these bonds or equities (Capasso et al., 2020). In addition, historical data tend to be of little use since they neither include realizations of extreme climate change effects nor the types of actions companies (may) have taken to mitigate these risks (e.g. risk transfer, hardening of facilities or shifting supply chains). Hence, more information at the company and sector level as a function of specific climate-related extreme risks is required (Huang et al., 2022).

To address these limitations at the fund portfolio level, financial policies have recommended that climate risk information be disclosed at the corporate level both under TCFD guidelines (TCFD, 2017), and IFRS-S2 (ISSB, 2023) accounting requirements (Eccles and

Krzus, 2019; Kusuma and Gani, 2024). The former includes: (1) Description of the specific climate-related issues that may significantly affect the organization's finances over different time horizons, including short, medium, and long-term periods; (2) Segment the risks by sector and geographic region; (3) Articulation of scenarios for strategic and financial planning. The International Financial Reporting Standard (IFRS-S2) goes further and requires: (1) Transparency about the inputs and parameters utilized to quantify climate risks, such as the sources of data and the scope of operations covered by the process; (2) Disclosure of the financial effects on corporate financial position, financial performance, and cash flows; (3) Estimation of both qualitatively and quantitatively changes in future financial performance and cash flows across short, medium, and long-term periods. However, no guidance is provided on recommended financial performance metrics.

3.2.2 Corporate Financial Flood Risk Exposures

We previously published a financial modeling approach to estimating property damage (PD) and business interruption losses (BIL) for global companies with facilities in regions with variable climate impacts on flooding (Abe and Adriaens, 2025). While the model was demonstrated using four companies in two industries (food and beverage, industrials), it indicated highly variable BIL and PD impacts as a function of company operations and global distribution of facilities, necessitating regional attribution of the risk exposure. Koks et al. (2015) and Dormady et al. (2022) categorized flood risks into both direct impacts and indirect critical infrastructure components. Pan and Qiu (2022) observed that fixed assets are a significant component of corporate financial flood risk given business investments through bonds and loans for acquisition of new equipment, land and assets and the construction or upgrades of properties.

Operational risks from flooding due to business interruption are accounted for by incorporating reduced net sales as an opportunity cost, as inferred by Taguchi et al. (2022) in their model linking flood risk and operational efficiency.

The impact of floods on direct property damage has generally been estimated using damage assessment of financial risk related to structural vulnerability (Pistrika and Jonkman, 2010; Englhardt et al., 2019). Damage curves of a building related to the depth of flooding are subject to the influence of structural attributes such as building material, archetype and layout (Suppasri et al., 2013; Huizinga et al., 2017; Masoomi et al., 2019; Postacchini et al., 2019; Jansen et al., 2020). The Joint Research Centre of the European Commission proposed flood damage ratios from various types of information across continents (Huizinga et al., 2017), while others have proposed different curves (Tomiczek et al., 2017; Wing et al., 2020; Loaiza et al., 2022).

It is important for companies to quantify flood risks on their operations and risk exposure in terms of property damage and business interruption by utilizing knowledge of climate science trends and causal relationships. Business interruption caused by floods has been analyzed in a wide range of academic studies (Tanoue et al., 2020; Taguchi et al., 2022), using either survey data (e.g. Dormady et al., 2022) or resilience characteristics of each industry sector (Yang et al., 2016). Yang et al. (2015) proposed an approach for evaluating business interruption loss from floods in Japan based on economic census data and surveyed information. The estimation employs functional fragility curves and accelerated failure time equations to estimate the extent of damage to production capacity and the time required for production recovery.

By informing financial risk from floods in banks and pension funds through exposure to potential defaults and credit risks, with facility-level flood risk from global climate and

hydrological models, I hypothesize that a quantitative geospatial understanding of risk distribution and regional attribution can be attained at the index portfolio scale. This will help asset managers such as pension funds and sovereign wealth funds understand sectoral and regional severity of climate-related flood risks in their investment portfolios. In turn, investment portfolios can be designed with minimized flood exposure risks (Bender et al., 2019; Mandel et al., 2021), equities subject to climate impacts can be better valued (Krueger et al., 2020), and companies will be able to make informed operational risk management decisions.

3.3 Data and Materials

3.3.1 Global Flood Depth Estimation

I used the global flood depth data derived from the Aqueduct Floods database produced by the World Resources Institute. Aqueduct Floods includes calculated global flood depth information based on multiple Global Climate Models (GCMs) and climate change scenarios (Ward et al., 2020), for coastal and riverine floods. The outputs utilized in the current study are based on a mode of river floods simulated under Representative Concentration Pathway (RCP) 4.5 and RCP 8.5, five types of GCMs (NorESM1-M, GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC-ESM-CHEM), three periods (2030, 2050 and 2080) and nine kinds of return periods (2, 5, 10, 25, 50, 100, 250, 500, and 1,000-year floods) (Ward et al., 2020). This dataset has served as hydrological data for previous academic research (Adshead et al., 2024; Assab, 2024; Ye et al., 2024; Abe and Adriaens, 2025).

3.3.2 Corporate Financial Performance Indicators

I used corporate financial data, for example fixed assets (Property, Plant and Equipment, PP&E), sales, location and number of employees for subsidiaries, derived from various resources including Bloomberg database, Orbis database, EDINET, and corporate annual reports. The Bloomberg dataset has been used as the basis for existing academic research (Zhang et al., 2023; Arian et al., 2024; Pata et al., 2024). The Orbis database, maintained by Moody's, comprises corporate and facility-level financial metrics, and has been used in previous academic research (Abe and Adriaens, 2025). For instance, this database has been used for analyzing global supply-chain networks in relation to specific degrees of physical climate exposure (Pankratz and Schiller, 2024). Since there are missing values from these databases, I obtained corporate information from EDINET, which is managed by the Financial Services Agency in Japan, and their annual reports.

In the current study, the average reported PP&E and sales for all companies in the Nikkei 225 from 2014 to 2023 were retrieved for the current model (Table 3.1). Since the make-up of the index is adjusted in corporate weightings twice yearly and component inclusion occasionally changed during periods as companies are replaced, the average value is based on the companies represented as of December 2024. Pan and Qiu (2022) pointed out the importance of fixed assets as a predictor regarding corporate financial flood damage. Dormady et al. (2022) indicated the relationship between business interruption and loss of sales. Fixed Asset Turnover (FAT) can be calculated as sales divided by PP&E to understand their efficiency of revenue generation from their fixed assets. For example, the communication services sector has achieved the highest FAT ratio of 7.66, highlighting its low reliance on fixed assets. In terms of industrial classification, we used 11 sectors of the Global Industry Classification Standard (GICS) based on Compustat

Financials, a database provided by S&P Global as of January 2025. The 225 companies represented in the index as of December 2024 comprise 18,657 facilities distributed across all continents. Regarding the geographical allocation of facilities, around 66% are distributed across Asia, with about 15% located in North America and roughly 10% in Europe.

Table 3.1 Summary table for 225 companies in Nikkei 225 index (PP&E and Sales values represent a 10-year average between 2014 and 2023)

Industrial sector	Number of corporations	PP&E (Billion USD)		Sales (Billion USD)		Fixed Asset Turnover	
		Mean	SD	Mean	SD	Mean	SD
Energy	3	18.89	8.39	48.34	39.82	2.68	1.87
Materials	25	5.84	5.67	12.70	11.53	2.39	0.73
Industrials	63	6.92	9.53	17.39	20.92	3.60	2.59
Consumer Discretionary	33	9.23	17.07	30.52	49.48	5.13	5.22
Consumer Staples	15	5.75	7.00	17.53	20.24	3.28	0.63
Health Care	13	2.09	2.20	7.22	5.39	5.27	4.63
Financials	22	5.40	6.68	22.11	27.83	4.93	4.25
Information Technology	28	2.39	2.35	9.68	9.70	5.80	4.75
Communication Services	12	13.40	24.63	24.22	32.83	7.66	9.84
Utilities	5	34.63	26.50	27.88	16.03	1.02	0.42
Real Estate	6	20.57	11.86	12.92	10.74	0.79	0.85
All Industries	225	7.55	12.47	18.61	27.03	4.24	4.30

3.3.3 Flood Damage and Business Interruption Analysis

Computation on flood risk to corporate fixed assets was based on the flood-depth damage ratio functions provided by the Joint Research Centre of the European Commission (Huizinga et al., 2017) as described in Abe and Adriaens (2025). Huizinga et al. (2017) described that the flood damage functions are based on various types of information from multilingual websites, and evaluated in light of land use, building structural characteristics and construction details.

Since facilities of the companies listed in the Nikkei 225 Index span multiple continents and regions (Asia, Africa, North America, Central and South America, Europe and Oceania), it is essential to use flood damage curves that are differentiated by region. The damage curves for industrial buildings were used in the study to estimate property damage from floods. Due to the absence of its damage curves for Oceania, I have used the global damage curve for facilities in this region.

To estimate financial flood risks due to Business Interruption Loss (BIL), I used estimated business interruption data based on corporate surveys by the Japanese Ministry (MLIT, 2023). This updated dataset replaces a former version (MLIT, 2005). Both datasets have been widely applied in academic studies (Tanoue et al., 2020; AL-Hussein et al., 2022; Nihei et al., 2023; Abe and Adriaens, 2025). The 2023 dataset was used for estimating BIL. Because of the lack of various regional datasets on relationships between flood depth and business interruption periods, I used the 2023 MLIT dataset as a proxy for disruption in other regions, assuming that facilities confront similar challenges after floods as a function of flood depth.

3.4 Methodology

The section introduces methods for assessing financial flood risks by integrating hydrological datasets, and corporate financial information, which was proposed in the previous research (Abe and Adriaens, 2025). Figure 1 shows the approach for assessment of corporate financial flood impacts applied to 225 companies listed in the Nikkei 225 Index in this research.

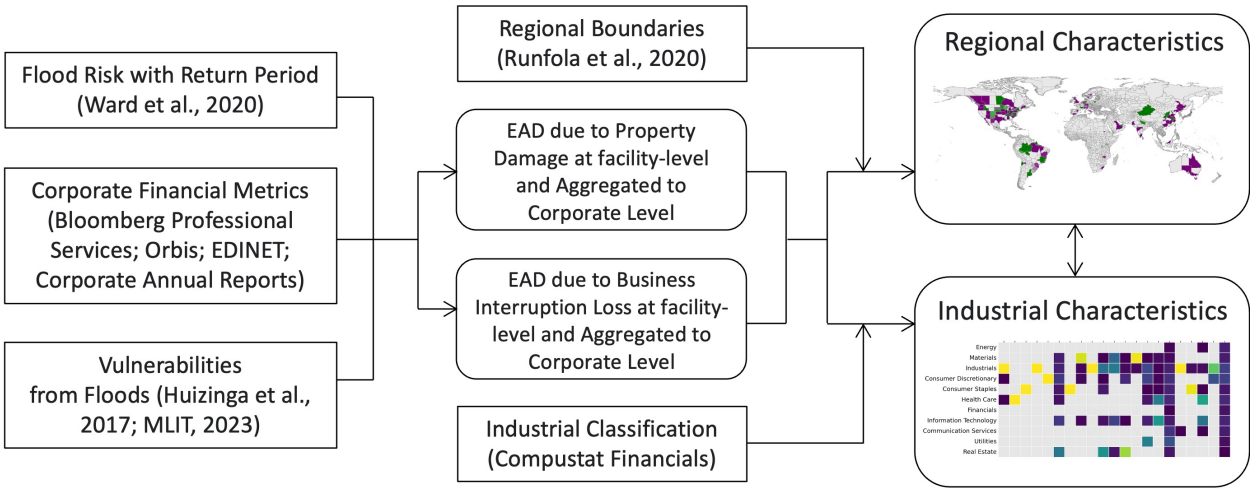


Figure 3.1 Approach and Information Flow for Assessment of Corporate and Industry-Level Financial Flood Impacts. No propagation of uncertainty in data inputs is implied. Input data is treated independently. Outputs are interpreted in an uncertainty framework.

As shown in Figure 3.1, the methodology integrates multiple datasets introduced in the previous section. This approach simulates flood impacts on physical damage to property and business interruption at a facility level and consolidates them to evaluate total financial flood risks as described in Abe and Adriaens (2025). This is similar to the approach of categorizing risks into both direct impacts and indirect components (Carrera et al., 2015; Koks et al., 2015; Dormady et al., 2022). The regional and industrial characteristics refer to geolocation of corporate facilities and industry sector attribution, which impacts investment in fixed assets and revenue (Table 3.1). The total financial risks from floods for a company is estimated by the following equation which was previously verified with actual corporate losses of four Japanese companies with a global facility footprint (Abe and Adriaens, 2025).

$$R = \sum_i d_i S_i + \sum_i r_i P_i \tag{3.1}$$

where R is total financial risks from floods for a company, d_i is business disruption for facility i, S_i is daily sales for facility i, r_i is flood damage ratio on fixed asset for facility i, P_i is PP&E for facility i. No autocorrelation among climate events and floods impacting facilities within the same hazard map is implied in the present analysis, as each facility is treated independently. However, we recognize that this assumption may underestimate the compounding risks arising from spatially dependent extreme events. Quinn et al. (2019) stressed that in order to estimate the total annual losses that might occur in more extreme flooding years the risk analysis needs to be based on more realistic spatial patterns of flooding. To address the uncertainty of flood risk associated with spatial autocorrelation, I am presenting my facility-level results in the context of regional administrative boundaries to capture the range of financial losses across multiple locations.

Expected Annual Damage (EAD) was calculated to estimate annual flood risks by taking various return periods of floods into account. Risk curves are commonly used for estimating EAD, and the relationship between EAD and exceedance probability from floods is formed by the integral under the curve as follows (National Research Council, 2000; Meyer et al., 2009).

$$EAD = \int_{p=0}^{1} D(p)dp \tag{3.2}$$

where $D(p)$ is the damage which occurs at the event with probability p. In the current study, various return periods were used (2, 5, 10, 25, 50, 100, 250, 500, and 1,000-year floods) provided by Aqueduct Floods. Velasco et al. (2018) analyzed direct damages using depth-damage curves and calculated the EAD by weighting the damages of each event with its

probability of occurrence. Zeng et al. (2023) carried out a cost-benefit analysis with EAD, considering the effects of flood risk reduction. Additionally, Olsen et al. (2015) estimated regional EAD by aggregating EAD in the study area as follows.

$$Regional\ EAD = \iint_{A\,p} D(p)\ dpdA \tag{3.3}$$

where $D(p)$ is the damage which occurs at the event with probability p in the region with area A.

It should be reiterated that uncertainties related to the inferred financial data for facilities, as well as the spatial autocorrelation of event impacts on flood risk, were not explicitly quantified or addressed in this study. In other words, no quantitative analysis was conducted regarding these uncertainties. This omission stems from the study's primary focus on standardizing financial methodologies to enable sectoral and regional comparisons. Nevertheless, spatial dependence, particularly in the tail of the distribution, can significantly influence the results (Nguyen et al., 2020). This limitation is especially critical, as accurately quantifying the potential for diversification of extreme flood events across sectors and regions is essential (Albrecher et al., 2020). Moreover, assumptions regarding spatial risk play a critical role in financial flood risk modeling at facility-level. In spite of my regional facility risk interpretation, oversimplification of spatial dependence, particularly in the tails of the distribution, can lead to inaccurate assessments of both local and aggregate risk. As highlighted in previous studies (e.g., Keef et al., 2009; Lamb et al., 2010), neglecting the spatial structure of extreme events, in the tail part of the distribution, on corporate facilities may significantly misrepresent the extent and severity of widespread flooding.

3.5 Results

3.5.1 Regional and Industry Sector Financial Flood Risk Analysis

The aggregate results of EAD computations are shown on the global map showing geographical financial impacts for the Nikkei 225 companies resulting from the geolocation of corporate assets. Because these maps present the entire index, the relative contributions of companies and their facilities are not discernable and will be discussed later. The intent of the maps is to explore macro trends, highlighting three observations (Figure 3.2). First, the patterns observed in the aggregate EAD distribution resulting from PD and BIL mirror one another in geographic distribution and intensity. This is expected given that the same portfolio of facilities in the same regions would be subject to interruptions and damage from floods, even if different industry sectors and their corporate assets may be affected differently, as will be discussed later. Second, by comparing the EAD 2080:2030 ratio, a decrease of 4% on average is predicted in Oceania, while other regions generally increase. This trend may be attributed to forecasted declines in rainfall in those regions driven by local factors at the catchment scale (Wasko et al., 2021), or potentially is the result of uncertainties in the prediction resulting from lack of observation such as satellite monitoring which informs changes in land use (Tellman et al., 2021). Third, the results demonstrate that the ratio of RCP 8.5 to RCP 4.5 is increasing within Australia implying that significantly more warming is expected in this region. While this may imply more severe flooding, hydrologic anomalies have shown that rainfall may be decreasing in the southern regions of the country (Wasko et al., 2021). While the selection of GCMs influences EAD results, regional features should be expected in warming and associated flood events instead of a uniform global trend (Adams et al., 2024).

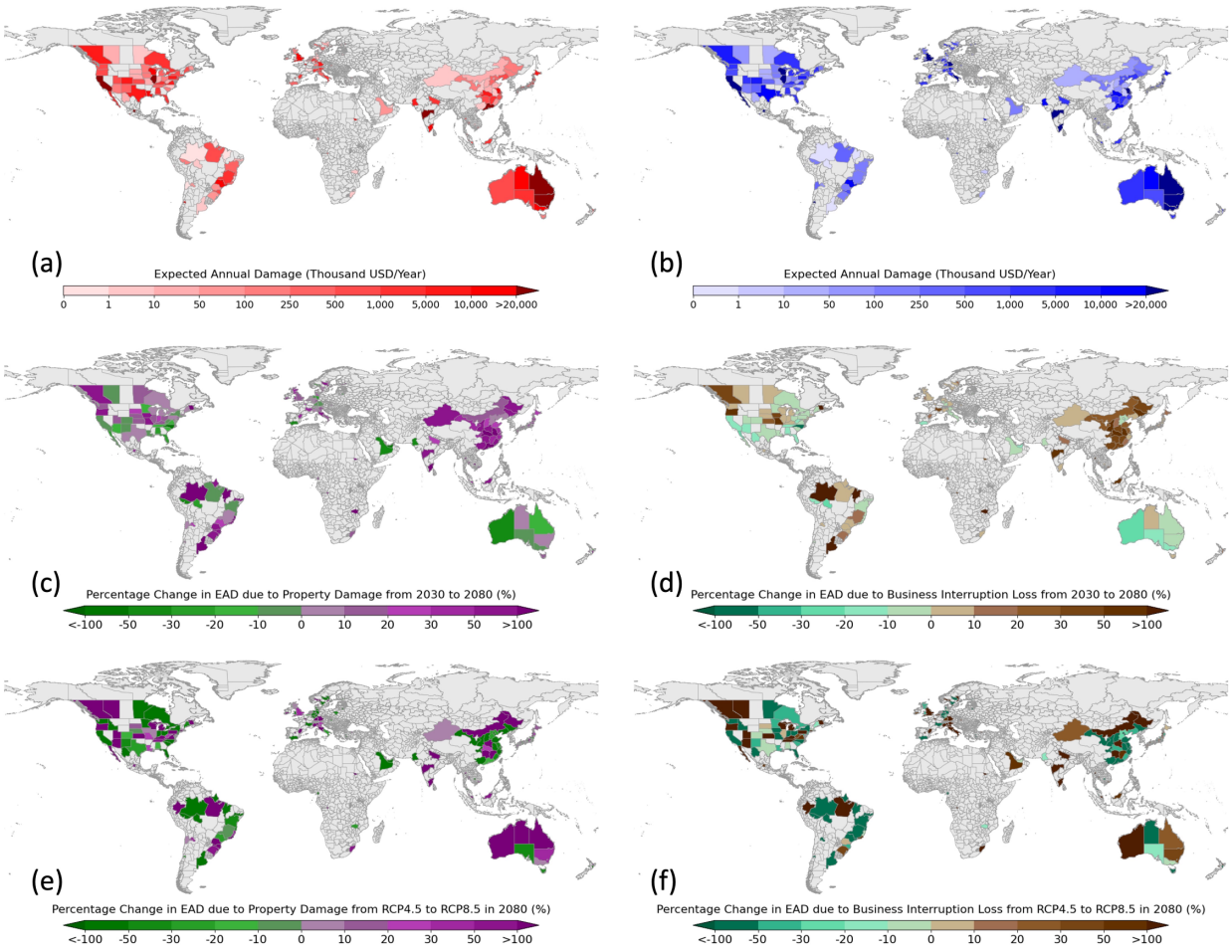


Figure 3.2 Global Maps of Aggregated EAD Values for the Nikkei 225 Corporations (a: EAD due to PD; b: EAD due to PIL; c: Ratio of 2080:2030 flood-related EAD due to PD; d: Ratio of 2080:2030 flood-related EAD due to BIL; e: Impact of RCP8.5/RCP4.5 ratio on EAD resulting from PD; f: Impact of RCP8.5/RCP4.5 ratio on EAD resulting from BIL.

The information of the global maps was disaggregated by region and industry sector, to understand EAD risk distribution. Table 3.2 shows the data for aggregate facility risk by region. The majority of losses was incurred by facilities located in Asia, followed by Europe and North America, accounting for nearly 92% of losses. The losses from business interruption exceeded those of property damage, in the case of European facilities by a factor of 4. When normalized by the number of facilities in each region, Africa and Europe exhibited the highest losses, though

the former was affected by a low number of operational assets. Importantly, business interruption losses in Europe were forecasted to be twice as high as those in Asia and North America, possibly due to differences in labor laws and welfare systems impacting corporate productivity and sales after environmental disasters (Tiraboschi, 2015).

Table 3.2 Summary Table for Regional Analysis (2030; RCP 8.5)

Region	Aggregated Expected Annual Damage (Million USD)					
	PD + BIL	%	PD	%	BIL	%
Europe	1,289	16	133	5	1,156	22
North America	804	10	263	9	541	10
Central & South America	118	1	51	2	67	1
Asia	5,273	64	2,140	75	3,133	58
Africa	44	1	15	1	29	1
Oceania	681	8	251	9	430	8
All regions	8,209	100	2,852	100	5,357	100

Note: PD: Property Damage; BIL: Business Interruption Loss

Since production and fixed assets are a major contributor in the EAD calculations, it is important to understand the country locations and industry sectors comprising the facilities. For example, Table 3.1 shows that the investment in fixed assets (PP&E) informing property damage is highest in the utilities, energy, and real estate sectors, closely followed by communications, consumer discretionary and industrials sectors. Similarly, mean sales numbers are dominant in the energy, utilities and consumer discretionary sectors, impacting BIL.

The EAD for Nikkei 225 corporations were categorized by country, and the distribution by sector for each country was represented as percentages (Figure 3.3). The horizontal axis of the heatmap shows the number (N) of facilities at risk in each country. The total number of facilities in the entire index 225 companies is 18,567, and it was found that 2,923 of these (16%) are

exposed to flood risk through property damage and business interruption losses. Sudan shows the highest value; however, since the number of facilities at risk is only one, it is likely that this facility does not represent an average value but rather a relatively large asset. Therefore, more facilities are needed to obtain a representative value for the country. Next, France shows the second highest value, with 6 facilities impacted, dominated by the Industrials sector.

Thailand's flood risk impacts on Japanese corporations in the Chao Phraya River basin have affected supply chain decisions and insurance applications (Haraguchi and Lall, 2015). Katano and Hashimoto (2011) reported that the 2011 flood in Thailand caused inundation damage in industrial parks where many Nikkei-affiliated companies had expanded, resulting in flooding of approximately 450 companies and the suspension of operations for many of them. In light of the damage to Japanese companies in the Chao Phraya River Basin during the 2011 flood, the results shown in Figure 3.3 - although not quantitatively analyzed - can be interpreted as reasonable in identifying Thailand as a country with relatively high flood damage per facility.

India has 13 facilities at risk and ranks seventh in terms of EAD per facility. Chuphal et al. (2024) indicate that climate change is increasing the risk of extreme rainfall and flooding in India. Therefore, when considering flood risk mitigation measures, it is important to analyze the increasing risks associated with climate change over time. New Zealand has 31 facilities at risk, with industry sectors spanning a wide range, including Industrials, Consumer Discretionary, and Real Estate. Fu et al. (2023) conducted a survey of flood risk practitioners in both the public and private sectors in Aotearoa New Zealand and pointed out issues such as the use of outdated information in decision-making processes. Mexico has 23 facilities at risk and ranks tenth in terms of EAD per facility. Zúñiga and Magaña (2018) pointed out that the frequency of floods in

Mexico is increasing, and they analyzed that the cause is not only more intense rainfall but also a consequence of increased vulnerability.

Lastly, the largest sample size of facilities is located in Japan, with 873 facilities across all industry sectors affected. However, the losses per facility are relatively low presumably due to many facilities exhibiting exposure to shallow flood depths. However, when considering the aggregate value across all facilities, Japan shows the highest EAD losses. Therefore, Japan should be regarded as a central focus for Nikkei 225 companies when considering flood risk reduction measures.

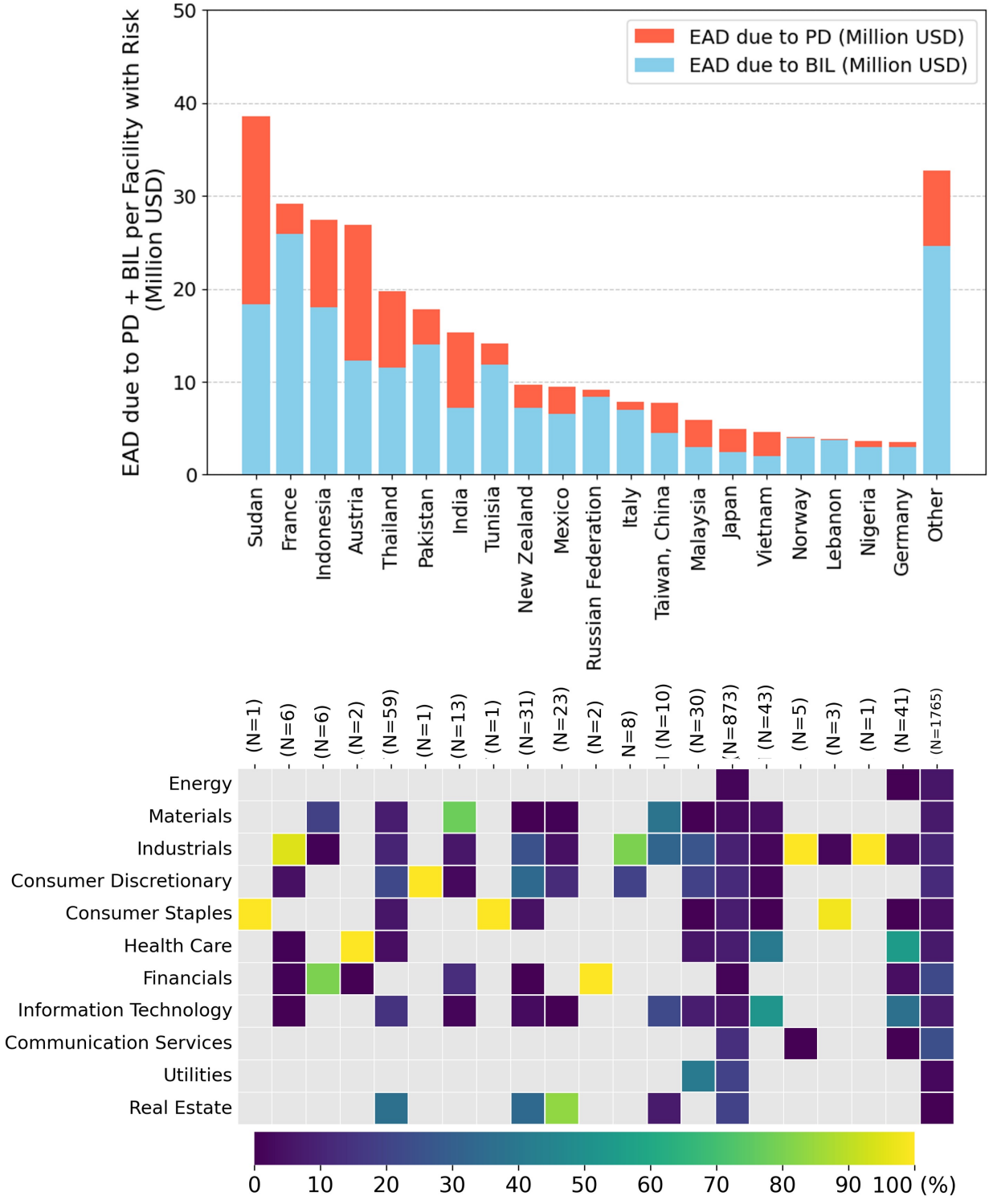


Figure 3.3 EAD Country Rankings and Breakdowns for 11 GICS Industries (Number of Total Facilities with Risk: 2,923; Year: 2080)

To gain further insight in the regional impacts of facility flood risk, and to illustrate divergence between global corporate portfolios, three companies were selected from the Nikkei 225 index with facility footprints in Europe (company A), Central and South America (company B) and Australia (company C). The outcomes from the regional EAD analysis are shown in Figure 3.4. The bar graphs illustrate the mean values calculated resulting from the use of each of the five GCMs, where error bars indicate the highest and lowest values across these models. This represents the total EAD of the facilities located within each region.

Company A owns and operates many facilities in Europe, and financial risks due to flooding, specifically due to Business Interruption Loss (BIL), have been estimated. One reason for the relatively low EAD value due to Property Damage (PD) may be due to the company's high Fixed Asset Turnover (FAT). Fixed asset turnover measures how effectively a company uses its fixed assets to generate revenue or how efficiently a company is utilizing its investments in property, plant, and equipment (PP&E) to generate sales. A higher ratio suggests better asset utilization and efficiency, while a lower ratio may indicate underutilized assets or inefficiencies. Hence, a high FAT and judiciary investment in fixed assets lowers the potential opportunity costs resulting from property damage during climate transition (Bressan et al., 2024). Additionally, since the facilities are located in Europe, the flood damage curve used to calculate EAD due to PD (Huizinga et al., 2017) may influence the results. For example, when the flood depth is 1 meter, the flood damage ratio is 0.48 in Asia, but only 0.27 in Europe—about 56% of the Asian value—so the EAD due to PD calculated based on PP&E tends to be smaller in Europe. Another noteworthy point is the width of the error bars in the regional EAD forecasts. In Northern Europe, the error bars for the predicted EAD values are wider than those in Western and Southern Europe. This suggests that the forecast results vary significantly depending on the

climate model used and its impact on sub-regional estimates. According to Dottori et al. (2023), river flood risk in Europe is expected to increase due to global warming and continued development in flood-prone areas. Alfieri et al. (2015) also show an increase in flood risk. However, Arnell and Gosling (2016) point out that there is significant regional variability in river flood risk, and substantial differences between climate models, highlighting the importance of conducting comprehensive analyses using multiple climate models.

For Company B, flood-related EAD has been observed in Southeast Asia. Arnell and Gosling (2016) pointed out that Asia is the region where future flood risks due to climate change are expected to increase the most. Winsemius et al. (2016) also noted that Southeast Asian countries are facing a significant increase in flood risk, with risks rising due to both climate change and socio-economic growth. In particular, a concentration of facilities in Central Thailand has led to high calculated EAD from flooding. This area is part of the lower Chao Phraya River basin, which was severely impacted by the 2011 floods. Katano and Hashimoto (2011) reported that approximately 450 Japanese companies were inundated during the 2011 floods in Thailand, and many of them were forced to suspend operations. From 2030 to 2080, the trend in EAD due to flooding shows an increase, indicating that this is a region where flood risk reduction measures for companies' financial impacts are particularly important. Furthermore, in Northern Thailand, although the average EAD due to flooding calculated from five different climate models shows an increasing trend, the wide range of error bars suggests significant uncertainty. This reinforces the importance of using results from multiple General Circulation Models (GCMs) in such analyses.

For Company C, the EAD due to flooding is shown for Oceania, particularly focused on Australia. Xuan et al. (2020) showed that in Australia, the projected flood magnitude varies

depending on the climate model, with some models indicating an increasing trend and others a decreasing trend. According to Wasko et al. (2021), southern Australia is affected by drought, which aligns with the trend shown in Figure 3.4, where the average flood risk in South East Australia—based on the results from multiple climate models—tends to decrease by 2080. However, due to the large error bars associated with the climate model results, the probability of increasing EAD from flooding should be considered substantial.

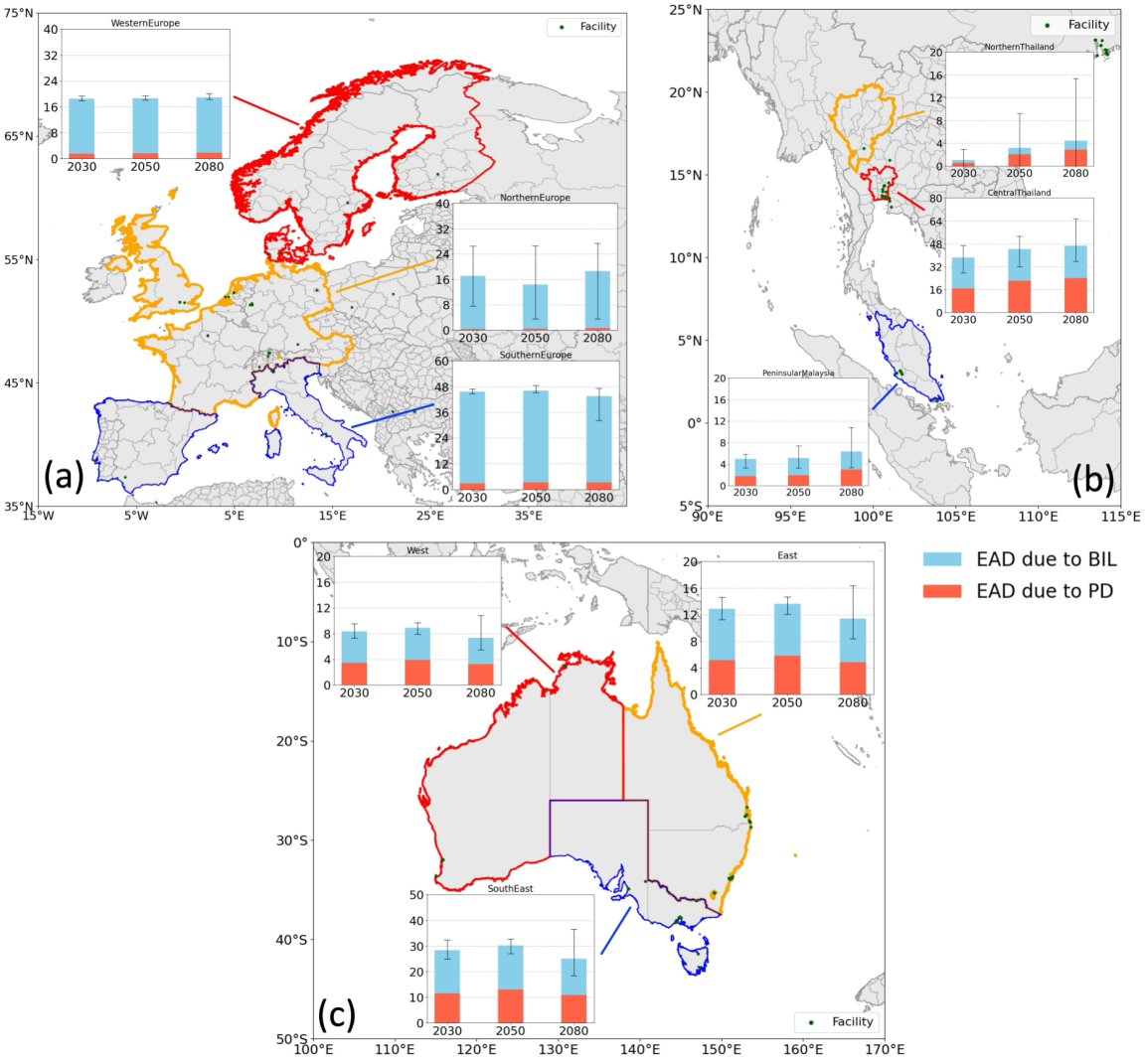


Figure 3.4 Regional Analysis for Individual Corporations in the Nikkei 225 index (a: EAD in Europe for Company A; b: EAD in East Asia for Company B; c: EAD in Australia for Company C; 2030 to 2080; RCP 8.5; 5GCMs; Unit of bar graphs: Million USD)

3.5.2 Nikkei 225 Industry Sector Financial Impact Analysis

To analyze the characteristics of EAD resulting from floods at the company level across different industries, statistical metrics were computed. Figure 3.5 displays EAD values for 2030 based on the RCP 8.5 scenario. The average forecasted values calculated from five GCMs were normalized by the company's investment in fixed assets (PP&E) or Sales to enable comparison between different size firms in each industry sector. While PP&E is obtained from the balance sheet and is on an accrual basis (i.e. investment over time, not annualized), and sales are annualized data from the income statement, normalization of EAD does provide insights in flood loss exposure at a corporate level. For example, mean normalized EAD values for the health care sector are the highest, while higher PP&E sectors such as energy, materials, industrials, consumer staples, and consumer discretionary are lower. For all industries, the average value of EAD due to property damage as a percent of PP&E is 0.125%, and the average value of EAD due to BIL as a percent of PP&E is 0.082%.

Next, the EAD values were normalized by net income (earnings) for each industry sector (Figure 3.6), as corporate risk management decisions are often based on this metric (Ding et al., 2021). Net income data were obtained from EDINET, and the average values over five years from 2019 to 2023 were used. This analysis aims to calculate the proportion of EAD relative to net income, so only the 188 companies (84%) with positive five-year average earnings were included. The upper part of Figure 3.6 shows a box-and-whisker plot including outliers. In some cases, the normalized EAD values exceed 100%, depending on the company. The lower part of Figure 3.6 presents the same plot with outliers excluded. A support line labeled "Major Risk" is drawn at the 5% mark as a benchmark. This serves as a reference point, indicating that when EAD exceeds 5% of net income, it may become a higher priority for companies to take action by

the investment committee. According to Waterstons[1], risk levels are categorized as follows: from 1% to 5% of profit is considered moderate (low), 5% to 10% is major (medium), and more than 10% is critical (high). Additionally, Snam[2], which is an Italian company, states that a materiality threshold equal to 1.5% of net profit is used to trigger corporate action. Although these thresholds vary among companies, setting the benchmark at 5% in this study is justified. According to Figure 3.6, the Utilities sector shows an average EAD due to property damage of approximately 5%, and when BIL is included, the total exceeds 5%. This suggests that for companies in this sector, flood risk should be prioritized among other risks such as market or reputational risk. In other sectors such as Materials, Consumer Discretionary, Consumer Staples, Industrials, and Information Technology there are companies exceeding the 5% benchmark of EAD:earnings ratio, indicating that flood-related financial risk should be considered a priority in corporate risk management strategies.

[1] Waterstons (n.d.), Risk management – Part 1: Exploring risk: Categorise the level of risk. https://www.waterstons.com/academy/risk-management/part-1-exploring-risk/categorise-level-risk. Accessed June 26, 2025.

[2] Snam. (2025). Annual report 2024. https://www.snam.it/content/dam/snam/pages-attachments-search/en/documenti/bilanci-annuali/2024/annual_report_2024.pdf. Accessed June 26, 2025.

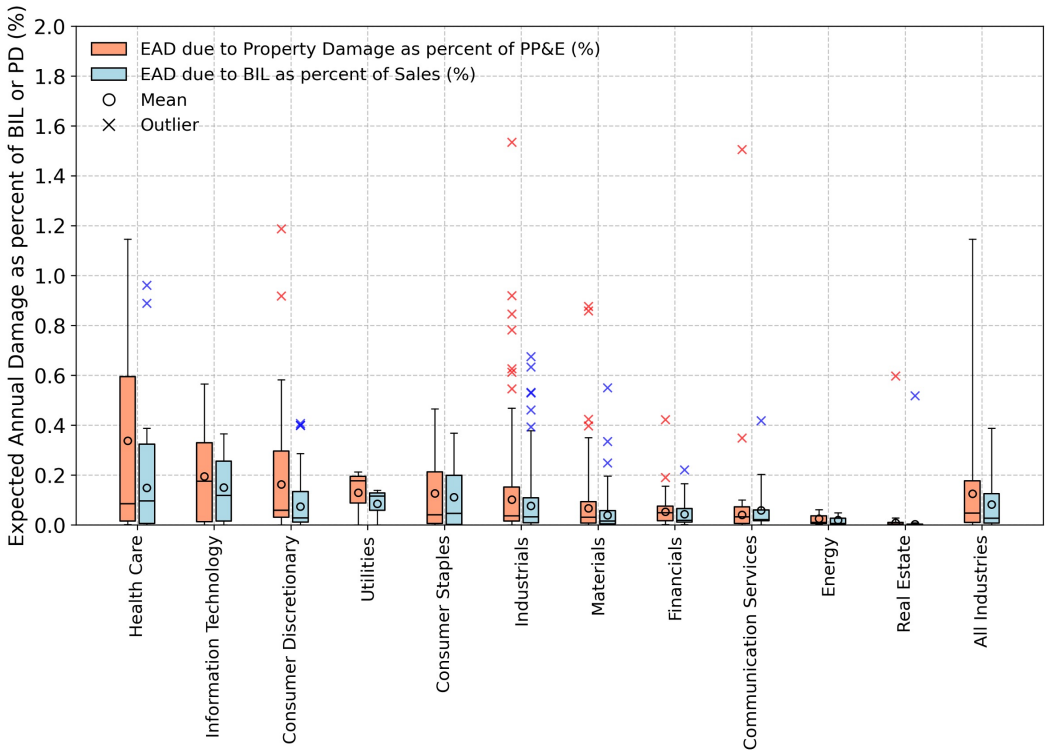


Figure 3.5 Corporate EAD as Percent of property damage (PD) or business interruption loss (BIL) by industry (2030; RCP 8.5 scenario)

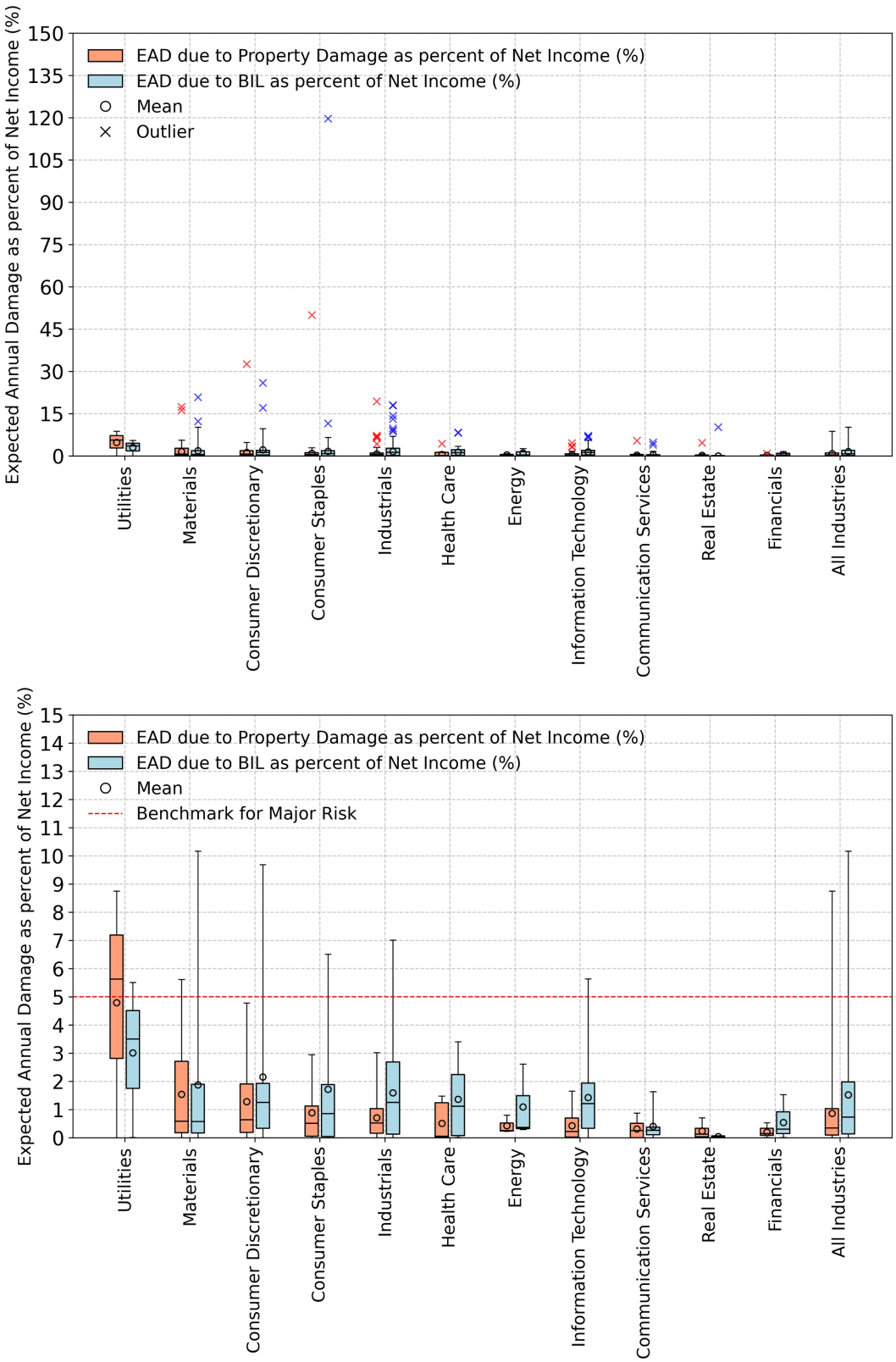


Figure 3.6 Percentage of Corporate EAD with Financial Values (2030; RCP 8.5 scenario) (Upper: Inliers with Outliers; Lower: Only Inliers with Benchmark for Major Risk).

3.6 Conclusion, Limitations and Policy Implications

3.6.1 Conclusions

This study sought to develop a quantitative understanding of risk distribution and regional attribution can be attained at the index portfolio scale. Using data from 2250 company-years and 18,657 facilities across 6 regions/continents, I estimated and forecasted PD and BIL at the regional, industry sector and facility level. The results are summarized as follows.

Based on the regional analysis, the total financial flood risk for the 225 companies in the Nikkei 225 is approximately 8.2 billion USD per year, with about 64% of this risk originating from Asia. A country-level analysis was also conducted, and the validity of the results was examined in comparison with findings from existing studies. For example, Thailand has 59 facilities at risk and was evaluated as having the fifth-highest EAD per facility. Although a quantitative analysis was not conducted, this result can be reasonably understood in light of reports such as Katano and Hashimoto (2011), which state that during the 2011 floods in Thailand, approximately 450 Japanese companies were inundated in industrial parks where many Nikkei-affiliated companies had expanded, and many were forced to suspend operations.

Furthermore, by using administrative boundaries of multiple countries and states, an analysis was conducted to assess the financial impact of flooding on individual companies. For example, in European regions, it was found that the range of values influenced by climate models varies depending on the specific region. Additionally, the relatively smaller EAD due to property damage compared to EAD due to BIL was attributed to factors such as higher Fixed Asset Turnover (FAT), explained in Section 3.5.1, among companies and the influence of the flood damage curve (Huizinga et al., 2017) used in calculating EAD due to property damage.

In the analysis by industry sector, EAD was standardized using net income, allowing for a discussion on how companies might prioritize responses to flood-related financial risks amid various other risks such as market and reputational risks. As a result, the Utilities sector showed an average EAD due to property damage of approximately 5%, and when BIL is included, the total exceeds 5%. This suggests that companies in this sector need to elevate the priority of addressing flood-related financial risks. In addition, for sectors such as Materials, Consumer Discretionary, Consumer Staples, Industrials, and Information Technology, there are companies that exceed the 5% benchmark. Therefore, it can be said that these sectors should also consider giving higher priority to addressing flood-related financial impacts.

3.6.2 Limitations of this Approach

The uncertainties in the flood damage functions were quantified through sensitivity analysis focusing on survey (MLIT, 2005; 2023) and fixed asset parameters (Huizinga et al., 2017). The results revealed that dominant parameters vary by corporations. Moreover, the surveys on business interruption days used to calculate BIL are based on flood events in Japan and applied to overseas facilities under the assumption that such estimates are transferable, though geographical differences may exist. Similarly, the fixed asset parameters used to estimate property damage rely on average data from existing studies (Huizinga et al., 2017) and do not account for facility-specific structural factors, such as critical manufacturing operations situated on specific floors or underground production processes, which constrain the accuracy of these estimates. The financial risk estimates do not take into account possible changes in land use or flood risk mitigation in forecasts between 2023 and 2030 or 2080.

The financial data for companies are based on the 10-year average from 2012 to 2021, with no additional adjustments made for projected growth for forthcoming years. This is because the inclusion of corporate growth rates and discount rates introduces more uncertainty in the assessment of the implications of future fluctuations in flood risk. Similarly, even though Orbis provides a rich dataset to estimate sales and PP&E from proxy values such as employees and addresses of facilities, the data are imputed and do not reflect actual financial disclosures as facilities are private properties. Hence, the forecasted EAD risks should be interpreted as order of magnitude values and patterns in space and time. As more information becomes available through future disclosures, the level of predictive accuracy can improve by use of AI models informed by a larger corpus of companies and facilities.

3.6.3 Policy Implications

It is crucial for governments and international organizations to identify which types of corporations are resilient to climate risks and which industry sectors and corporate facility portfolios are vulnerable to regional risks. Borowska-Stefańska (2024) emphasized that in regions where vulnerability significantly affects flood risk, it is essential for the community to be more engaged in the formulation of risk management strategies. Næss et al. (2006) emphasized that a key issue is how to advance adaptation to what appears as inevitable, yet uncertain, climate changes, by employing the existing knowledge regarding climate change and societal vulnerability. The information on vulnerability is crucial for facilitating effective adaptation planning and informed decision-making processes (Singhal et al., 2025). Specifically, the time needed for preparation for floods, the duration and scale of potential disruptions, and determining which industries should be prioritized though government financial risk

management programs. Although each corporation is basically conducting its own estimates for to meet financial disclosure requirements, the benchmarks introduced in the current study could serve as a useful reference for cross-referencing and additional uses.

The findings from this research, which encompass all GICS industrial sectors in the Nikkei 225, may serve as valuable reference information for risk transfer to insurance companies when estimating flood-related insurance premiums for businesses. Kunreuther (2008) indicates the principle that insurance premiums should be reflective of risk levels, and he points out that risk reduction can serve as a factor to facilitate lower premiums. EAD values can be associated with calculating insurance premiums (Paudel et al., 2013; Unterberger et al., 2019; Tesselaar et al., 2020). For example, the results may provide an opportunity to calculate and inform the design of parametric climate insurance to reflect regional distinctions. Lastly, since investors and fund managers are assessing the impact of climate risk on the performance of their portfolios, company- and sector-specific flood risk impacts on production, revenue generation and efficiency of investments in fixed assets inform profitability, cost of business and earnings. Hence, this study provides a bottom-up approach to understand the impact of climate-related floods on equity performance, and risk to corporate bonds holdings affecting banks and long-term investors. Trinh et al. (2024) identified that there exists a positive association between firm-level climate change exposure and the cost of debt financing. Thus, these insights are valuable information when financial institutions evaluate potential credits in industries that are resilient to climate risks.

Chapter 4 Integration of Hydrological and Financial Risk Models to Enhance Granularity in Time-Series Data Analysis

This chapter demonstrates how I integrate hydrological and financial risk models to address the issue discussed in the previous chapters with particular emphasis on improvements in temporal resolution of business interruption losses and property damage. This chapter is driven by the significance of enabling appropriate climate adaptation measures and wise investment decisions by corporations.

4.1 Introduction

Studies regarding the frequency and impact of flooding driven by climate change are being executed at various scales, including both local and global scales. The analysis of hydrological models focused on the global water cycle is experiencing significant progress, as the constraints of computational resources are being gradually diminishing (e.g. Oki and Kanae, 2006; Yamazaki et al., 2011; Alfieri et al., 2013; Sampson et al., 2015; Wing et al., 2024). For example, the Aqueduct Floods outlined in the previous chapters is based on the Global Flood Risk with IMAGE Scenarios (GLOFIRS) and was formulated using PCRaster Global Water Balance (PCR-GLOBWB) as its principal component (Ward et al., 2013; Winsemius et al., 2013; Sutanudjaja et al., 2018; Ward et al., 2020).

Since corporate financial disclosures are audited on a quarterly and annual basis, the aim of this chapter is to quantify the time series impact of financial risks from floods based on the use of highly temporally-resolved hydrological models combined with corporate financial modelling. Previous work used the outputs of the Aqueduct Floods module, which is limited to three time

periods (2030, 2050, and 2080). While these time periods are useful to observe aggregate impact trends of financial flood risk, the poor resolution presents a challenge for corporate risk management planning and investment decision-making and impedes disclosures in forward-looking annual financial statements. Using the 225 companies listed in the Nikkei 225 index, and their associated 18,000+ facilities, this study analyzes the temporal financial impacts of floods across different regions and industries, identifying the trends and differences that exist both regionally and by industry.

4.2 Role of Granularity in Time-Series Data Analysis of Financial Flood Risk

According to the TCFD guidelines (2017), recently promulgated in the EU as IFRS-S2, it is recommended that corporate disclosures reflect the resilience of their strategic strategies, considering a range of climate-related scenarios. However, Andersson and Arvidsson (2023) pointed out that although scenario analysis is a useful tool to take into account the potential impact of climate-related risks, corporations may lack comprehensive information associated with climate risk on their operations. Corporate disclosure of information on potential financial impacts of climate change remains insufficient for investors to assess climate-related risks into their investment evaluations (Johnson et al., 2021). The techniques implemented should be transparent and available for external evaluation and auditing, yet there exist few systems to ensure this will be realized. The conceptual gap between business needs and climate science is notably significant (Fiedler et al., 2021).

While corporate financial statements are disclosed on a quarterly or annual basis, flood risk assessments are typically considered over decadal time frames regarding estimating of climate change impacts, aligned with the long-term trends of climate change (Du et al., 2024). Long term predictions for future site location and risk management decisions are thus fraught

with uncertainty (Ryu et al., 2017; Leitold et al., 2021), impacting for example corporate investment, asset base composition, innovation, liquidity management, payouts, and mergers Campello and Kankanhalli, 2024). It has been argued that improvement of temporal specificity in financial flood risk assessment is necessary for advancing corporate risk management and making informed investment decisions for risk mitigation (Azizat, 2018; Jia et al., 2022). Carè (2023) points out that although the effects of climate change unfold gradually over decades, climate stress evaluations are often carried out over shorter periods, potentially leading to failures resulting from incomplete evaluation of the long-term consequences for financial stability. Climate risk evaluation demands not only an understanding of hazards across multiple spatial and temporal scales, but also a quantitative assessment of exposures (such as the geographical distribution of assets and value chains), and their vulnerabilities (Arribas et al., 2022).

Time-series analyses have been conducted to assess corporate financial risks associated with natural disasters. For example, Ai and Gao (2023) illustrated the susceptibility of firm headquarters in the United States to various extreme events from 1996 to 2017 obtained from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) data, indicating an upward trend in the number of headquarters affected by climate events over time. In terms of trade credit, Lai et al. (2022) present robust findings that trade credit tends to rise following a flood disaster, with this effect lasting for about two years by analyzing a sample of Chinese companies from 2014 to 2019.

My research hypothesis is that assessment of the financial impacts of floods using sufficiently high temporal (and geospatial) resolution is necessary to enable appropriate climate adaptation measures and investment decisions by corporations. Falconer et al. (2022) point out

that adaptation measures chosen based on insufficient information can lead to maladaptation. Maladaptive actions, in particular, increase the vulnerability of minority groups and low-income households (Barnett and O'Neill, 2010) and are likely to impact economic damage to companies as well. Delays in implementing adaptation not only widen the adaptation gap but also limit available options and increase residual risk (Muccione et al., 2024). In the field of climate projection, Hayhoe et al. (2024) argue that high-resolution climate forecasts are essential for informing adaptation strategies. Over time, risks accumulate (Magnan et al., 2021). Based on these insights, conducting analyses with sufficient resolution is a critical step for implementing effective and appropriate climate adaptation measures in the context of my work focused on understanding and quantifying financial risks to business operations and property.

4.3 Hydrological Data Sources

I used the global meteorological forcing data derived from Global Soil Wetness Project Phase 3 - WATCH Forcing Data Methodology Applied to ERA5 (GSWP3-W5E5) to verify hydrological model calculations described in Section 4.5.4 (Dirmeyer et al., 2006; Lange 2019; Cucchi et al., 2020). I used climate projection datasets from the MIROC-ESM-CHEM model, developed as part of the Coupled Model Intercomparison Project Phase 5 (CMIP5) to estimate corporate financial flood risk under climate change (Watanabe et al., 2011). This Global Climate Model (GCM) data is also used in Aqueduct Floods (Ward et al., 2020). The data was downscaled into 0.5° (~50km) in order to adjust the spatial resolutions for global land scheme process using Simple Biosphere with Urban Canopy (SiBUC) (Tanaka, 2004). In terms of land parameters, Global Land Cover Characterization (GLCC) v2 (U.S. Geological Survey, 2000), Monthly Irrigated and Rainfed Crop Areas 2000 (MIRCA2000) (Portmann et al., 2010), Spot

Vegetation (VITO, 1999), Ecosystem Climate Map (ECOCLIMAP) (Masson et al., 2003), Global Lakes and Wetlands Database (GLWD) (Lehner and Döll, 2004), Moderate Resolution Imaging Spectroradiometer Leaf Area Index (MODIS-LAI) (Zhang et al., 2006), Satellite-based Crop Calendar for Agricultural Production Assessment (SACRA) v1.0 (Kotsuki and Tanaka, 2015) are used for input data of SiBUC. Global Topography 30 (GTOPO30) (U.S. Geological Survey, 1996) is used as elevation for downscaling method for datasets from MIROC-ESM-CHEM model and input data of SiBUC. Multi-Error-Removed Improved-Terrain Digital Elevation Model (MERIT DEM) (Yamazaki et al., 2017) and MERIT Hydro (Yamazaki et al., 2019) are used for Catchment-based Macro-scale Floodplain model (CaMa-Flood) (Yamazaki et al., 2011). Table 4.1 summarizes the input data used for hydrological model calculations.

Table 4.1 Input Data for Hydrological Processes

Name	Description	unit	Spatial Resolution	Temporal Resolution	Source/Provider
GSWP3-W5E5	Global precipitation	kg/m²/s	0.5° (~50km) × 0.5° (~50km)	daily	Dirmeyer et al., 2006; Lange 2019; Cucchi et al., 2020
	Global surface air pressure	Pa			
	Global near-surface specific humidity	%			
	Global surfae downwelling longwave radiation	W/m²			
	Global surfae downwelling shortwave radiation	W/m²			
	Global near-surface wind speed	m/s			
	Global near-surface air temperature	K			
MIROC-ESM-CHEM (CMIP5)	Global precipitation	kg/m²/s	2.8125° (~310km) × 2.790° (~256km)	daily	Watanabe et al., 2011
	Global surface air pressure	Pa			
	Global relative humidity	%			
	Global surfae downwelling longwave radiation	W/m²			
	Global surfae downwelling shortwave radiation	W/m²			
	Global near-surface wind speed	m/s			
	Global near-surface air temperature	K			
GLCC v2	Global land cover	-	30sec (~1km)	-	U.S. Geological Survey, 2000
GTOPO30	Global elevation	m	30sec (~1km)	-	U.S. Geological Survey, 1996
MIRCA2000	Global irrigation and crop map	%	5min (~10km)	-	Portmann et al., 2010
SPOT VEGETATION	Global 10 day composite NDVI	-	1km	-	VITO, 1999
ECOCLIMAP	Global soil and vegetation parameters	-	30sec (~1km)	-	Masson et al., 2003
GLWD	Global lake and wetland data	-	30sec (~1km)	-	Lehner and Döll, 2004
MODIS-LAI	Global MODIS-based LAI	-	30sec (~1km)	-	Zhang et al., 2006
SACRA v1.0	Global cropping calendar based on VI	-	5min (~10km)	-	Kotsuki and Tanaka, 2015
FAO Country	Global administrative boundaries	-	5min (~10km)	-	FAO
DIVAGIS	Japanese administrative boundaries	-	-	-	Hijmans et al., 2005
MERIT DEM	Global elevation	m	15min (~30km), 1min (~2km)	-	Yamazaki et al., 2017
MERIT Hydro	Global hydrological parameters	e.g. m	15min (~30km), 1min (~2km)	-	Yamazaki et al., 2019

GSWP3: Global Soil Wetness Project Phase 3;W5E5: WATCH Forcing Data Methodology Applied to ERA5; ERA: ECMWF Re-Analysis; ECMWF: European Centre for Medium-Range Weather Forecasts; MIROC: Model for Interdisciplinary Research on Climate; ESM:Earth System Model; CHEM: Chemistry; CMIP: Coupled Model Intercomparison Project; GLCC: Global Land Cover Characterization; GTOPO: Global Topography; MIRCA: Monthly Irrigated and Rainfed Crop Areas; NDVI: Normalized Difference Vegetation Index; ECOCLIMAP: Ecosystem Climate Map; GLWD: Global Lakes and Wetlands Database; MODIS: Moderate Resolution Imaging Spectroradiometer; LAI: Leaf Area Index; SACRA: Satellite-based Crop Calendar for Agricultural Production Assessment; VI: Vegetation Index; FAO: Food and Agriculture Organization of the United Nations; GIS: Geographic Information System; MERIT: Multi-Error-Removed Improved-Terrain; DEM: Digital Elevation Model

4.4 Corporate Financial Datasets

To test the impact of the time-series flood predictions on corporate financial risk, I used the Nikkei 225 index, a stock market index for the Tokyo Stock Exchange. It is a price-weighted index, operating in Japanese Yen, and its component allocations are reviewed twice a year. In the current study, I used the 225 companies represented in the index as of December 2024. The index comprises 11 industry sectors, as described in Chapter 3. The rationale for choosing the Nikkei index sectors and corporations is based on the need to be able to compare the results of both chapters, the literature on flood impacts on Nikkei-listed Japanese companies (Fakhry et al., 2018) and the generally high levels of TCFD disclosures based on CDP data (Demers et al., 2024).

Corporate financial data (income statement and balance sheet) were obtained from Bloomberg Professional Services provided by Bloomberg, Orbis (Moody's, 2025), EDINET provided by the Financial Service Agency in Japan, and annual reports. Compustat Financials provided by S&P Global is used for identifying corporate GICS code. In terms of flood damage relationship between flood depth and ratio of asset damage, Huizinga et al. (2017) was used. In this study, the surveyed statistics by the MLIT in Japan was used (MLIT, 2023). Lastly, I used administrative boundaries from Runfola et al. (2020). Table 4.2 summarizes the input data used for financial risk assessment.

Table 4.2 Input Data for Financial Risk Assessment

Name	Description	Source/Provider
Bloomberg Professional Services	Sales Property, Plant, and Equipment	Bloomberg
Orbis	Sales Property, Plant, and Equipment Number of total corporate employee Number of employee at facilities Address of facilities	Moody's
Annual Reports	Number of total corporate employee	Public Companies
Compustat Financials	GICS code	S&P Global
Flood Damage Ratio	Relationship between flood depth and ratio of asset damage	Huizinga et al., 2017
Business Interrupted Days	Surveyed statistics between flood depth and business interrupted days	MILT, 2023
Administrative Boundaries	Boundaries at country and state levels	Runfola et al., 2020

4.5 Estimation Methodology

4.5.1 Integrated Hydrology-Financial Risk Analysis Approach

The methodological approach for assessing corporate financial flood impacts with hydrological models in the current study is shown in Figure 4.1. This study utilizes the RCP 8.5 scenario from the MIROC-ESM-CHEM model in the CMIP5 (Watanabe et al., 2011). This dataset was employed because it has been previously utilized in the Aqueduct Floods (Ward et al., 2020), which supports comparative analysis (Abe and Adriaens, 2025). The data usage period spans from 2006 to 2099, using daily data as a long-term dataset. This study used SiBUC (Tanaka, 2004) to compute daily runoff, which is then provided as input for CaMa-Flood (Yamazaki et al., 2011). The CaMa-Flood model was employed to simulate the depth of flood inundation. Using the flood inundation depth, the inundation depths for each return period of flood occurrences were calculated. By incorporating the globally-calculated flood inundation

depth for each return period as an input, the expected annual damage (EAD) due to property damage and business interruption loss (BIL) for each facility was estimated (Abe and Adriaens, 2025). The results are then sorted by region and industry to investigate the distinctions that exist across various regions and sectors.

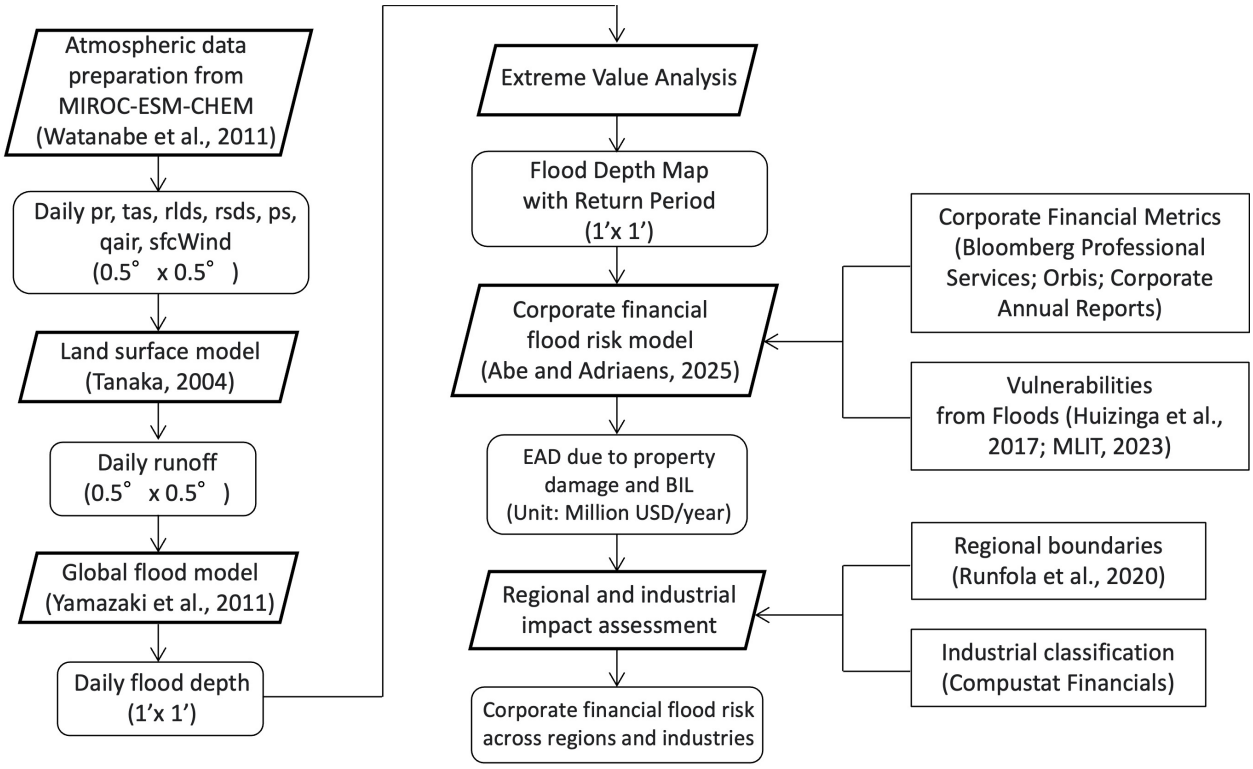


Figure 4.1 Approach and Information Flow for Assessment of Corporate Financial Flood Impacts

4.5.2 SiBUC Model Description

Simple Biosphere with Urban Canopy (SiBUC), a land surface model developed by Tanaka (2004), is based on the earlier Simple Biosphere (SiB) (Sellers et al., 1986) and SiB2 (Sellers et al., 1996) models, incorporating various processes: green areas, water bodies, and urban areas. This model has been widely applied across both regional and global scales (Kotsuki and Tanaka, 2013; Tinumbang et al., 2023; Touge et al., 2024; Sadyrov et al., 2025). Previous

research has involved the combination of SiBUC and CaMa-Flood through integrated modeling approaches (Kobayashi et al., 2015; Tasaka et al., 2022). The current study uses the SiBUC, which possesses a spatial resolution of 0.5° (~50km) and covers land regions globally. The computations were conducted hourly, producing daily output data. The runoff input for CaMa-Flood was calculated by aggregating the surface runoff and baseflow computed by SiBUC. This hydrological model can provide global analysis with various type of land use using remote sensing data, which is appropriate for calculating hydrological process for companies listed in Nikkei 225 which comprise over 18,000 facilities in all global regions.

4.5.3 CaMa-Flood Model Description

Catchment-based Macro-scale Floodplain (CaMa-Flood), a global flood model (GFM) developed by Yamazaki et al. (2011), incorporates the diffusive wave scheme for its computations. The CaMa-Flood model is widely used in evaluating the impacts of flood inundation associated with riverine flooding (Tanoue et al., 2020; Hirabayashi et al., 2021; Taguchi et al., 2022). In the current study, version 4.11 of the CaMa-Flood was used, and Multi-Error-Removed Improved-Terrain Digital Elevation Model (MERIT) DEM was used as the elevation data source (Yamazaki et al., 2017). Runoff computed by SiBUC was input at a spatial resolution 0.5° (~50km), with the output data was generated at 15-minute (~30km). Then, utilizing elevation data, the results were downscaled to a 1-minute (~2km) resolution. Hirabayashi et al. (2022) indicated that while the Aqueduct does not consider backwater effects, the CaMa-Flood incorporates the backwater process. The framework is suitable for evaluating flood depth at a global scale, aligning with the aims of the current analysis into geospatially-informed facility portfolios.

4.5.4 Verification Hydrological Model with Observed Data

The extent of flooding resulting from historical floods was computed with the SiBUC and CaMa-Flood models, and the validity of the hydrological framework was assessed against empirical data (Figure 4.2). The left figure shows the results on November 1, 2011, calculated through SiBUC and CaMa-Flood, employing GSWP3-W5E5 as the input information. The right figure shows the flooding that occurred on November 1, 2011, as observed by the MODIS sensor on NASA's Terra satellite (NASA, 2025). Based on visual observation, the figures demonstrate that the flooded regions were simulated with considerable agreement. It should be noted that the comparison of inundation maps for the validation of hydrological modeling approaches, as carried out in the current study, has also been conducted in other academic studies (Winsemius et al., 2013; Chono et al., 2018). For the purpose of cross-verification, the inundated region exceeding 1cm within the boundaries of Thailand (Runfola et al., 2020) was estimated to be about 65,825 km^2. This corresponds with the reported inundation of more than six million hectares (60,000km^2) within Thailand due to the 2011 flood, as reported by the World Bank (2012). Thus, it can be inferred that the simulation model demonstrates a reliable measure of accuracy.

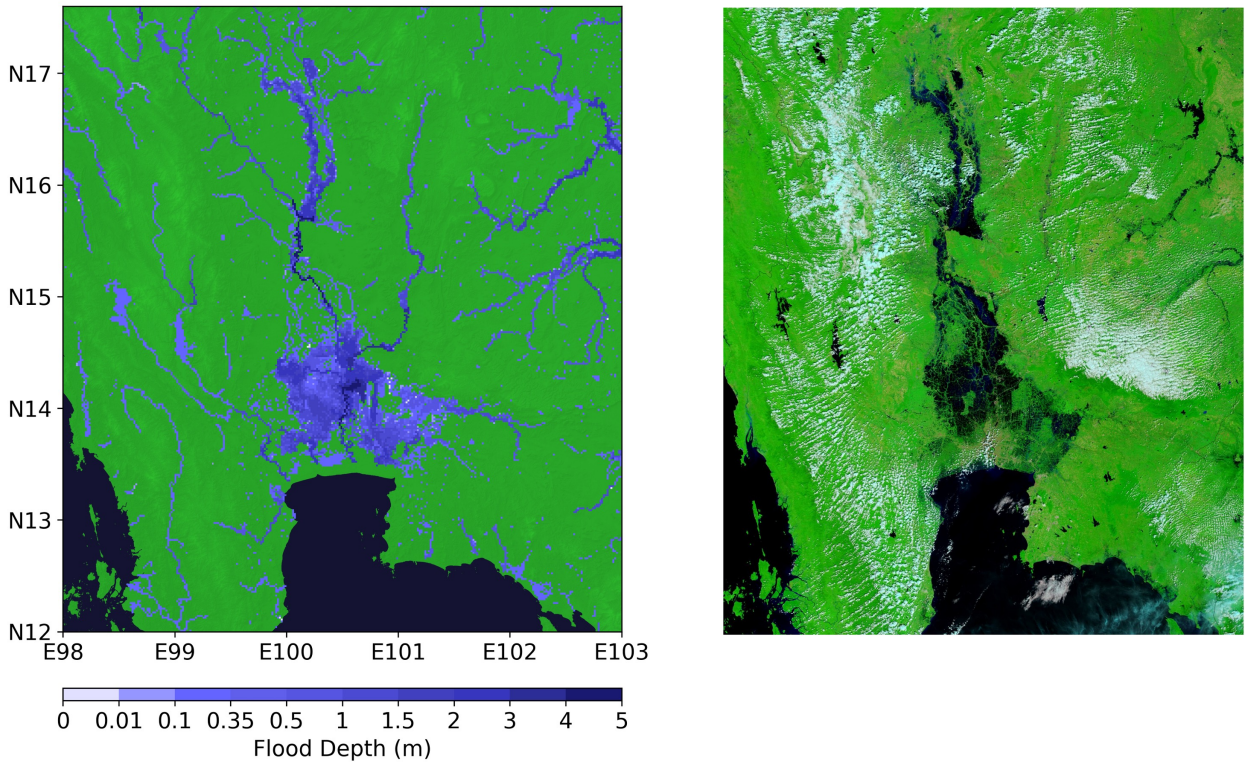


Figure 4.2 Comparison for flooded extension in Southeast Asia (Left: Calculated flooded extension for November 1, 2011; Right: Observed image captured by MODIS on NASA's Terra satellite on November 1, 2011)

4.5.5 Extreme Value Analysis (EVA)

EVA is a statistical method used to analyze and model the behavior of extreme or rare events within a dataset, such as flood depth predictions. The current study employed the L-moment approach (Hosking, 1990) to evaluate the flood depth at each return period. This method has previously been implemented using the outputs obtained by CaMa-Flood (Zhou et al., 2021; Kimura et al., 2023; Kita and Yamazaki, 2023). For the probability distribution function used to estimate parameters with the L-moment method, the Gumbel distribution was applied, as informed by the extant literature (Benito et al., 2021; Kimura et al., 2023; Kita and Yamazaki, 2023; Mishra et al., 2024). In this study, the annual maximum inundation depth for each grid was determined using a total of 21 years of data, which includes the specified year and the ten years

before and after to estimate the inundation depth across different return periods from 2020 to 2089. The classifications of return periods (2, 5, 10, 25, 50, 100, 250, 500, and 1,000-year) were aligned with those used in Aqueduct Floods (Ward et al., 2020). As indicated previously, I wanted to allow for direct comparison between time-granular financial analysis and the outputs reported by Abe and Adriaens (2025) in Chapter 2 and implemented on the Nikkei 225 Index in Chapter 3.

4.5.6 Comparison of Flooded Areas

A comparative analysis was conducted on the flooded areas computed globally through the combined application of SiBUC and CaMa-Flood models against the flooded areas derived from Aqueduct Floods datasets, categorized by depth (Table 4.3). For inundation depths between 0 and 1 meter, the Aqueduct Floods shows higher values; in contrast, for depths beyond 1 meter, the combination of SiBUC and CaMa-Flood produces higher values. This is likely due to the fact that Aqueduct Floods employs a kinematic wave scheme (Winsemius et al., 2013), while CaMa-Flood uses a diffusive wave scheme, which offers a superior representation of flooding dynamics (Yamazaki et al., 2011). In the case of kinematic wave analysis, water flow is mainly based on the digital elevation model (DEM) derived from the Shuttle Radar Topography Mission (SRTM) in Aqueduct Floods (Winsemius et al., 2013). However, Hirabayashi et al. (2022) argued that SRTM shows a stripe-type noise, and the flooded depth calculated by Aqueduct for the Mekong River basin is relatively smaller than other hydrological models, including CaMa-Flood. Winsemius et al. (2013) indicated that the result of inundation depth calculation is often underestimated, which may be because other flood processes aside from river flooding play a significant role, as well as the fact that SRTM data has a limited horizontal and vertical resolution and accuracy.

Table 4.3 Calculated Flood Area (GCM: MIROC-ESM-CHEM; Scenario: RCP8.5; Year: 2030; Return Period: 100-year; Type: River Flood; Region: Global)

		Area (km²)	
		Aqueduct Floods	SiBUC and CaMa-Flood
Flood depth (d; unit: m)	d=0	120,795,456	112,998,727
	0<d<1	8,005,683	6,519,617
	1≤d<2	848,507	3,020,484
	2≤d<3	305,474	2,170,606
	3≤d<4	145,853	1,532,944
	4≤d<5	80,395	1,057,842
	5≤d<6	38,848	771,100
	6≤d	66,800	2,524,340
Land		130,287,016	130,595,659
Sea		380,897,209	380,564,896
Total		511,184,225	511,160,556

4.6 Results

4.6.1 Regional Analysis

In this section, I analyze the regional characteristics by aggregating the facility-level EADs for the 225 companies in the Nikkei 225 by region. Regions are represented as states in the US or Australia, provinces in Canada, federative units (states and federal district) in Brazil and Europe, which is indicated as ADM1 (Runfola et al., 2020). Figure 4.3 presents the EAD calculations aggregated at this unit level, separated as the EAD due to property damage in 2030 (a), the EAD due to Business Interruption Loss (BIL) in 2030 (b), the ratio of EAD due to property damage between 2030 and 2080 (c), and the ratio of EAD due to BIL between 2030 and 2080 (d). As shown in Equation 4.1, the ratios in Figures c and d are calculated as the ratio of the aggregated EADs at each regional state level. For the calculation of future EAD values,

corporate sales and tangible fixed assets (PP&E) are fixed using the 10-year average from 2014 to 2023, hence, disregarding any changes due to company growth. This approach is intended to isolate the impact of climate change and is similar to the method used by Hirabayashi et al. (2013) and implemented by Abe and Adriaens (2025). From Figures a and b, it can be observed that companies with locations in Texas in the United States, the United Kingdom, and eastern Australia are projected to exhibit the highest financial risk exposures (EAD values) by 2030. Furthermore, Figures c and d indicate that future risk values by 2080 are increasing in parts of the United States, South America, East Asia, and southeastern Australia. Companies with facilities in these regions are likely to have a greater urgency to take measures to mitigate financial risk exposures and report these risks under TCFD or IFRS-S2.

Since regional and state-aggregated financial risks from business interruption and property losses are the result of the facilities sited in these locations, Table 4.4 shows aggregated EAD at each region and the percentage. Total EAD is 22.4 billion USD which is 2.7 times higher than the total EAD calculated based on the Aqueduct Floods in Chapter 3. The significant portion of the losses was incurred by facilities situated in Asia, with Europe, collectively representing about 88% of the total losses. When larger facilities with higher output productivity are exposed to flood risk, they will incur higher EAD values both on business interruption and property damage. Therefore, the number of facilities alone does not fully reflect the per-facility risk. By comparing the EAD 2080:2030 ratio, a decrease of about 20% on average is predicted in Africa. Also, Central and South America will see a decline of nearly 5%, with North America facing an anticipated reduction of around 3%, while the estimated increase of all regions is about 7% on average. The estimation for EAD in Asia in 2080 is expected to show an increase of

around 12% compared to the estimates for 2030. These results may serve as useful reference points for companies when conducting cost-benefit analyses of risk reduction measures.

$$Change\ in\ EAD_{2030,2080,k} = \frac{\sum_i EAD_{2080,k,i} - \sum_i EAD_{2030,k,i}}{\sum_i EAD_{2030,k,i}} \times 100 \quad (4.1)$$

where EAD is expected annual damage, i is facility, and k is region.

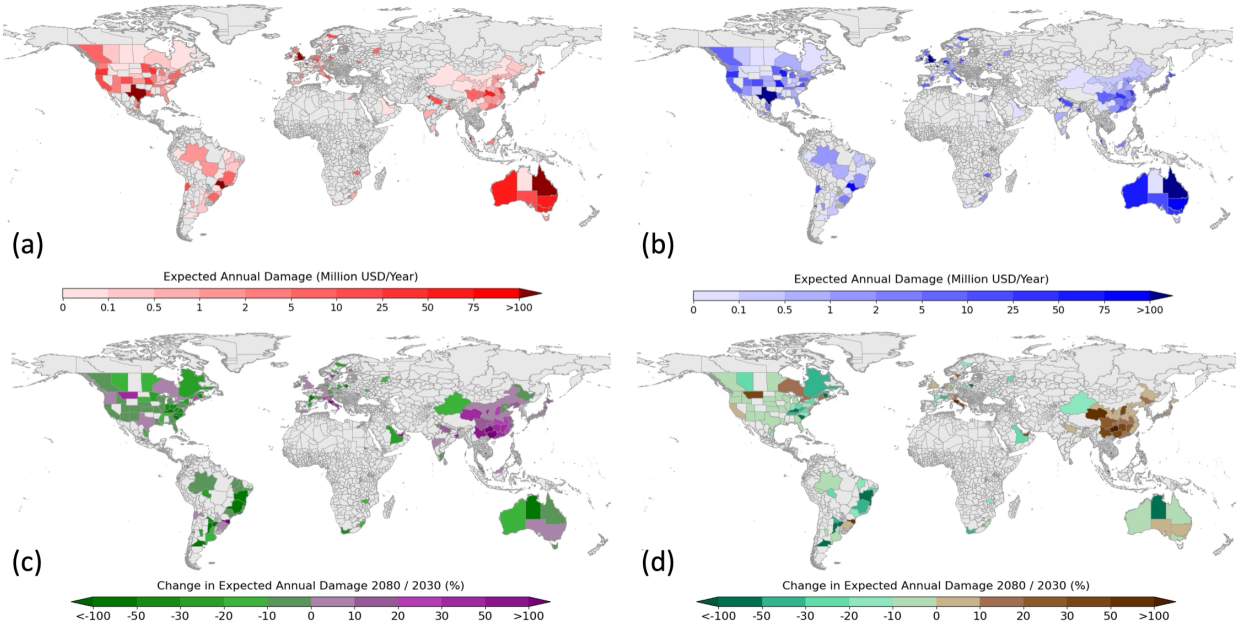


Figure 4.3 Global Map for EAD due to Property Damage and BIL under RCP 8.5 (a: EAD due to Property Damage in 2030; b: EAD due to BIL in 2030; c: Ratio of EAD due to Property Damage between 2030 and 2080; d: Ratio of EAD due to BIL between 2030 and 2080)

Table 4.4 Summary Table for Regional Analysis (Year: 2030; Scenario: RCP 8.5, GCM: MIROC-ESM-CHEM)

Region	Aggregated Expected Annual Damage (Million USD)					
	PD + BIL	%	PD	%	BIL	%
Europe	7,214	32	3,800	29	3,414	37
North America	914	4	470	4	444	5
Central & South America	580	3	349	3	231	3
Asia	12,435	56	7,971	60	4,464	48
Africa	251	1	96	1	155	2
Oceania	1,008	5	491	4	517	6
All regions	22,401	100	13,176	100	9,225	100

4.6.2 Time-series Analysis for Individual Corporations

This section describes the time-series results for three anonymized companies from different industry sectors. Table 4.5 presents, for each company, the total number of facilities, the number of facilities at risk, the regional breakdown of those at-risk facilities, and the average PP&E and sales of the at-risk facilities. Company 1 has a relatively large number of facilities, 18% of which are exposed to flood risk. Among the at-risk facilities, 69% are located in Asia. Company 2 has 19 out of 126 facilities exposed to flood risk, with 74% of those located in Asia. Company 3 has 11 out of 28 facilities (39%) exposed to flood risk. Among these at-risk facilities, 36% (4 facilities) are located in Oceania, followed by 27% (3 facilities) in Europe. In terms of average PP&E and sales among the at-risk facilities, Company 3 ranks the highest, followed by Company 1 and then Company 2.

For each company, the annual financial impacts of flooding from 2020 to 2089 are calculated (Figure 4.4). The black dashed line represents the EAD due to property damage, while the solid black line represents the total EAD, combining both property damage and BIL. For Figure a, it can be observed that the EAD shows an overall increasing trend, particularly in the Asia region from a regional perspective. For Company 1, given that 69% of its facilities are

located in Asia and that flood risk in the region is on the rise, it is considered necessary to prioritize the implementation of flood risk mitigation measures for its facilities in Asia.

In contrast, Figure b shows a decreasing trend in EAD. Regionally, values in Central and South America are declining, while other regions remain relatively stable. It was found that there are cases, such as Company 2, where the financial impacts of flooding are expected to decrease over time in the regions. Hence, risk mitigation measures are still necessary, and the scale of such measures is aligned with the projected future risk. Corporate strategic decision-making focuses on risk prioritization of its facility portfolio of assets as measured using return (sales) on the fixed income investment (PP&E) in these assets. Shifts in regional facility portfolio risk allocation should be taken into account in assessing production capacities and supply chain decisions (Ghadge et al., 2020).

As for Figure c, it is expected that the EAD will peak between 2030 and 2060, followed by a slight decline thereafter. Regionally, fluctuations are observed in Oceania, while other regions remain relatively stable. For Company 3, 36% of its facilities exposed to flood-related financial risk are located in Oceania (mainly Australia), and since the risk for these facilities is projected to peak between 2030 and 2060, future decisions on flood risk countermeasures may be necessary (Leitold et al., 2021). Although the risk remains higher than in 2020 even after 2060, a declining trend is observed post-peak. Therefore, it may be more effective to implement a combination of structural and non-structural measures—such as hardening facilities and increasing insurance coverage for flood damage during the 2030–2060 period (Du et al., 2024).

Table 4.5 Summary Information for the Anonymous Corporations in the Nikkei 225 Index Selected for Analysis

Company	Number of All Facilities	Number of Facilities at Risk	Number of Facilities at Risk						Averaged PP&E for Facilities at Risk (Million USD)	Averaged Sales for Facilities at Risk (Million USD)
			Europe	North America	Central and South America	Asia	Africa	Oceania		
1	218	39	6	2	4	27	0	0	23.92	83.03
2	126	19	1	1	1	14	0	2	4.72	10.16
3	28	11	3	0	1	2	1	4	118.77	316.16

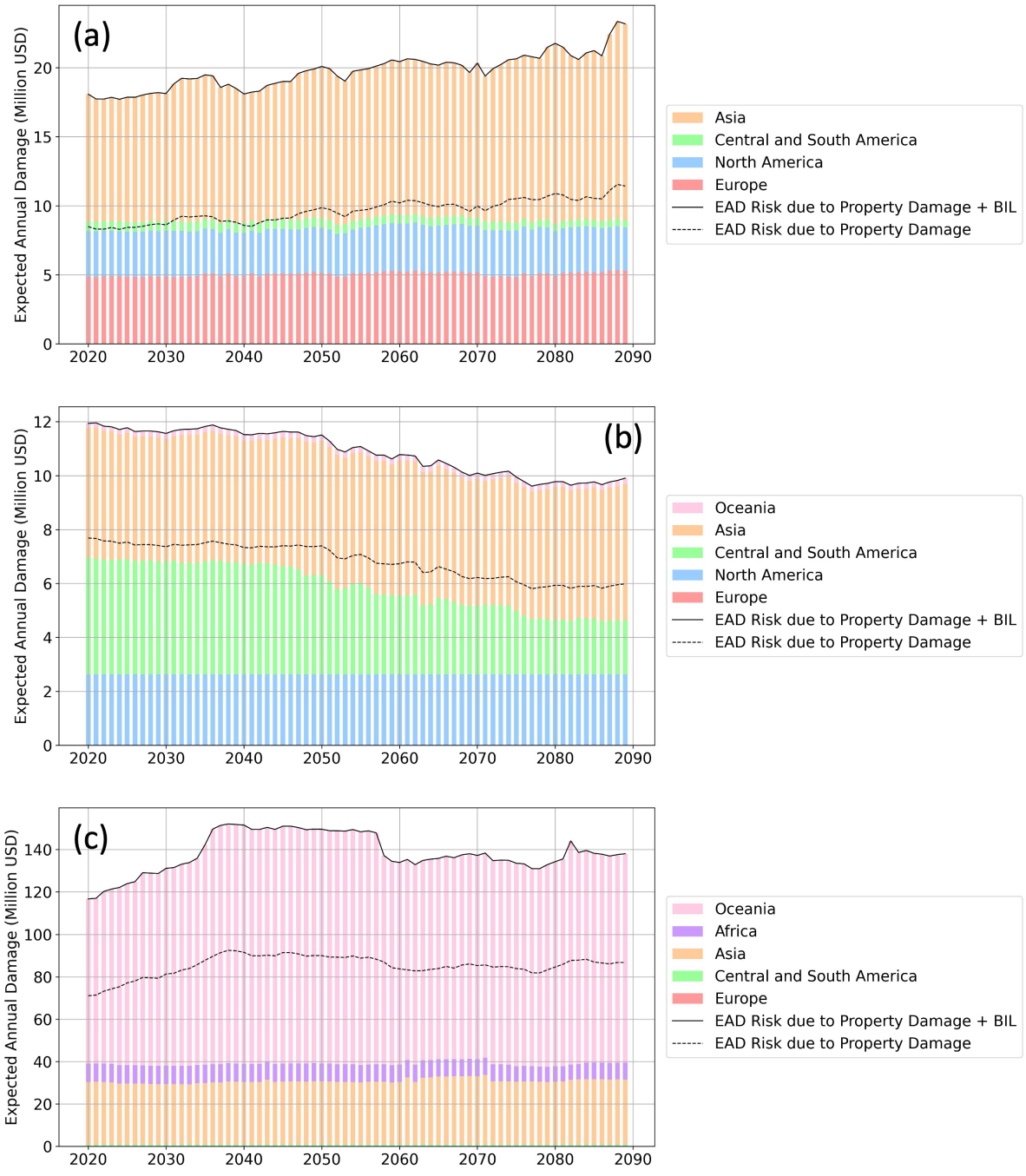


Figure 4.4 Time-series Analysis for Anonymous Corporations in the Nikkei 225 index (a: company 1; b: company 2; c: company 3)

4.6.3 Time-series Analysis by Regions

I analyze the characteristics such as the amount and rate of change in depth of flooding and associated EAD impacts over time by aggregating the results calculated for the 225 companies in the Nikkei 225 by regional units. The units comprise 66% of facilities distributed across Asia, approximately 15% located in North America and nearly 10% in Europe. Figure 4.5 presents the aggregated EAD values for six regions—Asia, Europe, Central and South America, North America, Oceania, and Africa—from 2020 to 2089, with each year's value indexed to the baseline year of 2020. The EAD due to property damage (a), the EAD due to BIL (b), and the total EAD (property damage + BIL) (c) are shown separately. As with previous analyses, corporate growth rates over time are not taken into account, so the figures reflect how much of the financial impact is attributable to climate change and increasing flood risk only. The regions are divided into two groups: those with an increasing trend in EAD (Oceania, Asia, and Europe) and those with a decreasing trend (Central and South America, North America, and Africa). In particular, for Oceania, the EAD value in 2089 is projected to increase by more than 20% due to property damage and by more than 10% due to BIL, compared to 2020, with 269 out of the 610 facilities located in Oceania (44%) being exposed to financial risk (Table 4.6). This highlights the importance of climate change affecting the Pacific Ocean-influence weather patterns affecting Australia, New Zealand, and other islands within the region. This proportion is higher compared to other regions, indicating that Nikkei 225 companies tend to have facilities in this region which is characterized by relatively high flood risk (Campbell, 2023). On the other hand, for Africa, the EAD from flood risk is projected to decrease by more than 15% due to property damage and by more than 20% due to BIL. On average across all regions, the EAD value in 2089

is projected to increase by approximately 10% or more due to property damage and by a few percent due to BIL, compared to 2020.

This regional trend in financial risk exposures for corporate facilities can be validated by findings from existing studies from climate change and flood models, thereby enhancing the credibility of the results. First, regarding Asia, many previous studies have indicated an increase in future flood risk. For example, Arnell and Gosling (2016) show that while there is significant variation depending on the region and climate models used, Asia is projected to experience the most severe impacts—an observation that aligns with the results of this study (Figures 4.3 and 4.5). In addition, Winsemius et al. (2016) conducted a socioeconomic impact assessment of flood risk and found that severe flood risks are expected to increase in Southeast Asia. Regarding Europe, Dottori et al. (2023) estimate that flood risk from rivers will increase due to global warming, which is consistent with the direction of this study's findings. Furthermore, Alfieri et al. (2015) assessed the socioeconomic impacts of floods under climate change and projected a 220% increase in flood risk in Europe. Although the scope of their study differs from this one, making a direct comparison difficult, they similarly indicate a significant increase in flood risk.

Regarding the United States, van Dusen et al. (2020) reported that flood risk is projected to decrease in the southwestern region, while it is expected to increase in the northern and eastern regions during certain seasons. This is generally consistent with Figure 4.3 of this study, which also indicates a decrease in flood risk due to property damage in the southwestern U.S. Although it also shows that flood risk due to BIL may increase in some parts of the southwest, the overall trend aligns with previous findings. On the other hand, some studies report an increase in flood risk for the United States as a whole; however, since these are national-level analyses, they may not capture regional variations in flood exposure (Alfieri et al., 2017). As for

Africa, Pillay and Simatele (2024) indicate a decreasing trend in flood risk, which aligns with the results of this study. Alfieri et al. (2017) also suggest that while flood risk tends to decrease in West Africa, it is expected to increase in some parts of Southern Africa, indicating regional differences within the continent. It should be noted that the number of facilities owned by Nikkei 225 companies in Africa is relatively small compared to other continents. Therefore, to conduct a more robust discussion, it would be preferable to analyze companies that have facilities in specific regions within Africa (Table 4.6).

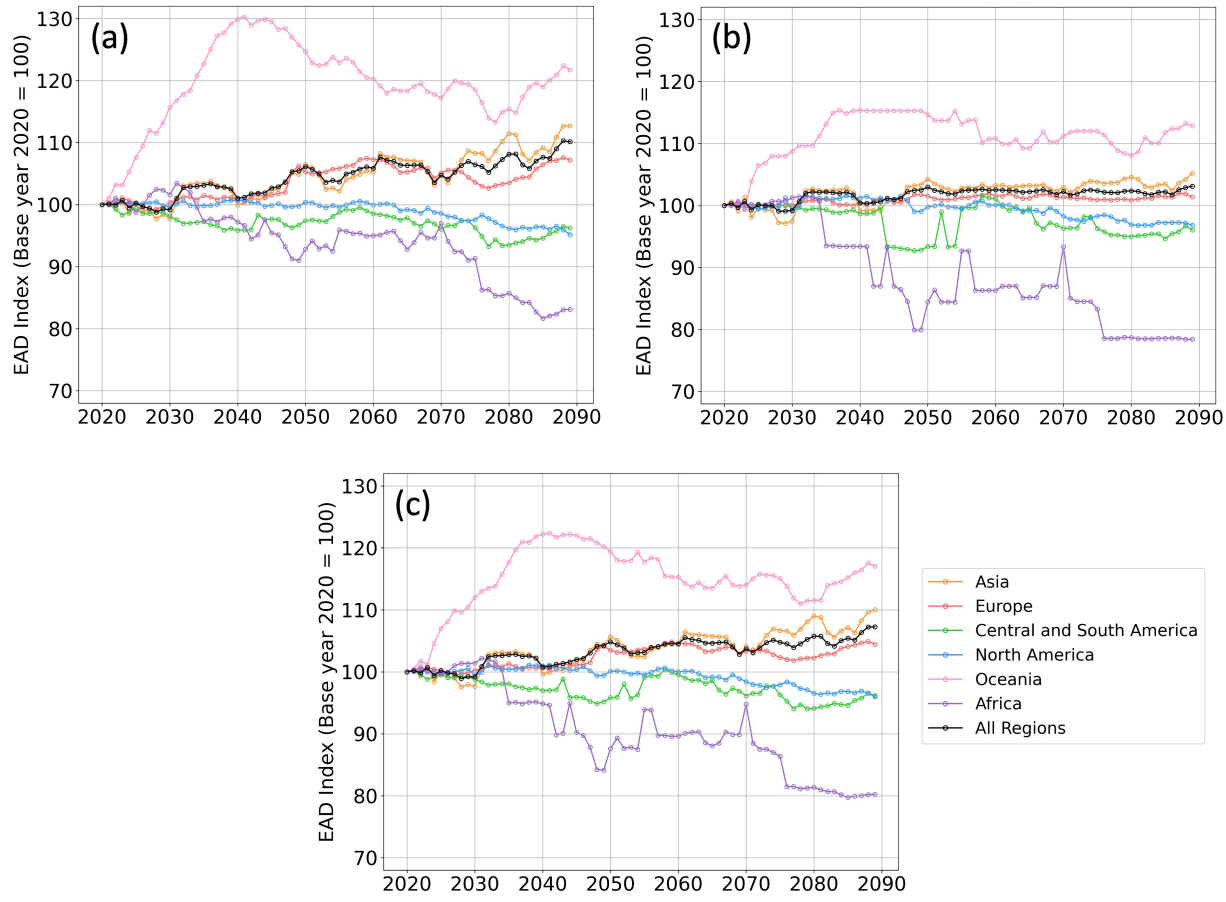


Figure 4.5 Time-series by regions (a: EAD due to property damage; b: EAD due to BIL; c: EAD due to property damage and BIL)

Table 4.6 Summary Information for 225 Corporations in the Nikkei 225 index by regions

Region	Number of All Facilities	%	Number of Facilities at Risk	%	Averaged PP&E for Facilities at Risk (Million USD)	Averaged Sales for Facilities at Risk (Million USD)
Europe	1,912	10	833	19	43.43	122.66
North America	2,824	15	528	12	14.11	42.53
Central and South America	817	4	205	5	7.78	29.90
Asia	12,306	66	2,505	57	60.60	147.70
Africa	169	1	32	1	65.49	395.34
Oceania	610	3	269	6	13.24	47.13
NoCountry	19	0	0	0		
Total	18,657	100	4,372	100		

4.6.4 Time-series Analysis by Industry Sector

The characteristics of EAD exposure was analyzed by aggregating the results for the 225 companies in the Nikkei 225 by industry sector. Figure 4.6 presents the aggregated EAD values from 2020 to 2089 for each of the 11 sectors: Consumer Staples, Energy, Industrials, Consumer Discretionary, Real Estate, Health Care, Communication Services, Materials, Information Technology, Financials, and Utilities. The GICS sector classification as of January 2025 was obtained from Compustat and was used in this analysis. The aggregate facilities associated with each sector and the average PP&E and sales of the facilities exposed to risk are summarized in Table 4.7. According to Table 4.7, among the facilities exposed to financial risk due to flooding, the Industrials sector accounts for the largest share at 37%, followed by the Consumer Discretionary sector at 19%. Figure 4.6 presents the EAD Index, which shows the time-series changes through 2089, using 2020 as the baseline (=100). The baseline year of 2020 was selected based on the calculation period from 2006 to 2099, the use of a 10-year window before and after each year in the Extreme Value Analysis for calculating probabilistic flood years, and the decision to set time points at 10-year intervals. As with the regional analysis, (a) shows the EAD

due to property damage, (b) shows the EAD due to BIL, and (c) shows the total EAD (property damage + BIL). Corporate growth rates are not considered, as in previous analyses, so the trends reflect how financial impacts to the companies and the sectors they represent change solely due to the impact of flooding due to climate change.

The results indicate that while some sectors show EAD values that fall below the 2020 baseline at certain points between 2020 and 2089, particularly for the Real Estate sector, the comparison between 2089 and 2020 shows that EAD increases across all industry sectors. According to Table 4.8, out of 301 facilities in the Real Estate sector, 49 facilities (16%) are exposed to flood risk, particularly from business interruption losses. Among these at-risk facilities, 18 (37%) are located in Oceania and 25 (51%) are located in Asia. Existing studies have reported both increases and decreases in flood risk and flood intensity depending on the climate model and region, such as in Oceania (Xuan et al., 2020) and North America (van Dusen et al., 2020). Therefore, it is reasonable to attribute these differences to the geographical distribution of the facilities.

For the Energy sector, out of 218 facilities, 33 (15%) are exposed to flood risk. Among these, 19 facilities (58%) are in Asia, 6 (18%) in Oceania, 4 (12%) in Central and South America, and 3 (9%) in Europe. This geographical distribution closely resembles the pattern of EAD due to property damage by region shown in Figure 4.5. In terms of short- to long-term time-series fluctuations, the Consumer Discretionary sector, in particular, the EAD due to property damage peaks in 2088, and by 2089, the EAD value increases by more than 20% compared to 2020. The EAD due to property damage in the Financials sector indicates some fluctuations, but by 2089, it increases by more than 20% compared to 2020. For the Energy sector, the EAD due to property damage reaches an increase of over 10% compared to 2020

around 2035, earlier than in any other sector. After that, the Energy sector presents some fluctuations and an increase of approximately 15% by 2089 compared to 2020. For the Real Estate and Materials sectors, the total EAD due to property damage and BIL indicates a decline between approximately 2066 and 2071. However, after that period, the total EAD in both the Real Estate and Materials sectors shows an upward trend. By 2089, the total EAD increases by approximately 18% in the Real Estate sector and by about 14% in the Materials sector, compared to 2020.

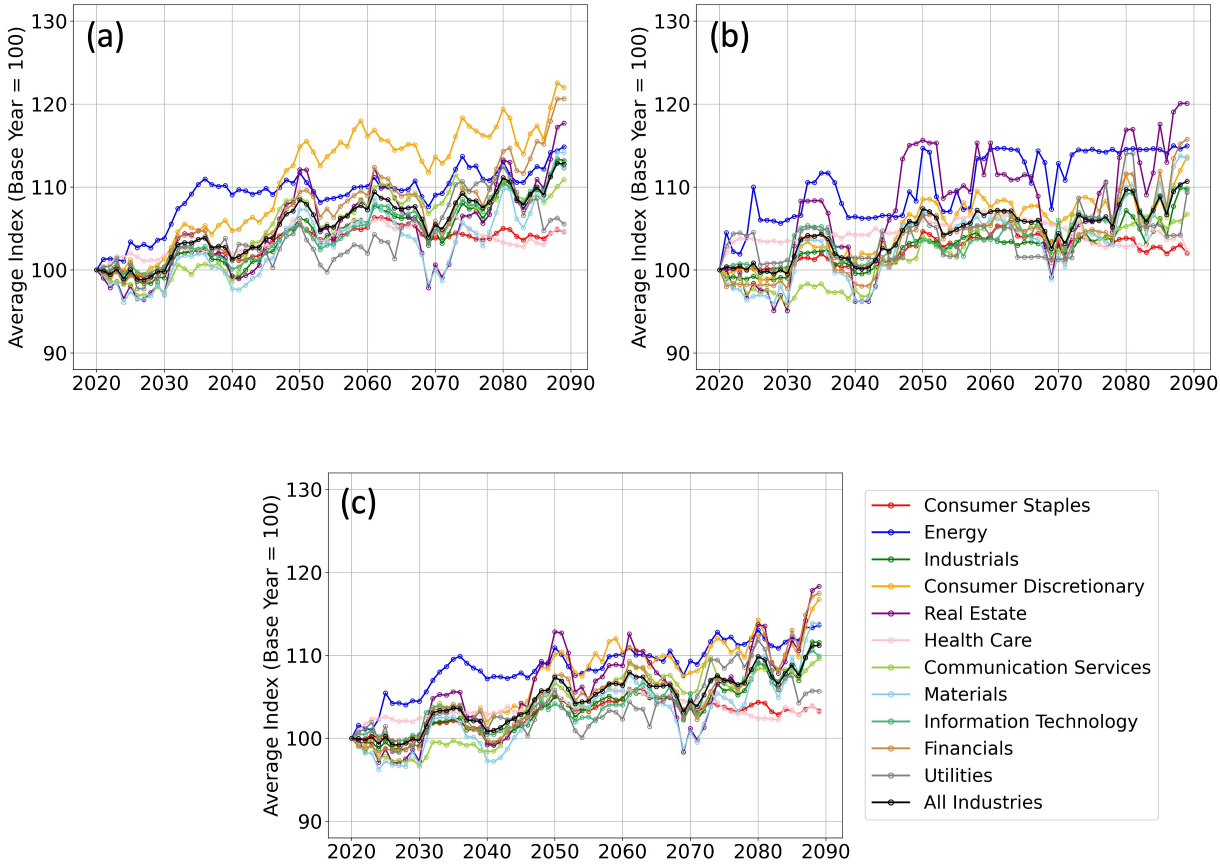


Figure 4.6 Time-series by industry where (a) is EAD due to property damage, (b) is EAD due to BIL, and (c) represents total EAD (property damage + BIL)

Table 4.7 Summary Information for 225 Corporations in the Nikkei 225 index by industry sector

Industry	Number of All Facilities	%	Number of Facilities at Risk	%	Averaged PP&E for Facilities at Risk (Million USD)	Averaged Sales for Facilities at Risk (Million USD)
Health Care	425	2	101	2	48.66	172.39
Financials	1,190	6	274	6	34.48	144.23
Energy	218	1	33	1	45.86	185.57
Information Technology	1,778	10	444	10	31.41	112.06
Materials	1,944	10	362	8	36.34	74.85
Communication Services	1,196	6	206	5	87.02	158.12
Industrials	6,765	36	1,611	37	26.55	81.23
Utilities	170	1	59	1	360.55	276.74
Consumer Discretionary	3,273	18	829	19	56.92	203.84
Real Estate	301	2	49	1	458.76	274.78
Consumer Staples	1,397	7	404	9	19.95	59.33
Total	18,657	100	4,372	100		

Table 4.8 Summary Information for 225 Corporations in the Nikkei 225 index by industry sector

Industry	Number of All Facilities	Number of Facilities at Risk	Number of Facilities at Risk											
			Europe	%	North America	%	Central and South America	%	Asia	%	Africa	%	Oceania	%
Health Care	425	101	25	25	19	19	9	9	47	47	1	1	0	0
Financials	1,190	274	79	29	30	11	4	1	120	44	1	0	40	15
Energy	218	33	3	9	1	3	4	12	19	58	0	0	6	18
Information Technology	1,778	444	92	21	78	18	28	6	213	48	1	0	32	7
Materials	1,944	362	43	12	36	10	11	3	258	71	0	0	14	4
Communication Services	1,196	206	39	19	64	31	13	6	62	30	1	0	27	13
Industrials	6,765	1,611	428	27	180	11	77	5	835	52	22	1	69	4
Utilities	170	59	2	3	14	24	0	0	40	68	0	0	3	5
Consumer Discretionary	3,273	829	82	10	88	11	48	6	592	71	2	0	17	2
Real Estate	301	49	2	4	4	8	0	0	25	51	0	0	18	37
Consumer Staples	1,397	404	38	9	14	3	11	3	294	73	4	1	43	11
Total	18,657	4,372	833	19	528	12	205	5	2,505	57	32	1	269	6

Note: Percentages (%) represent the share relative to 100% of the facilities at risk within the respective industry.

4.7 Conclusions

In this study, global, regionalized, and location-specific flood depths were calculated using land surface and river flood models based on projections from a global climate model.

Probabilistic floods were then estimated using extreme value analysis to generate time-series data for each probability-based flood event. Using corporate facility information, a financial impact assessment of flooding was conducted for the 225 companies in the benchmark Nikkei 225 Index. By examining the time-series changes in EAD by region for each company, the analysis revealed that the regions vulnerable to flood risk vary depending on the company.

Flood-related financial impact risks were also calculated over time for individual companies in the Nikkei 225. The results revealed that, due to the geographical distribution of facilities owned by companies and region-specific changes in weather patterns caused by climate change, the nature of flood risk varies by company. Some companies are projected to experience an increase in flood-related financial risk, while others may see a decrease. In some cases, the risk peaks between 2030 and 2060, then slightly declines, yet still remains higher in 2089 compared to 2020. These findings indicate that the way flood risk evolves over time differs significantly across companies.

Time-series analyses were also conducted by categorizing the facilities of Nikkei 225 companies by region and by industry sector assignment. The trend of increasing flood risk in regions such as Asia and Europe was found to be generally consistent with existing studies on the frequency of floods caused by climate change. On the other hand, in regions such as Oceania, North America, and Africa, flood risk appears to be unevenly distributed depending on finer regional characteristics when compared to data at the national level. Moreover, since existing studies show differing views for these regions, we acknowledge that the trends observed in this study may not fully capture the complexities. Further multifaceted analyses, including improvements in climate models and assessments involving other companies, will be necessary. Regarding industry sectors, the observed trends are also likely influenced by the geographical

distribution of facilities. However, since the impact of flooding—particularly inundation—may vary depending on the nature of the industry, using only the type of average impact functions applied in this study may not fully capture sector-specific differences.

The following four limitations of this analytical approach need emphasizing. First, the resolution of the GCM used in the current analysis is insufficient for facility location-specific assessment of financial risk. While GCMs have achieved progress in predicting climate changes between present and future conditions at a fairly granular level, they are still limited in their ability to simulate phenomena such as typhoon formation and localized heavy rainfall that cause flooding. Therefore, challenges remain in their application to flood analysis. The TCFD guidelines recommend using the latest available projections, so it is expected that these limitations are understood in the disclosures and that utilizing the most up-to-date climate projections meets the intent of regulations. Second, the analysis does not account for factors such as temporal change in company size, as measured using fixed asset investment and revenue. For growing companies, future revenues and annual investment in capital stock may significantly affect the results and cannot be ignored. Therefore, incorporating the revenue growth rate of individual companies would make the analysis more realistic. Third, the flood damage functions and the number of business interruption days used in this study were assumed based on values from the literature or surveys. For example, in cases where the first floor of a facility is a waterproofed parking area and critical production activities take place on the second floor, it is entirely possible that no facility damage or business interruption would occur unless the second floor is flooded. Therefore, the damage functions applicable to each company may differ in shape. To address this, each company should analyze its own facilities and past disaster records and set appropriate function values, which would enable a more accurate assessment of the

financial impacts of flooding as I discussed in detail in the Chapter 2 model verification with disclosed corporate data. Lastly, even though regional analysis of facilities was conducted for financial risk estimation purposes, no attempts were made to include autocorrelation of spatial flood events and their impact on flood depth and ensuing EAD risk.

It is hoped that, through future discussions with various stakeholders, these results will be updated and will contribute to improving corporate understanding of financial risk and support the implementation of risk reduction measures.

Chapter 5 Conclusions and Future Recommendations

5.1 Conclusions and Contributions

The modeling approach employed in this study provides novel insights into a facility-level analysis and aggregation of global geospatial financial impacts of floods on corporations. These insights contribute to closing the financial gap in corporate transition to address climate change by supporting and informing strategies to reduce such risks.

The integration approach of hydrological model outputs and facility-level corporate financial data presented in Chapter 2 demonstrated the feasibility of quantifying corporate risks from floods, including property damage and business interruption losses. This methodology was developed and tested using four listed Japanese companies using comparative analysis of model predictions and corporate disclosures, to support the credibility of the approach. Future directions include reducing the uncertainties associated with the data and calculation methods used. For example, conducting calculations using hydrological models, such as those presented in Chapter 4, would allow for the use of spatial higher-resolution and enable analysis of model uncertainty through comparisons across multiple models. Future work may include the integration of spatial dependences of inundation depths for each grid cell impacting regional proximity of facilities, since spatial dependence of extreme hazards on different facilities was observed in flood risk analysis (Brunner et al., 2019; Quinn et al., 2019; Koh et al. 2025).

In order to improve the accuracy of the method, incorporation of more detailed facility-specific financial information is significant. Since individual corporate facilities are private, the disclosed information is limited to location, employee size, type of facility (production, R&D,

administrative), as well as revenue information for a fraction of firms. The method development in Chapter 2 describes the use of proxy information and imputation to generate a complete dataset for my analysis. I am aware of the limitations of this approach and foresee future opportunities for data improvement using A.I. approaches to limit the under- and over-estimates on my estimates of EAD values for property damage and business interruption. Nevertheless, I quantified and described the uncertainties in my estimates, based on the facilities that are exposed to flood risk depth of inundation, including the financial data limitations and geographic delineation of facilities using the Aqueduct Floods, and the geospatially diverse damage conversion curves approach widely used and referred to in the literature. This allowed me to explore an attempt to apply this approach to a wide range of companies.

In Chapter 3, the proposed methodology was applied to all 225 companies listed in the benchmark Nikkei 225 Index, revealing regional and industry sector characteristics that affect the EAD estimates by company. Recall that the current model aggregates EAD risks for property damage and business interruption at the facility scale. Given the need to develop a database for over 18,000 facilities across 225 companies, in different climate and flood regimes, there is considerable error propagation to consider and quantify in an uncertainty framework. This allowed us to understand sector and regional- (or state-) based attributes of the corporate universe that allows me to understand systemic risks to the broader economy. Given the interest of investors, asset managers and banks to understand systemic and idiosyncratic risks in portfolios and benchmark indices, these data and estimates have the potential to inform risk pricing and financial risk management. While individual risks were quantified, the weighted risks to a portfolio or sector requires time series analysis and incorporation of allocation weights of the index components. Given that indexes and portfolios are weight-adjusted often twice a

year, this analysis and potential forecasting presents a major challenge. Enhancing spatial and temporal resolution remains a challenge as well; however, an attempt to improve temporal resolution of hydrological predictions was pursued next.

In Chapter 4, hydrological modeling based on climate model data was used to estimate the annual financial impacts of floods on corporations, thereby revealing flood-related financial risks at a finer temporal scale. This approach was necessary, since corporate financial disclosures are required and available at a quarterly and annual frequency, strategic decisions are based on financial risk impacts to earnings (net income) in fairly short time frames, and risk transfer decisions through insurance are priced on at most a yearly basis. Annual estimates of flood risk resulting from integrating climate models with the CaMa-flood model allowed to quantify EAD exposure associated with property damage and business interruption thus providing valuable information for corporate climate risk disclosure in line with voluntary TCFD expectations, and mandatory IFRS S2 accounting requirements, as well as for cost-benefit analyses of risk reduction measures. The results showed significant granular differences in regional and sector flood risks over time, with the energy sector being most exposed. It should be noted that I held revenues and investment in fixed assets constant to isolate the effect of climate change projections. A future direction is to incorporate revenue growth models and fixed asset investment trends in the financial model, since the expectation is that EAD as estimated in my current chapter likely underestimates future risks. This can be further enhanced by utilizing CMIP 6 and updated information from the CMIP 7 climate projections expected in the future.

The insights gained from the application of the methodology developed in this dissertation provide a pathway for corporations to respond to climate risks. As climate risks become increasingly severe and sectors respond differently to mitigate their facility portfolio

exposures, quantitative uncertainty analysis of facility risk ranking and financial impact are essential to accelerate disaster-resilient, resilient, and sustainable corporate climate transition.

5.2 Future Research Recommendations

Several opportunities for future work have been briefly highlighted in section 5.1. In addition, the following future recommendations warrant further exploration to extend the applications and implications of my work: (1) Further study on uncertainty propagation for assessing corporate financial flood risk, (2) Supply chain risk estimates from floods, and (3) Flood risk transfer through insurance. First, in risk analysis, understanding and reducing uncertainty is critically important. For example, one approach is to use various flood damage curves (e.g., from the US Army Corps of Engineers and the Federal Emergency Management Agency, FEMA, etc.) and interpret the range of these curves in uncertainty quantification, thereby incorporating variability into the calculation of risk estimates. Xu et al. (2023), for instance, assess property damage using multiple damage curves. Similarly, for the Business Interruption Loss (BIL) relationship values provided by MLIT, if alternative curves can be identified, it would be possible to conduct an uncertainty analysis using a range of values. In addition, the MLIT function simplifies the average number of business disruption days by inundation depth (MLIT, 2023). However, since there remains uncertainty in the rehabilitation process of affected facilities, it is also feasible to analyze the impact of continuous facility operation by assuming a rehabilitation curve. Yang et al. (2015) and others have modeled the rehabilitation process of damaged facilities using probabilistic models and have conducted analyses that take into account the recovery of affected facilities.

In terms of spatial correlation among facilities, appropriate evaluation with auto-correlation observed in each grid cell for flooded depth can be significant for flood risk analysis (Brunner et al., 2019; Quinn et al., 2019). The present study assumes spatial independence of facilities across the same or adjacent hazard grid scale, yet this simplification can significantly distort risk estimates, particularly in the upper tail of the distribution where extreme losses occur. In other words, I did not conduct any explicit uncertainty analysis on the spatial-dependence assumption, as suggested by the extant literatures. For instance, Nguyen et al. (2020) highlight that ignoring spatial tail dependence can lead to serious underestimation of national and continental flood risk. Duha et al. (2020) similarly demonstrate how different assumptions regarding spatial dependence can meaningfully alter large-scale risk estimates and stress the need to represent spatial correlations in both flood peaks and damage. Falter et al. (2015) further illustrate that hydrologic modeling which respects spatial heterogeneity and correlation across catchments leads to more realistic flood scenarios than traditional models assuming homogenous return periods. Moreover, Brunner et al. (2019), Quinn et al. (2019), and Koh et al. (2025) observed that extreme hazard correlations among facilities are non-negligible and can significantly affect regional flood impact assessments. Therefore, future research should incorporate spatial dependence structures, such as inundation depth autocorrelations across grid cells, into financial flood risk models to better reflect the clustered nature of extreme events. This would enhance the robustness and realism of corporate financial flood risk assessments across sectors and regions.

Second, the assessment of corporate supply chain risks caused by floods is a key area for future research. While my dissertation analyzed the impacts of floods on fixed assets and business interruption in terms of lost revenue and property damage, in reality, supply chains may

be disrupted when multiple facilities are affected by flooding, potentially causing compounded operational issues across multiple sites (Haraguchi and Lall, 2015). This is often referred to as systemic (as opposed to systematic) risk, whereby a single entity or a small number of interconnected entities impact a market or financial system. One promising approach is the use of cascading failure models in complex supply chain networks informed by financial transactional relationships, to examine interdependencies among companies and facilities affected by flood-induced supply chain disruptions (Liu and Adriaens, 2025). In addition, studies on the resilience of disaster-affected facilities (Yang et al., 2015; Yang et al., 2016; Li and Zobel, 2020) suggest the potential for evaluating resilience strategies such as inventory management, constructing backup facilities and diversifying suppliers to mitigate supply chain risks. Challenges include data availability and establishing the basis for operational substitution (capacity redundancy) rates. Although various business databases exist such as Bloomberg, FactSet and Orbis, even those containing corporate transaction data often provide limited information particularly when private companies or facilities are included. Therefore, it may be necessary to estimate missing data using imputation techniques using machine learning models as Tian and Adriaens (2025) used for missing corporate water risk disclosures. As for substitution rates, they vary significantly by industry and company, meaning that detailed corporate information is required to set accurate values, or run simulations to quantify the model sensitivity to uncertainty. However, interim solutions may include the use of industry-level substitution rates or applying assumed rates based on extended operating hours.

Third, the opportunity to leverage the financial risk exposures computed here to inform the development of parametric insurance models for climate-related flood risks is an important extension and research topic. In this context, the increasing adoption of parametric insurance

refers to a mechanism where a pre-arranged contract triggers a payout when a specific parameter, such as flood depth or rainfall, exceeds a defined threshold. My dissertation quantified the financial impact risks of floods on corporations. While we did not explore insurance coverage or actuarial models to price risk premia, the estimated annual damage (EAD) may inform an upper level of coverage companies may require to offset financial losses (Kunreuther, 2008; Paudel et al., 2013). Previous work has shown that the eligibility for insurance coverage is conditional on the implementation of risk reduction measures that are implemented by the facility operator or corporate holding, and premiums are adjusted based on local flood risk levels (Surminski et al., 2017). Key challenges include the method of threshold setting given climate and flood uncertainties, the robustness of the payout mechanism to cover expected losses while maintaining insurance capital holding requirements to meet their financial obligations to policyholders, and market demand analysis for both the exposed party (company) and the speculating party (insurer or reinsurer) interests. Threshold determination requires highly accurate climate forecasting models, which may be addressed through advances in climate modeling and improvements in the spatial resolution of flood forecasting systems. For example, the use water level measurements at specific monitoring points or remote sensing data represent a possible approach. Given the extent of data requirement to make these assessments, and the trust-verification required for risk transfer, decentralized architectures using smart contracts (Chung and Adriaens, 2024) are increasingly being explored by (re)insurers to ensure the robustness of the payout system. As for demand analysis, it is critical to conduct in-depth interviews and surveys with potential clients to avoid the pitfalls of product-out development. Current competing risk transfer solutions by using captive insurance models (internal corporate risk transfers) instead of third-party insurers are being considered to manage cost and data

propriety. In Japan, the national government has implemented surveys to understand economic damages due to floods, and to potentially explore working with corporate insurers to provide attractive policies for flood risks in Japan during climate transitioning. Ensuring the product addresses actual needs will be key to successful implementation.

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