Analysis and Refinement of the Quantification and Integration of Flood Risk into ABN AMRO's Mortgage Models

Literature Study

by

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Master Thesis

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Abstract

Extreme climate events are becoming more frequent and pose growing risks to residential properties worldwide [1–4]. Climate risk can affect various other types of risk, including business, operational and market risk. In the Netherlands—where the majority of the surface lies below sea level—flood risk in particular presents a significant challenge [5]. Although the Dutch government has committed to improving defence against floods, which mitigates the probability of major flood events in the coming years [6], the residual risk remains relevant. These risks can cause issues for banks, as they can impact clients' creditworthiness and the value of the underlying collateral, thereby increasing banks' credit risk for mortgages.

Credit risk is typically quantified using credit risk models. Therefore, the integration of climate-related events into such models provides the foundation for quantifying the impact of climate risks on credit risk metrics. Climate-related damage thus directly links to credit risk models. Moreover, from 2026 onwards, it will be mandatory under regulatory requirements for banks to integrate climate risks into their credit risk management [7].

This literature report provides the theoretical foundation for research focused on incorporating flood risk into *ABN AMRO Bank*'s credit risk models for residential mortgages. It does so by introducing key credit risk metrics, such as Probability of Default, Loss Given Default, and regulatory capital, followed by relevant regulatory frameworks [8–10], and concludes with an overview of climate risk concepts and a review of a leading methodology for flood risk integration into RRE models [11].

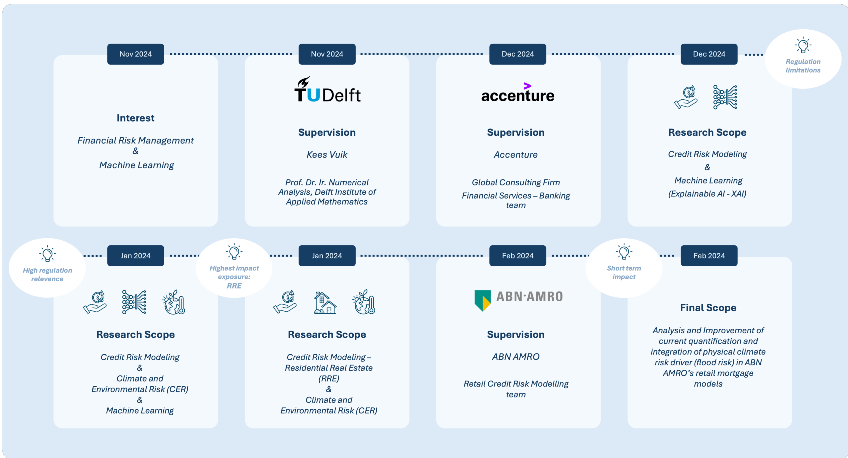
Given the many assumptions involved in both flood and credit risk modelling, and the early stage of development of these modelling approaches [12], this study highlights the need for critical evaluation and potential refinement—providing motivation for deeper investigation in the next phases of this research.

Preface

This literature report serves as the theoretical foundation for my master's thesis in Applied Mathematics at TU Delft. It explores the academic landscape of credit risk and climate risk, with a specific focus on residential mortgages as the exposure class, and flood risk as the key physical climate risk driver. In addition, it identifies an existing methodology and theoretical framework that connects these domains.

The road to this final thesis topic was not quite linear. From the outset, I set a strong requirement for myself: the research had to be as directly relevant to industry practice as possible. While this seemed like a great guiding principle, it also made the search for the right focus a more complex and iterative journey.

Throughout the past months, I explored multiple directions—ranging from broad financial risk modeling to machine learning applications, from explainable AI to integrating climate factors into risk assessment. Conversations with experts at TU Delft, Accenture, and later ABN AMRO played a key role in defining my focus. Each discussion provided new insights and helped me critically assess what was feasible, relevant and valuable. Each pivot was necessary to arrive at a topic that is both academically interesting and practically useful. To illustrate this process, I have included a visual representation of how the research topic evolved over time. This chart reflects not just the changes in scope, but also the thought process behind narrowing down to a research question that aligns with both academic relevance and industry needs.



As can be seen, several topic iterations happened throughout the process. It started with an interest in both financial risk management and machine learning, as I saw a lot of potential in the combination of these fields. At a certain point, the decision was made to move away from the machine learning focus, based on advice from experts who mentioned that regulatory constraints would make the topic less directly applicable.

Not long after, climate risk came into the picture—a topic that's gaining a lot of attention in the credit risk field. From 2026 onwards, banks will be required to include climate risk in their models, which made it a great fit for the kind of relevance I was looking for.

After comparing different exposure classes (see Appendix), the decision was made to focus on residential real estate (RRE). This is the largest class, as it typically makes up more than a quarter of a bank's total credit exposure, representing the largest share [13]. With input from ABN AMRO, I chose to work with their existing climate risk models, focusing specifically on flood risk, with the goal of analyzing and improving the current quantification.

While this literature study is a milestone in my thesis journey, it is by no means the final step. The insights gained during this phase will help guide the next stages of the research, ensuring that the work remains grounded in both theoretical foundations and practical relevance.

List of Abbreviations

Abbreviation	Definition
BCBS	Basel Committee on Banking Supervision
BIS	Bank for International Settlements
CAR	Capital Adequacy Ratio
CDF	Cumulative Distribution Function
CER	Climate-Related and Environmental Risks
CBS	Centraal Bureau voor de Statistiek
CET1	Common Equity Tier 1
CRD	Capital Requirements Directive
CRR	Capital Requirements Regulation
CSRD	Corporate Sustainability Reporting Directive
C-VaR	Credit Value at Risk
DNB	De Nederlandsche Bank
DTI	Debt-to-Income Ratio
E&S	Environmental and Social
EAD	Exposure at Default
EBA	European Banking Authority
ECB	European Central Bank
EL	Expected Loss
ESG	Environmental, Social and Governance
FINREP	Financial Reporting
GDP	Gross Domestic Product
GHG	Greenhouse Gases
IRB	Internal Ratings-Based
K	Capital Requirement
LGD	Loss Given Default
LGL	Loss Given Loss
LRA DR	Long-Run Average Default Rate
LIWO	Landelijk Informatiesysteem Water en Overstromingen
LTI	Loan-to-Income Ratio
LTV	Loan-to-Value Ratio
NHG	Nationale Hypotheek Garantie
PD	Probability of Default
RWA	Risk-Weighted Assets
SA	Standardised Approach
SSM	Single Supervisory Mechanism
SSM2017	Standard Method for Calculating Flood Damage in The Netherlands (2017)
UL	Unexpected Loss
VaR	Value at Risk
WCDR	Worst-Case Default Rate
WOZ	Waardering Onroerende Zaken

Table 1: List of used Abbreviations.

List of Symbols

Symbol	Definition
A_p	Floor area of property p
$CET1$	Core equity capital
$CET1$ ratio$_0$	Initial CET1 ratio
$CET1$ ratio$_S$	CET1 ratio under flood scenario S
δ'	Vector of coefficients for control variables
ΔEL_S	Difference in expected loss under flood scenario
ΔRWA_S	Scenario-specific change in risk-weighted assets
h	Flood depth
$K_{i,b}$	Initial capital requirement factor
K_S	Flood S scenario-specific capital requirement
$K_{S,i,b}$	Capital requirement for loan i of bank b under flood scenario S
L	Loss variable in VaR calculation
LGL_i	Loss Given Loss
$LGL_{S,i}$	LGL under flood scenario S
$LGD_{i,b}$	LGD of loan i at bank b before flood
$LGD_{S,i,b}$	LGD of loan i at bank b under scenario S
$LGD_{S,i}$	LGD under flood scenario S
$LTV_{0,i}$	Initial Loan-to-Value ratio
$LTV_{S,i}$	LTV under flood scenario S
$max\ damage_t$	Maximum structural damage per m^2 for property type t
m^S_{LGD}	Scenario-specific LGD multiplier
m^S_{PD}	PD multiplier under scenario S
m^S_{RW}	Scenario-specific RWA multiplier
p	Property index
Φ	CDF of standard normal distribution
Φ^{-1}	Inverse CDF of standard normal distribution (quantile function)
PD_α	Worst-Case Default Rate
$property\ value_p$	Observed collateral value of property p
ρ	Correlation factor for systematic risk
$RWA_{i,b}$	Initial RWA for loan i of bank b
$RWA^S_{i,b}$	RWA for loan i of bank b under flood scenario S
$sales\ ratio^S_p$	Liquidation value to market value ratio under scenario S
t	Property type
τ	Inflation correction factor
T	Final reporting period
$\theta(h)^S_t$	Damage function for flood depth h, property type t in scenario S
$u_{i,b,t}$	Error term
VaR_α	Value at Risk at confidence level α
$VaR_\alpha(PD)$	VaR of default probability
w_b	Weight of bank b in system exposure
w_i	Weight of loan i in bank exposure
$X_{i,b,t}$	Vector of control variables
$y_{i,b,t}$	Default status of borrower i at bank b at time t
$Z_{i,b,t}$	Vector of primary independent variables
$Z_{S,i,b,T}$	Independent variables under scenario S at time T

Symbol	Definition
β'	Vector of coefficients for primary independent variables
ϕ_p^S	Fraction of collateral value of property p lost due to flooding in scenario S
α	Confidence level

Table 2: List of used symbols.

Contents

1 Introduction

Risk management supports the stability and integrity of the banking industry. Within this field, credit risk measures the potential losses incurred when borrowers fail to meet their financial obligations, playing a pivotal role in the process. Effective credit risk management is crucial, influencing not only the health of financial institutions but also the broader economic ecosystem.

Traditionally, credit risk in the banking sector has been viewed through a regulatory or financial lens. In recent years, climate and environmental risk has emerged as a relevant external driver that affects traditional risk categories, including credit risk. Climate risk is defined as the potential for problems for societies or ecosystems from the impacts of climate change. The assessment of climate risk is based on formal analysis of the consequences, likelihoods and responses to these impacts. This broad category can be divided into two types of risks. Physical risks arise from the direct impacts of climate-related events, such as increased flooding, storms and wildfires. Transition risks are associated with the economic adjustments required as societies shift towards low-carbon technologies and policies.

The increasing prevalence of climate risks is undeniable, translating into both physical impacts [1–5] and transitional consequences [14, 15]. There are significant implications across many sectors, including credit risk management within the Dutch banking industry. Recognizing this, regulatory frameworks have begun to adapt. The Basel Accords are the official regulatory standards issued by the Basel Committee on Banking Supervision, designed to ensure that financial institutions maintain adequate capital and follow sensible operational practices. The latest iteration of these regulations, known as Basel IV, was finalized at the beginning of 2023. The integration of climate and environmental risk into credit risk models is primarily being shaped at the European level. Requirements formulated in the so-called Capital Requirements Regulation (CRR) and Capital Requirements Directive (CRD) are being translated into binding supervisory expectations through the EBA Guidelines on ESG Risk Management [7, 16], which will apply from January 2026. Additionally, the ECB's Guide to Internal Models emphasizes that banks must consider climate and environmental risks when developing and maintaining their internal credit risk models [17].

Despite these regulatory guidelines, the development and adoption of climate risk within bank's internal credit risk models are still in their early stages. Implementation varies widely among financial institutions, some are already testing and validating integration strategies, while others remain in denial about the need to adapt [12]. This difference in responses highlights that the integration of climate risk in the banking sector is still in its early phase.

A particularly interesting aspect within this context is the exposure class of residential mortgages. The consequences for banks must be considered when collateral—often regarded as the bank's main security when granting a mortgage loan—is severely affected by flooding or when new climate policies significantly impact borrowers' repayment capacity. Although residential mortgages represent a critical exposure class, the development of robust models that integrate climate and environmental risks remains in an early stage. This is not only due to limited data availability, but also because methodological approaches are still evolving. One of these climate-related risks still in its early stages of integration is flood risk. Better quantification of its potential impact on mortgage credit risk is needed in order to support more accurate and forward-looking risk assessments. Currently, some climate-related risk drivers are excluded from credit risk modelling—not because they are deemed negligible, but because the available data and modelling techniques do not yet support their proper incorporation. This thesis aims to contribute to bridging that gap by exploring improved methods to quantify flood risk within credit risk models for residential mortgages.

For several years, banks have been exploring the integration of climate-related risks into credit risk management. One of the major Dutch banks involved in this field is ABN AMRO (ABN AMRO Bank N.V.). Like any modelling journey, this process involves challenges, one of which is quantifying the impact of climate risks, including flood risk. This thesis will support ABN AMRO in refining the assessment of flood risk within credit risk modelling for residential mortgages.

This research will therefore focus on providing new insights within this context, specifically examining one type of climate risk, defining the research topic as follows

Integrating Physical Climate Risk into Credit Risk Modelling: Analysis and Refinement of Flood Risk Assessment for ABN AMRO's Mortgage Portfolio

This literature study is organized to review the foundational aspects of credit risk and climate risk within the banking sector. It begins with a deep dive into credit risk modeling, exploring fundamental concepts, theoretical foundations and key metrics such as Probability of Default (PD) and Loss Given Default (LGD). Additionally, the credit risk exposure of retail mortgages is briefly discussed. Following this, an overview of regulatory frameworks is provided—including the Basel Accords and recent developments in climate-related and environmental risk (CER) regulation—which serves as a bridge to more refined modelling approaches and offers a conceptual framework within which these can be developed. The next section introduces climate and environmental risks, with a particular focus on flood risk and its relevance to credit risk modeling. The final section presents a review of a state-of-the-art flood risk integration methodology in the Netherlands, offering theoretical insights and practical implications for incorporating flood risk into credit risk metrics, thereby forming the basis for the modeling phase of this research.

1.1 Research Questions and Scope

This research investigates how flood risk is currently quantified and integrated into ABN AMRO's credit risk models for retail mortgages, with a specific focus on the role of modelling assumptions. The central research question guiding this study is formulated as follows

> *To what extent do the assumptions underlying ABN AMRO's current flood risk quantification affect its integration into retail mortgage credit risk models, and how can this be evaluated and improved?*

To systematically address this question, the following sub-questions are defined. Together, they represent the structure of the research process, with each sub-question contributing a necessary component to the overall analysis. Moreover, the sub-questions are ordered chronologically, reflecting the intended sequence in which they will be addressed throughout the research. When answered collectively, they provide a comprehensive response to the main research question.

1. What is the current structure of ABN AMRO's flood risk quantification for retail mortgage models?

- *How is flood damage estimated and translated into collateral value impact?*
- *In what way is flood risk currently translated into credit risk parameters such as LGD and PD?*
- *What data sources are used for flood risk modeling?*

2. What are the key assumptions underlying the current quantification and integration of flood risk into retail mortgage credit risk models?

- *What types of assumptions are made throughout the model structure?*
- *How can these assumptions be categorized (e.g., data-related, methodological, scenario-based)?*
- *How are assumptions interconnected or dependent on each other within the model structure?*

3. What mathematical or statistical methods can be used to evaluate the robustness and sensitivity of the identified assumptions?

- *Which techniques can be applied to test assumption sensitivity?*

- *Can uncertainty quantification or simulation-based methods be applied in this context?*
- *How can the selected methods support a better understanding of model reliability and the impact of assumptions?*

4. Based on the selected methodology, what can be concluded about the robustness and sensitivity of key assumptions?

- *Which assumptions or parameters appear highly sensitive within the current model structure?*
- *Which assumptions or parameters have minimal influence on model outcomes?*

5. What recommendations can be formulated—based on the research findings—for enhancing the quantification and integration of flood risk in ABN AMRO's retail mortgage models?

- *Which insights from the model evaluation suggest directions for improvement?*
- *What conceptual refinements could support more robust flood risk integration in the future?*

The reasoning behind the order of the sub-questions is to first obtain a comprehensive understanding of the current situation, followed by a detailed mapping of all assumptions embedded within it. Next, appropriate mathematical and statistical techniques are identified to assess these assumptions, after which results are generated based on the selected methodology. Finally, these findings are translated into a set of recommendations, with the aim of providing ABN AMRO's Climate and Environmental Risk team with valuable insights and concrete, actionable suggestions. By answering the sub-questions in this specific sequence, a reasoned and evidence-based answer to the main research question may be formulated.

Before these research questions can be addressed, first a solid knowledge foundation must be established across several domains: credit risk and climate risk. This includes a more in-depth understanding of how residential real estate exposures are modelled within credit risk frameworks, as well as a focused introduction to flood risk as a key component of physical climate risk. Finally, it is essential to explore existing research at the intersection of these two domains. Establishing this theoretical foundation is the primary objective of the initial phase of this research—of which this literature report is the main deliverable.

2 Credit Risk Modelling

Credit risk modeling is a fundamental aspect of financial risk management, providing methodologies to quantify and mitigate risks associated with lending activities. These models aim to estimate the financial losses that may occur if borrowers are unable to meet their repayment obligations. Given its central role in ensuring financial stability, credit risk modeling has evolved into a structured field, incorporating both theoretical frameworks and empirical applications.

This section provides an overview of the key components of credit risk modeling. It begins with a set of fundamental concepts and terminology that are essential for understanding the structure and function of credit risk models (§ 2.1). Next, the theoretical foundation is discussed, including the statistical and mathematical principles underlying capital requirements and loss estimation (§ 2.2). This is followed by a high-level overview of common modeling techniques for Probability of Default (PD) and Loss Given Default (LGD), with a focus on practices observed in the Dutch banking sector (§ 2.3). Finally, the section explores the specific characteristics of residential mortgage exposures, identifying key risk drivers that influence credit risk modeling within this exposure class (§ 2.4).

To establish a foundational understanding, it is essential to first revisit the concept of financial risk in general. Risk is formally defined as follows:

Definition 1. *Risk is any event or action that may adversely affect an organization's ability to achieve its objectives and execute its strategies.*

This definition can be categorized into distinct types of risk [18]:

- **Market Risk**: The risk of changes in the value of a financial position or portfolio due to movements in underlying components such as stock prices, bond prices, exchange rates, or commodity prices .
- **Credit Risk**: The risk of not receiving promised repayments on outstanding investments due to the default of a borrower. This risk is the focus of this research.
- **Operational Risk**: The risk of losses resulting from inadequate or failed internal processes, people, systems, or external events.
- **Liquidity Risk**: The risk associated with the lack of marketability of an investment, where it cannot be sold quickly enough to prevent a loss.
- **Model Risk**: The risk of using a misspecified or inappropriate model to measure financial risk.

This research specifically addresses credit risk, which represents the likelihood of a borrower failing to meet contractual obligations, resulting in financial losses for the lender. Credit risk is crucial in the context of financial institutions, particularly in lending activities such as mortgages, loans and credit facilities.

2.1 Fundamentals

The field of credit risk modeling covers a wide variety of models, exposure classes and methodologies that often differ significantly between institutions. Despite this diversity, establishing a clear and consistent framework of foundational terminology is essential to ensure effective communication and understanding. This section introduces a set of key terms that frequently appear in credit risk modeling, including throughout this report. A simple illustrative example is also included to clarify how these metrics might look in practice.

- **Exposure Class**: A regulatory category that groups similar types of loans based on their characteristics and risk profiles. Common exposure classes include retail mortgages, corporate loans and exposures to governments or financial institutions. Each class follows different regulatory rules and modeling requirements. For example, residential mortgages form a separate exposure class with their own capital requirements and risk drivers.

- **Probability of Default (PD)**: The likelihood that a borrower will fail to repay their loan within a specific period, usually one year. It reflects how risky the borrower is. PD is one of the key metrics in credit risk modeling. The way in which this value is determined depends on the regulatory approach a bank is required to follow. Under more advanced regulatory approaches, banks are allowed to develop their own PD models using internal historical data. These models are typically tailored to specific exposure classes and reflect the characteristics of the bank's own portfolio.

- **Exposure at Default (EAD)**: The amount of money that is at risk at the moment the borrower defaults. For a simple loan, this is just the outstanding balance. For credit cards or other flexible credit lines, it also includes the unused part that the borrower might still withdraw before defaulting. In that case, the amount is adjusted using a so-called Credit Conversion Factor (CCF). So in general the EAD is given by

$$\text{EAD} = \text{Drawn Balance} + (\text{Undrawn Balance} \cdot \text{CCF})$$

  Estimating EAD accurately is important, especially for products where the borrower still has room to borrow more before defaulting. For the exposure class of residential mortgages specifically, EAD is typically set equal to the outstanding loan balance, as no additional credit can be drawn.

- **Loss Given Default (LGD)**: The percentage of the loan that is lost if the borrower defaults, after taking into account any money the bank recovers—such as by selling collateral (e.g. a house). It is calculated as

$$\text{LGD} = 1 - \frac{\text{Recovery Amount}}{\text{Exposure at Default}}$$

  The recovery amount depends on many factors, like the value of the collateral and how easy it is to sell. A higher LGD means that the bank loses more money if things go wrong. Just like PD, LGD can be estimated using internal models, based on historical recovery data, or can be set by regulation.

- **Expected Loss (EL)**: The amount of money the bank expects to lose on a loan. It combines three components: how likely a borrower is to default (PD), how much is lost if that happens (LGD) and how much money is at risk (EAD), so it is given by the following

$$\text{EL} = \text{PD} \cdot \text{LGD} \cdot \text{EAD} \tag{1}$$

  This expected loss is treated as a regular cost of doing business. Banks usually include it in the interest rate they charge or account for it by setting money aside (called provisions).

- **Unexpected Loss (UL)**: The part of the loss that goes beyond what the bank expected. Even if the expected loss is low, actual losses can sometimes be much higher—especially during a crisis. UL is used to calculate how much extra capital a bank needs to keep as a safety buffer. The idea is: if things go worse than expected, the bank should still be able to absorb the shock without getting into trouble.

- **Stress Testing**: A way to check what would happen to the bank's loans if the economy suddenly takes a turn for the worse. For example, what if house prices fall sharply, or unemployment rises? In a stress test, banks simulate such scenarios and estimate how much the PD, LGD, EAD, and the corresponding losses would increase. This helps them prepare for extreme but plausible situations and is also required by regulators.

To make these definitions more concrete, the following example illustrates how the different components — PD, LGD, EAD, and EL — interact in a simplified mortgage case. It shows how a bank estimates the potential loss on a loan by combining these key metrics.

Example 2.1. *Consider the following simplified mortgage case: a borrower receives a mortgage of $400,000 to buy a house worth $500,000. This means the initial Loan-to-Value (LTV) ratio is 80%. Over time, the borrower repays part of the loan, and at some specific time the outstanding balance is reduced to $360,000. This remaining amount is the Exposure at Default (EAD) — the amount that would still be at risk if the borrower defaults.*

Now assume the borrower defaults. The bank repossesses the property and sells the house. Let's say it manages to sell the house for $342,000, which is lower than the original house value—typically due to the urgency and price pressure associated with a forced sale, or adverse economic cycle conditions. This means the bank recovers part of the exposure, but not all of it. There is a loss of:

$$\textit{Loss} = \$360{,}000 - \$342{,}000 = \$18{,}000$$

Based on this, the Loss Given Default (LGD) can be calculated as the percentage of the EAD that is lost:

$$LGD = 1 - \frac{\textit{Recovery Amount}}{\textit{Exposure at Default}} = 1 - \frac{342{,}000}{360{,}000} = 0.05$$

Next, assume the Probability of Default (PD) is estimated to be 25%, i.e. 0.25. This means there is a 1 in 4 chance that a similar borrower will default within a year.

Now that we have PD, LGD and EAD, we can calculate the Expected Loss (EL):

$$EL = PD \cdot LGD \cdot EAD = 0.25 \cdot 0.05 \cdot 360{,}000 = \$4{,}500$$

This means that on average, the bank expects to lose $4,500 on this mortgage. This expected loss is usually covered by the interest charged on the loan or through provisions set aside for credit losses.

With a clearer understanding of the fundamental components of credit risk modeling, the focus now shifts to a deeper exploration of the theoretical framework behind these concepts. The following section discusses the mathematical and regulatory principles that form the foundation of credit risk models.

2.2 Theoretical Foundation

A key objective of credit risk modeling is to determine how much economic capital a bank should hold internally to remain solvent during severe financial stress. This internally determined capital serves as a cushion against unexpected losses. In parallel, banks are also required to hold regulatory capital — a minimum amount of capital mandated by international regulatory standards. This regulatory capital underpins the capital ratio that banks must meet to safeguard financial stability.

The required amount of regulatory capital is expressed in terms of Risk-Weighted Assets (RWA), which adjust a bank's exposures for their associated risk. A fixed percentage of these RWA must be covered by regulatory capital; currently this requirement is set at 8% [8]. In other words, the RWA figure appears in the denominator of the capital ratio and plays a key role in determining whether a bank meets its regulatory obligations.

The calculation of RWA relies on the Capital Requirement K, which represents the risk-sensitive capital buffer required per unit of exposure. Informally, K reflects the proportion of an exposure deemed sufficiently risky to require additional capital. There are different levels of flexibility in how banks may determine these values, which correspond to different approaches. The so-called Standardized Approach (SA) applies fixed regulatory risk weights, whereas the Internal Ratings-Based (IRB) approach allows banks to use internal models to estimate risk components such as PD, LGD and EAD. These approaches will be discussed in more detail in regulatory section 3.

Given that these concepts may be difficult to grasp without prior exposure to credit risk modeling, this section aims to provide the theoretical and mathematical foundations necessary for their understanding. The key concepts presented here will also serve as the basis for Section 3, which provides a broader overview of the regulatory framework and its historical development. Since the capital formulas used in IRB models consist of several components, this section starts from the most fundamental element: the potential losses a financial institution might face. This naturally leads to the question of how such losses are distributed and what underlying assumptions shape their behaviour.

2.2.1 Loss Distribution Function

The estimation of economic capital relies on the probability distribution function of credit losses, commonly referred to as the loss distribution of a credit portfolio or credit loss function [19, 20]. This distribution represents the range of possible losses a bank may incur due to credit risk. A visual representation of this distribution is given in Figure 1.

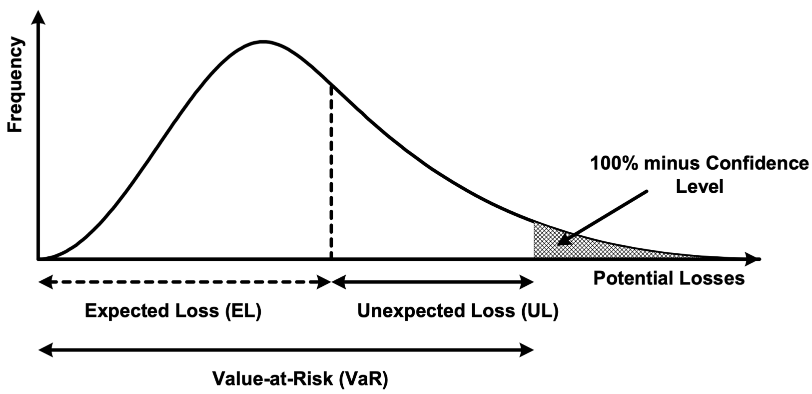


Figure 1: Credit Loss Function [20].

The loss distribution is characterized by its skewed nature, where small losses are significantly more probable than large ones. The x-axis represents the potential credit losses, while the y-axis denotes the probability density of these losses occurring. Several key risk measures are directly linked to this distribution. Expected Loss (EL) corresponds to the average credit loss a bank expects over a given time horizon. It is considered a normal cost of doing business and is typically covered by pricing strategies and provisions. In contrast, Unexpected Loss (UL) represents the deviation from the expected loss due to uncertainty in credit outcomes. Banks must hold capital to absorb UL, to be able to withstand crisis credit events.

A critical measure associated with stress scenarios is the Value at Risk (VaR), which is defined as the maximum potential loss a bank is expected to sustain with a given confidence level over a specific time horizon. Mathematically, VaR at confidence level α is given by

$$P(L > \mathrm{VaR}_\alpha) = 1 - \alpha, \tag{2}$$

where L represents the loss variable under consideration. In credit risk management, VaR is often referred to as C-VaR, the Credit Value at Risk, a convention that will also be followed here. By regulation, a confidence level of $\alpha = 0.999$ is generally applied in credit risk assessments to ensure adequate capital buffers against unexpected losses.

The difference between the EL and the C-VaR defines the stress loss, representing the probability that actual losses exceed both EL and UL. This corresponds to the right tail of the loss distribution. The relationship between UL, EL and C-VaR naturally links to the regulatory capital requirements. The next section explains how these requirements are calculated under the Basel framework.

2.2.2 Capital requirement and Risk Weighted Assets

Under the Basel framework, capital requirements are directly linked to unexpected losses (UL). How this relationship is established—along with a simplified outline of the derivation of regulatory capital—will be explained throughout this section. It is important to note that under the Standardized Approach (SA), prescribed regulatory risk weights are applied to determine capital requirements. In contrast, under the Internal Ratings-Based (IRB) approach, capital requirements are calculated based on risk parameters such as PD and LGD. For the IRB approach, the regulatory formula defined in CRE31, paragraph 31.14 [8], for retail residential mortgage exposures that are not in default, is given by the following equation:

$$\textit{Capital requirement} = K = LGD \cdot \Phi\left(\frac{\Phi^{-1}(PD)}{\sqrt{1-\rho}} + \sqrt{\frac{\rho}{1-\rho}} \cdot \Phi^{-1}(0.999)\right) - PD \cdot LGD, \tag{3}$$

where Φ denotes the cumulative distribution function (CDF) of the standard Gaussian distribution and Φ^{-1} denotes its inverse, the quantile function of the standard Gaussian, which maps a probability p to the corresponding quantile value. PD denotes the probability of default, LGD represents the loss given default and ρ is referred to as the correlation, a parameter that captures systematic risk and serves as a proxy for exposure to the general economy. Under the currently applicable regulatory framework, a fixed correlation value of $\rho = 0.15$ is prescribed for retail residential mortgage exposures. To illustrate, for corporate loans this correlation is generally set to a higher value by regulators, as corporate loans are assumed to be more sensitive to the general economy than residential mortgages [1].

The capital requirement equation (3) may seem to appear out of nowhere, but its derivation is based on a quite extensive mathematical framework. A detailed exploration is not necessary for the scope of this study, a simplified derivation can be provided to offer some intuitive understanding, using the following definitions [10]:

$$K = VaR_\alpha(PD) \cdot LGD, \tag{4}$$

$$VaR_\alpha(PD) = PD_\alpha - PD, \tag{5}$$

$$PD_\alpha = \Phi\left(\frac{\sqrt{\rho}\Phi^{-1}(\alpha) + \Phi^{-1}(PD)}{\sqrt{1-\rho}}\right). \tag{6}$$

where $VaR_\alpha(PD)$ denotes the Value-at-Risk of the default probability at confidence level α, and PD_α is the critical value of PD at confidence level α, commonly referred to as the Worst-Case Default Rate (WCDR) or downturn PD.

Using these expressions, the capital requirement as specified by regulation follows directly:

[1] Note that: ρ cannot be zero, as this would imply $K = 0$. To prevent banks from underestimating systematic risk, Basel II established minimum values for ρ across different exposure classes.

$$
\begin{aligned}
K &= VaR_\alpha(PD) \cdot LGD, \\
&= (PD_\alpha - PD) \cdot LGD, \\
&= \left(\phi \left(\sqrt{\frac{1}{1-\rho}} \Phi^{-1}(PD) + \sqrt{\frac{\rho}{1-\rho}} \Phi^{-1}(\alpha) \right) - PD \right) \cdot LGD, \\
&= LGD \cdot \phi \left(\sqrt{\frac{1}{1-\rho}} \Phi^{-1}(PD) + \sqrt{\frac{\rho}{1-\rho}} \Phi^{-1}(\alpha) \right) - PD \cdot LGD.
\end{aligned}
$$

Finally, the connection between the capital requirement (3) and the loss distribution presented in Figure 1 can be further clarified. The right-hand side of Equation (3) corresponds to the expression for the Expected Loss, i.e. $EL = PD \cdot LGD$. It is important to note that, for explanatory purposes, EL is now expressed as a percentage of the EAD, whereas the actual EL can be represented as an absolute value (1). This absolute value is obtained by multiplying the percentage by the EAD. The left-hand side, $LGD \cdot \Phi\left(\frac{\Phi^{-1}(PD)}{\sqrt{1-\rho}} + \sqrt{\frac{\rho}{1-\rho}} \cdot \Phi^{-1}(0.999)\right)$, corresponds to the so-called conditional expected loss, which is equivalent to the previously introduced Credit Value at Risk (C-VaR). This can also be expressed as the product of the conditional probability of default and loss given default, i.e. $C\text{-}VaR = PD_\alpha \cdot LGD$, with $\alpha = 0.999$. Taking this into account, referring back to Figure 1, as previously mentioned, the unexpected loss is obtained by subtracting the expected loss from the C-VaR, i.e. $UL = C\text{-}VaR - EL$. This completes the framework, as this exactly corresponds to the subtraction observed in the capital requirement (3). It follows that the capital requirement corresponds to the unexpected loss component, confirming the earlier statement that these metrics are directly linked.

After determining the capital requirement (3) as a percentage of the exposure, the next step is to calculate the Risk-Weighted Assets (RWA). This is done by multiplying K by the Exposure at Default (EAD) and a factor of 12.5. This factor represents the reciprocal of the minimum capital ratio of 8% [2], ensuring consistency with regulatory requirements. The formula is given by:

$$
RWA = 12.5 \cdot K \cdot EAD. \tag{7}
$$

Another key metric is the Common Equity Tier 1 (CET1) ratio [9], it is used to assess a bank's financial strength. It reflects the proportion of a bank's capital, consisting of its highest quality assets, relative to its risk-weighted assets. The formula for calculating the CET1 ratio is:

$$
CET1 \text{ ratio} = \left(\frac{CET1 \text{ capital}}{RWA} \right) \cdot 100\% \tag{8}
$$

where we have that the *CET1 capital* represents the bank's core equity capital, such as it's common shares and share surplus, retained earnings and capital from subsidiaries.

Regulatory requirements require that banks maintain a minimum CET1 ratio to ensure they have sufficient capital to absorb losses and continue operating during periods of financial stress. The minimum CET1 ratio requirement is $> 4.5\%$.

To make the capital requirement formula more tangible, the following example illustrates its application using a hypothetical retail mortgage exposure and standard Basel parameters.

Example 2.2. *For retail mortgage exposures, banks are allowed to develop their own internal models for estimating the Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD).*

[2] The factor of 12.5 ensures consistency with the regulatory capital framework set by the ECB and is based on the reciprocal of the minimum capital ratio of 8%. This is discussed in more detail in Section 3. See also [8].

This is part of the so-called Advanced Internal Ratings-Based (A-IRB) approach. More details on this are provided in the regulatory section 3. For this example, the input values are assumed to be given.

To illustrate the calculation of regulatory capital and Risk-Weighted Assets (RWA) under the IRB approach, we consider a simplified case in which the bank has only one retail mortgage exposure. In reality, the capital requirement is computed per individual loan, after which the results are aggregated across all exposures to determine the total RWA. However, for illustrative purposes, we focus here on a single exposure.

Regarding the confidence level, a value of $\alpha = 0.999$ *is commonly used in IRB-based credit risk capital calculations to ensure sufficient capital is held for extreme but plausible credit events.*

Let's assume a bank has a retail mortgage exposure with the following characteristics

- *Probability of Default (PD):* 1% *or* 0.01
- *Loss Given Default (LGD):* 40% *or* 0.40
- *Exposure at Default (EAD): €100,000*
- *Correlation* $\rho = 0.15$ *(Basel-prescribed for retail mortgages)*
- *Confidence level* $\alpha = 0.999$,

The capital requirement K *is given by the IRB formula*

$$K = LGD \cdot \Phi\left(\frac{\Phi^{-1}(PD)}{\sqrt{1-\rho}} + \frac{\sqrt{\rho}}{\sqrt{1-\rho}} \cdot \Phi^{-1}(0.999)\right) - PD \cdot LGD,$$

recall equation (3). This leads to the following calculations

$$\Phi^{-1}(PD) = \Phi^{-1}(0.01) \approx -2.33$$

$$\Phi^{-1}(0.999) = 3.09$$

$$\sqrt{1-\rho} = \sqrt{0.85} \approx 0.922, \quad \sqrt{\rho} \approx 0.387$$

$$\frac{-2.33}{0.922} \approx -2.527, \quad \frac{0.387}{0.922} \cdot 3.09 \approx 1.297$$

$$\Phi(-2.527 + 1.297) = \Phi(-1.23) \approx 0.109$$

$$K = 0.40 \cdot 0.109 - 0.01 \cdot 0.40 = 0.0436 - 0.004 = 0.0396$$

So the capital requirement is approximately 3.96% *of the EAD. Next, we compute the Risk-Weighted Assets (RWA):*

$$RWA = 12.5 \cdot K \cdot EAD = 12.5 \cdot 0.0396 \cdot €100,000 = €49,500$$

Finally, if the bank has €8,000 in CET1 capital for this exposure:

$$CET1\ ratio = \left(\frac{€8,000}{€49,500}\right) \cdot 100\% \approx 16.16\%$$

Since this is above the minimum required CET1 ratio of 4.5%, *the bank satisfies the regulatory requirement.*

Banks have some degree of flexibility in modeling PD, LGD and EAD, leading to potential variation in capital requirements across institutions. As evident from the capital requirement (3), accurate estimation of PD and LGD is crucial for banks to balance capital efficiency and risk coverage, ensuring that they hold sufficient capital without excessive reserves that could limit financial performance.

2.3 Probability of Default (PD) and Loss Given Default (LGD) Modelling

The development of Probability of Default (PD) and Loss Given Default (LGD) models is tailored to each individual bank. This section provides a general overview of examples of typical structures used by Dutch banks. While implementation details may vary, the core framework and regulatory context share many common elements across institutions operating within the Netherlands. The two key metrics, PD and LGD, will both be discussed separately to provide a general understanding of their typical modeling approaches.

2.3.1 Probability of Default (PD) modeling

The Probability of Default (PD) is a key metric in credit risk modelling, used not only in the calculation of regulatory capital under the Internal Ratings-Based (IRB) approach, as discussed in Section 2.2.2, but also in areas such as credit acceptance, economic capital modelling, loan pricing, provisioning and portfolio monitoring. Although the way PD is modelled is bank-specific, there is a common structure in terms of general steps that are typically applied. At the start of the PD modelling process, a selection of relevant risk drivers is made. Based on this selected set of drivers, a statistical model is used to produce a certain score. This score is used to define different risk profiles—also referred to as 'pools'. These pools are then calibrated, followed by final adjustments, ultimately resulting in the final PD used in each of the aforementioned applications. The PD estimation process is therefore generally structured in two phases: risk differentiation and risk quantification, both of which will be briefly explained in this section.

Phase 1: **Risk differentiation (ranking)**
In the first phase, statistical models such as logistic regression are employed to rank borrowers according to their credit risk. These models take loan- or borrower-specific risk drivers $x_1, x_2, \ldots, x_k$ as input and produce a continuous score that reflects the relative likelihood of default. For example, in a logistic regression setting, the output score is given by

$$\text{score}(x) = \frac{1}{1 + \exp(-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k))}$$

Although this score lies between 0 and 1 and resembles a probability, it does not yet represent the final PD. Rather, it provides a risk ranking that allows the institution to assign exposures to so-called discrete rating grades or pools, each bounded by lower and upper score thresholds.

Phase 2: **Risk quantification (calibration)**
In the second phase, each rating grade is assigned a PD estimate that reflects the average default experience observed historically for exposures in that grade. This is typically based on the *Long-Run Average Default Rate* (LRA DR), computed as the average of annual default rates over a sufficiently long and representative period of time. The use of long-run averages ensures that the PDs reflect both benign and adverse credit conditions.

After assigning the LRA DR, institutions may apply *appropriate adjustments (AA)* to account for structural breaks, data inconsistencies or observed jumps in default rates. Finally, a *Margin of Conservatism (MoC)* is added to reflect estimation uncertainty, particularly in cases of data limitations or model uncertainty. The final output—referred to as the *regulatory PD*—is then used in capital requirement calculations.

To make the process more intuitive, a hypothetical example is provided below.

Example 2.3. *Consider a bank estimating the probability of default (PD) for residential real estate (RRE) exposures under the IRB approach. The institution collects historical data on 100,000 mortgage loans, including borrower- and loan-specific variables such as loan-to-value ratio (LTV), borrower age, debt-to-income ratio (DTI) and delinquency history.*

Step 1: Risk differentiation: A logistic regression model is trained to estimate a credit risk score for each borrower. For a particular borrower, the model outputs a score of 0.014. Although this value lies between 0 and 1, it does not yet represent a final PD—it serves to rank borrowers by relative credit risk.

Step 2: Score segmentation: Based on the score distribution, the bank defines ten rating grades (pools), with pools A through I equally spaced between 0.0000 and 0.0400, and pool J capturing all scores above 0.0400. The segmentation is shown below:

Rating grade	**Score range**
A	*[0.0000 – 0.0040)*
B	*[0.0040 – 0.0080)*
C	*[0.0080 – 0.0120)*
D	*[0.0120 – 0.0160)*
⋮	⋮
H	*[0.0280 – 0.0320)*
I	*[0.0320 – 0.0400)*
J	*[0.0400 – 1]*

Our example borrower (score = 0.014) is assigned to rating grade D.

Step 3: Calibration using the LRA DR: The bank calculates the long-run average default rate (LRA DR) for each pool using historical default data over a 10-year period. For pool D, the LRA DR is estimated at 0.15%.

Step 4: PD best estimate: Based on current performance data and model calibration, the bank estimates the best estimate PD for pool D to be slightly lower than the LRA DR, at 0.14%.

Step 5: Margin of Conservatism (MoC): To account for data limitations and estimation uncertainty, a conservatism margin of 0.02 percentage points is added.

The final regulatory PD for rating grade D is therefore:

$$PD_{final} = 0.14\% + 0.02\% = 0.16\%$$

This PD is subsequently used as an input in the IRB capital requirement calculation.

Each exposure class relies on a distinct set of risk drivers for PD estimation. For residential real estate portfolios, relevant drivers may include the loan-to-value ratio, borrower age, loan size and delinquency history. These variables serve as inputs to the risk differentiation model, which produces a credit risk score used to assign exposures to rating pools. Historical performance data is then used to calibrate PDs for each grade, with appropriate adjustments and conservative uplifts applied as needed, in line with ECB expectations and Basel requirements.

2.3.2 LGD modeling

Loss Given Default (LGD) quantifies the percentage loss a bank incurs in the event of a borrower's default. While the general definition is consistent across institutions, the modelling of LGD can differ significantly, depending on factors such as data availability, portfolio characteristics, and internal methodologies. This section illustrates an example of a commonly applied modelling technique, in which LGD is decomposed into three components: the *probability of cure*, the *Loss Given No Cure* (LGNC), and the *Loss Given Cure* (LGC).

The rationale for this decomposition lies in the fact that, when a borrower defaults, it does not necessarily result in a full loss of the outstanding exposure. Several mitigating factors can reduce the realised loss, including the possibility that the borrower cures (i.e. returns to a performing status), enters into a restructured agreement, benefits from third-party guarantees, or provides collateral that can be liquidated to recover part of the exposure. As a result, an LGD model must distinguish between different default outcomes and their respective loss implications.

The first component, the *probability of cure*, estimates the probability that a borrower who has defaulted will return to a non-default status within a defined period. This probability, known as the *cure rate*, reflects the fraction of defaulted exposures that do not result in a write-off. It is a crucial input to determine the weighting between LGNC and LGC in the overall LGD formula. The cure rate is often estimated using logistic regression models, similar to Probability of Default (PD) models. These models require careful risk driver selection, including borrower characteristics, loan terms and macroeconomic indicators.

The second component, the *LGNC*, estimates the expected percentage loss for loans that do not cure. Rather than focusing directly on losses, this component can be framed in terms of the earnings the lender expects to recover from the exposure at default. These earnings may include proceeds from the sale of the collateral, remaining savings or deposits, recoveries from insurance policies, or any other financial inflows following default. LGNC is then expressed as the complement of the expected recovery ratio

$$\text{LGNC} = \frac{\text{Total expected loss}}{\text{EAD}} = 1 - \frac{\text{Total expected earnings}}{\text{EAD}}$$

This ratio expresses the share of the exposure at default that remains unrecovered in non-cured cases.

The third component, the *LGC*, captures the small but mostly non-zero loss that may still occur in cured cases. Even though the borrower repays the full principal, a loss may arise due to delayed cashflows. The lender receives the expected payments later than planned, resulting in an economic loss driven by the time value of money. This can be represented by:

$$\text{LGC} = \Delta r$$

Here, Δr reflects the difference in return between receiving payments as originally scheduled and receiving them with delay. Since no principal is lost and other costs are limited, LGC tends to be low and relatively stable.

The three components are then finally combined into a single LGD estimate using a weighted average structure

$$\text{LGD} = (1 - \text{Cure Rate}) \cdot \text{LGNC} + \text{Cure Rate} \cdot \text{LGC}$$

This structure ensures that the overall LGD reflects the probability-weighted losses across both cured and non-cured paths. To make this more intuitive, an illustrative example is presented below.

Example 2.4. *Consider a portfolio of residential mortgage loans, where borrowers are classified as in default after missing three consecutive monthly payments. Let the outstanding amount at the moment of default, i.e. the Exposure at Default (EAD), to be €200,000.*

Historical data indicates that 20% of defaulted loans cure within the defined observation period, resulting in a cure rate of 0.20. Accordingly, 80% of the loans are classified as non-cured.

For the non-cured loans, the lender expects to recover €130,000 through collateral liquidation, offsetting deposits, insurance payouts or other sources. The resulting loss is €70,000, leading to:

$$LGNC = \frac{200{,}000 - 130{,}000}{200{,}000} = \frac{70{,}000}{200{,}000} = 0.35$$

For the cured loans, the full principal is eventually recovered, but a small loss is still incurred due to delayed payments. Suppose this timing-related loss is estimated at €6,000 per loan. Then:

$$LGC = \frac{6{,}000}{200{,}000} = 0.03$$

The final LGD is obtained by combining the two components according to the weighted average structure:

$$LGD = (1 - 0.20) \cdot 0.35 + 0.20 \cdot 0.03 = 0.28 + 0.006 = 0.286$$

$$\Rightarrow LGD = 28.6\%$$

While banks often rely on internally developed LGD models tailored to their specific portfolios, the underlying metric is generally structured around some form of combination of the three components discussed: the probability of cure, LGNC and LGC. This structure ensures that the resulting LGD reflects both the larger loss in non-cured cases and the smaller, timing-related loss in cured cases. Moreover, the use of EAD as a denominator ensures comparability across loans of varying sizes.

2.4 Residential Real Estate (RRE) Exposure

Since the focus of this research is on the exposure class of residential mortgages—i.e. residential real estate (RRE)—it is useful to first provide some background on the common factors that influence credit risk models within this class. These factors are commonly referred to as **risk drivers**, as they affect key credit risk metrics.

Each bank develops its own set of significant risk drivers, with internal modeling and weighting applied to each. However, a common set of drivers can be identified that is applicable to RRE portfolios [8, 13, 21].

These common risk drivers can be grouped into four main categories: borrower characteristics, loan and transaction characteristics, property characteristics, and external factors. Each category represents a different aspect of the risk profile and contributes in its own way to the overall risk assessment.

In this section, the most relevant risk drivers will be given and briefly explained for each category.

I. Borrower Characteristics

- *Creditworthiness of the borrower*: Includes credit history, existing debt and behavioural scoring models. For RRE, the borrower's creditworthiness influences the probability of default (PD) in internal rating models.
- *Income and employment status*: A stable income is essential for mortgage repayment. Metrics such as the *Debt-to-Income (DTI)* and *Debt Service-to-Income (DSTI)* ratios are widely used, these metrics are given by
$$\text{DTI} = \frac{\text{Total Debt}}{\text{Gross Annual Income}}, \quad \text{DSTI} = \frac{\text{Annual Debt Payments}}{\text{Gross Annual Income}}. \tag{9}$$
High DTI or DSTI values are associated with increased credit risk in RRE portfolios.
- *Type of borrower*: Whether the borrower is a salaried employee, self-employed or retired can affect income stability and thus risk exposure in RRE lending.

II. Loan and Transaction Characteristics

- *Loan amount*: A larger mortgage relative to income or property value increases the risk of default and loss given default (LGD) in case of foreclosure.
- *Loan-to-Value (LTV) ratio*: A key risk driver for RRE. It measures the size of the loan relative to the collateral value:
$$\text{LTV} = \frac{\text{Loan Amount}}{\text{Collateral Value}} \tag{10}$$
Higher LTVs are typically associated with increased LGD, as they reduce the collateral buffer in case of a property price decline.
- *Loan-to-Income (LTI) ratio*: Expresses the loan amount as a multiple of the borrower's income, indicating affordability:
$$\text{LTI} = \frac{\text{Loan Amount}}{\text{Gross Annual Income}} \tag{11}$$
In RRE portfolios, high LTI values can signal vulnerability to income shocks, which typically impacts the PD.
- *Loan maturity*: Longer maturities imply longer exposure to macroeconomic volatility. For RRE, this affects both default timing and prepayment behaviour.
- *Interest rate type*: Variable-rate mortgages (VRMs) expose borrowers to interest rate risk, potentially increasing payment shock and default risk in RRE loans.
- *Presence of guarantees*: Guarantees (e.g. from a government scheme) reduce the effective risk to the lender in case of borrower default.

III. Property Characteristics

- *Property value*: The market and stressed value of the property is central to estimating LGD. This is also a key input for LTV calculations.
- *Property quality and maintenance*: Poorly maintained homes are more likely to lose value, reducing collateral recoverability in RRE loans.
- *Energy performance*: Properties with higher energy efficiency often have higher market value and lower utility costs, improving affordability and reducing default likelihood. In the EU, Energy Performance Certificates (EPCs) are used to capture this effect.

IV. External Factors

- *Economic conditions*: Variables such as GDP growth, interest rates, and unemployment directly affect default probabilities and borrower affordability in RRE.
- *Housing market developments*: Supply-demand imbalances, price trends, and liquidity in the housing market determine both collateral value and loss severity in case of default.
- *Regulations*: Loan caps, minimum down payments, and macroprudential measures influence lending standards and indirectly affect the risk profile of RRE portfolios.
- *Social risks*: Demographic shifts (e.g. ageing population, urbanisation) and behavioural changes (e.g. preference for renting) influence demand and price dynamics in the residential housing market.

Understanding these risk drivers is essential for lenders to effectively assess and manage the credit risk associated with residential mortgages. It is also important to have a clear overview of the metrics that directly impact credit risk models within RRE, as this helps build a deeper understanding for later decisions on integrating climate risk into RRE models.

3 Regulations

To safeguard the financial system from excessive risk-taking and instability, regulatory frameworks have evolved to ensure that banks maintain sufficient capital buffers, manage risks effectively and operate transparently. This section outlines key regulatory structures relevant to this research, providing a clear foundation for the regulatory terminology used throughout.

3.1 Regulatory Framework

One of the key institutions in global banking regulation is the *Bank for International Settlements (BIS)*, founded in 1930 and headquartered in Basel, Switzerland. The BIS acts as a hub for central banks, promoting international financial cooperation and monetary stability [22]. Within the BIS, the *Basel Committee on Banking Supervision (BCBS)* was established to develop consistent regulatory standards for banks worldwide. This committee has introduced several regulatory frameworks, known as the *Basel Accords*, which define capital adequacy and risk management requirements.

The Basel Accords provide a series of internationally recognized guidelines designed to enhance financial stability by standardizing capital and risk management requirements across the banking sector [22]. These frameworks have evolved over time in response to financial crises, addressing emerging risks and regulatory shortcomings. However, since the BCBS is not a regulatory authority, its frameworks must be implemented by national and regional regulators.

In the European Union (EU), banking regulation builds upon the Basel Accords and is further shaped by several key institutions. The *European Central Bank (ECB)* and the *European Banking Authority (EBA)* play central roles in ensuring financial stability and regulatory compliance. The ECB, apart from its role in monetary policy, is responsible for banking supervision through the *Single Supervisory Mechanism (SSM)*. The SSM acts as a framework that standardizes banking oversight across the eurozone. It ensures that all participating countries apply banking regulations consistently and that large, cross-border banks are monitored centrally [23].

Within this framework, the ECB directly supervises large and systemically important banks — that is, banks whose failure could threaten the stability of the European financial system. Smaller banks remain under the supervision of national regulators, who operate within the SSM but retain responsibility at the national level. In the Netherlands, this role is fulfilled by *De Nederlandsche Bank (DNB)*, which oversees smaller Dutch banks and assists the ECB in supervising larger institutions such as ING, ABN AMRO, and Rabobank [24]. By working together within the SSM, the ECB and national regulators like the DNB aim to maintain a stable and resilient European banking sector.

The *European Banking Authority (EBA)*[3], established in 2011, plays a crucial role in harmonizing banking supervision across EU member states. It helps ensure that regulatory frameworks, such as the Basel Accords, are applied consistently within the EU. The legal rules themselves—such as the *Capital Requirements Directive (CRD)* and the *Capital Requirements Regulation (CRR)*—are drafted by the European Commission and adopted by the European Parliament and Council. These texts are based on the Basel Accords but are adapted to fit the European legal and institutional framework. Based on the CRD and CRR, the EBA develops *EBA Guidelines* to support uniform interpretation and application across member states. In addition, the ECB sometimes publishes its own non-binding guides to clarify how it interprets these rules in its supervision. Unlike the ECB, the EBA does not directly supervise banks, but instead provides a common set of supervisory guidelines that both the ECB and national regulators, such as DNB, are expected to follow.

[3]Previously coordinated by the *Committee of European Banking Supervisors (CEBS)*, but after the 2008 financial crisis reshaped into the EBA for stronger regulatory enforcement.

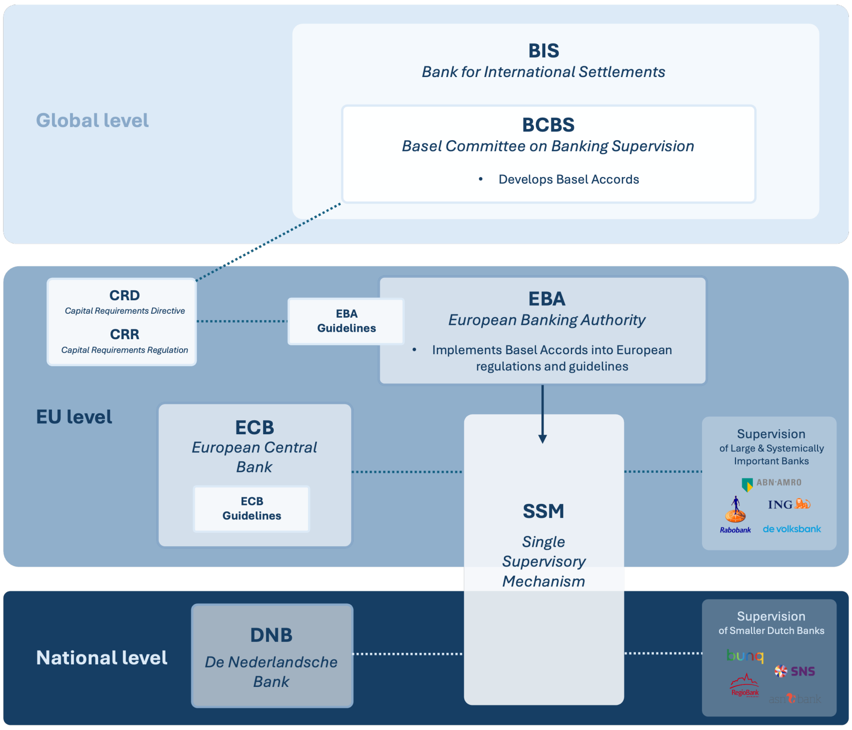


Figure 2: Overview of the Banking Regulatory and Supervisory Framework in the Netherlands

3.2 Basel Accords

The Basel Accords are the international regulatory frameworks developed by the Basel Committee on Banking Supervision (BCBS). This section provides a high-level overview of key developments, focusing on aspects relevant to this research, aiming to establish a basic understanding of the currently permitted credit risk models.

3.2.1 Basel I

Basel I, introduced in 1988, marked the first global effort to establish minimum capital requirements for banks. It primarily focused on credit risk, categorizing assets into broad risk classes with fixed risk weights. Under this framework, banks were required to maintain a minimum capital adequacy ratio (CAR) of 8%, meaning they had to hold at least 8 cents of capital for every euro of risk-weighted assets (RWA) [25]. For example, residential mortgages were assigned a fixed risk weight of 50%, meaning that only half of the mortgage exposure counted toward the bank's total RWA, regardless of the borrower's creditworthiness [26]. While this approach provided a simple and standardized method for capital regulation, it lacked risk sensitivity, as it did not differentiate between loans with different default probabilities or loss severities.

3.2.2 Basel II

To address these limitations, Basel II was introduced in 2004 [27], offering a more risk-sensitive approach. The assumption that all loans within the same category should receive a fixed risk weight was abandoned. Instead, banks were given two options to determine capital requirements for credit risk:

- *Standardised Approach (SA)*: This method assigns fixed risk weights to exposures based on external credit ratings, without considering the bank's own risk assessment.
- *Internal Ratings-Based (IRB) approach*: Banks were allowed to use internal models to estimate their own risk weights, making capital requirements more sensitive to actual credit risk.

The IRB approach introduced two variants [21]:

- *Foundation IRB (F-IRB)*: Banks were permitted to estimate the probability of default (PD) for their exposures, but were required to use standard supervisory values for other parameters, such as the loss given default (LGD) and exposure at default (EAD), as defined by regulators.
- *Advanced IRB (A-IRB)*: Banks were allowed to fully estimate their own risk parameters, including the probability of default (PD), loss given default (LGD), and exposure at default (EAD), based on their internal data and models.

Basel II additionally introduced three pillars: 1 - *Minimum Capital Requirements*, 2 - *Supervisory Review*, and 3 - *Market Discipline*. In short, the first two pillars ensure that, even within the IRB approaches, minimum capital requirements per exposure class remain in place and that models are regularly assessed to ensure their reliability, even under stressed conditions. In addition to establishing a more risk-sensitive framework, Basel II also formalized the capital requirement (K), risk-weighted assets (RWA) and Common Equity Tier 1 ($CET1$) calculations, as discussed previously in equations (3), (7) and (8) for retail mortgage exposures specifically. These formulas, particularly relevant under the IRB approach, remain fundamental in regulatory capital assessments today, linking capital requirements directly to estimated credit risk parameters PD, LGD, and EAD. The third pillar establishes disclosure requirements, which for example includes mandating that banks publicly report whether they use the SA or IRB approach, as well as details on their capital structure and sectoral exposures. This transparency allows market participants and regulators to better assess a bank's financial stability.

3.2.3 Basel III

The 2008 financial crisis exposed weaknesses in Basel II, particularly its reliance on internal risk models, which underestimated systemic risk and led to insufficient capital buffers. In response, Basel III was introduced in 2010, maintaining the three-pillar structure of Basel II but introducing improvements to strengthen financial stability [28]. In short, the improvements under the first pillar included higher capital requirements, the introduction of the *capital conservation buffer* and *countercyclical buffer*, and the implementation of a *leverage ratio* to prevent excessive risk-taking. Under the second pillar, regulatory oversight was strengthened by introducing mandatory stress testing and incorporating liquidity risk assessments. For the third pillar, transparency requirements were expanded, obligating banks to disclose their leverage ratios, capital composition and liquidity coverage to ensure greater market discipline.

3.2.4 Basel IV

Basel IV, often referred to as the finalization of Basel III [29], again builds upon the existing three-pillar structure. Below is an overview of the key improvements introduced under each pillar.

Pillar 1 – Minimum Capital Requirements: The already existing Standardized Approaches (SA) have been refined under Basel IV. In short, the SA refinements include the creation of more specific risk categories and the incorporation of additional parameters in the calculation of risk weights within these categories. For example, for certain exposure classes, the creditworthiness of the borrower now plays a greater role in determining risk weights. Another refinement includes tighter conditions for the use of external credit ratings (i.e. ratings from agencies such as Moody's or S&P).

Additionally, Basel IV introduces an *output floor*, requiring that internally modeled risk-weighted assets (RWAs) cannot be lower than *72.5%* of the standardized approach calculations. This measure ensures that banks relying on internal models do not significantly underestimate their risks. For retail mortgage exposures specifically, under the Standardized Approach, the risk weights depend on the loan-to-value (LTV) ratio of the asset loan (10), with the corresponding values shown in Figure 3. These exposures refer to residential mortgages where repayment is primarily based on the borrower's income rather than rental or investment cash flows, which aligns with the exposure class that this research focuses on. Consequently, due to the output floor requirement, the IRB risk weights must be at least 72.5% of the risk weights presented in the table.

Whole loan approach risk weights for regulatory residential real estate exposures that are not materially dependent on cash flows generated by the property						Table 11
	LTV ≤ 50%	50% < LTV ≤ 60%	60% < LTV ≤ 80%	80% < LTV ≤ 90%	90% < LTV ≤ 100%	LTV > 100%
Risk weight	20%	25%	30%	40%	50%	70%

Figure 3: Risk Weights for Retail Mortgage Exposures under the Standardized Approach, based on the Loan-to-Value (LTV) Ratio of the Underlying Asset [30].

Furthermore, Basel IV restricts the use of the *Internal Ratings-Based (IRB) approach* for certain asset classes with low default rates, such as *large corporates with revenues exceeding €500 million* and financial institutions. These exposures must now be assessed using the standardized approach, ensuring more consistent and reliable risk calculations across banks.

Finally, stricter *data requirements* have been introduced for internal models, particularly regarding *historical data coverage* and *input floors* for Probability of Default (PD) and Loss Given Default (LGD) estimates. This includes a minimum *PD input floor* of 0.05% for most exposure classes [17].

Pillar 2 – Supervisory Review Process: Supervisors are provided with detailed guidelines to assess banks' internal models and risk management practices. Basel IV introduces new *validation requirements* for internal models, including stricter *back-testing* and *benchmarking against external data*. Banks must now conduct more frequent reviews of their Probability of Default (PD) and Loss Given Default (LGD) estimates, ensuring that assumptions remain conservative and aligned with real-world default data [17].

Pillar 3 – Market Discipline: Basel IV expands the scope of disclosures related to credit risk. Banks are now required to provide more detailed transparency on their risk-weighted asset calculations, including a comparison between their internally modeled RWAs and those calculated under the standardized approach. Disclosures must also cover the *impact of the output floor* on capital requirements and the assumptions used in internal models [29].

3.3 Climate-Related and Environmental Risks (CER) Regulation

Understanding the regulatory landscape surrounding Climate and Environmental Risks (CER) is essential for this research, as it defines the expectations for how internal credit risk models should incorporate these risks.

Three key regulatory documents have been selected based on their significance and timeline. The ECB Guide on Climate-Related and Environmental Risks (2020) [9] provides the earliest complete published regulatory perspective, outlining broad expectations for how banks should manage CER. Rather than prescribing methodologies, it sets foundational principles that later regulations build upon. The EBA Report on the Role of Environmental and Social Risks in the Prudential Framework (2023) [16] evaluates the extent to which ESG risks have been integrated into the prudential framework and presents recommendations for further improvement. The most recent document, the EBA Guidelines on ESG Risks Management (2025) [7], introduces practical methodologies for banks to measure, manage, and integrate ESG risks into their credit risk models.

As all three regulatory documents are quite extensive and broadly applicable across various areas of the financial sector, it is important to clarify that this section does not aim to provide a comprehensive regulatory analysis. Instead, a focused selection has been made and summarized to highlight the aspects most relevant to this research, particularly those concerning the integration of CER into internal credit risk models for residential mortgages. Each of the three regulatory documents will be discussed separately in this section, after which a schematic summary can be found in Figure 4.

3.3.1 ECB Guide on climate-related and environmental risks (November, 2020)

In November 2020 [9], the European Central Bank (ECB) published its first comprehensive final document outlining supervisory expectations regarding climate-related and environmental risks (CER) within the financial sector. This guide emphasizes that climate risks should not be viewed as standalone risks but rather as drivers of existing risk categories, such as credit risk, operational risk, market risk and liquidity risk. The document consists of 13 main expectations, several of which specifically address credit risk. The aspects derived from the report, particularly relevant to the context of this research, can be summarized as follows:

1. *Consideration of CER at all relevant stages of the credit risk modeling process*, [9] - *Expectation 8*.
   - Climate risks may lead to cash outflows or a reduction in liquidity buffers, requiring adjustments in liquidity risk management.
   - PD and LGD may increase in sectors or regions exposed to physical risks, such as real estate in flood-prone areas, due to declining collateral values.
   - Stricter energy efficiency regulations can result in higher adaptation costs and lower corporate profits, increasing PD and reducing collateral values.
2. *Integration of CER into stress testing and scenario analysis*, [9] - *Expectation 11*.
   - Stress testing and scenario analysis should account for:
     - the impact of physical and transition risks on financial exposures.
     - how climate risks may evolve under different future scenarios, acknowledging that historical data may not fully capture them.
     - the potential manifestation of climate risks over short, medium and long-term horizons.
3. *Data collection and disclosure of CER-related information*, [9] - *Expectation 13*.
   - Institutions must define how they assess material climate risks, including disclosure frequency and methods.
   - Credit risk exposures and collateral values should be disclosed by geography, highlighting areas with high physical risk.

3.3.2 EBA Report on Environmental & Social Risks in Prudential Framework (October, 2023)

In October 2023 [16], the European Banking Authority (EBA) published a report assessing the role of environmental and social (E&S) risks within the prudential framework. The report aims to evaluate the extent to which these risks have been integrated into existing risk management practices and capital requirements, while also identifying areas where further regulatory guidance may be necessary.

The report states that at the time of publication, there were no banks which already explicitly incorporated E&S risks into their internal ratings-based (IRB) credit risk models. Where such risks were considered, they were primarily integrated through qualitative adjustments, such as expert judgment overrides, rather than through structural modifications to probability of default (PD) or loss estimation models. Many institutions assumed that these risks would be indirectly captured through existing model inputs, such as collateral valuation or financial indicators, rather than requiring dedicated E&S risk factors. The absence of a standardized approach meant that implementation varied significantly across institutions, and no clear industry consensus had been reached regarding how to systematically integrate these risks into IRB models.

While some banks had begun exploring the inclusion of environmental and social (ES) risk drivers in credit models, the process remained in its early stages. A key challenge is the lack of historical data linking environmental risk factors to credit performance, making it difficult to quantify their impact in a statistically robust manner. Moreover, climate and environmental risks are inherently forward-looking, meaning that even if historical data were available, they would not necessarily provide reliable insights into future credit outcomes. Some institutions had developed climate-informed shadow PDs to supplement existing models, while others relied on manual overrides to adjust risk assessments where necessary. Additionally, banks were considering ways to incorporate forward-looking assessments into their risk frameworks but faced difficulties in determining the appropriate assumptions and methodologies. Despite these efforts, practical implementation remained limited, as banks struggled with both data availability and regulatory uncertainty.

To address these gaps, the EBA recommended that banks take a cautious approach when dealing with missing or unreliable E&S risk data. The report suggested that financial institutions should consider applying adjustments where uncertainty exists, ensuring that climate and environmental factors are not underestimated in risk assessments. Furthermore, the EBA proposed that expert-based qualitative variables could be used in rating systems where quantitative metrics were not yet fully developed. In the longer term, the EBA intends to explore the potential for formally incorporating specific E&S risk drivers into existing regulatory guidelines for credit risk modeling. However, further empirical research and industry collaboration will be necessary to establish a more standardized approach to integrating these risks into prudential frameworks.

3.3.3 EBA Guidelines on the management of ESG risks - Final Report (January, 2025)

The 2023 EBA report highlighted the need for a more formal and conceptual approach to ESG risk management [7]. In response, at the beginning of 2025, the EBA published the *Guidelines on the Management of ESG Risks* [7] final report, introducing explicit reference methodologies to standardize the identification, measurement, management and monitoring of ESG risks. This report is based on Article 87a (5) of the Capital Requirements Directive (CRD VI), which mandates the EBA to issue guidelines on these matters. For large institutions, the guidelines will generally apply from 11 January 2026, while small and non-complex institutions will have an extended transition period until 11 January 2027. A structured way to summarize the content of this report is by distinguishing between modeling requirements and data requirements. The aspects most relevant to this research can be summarized as follows [31]:

Modeling Requirements

- *ESG factors must be explicitly embedded into credit underwriting, risk classification, and portfolio management.* Banks can no longer treat ESG risks separately but must integrate them into existing credit risk models.
- *Materiality assessments should analyze the financial impact of ESG risk drivers on counterparties, sectors, regions, and loan (sub-)portfolios.* Banks must assess how environmental risks impact different regions and loan portfolios. For example, flood risks may affect collateral values, increasing credit risk in certain areas.
- *The guidelines stress the importance of quantifying environmental risks, including physical and transition risks.* Banks must move from qualitative assessments to measurable financial impacts, integrating climate risk scores and adjusting PD/LGD estimates accordingly.
- *Clarity on using proxies and scenario analysis, allowing flexibility as data improves.* Since ESG data is evolving, banks may use proxies and scenario-based analysis to estimate risks. Overlays can be applied temporarily, similar to how banks handle novel risk factors.

Data Requirements

- *Data collection is now based on the ESG risk materiality assessment, allowing flexibility in granularity.*

Instead of collecting all ESG data, banks may prioritize data based on a materiality assessment, ensuring focus on key risk areas.

- *The alignment with CSRD disclosures is emphasized, meaning banks should use publicly available data, especially on emissions and climate plans.* Banks should rely on CSRD-reported ESG data, which simplifies data collection but also requires frequent model updates as new data becomes available.
- *The use of proxies when data is unavailable is allowed, but a reduction over time is expected.* Banks may use proxies for missing ESG data, but these should be gradually phased out as direct ESG reporting improves.
- *Specific data points are required, such as GHG emissions, energy consumption, social standards and governance issues.*[4] Banks must collect GHG emissions, energy usage, and governance-related factors, ensuring borrower engagement where necessary. CSRD data should be prioritized for compliance.

A schematic summary of the three discussed documents is presented in Figure 4.

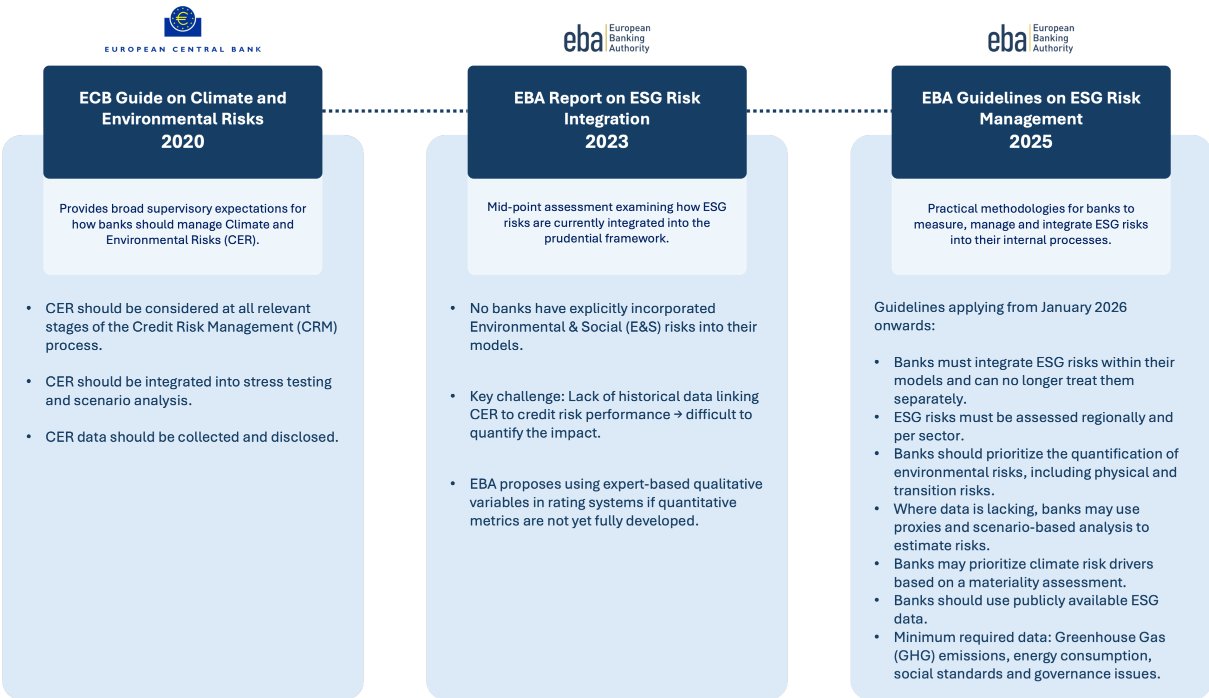


Figure 4: Overview and Timeline of Climate-Related and Environmental Risk (CER) Regulations.

Overall, the actual adoption of Climate and Environmental Risk (CER) integration within the Dutch banking industry remains limited. However, with the upcoming enforcement of stricter regulatory requirements, the urgency for further research on this topic within the Dutch banking sector becomes increasingly important. This necessity sets the stage for the next section, which examines the current state of progress within a specific area of climate and environmental risk.

[4] GHG emissions refer to the amount of greenhouse gases released by an entity's operations. Social standards include factors like employee rights, working conditions and community impact. Governance issues relate to internal controls, board structure and transparency. The CSRD (Corporate Sustainability Reporting Directive) is an EU regulation that mandates standardized sustainability disclosures from companies.

4 Climate and Environmental Risks

This section provides the theoretical basis for climate and environmental risks, beginning with their definitions and relevance to the financial sector. This research will be focussing on one category of physical risks: flood risk. For each category, a structured analysis of its definition, scope and current methodologies for quantification and integration into financial models is provided. Particular attention is paid to the techniques used for risk assessment and the data sources underlying these models.

4.1 Risk Taxonomy

To establish a foundational understanding, it is essential to define climate and environmental risk (CER) in a structured way. Climate-related and environmental risks are generally understood to be defined as follows

Definition 2. *Climate and Environmental Risk (CER) is the potential financial impact resulting from climate change and environmental degradation, influencing financial stability through direct and indirect channels, affecting asset valuations, business operations and overall market dynamics. [9]*

Climate-related and environmental risks can be broadly categorized into two categories: *physical risks* and *transition risks*, each with distinct implications for financial stability and economic activity. Both categories are briefly introduced below.

Physical risks result from the direct impacts of climate change and environmental degradation on economic assets and infrastructure. These risks can be divided into **acute risks**, which result from extreme weather events such as hurricanes, floods and drought, and **chronic risks**, which result from long-term shifts in climate patterns, including sea level rise, temperature rise and biodiversity loss. The financial implications of physical risks include direct asset damage, business disruptions and supply chain vulnerabilities, which can ultimately lead to broader macroeconomic instability.

Transition risks arise from the process of shifting to a lower-carbon and more sustainable economy. These risks are caused primarily by regulatory changes, technological advances, shifts in market sentiment and changing consumer preferences. Institutions may face financial losses due to changes in asset valuations, increased operating costs or reduced market demand for carbon-intensive industries. If the transition occurs in a disordered manner - for example, through abrupt policy implementations or rapid shifts in investor behavior - the financial system may face increased volatility and systemic risk.

Both physical and transition risks interact with existing financial risk categories, such as credit risk, market risk, liquidity risk and operational risk. The extent of their impact depends on institutions' exposure to climate-sensitive sectors and the effectiveness of risk mitigation strategies. To better illustrate the impact of climate and environmental risks on financial institutions, Figure 5 presents an overview table of the key risk drivers categorized into physical and transition risks, published by the ECB [9]. In particular, credit risk is significantly influenced by these risk factors, as changes in climate conditions or policy transitions can alter default probabilities (PD), loss given default (LGD) and collateral valuations.

In this research, the focus is specifically on physical risks—more precisely, flood risk—which will be discussed in the following section. Flooding is a particularly relevant hazard in the context of residential real estate in the Netherlands, given the country's low elevation and vulnerability to rising water levels. It can directly affect property values and increase default risk. Moreover, flood risk is increasingly acknowledged in both regulatory and academic contexts as a key driver of climate-related financial losses.

4.2 Flood Risk

Flood risk is commonly defined as a function of two key components: the probability of a flood event occurring and the impact it would generate if realized. While flood probability depends on geographic and

Table 1
Examples of climate-related and environmental risk drivers

	Physical		Transition	
Risks affected	**Climate-related**	**Environmental**	**Climate-related**	**Environmental**
	• Extreme weather events • Chronic weather patterns	• Water stress • Resource scarcity • Biodiversity loss • Pollution • Other	• Policy and regulation • Technology • Market sentiment	• Policy and regulation • Technology • Market sentiment
Credit	The probabilities of default (PD) and loss given default (LGD) of exposures within sectors or geographies vulnerable to physical risk may be impacted, for example, through lower collateral valuations in real estate portfolios as a result of increased flood risk.		Energy efficiency standards may trigger substantial adaptation costs and lower corporate profitability, which may lead to a higher PD as well as lower collateral values.	
Market	Severe physical events may lead to shifts in market expectations and could result in sudden repricing, higher volatility and losses in asset values on some markets.		Transition risk drivers may generate an abrupt repricing of securities and derivatives, for example for products associated with industries affected by asset stranding.	
Operational	The bank's operations may be disrupted due to physical damage to its property, branches and data centres as a result of extreme weather events.		Changing consumer sentiment regarding climate issues can lead to reputation and liability risks for the bank as a result of scandals caused by the financing of environmentally controversial activities.	
Other risk types (liquidity, business model)	Liquidity risk may be affected in the event of clients withdrawing money from their accounts in order to finance damage repairs.		Transition risk drivers may affect the viability of some business lines and lead to strategic risk for specific business models if the necessary adaptation or diversification is not implemented. An abrupt repricing of securities, for instance due to asset stranding, may reduce the value of banks' high quality liquid assets, thereby affecting liquidity buffers.	

Source: ECB.

Figure 5: Examples of climate-related and environmental risk drivers, categorized into physical and transition risks [9].

climate factors, the impact is determined by the extent of economic and financial damages inflicted on affected areas. The interplay between these factors makes flood risk assessment an important component of disaster preparedness, urban planning and financial stability analysis.

Given the Netherlands' unique vulnerability to flooding—particularly due to its below-sea-level geography and the exclusion of flood damage from standard property insurance policies—the potential implications for financial institutions are considerable. Although the Dutch government actively invests in flood defense and mitigation measures [6], the risk of extreme flood events remains relevant. Existing studies have attempted to quantify how extreme flood events could impact bank capital positions, offering valuable insights into the intersection of climate risk and financial stability.

Understanding flood risk at a granular level is essential for assessing its potential consequences for property values, credit markets and financial institutions. The following section outlines a state-of-the-art methodology used to model flood exposure, estimate financial losses and evaluate their impact on key banking metrics in the Netherlands. A specific study will be used as a reference point, the discussion paper *Floods and Financial Stability: Scenario-based Evidence from Below Sea Level* by Francesco G. Caloia, Kees van Ginkel, and David-Jan Jansen (2023) [11], which examines the potential financial stability risks posed by floods in the Netherlands. This paper was conducted by a joint research group affiliated with Erasmus University Rotterdam, the University of Amsterdam (UvA), and Vrije Universiteit Amsterdam (VU). Additionally, the study was later published by De Nederlandsche Bank (DNB) as a working paper, aiming to provide insights relevant to financial supervision and policy development.

The study employs a scenario-based methodology to assess how flood-related property damages could impact bank capital through increased credit risk. It builds upon findings from major studies on flood scenario modeling, flood damage estimation and financial exposure assessment, integrating insights from both hydrological and economic research. The relevance of this study is underscored by its large-scale dataset, covering approximately EUR 650 billion in real estate exposures—referring to outstanding loan amounts—across more than three million residential properties.

4.2.1 Scenario-based Approach

As can be inferred from its title, this paper operates based on a set of stress scenarios. In the context of flooding in the Netherlands, it is natural to define these stress scenarios in terms of dike breaches, as failures in the flood defense system represent the primary mechanism through which large-scale inundations occur. This approach is also adopted in this study, where a total of 38 flood scenarios are analyzed. Of these, 32 scenarios represent single-breach flood events, while the remaining 6 correspond to extreme multi-breach scenarios, as identified in the research by Dutch flood experts [32]. The single-breach scenarios are based on the *Landelijk Informatiesysteem Water en Overstromingen* (LIWO) [33], an open-source system that models thousands of potential flood events across the country. From this dataset, the study selects scenarios with the highest expected economic impact, specifically those where estimated property damages exceed EUR 500 million. In contrast, the extreme multi-breach scenarios originate from an expert study conducted in 2007, which examines the consequences of simultaneous dike failures across multiple regions.

This section provides a detailed overview of the methodology employed in the paper. First, the dataset used in the study is introduced, outlining the sources and characteristics of the financial and geographic data. Next, the study's flood damage estimation process is examined, explaining how flood scenarios were selected and how property damages were calculated. Finally, the methodology used to quantify the impact on credit risk modeling and bank capital adequacy is discussed, focusing on how flood-induced property devaluations influence credit risk metrics, such as loss-given-default (LGD) and probability of default (PD), ultimately impacting banks' capital positions.

This methodological overview is particularly relevant for this thesis, as it informs the questions concerning how flood risk is currently quantified and incorporated into credit risk models, while also illustrating a set of assumptions made in this process. By reviewing an established scenario-based approach, this section provides a publicly available reference point for identifying potential directions for model refinement.

4.2.2 Data

The methodology in this study is based on a combination of three key data sources, each contributing to different aspects of the flood risk assessment and its financial implications. By integrating granular loan-level data, administrative property data, and regulatory bank disclosures, the study provides a comprehensive foundation for analyzing the credit risk impact of flood-related property devaluations.

Loan-level data. A core component of the study is the use of loan-level data, which provides detailed information on mortgage and commercial real estate exposures of Dutch banks. These datasets, generally sourced from financial institutions, contain specific information on individual loan contracts, such as the outstanding loan amount, repayment structures, and borrower-specific characteristics (e.g. income and credit history). Additionally, this part of the dataset captures loan developments, allowing for the tracking of trends in loan-to-value (LTV) ratios and other credit risk parameters. This data is crucial for assessing how flood-induced property devaluations affect mortgage portfolios.

Property Microdata. To estimate the impact of flooding on property values, the study incorporates administrative microdata from *Statistics Netherlands (CBS)*. This dataset contains essential property-level information, including the official property valuation (WOZ value), which is determined by municipalities for taxation purposes. Additionally, it includes structural characteristics of properties, such as floor area (m^2), geographic location at the postal-code level, and classification into residential or commercial real estate. By integrating this data with flood scenario modeling, the study can estimate the extent of property damage in different locations and assess how such damages translate into changes in collateral values.

Supervisory Bank-specific data. To quantify the financial implications of flood risk, the study utilizes supervisory data reported by Dutch banks under the Common Reporting (COREP) and Financial Reporting (FINREP) frameworks. These regulatory filings provide critical insights into the financial health of banks, including balance sheet compositions, capital adequacy metrics, and asset quality assessments. Specifically, this dataset includes information on banks' total loan exposures, profitability measures related to mortgage lending and the level of capital held against potential credit losses. By linking this data with loan-level and property valuation data, the study evaluates how flood-related shocks could affect key banking stability indicators.

Data Category		
Loan-Level Data	**Property Microdata**	**Supervisory Bank-Specific Data**
Loan contract details (amount, outstanding debt)	WOZ property valuation (municipal assessment)	Bank balance sheets (total loan exposures)
Loan type (fixed vs. variable rate)	Structural characteristics (floor area, number of floors)	Profitability metrics (loan performance, earnings)
Insurance coverage information	Geographic location (postal code level)	Capital adequacy (CET1 ratios, buffers)
Borrower characteristics (income, credit history)	Property classification (residential vs. commercial)	Asset quality assessments (risk-weighted exposures)
Quarterly loan trend data		

Table 3: Overview of data sources used in the study, categorized into three main types, with corresponding examples of data entries.

Table 3 provides a summarized overview of the data sources used in the study, grouped into categories, with examples of relevant data entries included for each. By combining three complementary data sets, the study enables a detailed assessment of how extreme flood events could translate into financial vulnerabilities for the banking sector. While the paper does not specify the technical integration procedure in detail, it outlines how each source contributes to distinct steps in the modeling chain: property damage estimation, credit risk parameter calculation and capital adequacy analysis. The granularity of the data allows for scenario-based stress testing, providing a forward-looking analysis of the potential credit risk implications of climate-related flooding.

4.2.3 Flood Damage Methodology

As previously mentioned, the methodology by Caloia et al. [11] is based on stress-testing flood scenarios, considering floods originating from either the sea or major rivers, specifically in areas currently protected by flood defenses. The methodology relies on two primary scenario types, each differing in severity and source.

The first type consists of 32 single-breach flood scenarios, in which localized failures in flood defense systems result in the inundation of specific areas. These scenarios were obtained from the Landelijk Informatiepunt Water en Overstromingen (LIWO), an open-source national database containing over 5,000 flood scenarios. To select the most relevant scenarios, two criteria were applied. First, the study includes only areas vulnerable to breaches in primary flood defense systems, classified as ‘type B’ floods. In other words this refers to flooding in areas where the water system is classified as "main" (e.g. major rivers such as the Rhine and Meuse) and where flood protection is present. Despite the presence of flood defenses, these areas remain at risk due to extreme weather events or failures in the protection system. Notably, property damages resulting from this flood type are typically excluded from coverage by standard insurance policies. Second, within each region, the scenario leading to the highest estimated property damage—exceeding a threshold of EUR 500 million—was selected. This approach ensures a focus on tail risks, highlighting the worst-case impacts on financial stability rather than the average expected damages.

Additionally, as second type the study incorporates six extreme multiple-breach flood scenarios. These scenarios, developed by Dutch flood experts in 2007, depict instances where multiple dike breaches occur simultaneously, representing highly unlikely but still conceivable extreme flood events. The objective of including these cases is to assess the potential implications of severe flooding on the financial sector under worst-case conditions.

To provide a visual perspective, Figures 6 and 7 illustrate the extent of flooding in the case of different scenarios.

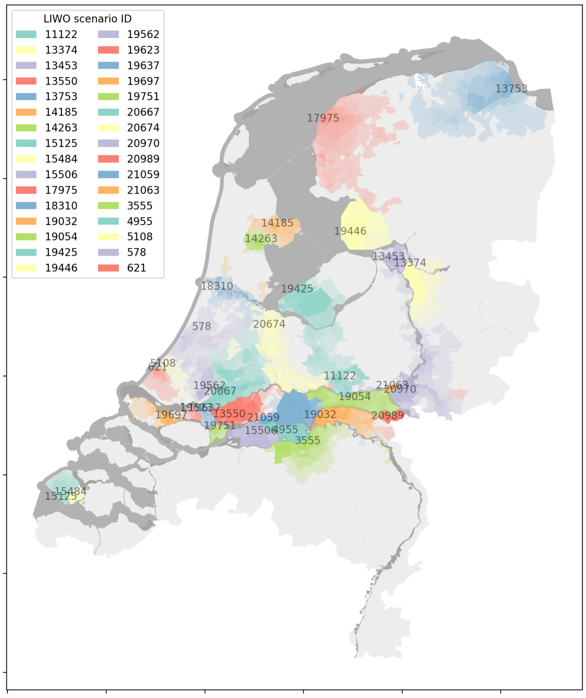
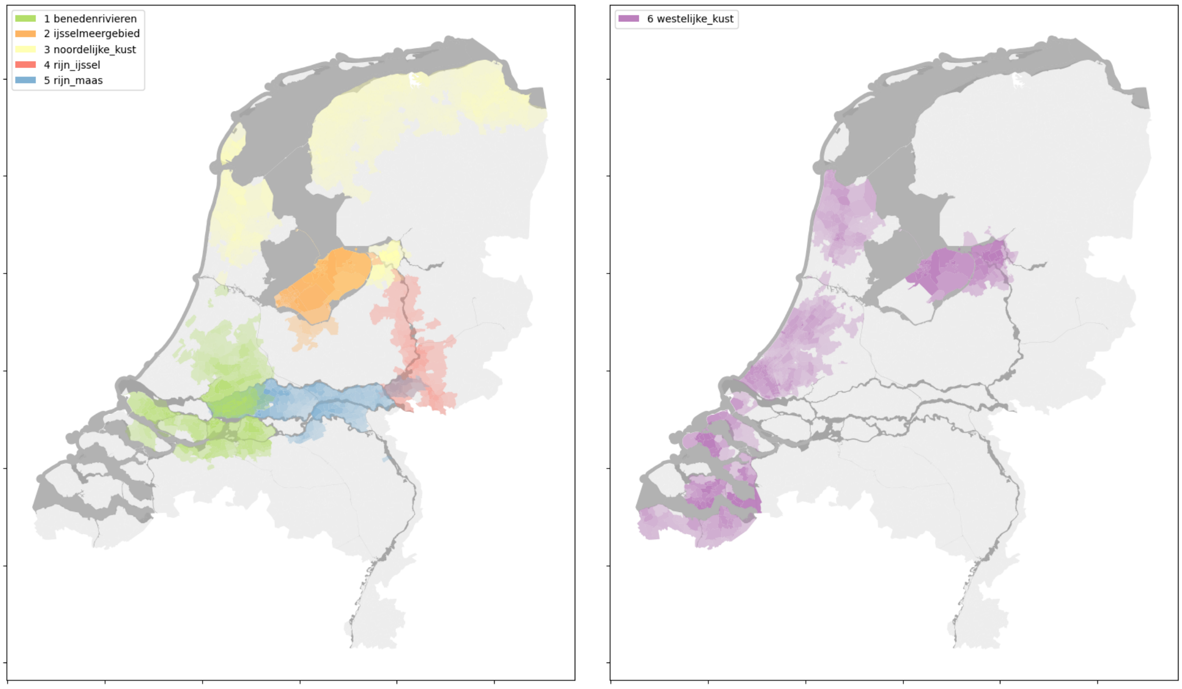


Figure 6: Scenario set for single-breach floods.

A crucial aspect of the impact assessment is the estimation of flood depths in the classified affected areas. The LIWO system provides data at a high spatial resolution, offering flood depth estimates at a minimum scale of 100×100 meters. However, since the financial data used in this paper is only available at the level of four-digit postal codes, the flood depth data had to be aggregated accordingly, despite originally being available at a much finer resolution of 100×100 meters. Therefore, this study uses a mean water depth per postal code to align the flood impact data with financial exposure data. While this aggregation allows for compatibility between both datasets, it introduces a limitation.

To estimate the inundation depth at the postal-code level, the study employs a multi-step aggregation method. First, it isolates built-up areas within each postal-code zone, excluding land use types such as agricultural fields and infrastructure, which are not directly relevant for property damage estimation. The mean water depth is then computed over the remaining built-up area. Notably, locations within a postal-code region that remain dry during a flood event are assigned a depth of zero, ensuring that the computed average



(a) Extreme scenarios 1 to 5

(b) Extreme scenario 6

Figure 7: Scenario set for extreme multiple-breach floods. [11]

depth reflects the overall conditions affecting properties within the area. While this simplification is necessary for linking flood data with financial exposures, it introduces another limitation: localized variations in water depth within a postal-code area are not captured, potentially leading to an overestimation or underestimation of damages in certain sub-regions.

A key step in quantifying the financial impact of flood risk on retail exposures involves establishing a parameter that links flood risk to collateral value. Part of this parameter, is a flood damage parameter adopted from a previous national study, specifically the most recent *Standard Method for Calculating Flood Damage in The Netherlands* (SSM2017) (Slager and Wagenaar, 2017 [34]). This methodology estimates the maximum possible damage to a residential property, expressed per square meter, depending on the type of property. A distinction is made between structural damage to the building itself and damage to the household contents. Since this study focuses solely on the collateral value of properties, only the structural damage component to the building itself is considered. This parameter is denoted as '$max\ damage_t$' in the following formulas.

To quantify the flood-induced reduction in collateral value, this study defines a parameter ϕ_p^S, representing the fraction of a property's collateral value lost due to flood damage under scenario S for property p. This is given by

$$\phi_p^S = \min\left(\frac{damage_p^S}{property\ value_p}, 1\right), \tag{12}$$

where $property\ value_p$ represents the observed collateral value of the property in the loan-level dataset, i.e. its current market value. This upper bound of 1 makes sense, as the reduction in a property's collateral value due to flood damage cannot exceed its total value. Within the previous formula, the total flood-induced damage to property p in scenario S is computed as

$$damage_p^S = \theta(h)_t^S \cdot max\ damage_t \cdot A_p \cdot \tau, \tag{13}$$

where the parameters can be described as follows

- $\theta(h)_t^S$ is the *damage function*, a value between 0 and 1 that determines the fraction of the maximum possible damage as a function of the inundation depth h. Different property types have distinct damage curves, originally specified by Slager and Wagenaar (2017). The function $\theta(h)_t^S$ is scenario-specific and property-type-specific, meaning that for each flood scenario S and property type t, it assigns a damage fraction based on the floodwater depth at that location. Due to data limitations, this study applies a small adjustment specifically for apartments by using a weighted average of the damage functions for ground-floor and first-floor apartments, rather than directly adopting the original values from SSM2017. To illustrate the damage functions applied in this study, Figure 8 presents the relationship between inundation depth and the fraction of maximum possible damage for residential real estate. The figure shows that the damage fraction increases non-linearly with water depth, with apartments exhibiting a steeper increase compared to single-family homes.
- $max\ damage_t$ represents the *maximum structural damage* (in euros per m^2, in 2011 prices) that a given property type t can sustain in the event of flooding. As previously mentioned, this value is derived from SSM2017, considering only the component related to direct damages to the building itself.
- A_p denotes the *floor area* (in m^2) of property p, sourced from administrative microdata provided by Statistics Netherlands (CBS).
- τ is an *inflation correction factor* that adjusts the estimated damage values from their original reference year (2011) to align with 2020 price levels, ensuring consistency with the loan-level data.

The computed parameter $\theta(h)_t^S$ is crucial as it directly links to the estimation of loan-to-value (LTV) ratios under flood scenarios, forming the basis for subsequent credit risk modeling. Notably, the values of ϕ_p^S are restricted to the interval $[0, 1)$ to prevent cases where flood-induced losses would exceed the entire collateral value of a property.

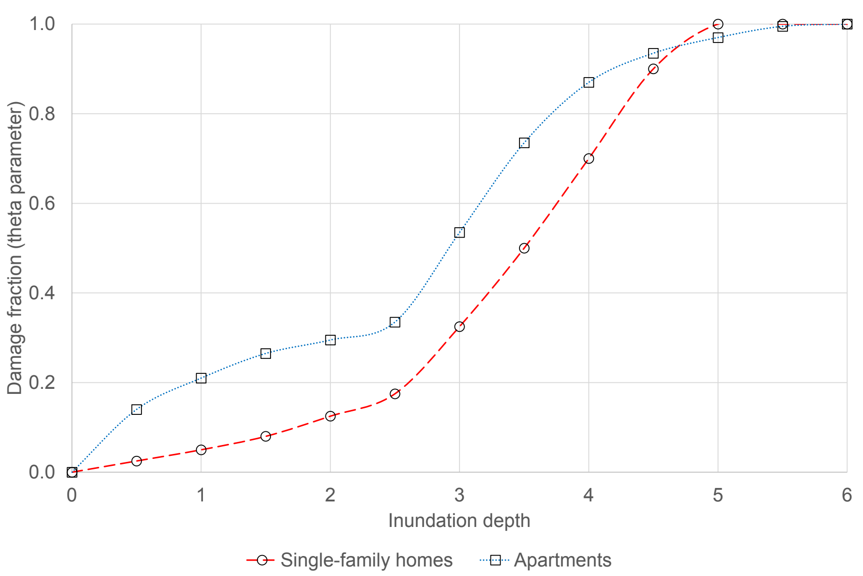


Figure 8: Relationship Between Inundation Depth and Damage Fraction for Residential Properties. [11]

Example 4.1. *To illustrate the application of the damage calculation methodology, consider a hypothetical flood scenario in Rotterdam. The damage estimation framework is applied to a specific property affected by the flood, using the relevant parameters and equations outlined in the methodology.*

- *Scenario (S): A single-breach flood scenario in Rotterdam, indexed as $S = 10$, corresponding to for example LIWO single-breach scenario ID 19637 (see Figure 6).*
- *Property (p): Within this flooded region, let a specific property be selected as property number 42, located in a residential area of Rotterdam. The parameter $p = 42$ serves as the property index, uniquely identifying this property.*
- *Type of property (t): Property number 42 is classified as a single-family home. The parameter t represents the property type, in this case, "single-family home".*
- *Inundation depth (h): The inundation depth at property number 42 corresponds to the water level at that specific location. This data is derived from flood simulations (SSM2017) and presented in water depth maps. Assume that the water depth at property index 42 is $h = 3.25$ meters.*
- *Damage factor ($\theta(h)_t^S$): The damage factor depends on the property type (t) and inundation depth (h). Suppose a reference table indicates that for a single-family home (t) at a water depth of 3.25 meters (h), the corresponding damage factor is $\theta(h) = 0.4$.*
- *Maximum damage (max $damage_t$): The maximum possible damage per square meter also depends on the property type (t). According to Slager and Wagenaar (2017), the maximum structural damage for a single-family home is €2,500 per m^2 (in 2011 price levels).*
- *Property area (A_p): The total floor area of property number 42, the single-family home, is $A_p = 120$ m^2.*
- *Price level correction factor (τ): To adjust for inflation and align damage estimates with 2020 price levels, a correction factor of $\tau = 1.15$ is applied.*

Using these parameters, the estimated flood damage for property number 42 ($p = 42$) is calculated as:

$$\begin{aligned} damage_{42}^{10} &= 0.4 \cdot 2500 \text{ €}/m^2 \cdot 120 \ m^2 \cdot 1.15 \\ &= 138,000\text{€} \end{aligned}$$

Thus, the estimated damage for this specific scenario ($S = 10$), property ($p = 42$), being a single-family home (t = single-family home), in this flood scenario equals €138,000.

Using this, the flood-induced decline in the collateral value can be calculated. In this case, the estimated damage is $damage_p^S = 138,000$. Let the property value be assumed to be €600,000. Substituting these values gives $\phi_p^S = \min\left(\frac{138{,}000}{600{,}000}, 1\right) = 0.23$. This implies that the collateral value of property index 42 has decreased by 23% as a result of the flood event in scenario $S = 10$.

The methodology outlined above aligns with prior flood damage modeling approaches but introduces key modifications tailored to the financial sector. Unlike standard SSM2017 applications, which estimate damages for all properties in an affected area, this method focuses exclusively on properties serving as collateral for bank loans. Additionally, the use of mean inundation depths per four-digit postal-code areas—rather than high-resolution grid-based flood data—reflects the need to align the geographical scale of flood data with that of bank exposure datasets. Although the paper does not provide full transparency on the technical integration between datasets, it implicitly raises important questions about the assumptions underlying this step. Understanding the nature and justification of these assumptions can be important for evaluating the robustness of the resulting risk estimates and is directly relevant to the broader research question of how flood risk is operationalized within credit risk models.

4.2.4 Credit Risk Impact Methodology

The methodology by Caloia et al. [11] further quantifies flood risks specifically in relation to banking metrics, utilizing key credit risk parameters. In the flood damage methodology, a connection is established between collateral value and flood risk, which in the context of credit risk translates into effects on the credit risk parameters Loss Given Default (LGD) and Probability of Default (PD), as discussed in Section 2.3. Additionally, a link is made to another key measure in financial supervision, the CET1 ratio, as described in (8). The analysis is conducted using end-2020 data as the starting point, with a one-year horizon.

1. LGD Impact
A key component in assessing the credit risk impact of flood-induced damages is the Loss Given Default (LGD). Flood-related property devaluations increase the Loan-to-Value (LTV) ratio, which in turn raises LGD estimates. The study defined a new parameter LTV_i^S, the *LTV of a loan i under flood scenario S* as follows

$$LTV_i^S = LTV_i^0 \cdot \frac{1}{1 - \phi_p^S} \tag{14}$$

where LTV_i^0 is the starting-point LTV, and ϕ_p^S denotes the flood-induced decline in collateral value, as previously defined (12).

To determine whether a bank can recover its outstanding loan exposure through collateral liquidation, the metric *Loss Given Loss (LGL)* is introduced. The LGL measures the fraction of the exposure that remains uncovered after selling the property in a distressed sale scenario. It is defined as

$$LGL_i = \max\left(0, \frac{exposure - liquidation\ value}{exposure}\right) \tag{15}$$

where the $liquidation\ value$ is the estimated value at which the property can be sold post-damage. The LGL under flood scenario S is further refined as

$$LGL_i^S = \max\left(0, \frac{LTV_i^S - sales\ ratio_p^S}{LTV_i^S}\right) \tag{16}$$

Here, the sales ratio denotes the ratio between the liquidation value under flood-scenario S and the current market value of the property. The market value of a property is the price it would fetch under normal conditions. The liquidation value, on the other hand, is the price actually obtained in a forced sale, which is often lower than the market value due to the urgency of the sale. In the paper, it is assumed that the calculation of liquidation value additionally takes into account the costs required to prepare the property for sale due to flood damage. In other words, it can be calculated as follows

$$sales\ ratio_p^S = sales\ ratio_p^0 \cdot (1 - \phi_p^S) = \frac{\text{pre-flood liquidation value}}{\text{current value of the property}} \cdot (1 - \phi_p^S). \tag{17}$$

Using the computed LGL, the LGD of loan i in flood scenario S is given by

$$LGD_i^S = (1 - probability\ of\ cure) \cdot LGL_i^S + costs \tag{18}$$

where:

- $1 - probability\ of\ cure$ denotes the fraction of loans that remain in default after restructuring and management of arrears.

- *Costs* refer to the administrative expenses incurred by the bank when selling the collateral property, which represent a fraction of the current exposure.

To ultimately link the scenario-specific LGD to the actual LGD, the final step introduces the *scenario-specific LGD multiplier* m^S_{LGD}. This multiplier reflects how the overall LGD changes under a given flood scenario S, accounting for differences in exposure across banks and loan types. The multiplier is computed as

$$m^S_{LGD} = \sum_b \sum_i w_b w_i \frac{LGD^S_{i,b}}{LGD_{i,b}}, \tag{19}$$

where $\frac{LGD^S_{i,b}}{LGD_{i,b}}$ represents the relative change in LGD for loan i at bank b under flood scenario S. The weights w_b and w_i play an important role in this calculation, as the objective of the paper is to estimate the overall impact of floods on Dutch bank capital. The *bank weight* w_b represents how much exposure a particular bank has relative to the total exposure across all banks in the system. Larger banks with more outstanding loans will naturally have a greater weight, as they hold a larger share of the total credit risk. Because this paper focuses on systemic risk, it uses a sample of eight major Dutch banks, covering the vast majority of the Dutch mortgage market. The *loan weight* w_i accounts for the relative size of an individual loan within a bank's total exposure. This means that larger loans, or loans with a higher outstanding balance, contribute more to the final LGD calculation than smaller ones.

By combining these weights, the LGD multiplier captures how each bank is affected by the flood scenario in proportion to its exposure. A bank with significant lending in flood-prone areas will experience a stronger impact than one with limited exposure to these regions. To provide further intuition, the following presents a hypothetical example illustrating the impact of LGD, using the collateral value parameter $\phi^S_p = 0.23$ from the previous example.

Example 4.2. *Suppose that the initial loan characteristics and flood-induced impact are defined as follows*

- *Loan-to-Value ratio (LTV^0_i): The initial Loan-to-Value ratio is 60%, i.e. 0.6.*
- *Flood-induced decline in collateral value (ϕ^S_p): The reduction in property value due to flooding is assumed to be 0.23.*
- *Exposure: The outstanding loan balance for the given property is €250,000.*
- *Initial sales ratio (Sales ratio^0_p): Before the flood event, the sales ratio is 0.90.*
- *Probability of cure: The probability that a loan recovers after initial delinquency is assumed to be 0.15.*
- *Costs: Administrative costs incurred by the bank in the event of forced liquidation amount to €3,000. Relative to the exposure, this equals 0.012.*

Using the just defined LGD methodology, the following values are obtained for loan i after the flood

1. *Post-flood Loan-to-Value ratio:* $LTV^S_i = 0.6 \cdot \frac{1}{1-0.23} = 0.779$
2. *Post-flood sales ratio:* $sales\ ratio^S_p = sales\ ratio^0_p \cdot (1 - \phi^S_p) = 0.90 \cdot (1 - 0.23) = 0.693$
3. *Post-flood Loss-Given-Loss:* $LGL^S_i = \max\left(0, \frac{LTV^S_i - sales\ ratio^S_p}{LTV^S_i}\right) = \max\left(0, \frac{0.779-0.693}{0.779}\right) = 0.086$
4. *Loss-Given-Default:* $LGD^S_i = (1 - probability\ of\ cure) \cdot (LGL^S_i + costs) = (1 - 0.15) \cdot 0.086 + 0.012 = 0.0851$

Thus, the LGD for this individual loan i under flood scenario S is 0.0851. To compute the LGD multiplier, the initial LGD for loan i before the flood is required. Assume that $LGD_i = 0.04$. Now, extending the analysis to the banking system. Suppose a specific bank b is analyzed with the following characteristics

- w_b *(Bank-level exposure share): 0.10 (this bank holds 10% of the total outstanding mortgage loans in the system)*

- *The bank has 1,000 loans in the affected postal code. For simplicity, assume that all loans have the same characteristics as loan i.*

The entire financial system consists of multiple banks (assumed to be 8 in total). To simplify the example, it is assumed that none of the other banks have loan exposure in the affected postal code, meaning their LGD remains unchanged at the initial value. The scenario-specific LGD multiplier can be calculated as follows

$$m^S_{LGD} = \frac{\sum_b \sum_i w_b w_i LGD^S_{i,b}}{\sum_b \sum_i w_b w_i LGD_{i,b}} = \frac{(0.10 \cdot 1 \cdot 0.0851) + (0.90 \cdot 1 \cdot 0.04)}{(0.10 \cdot 1 \cdot 0.04) + (0.90 \cdot 1 \cdot 0.04)} = \frac{0.00851 + 0.036}{0.004 + 0.036} = \frac{0.04451}{0.04} = 1.113.$$

Thus, the scenario-specific LGD multiplier is 1.113. This implies that, on average across the financial system, the LGD has increased by 11.3% as a result of the flood scenario S.

Note that this example is intended purely for illustrative purposes, to provide an intuitive understanding of how flood scenarios might impact the LGD metric, and no particular significance should be attached to the hypothetical values used.

2. PD Impact

Following the discussion on how flood damage can reduce collateral value and consequently affect the Loss Given Default (LGD), attention should also be given to another key dimension of credit risk: the Probability of Default (PD). At first glance, PD might appear less directly relevant in the context of physical damage to real estate. After all, the primary impact of a flood is a reduction in collateral value, which immediately increases the potential losses in case of default (LGD). However, empirical research demonstrates that the likelihood of a borrower defaulting on their loan (PD) is often highly correlated with the Loan-to-Value (LTV) ratio [11]. This means that an increase in the LTV ratio caused by flood-related property damage not only amplifies the potential losses upon default but can also increase the probability of that default occurring. For this reason, the paper extends its analysis by incorporating a statistical model to estimate how changes in the LTV ratio, resulting from flood-induced real estate damage, influence the probability of borrowers defaulting on their loans.

The probability that a borrower defaults, conditional on the different flood scenarios, is estimated using the following regression model

$$y_{i,b,t} = c_b + \beta' \mathbf{Z}_{i,b,t} + \delta' \mathbf{X}_{i,b,t} + u_{i,b,t}, \tag{20}$$

where $y_{i,b,t}$ is the dependent variable, representing the default status of borrower i at bank b at time t. This is a binary variable that takes the value 1 in case of default and 0 otherwise.

The term c_b is the constant, representing the baseline default probability when all other variables in the model are set to zero. In practice, this serves as an intercept that captures the average probability of default, incorporating all unobserved influences not explicitly included in the model.

The term $\beta' \mathbf{Z}_{i,b,t}$ represents the key independent variables affecting the probability of default, where

- $\mathbf{Z}_{i,b,t}$ is a vector of primary independent variables that are expected to have a direct effect on the probability of default under flood scenarios. In this study, these include the Loan-to-Value (LTV) ratio, the mortgage interest rate and regional GDP growth. The LTV ratio plays a central role as it is directly impacted by flood-induced property devaluation.

- β' is a vector of coefficients that quantify the magnitude and direction of the effect of each independent variable in $Z_{i,b,t}$ on the probability of default $y_{i,b,t}$. A positive coefficient indicates that an increase in the corresponding independent variable raises the likelihood of default, while a negative coefficient implies the opposite.

The term $\delta'\mathbf{X}_{i,b,t}$ accounts for so-called control variables, including

- $\mathbf{X}_{i,b,t}$ being a vector of additional variables that may influence the probability of default but are not the primary focus of this study. Including these variables allows for isolating the direct impact of flood-induced changes in the LTV ratio. Control variables include mortgage type, interest type, remaining loan term, initial LTV, property type and whether the mortgage benefits from the National Mortgage Guarantee (NHG) [5].
- δ' is a vector of coefficients that capture the effect of the control variables in $X_{i,b,t}$ on the probability of default.

Finally, $u_{i,b,t}$ is the error term, representing unobserved factors and random variation that affect the probability of default but are not explicitly included in the model.

Based on the estimated probability of default (20), a PD multiplier is derived to quantify the relative increase in default probabilities under flood scenario S. The system-wide PD multiplier for scenario S is given by

$$m^S_{PD} = \frac{\sum_b \sum_i w_b w_i \mathbb{E}(y_{i,b,T}|\mathbf{Z}^S_{i,b,T}, \mathbf{X}_{i,b,T})}{\sum_b \sum_i w_b w_i \mathbb{E}(y_{i,b,T}|\mathbf{Z}_{i,b,T}, \mathbf{X}_{i,b,T})} \tag{21}$$

where $y_{i,b,T}$ represents the default status of borrower i at bank b at the final reporting period T. Since it is a binary variable (1 for default, 0 otherwise), its expected value $\mathbb{E}(y_{i,b,T}|...)$ corresponds to the probability of default at a specified moment T and under scenario S.

$\mathbf{Z}^S_{i,b,T}$ is the vector of independent variables under the flood scenario S. The key difference compared to the baseline vector $\mathbf{Z}_{i,b,T}$ is that the LTV ratio has been adjusted to reflect flood-induced property devaluation.

As in the LGD case, it is again the case that w_b represents the bank-level weight, which reflects each bank's exposure as a share of total system-wide exposure, and w_i represents the loan-level weight, which accounts for each individual loan's exposure relative to the total exposure of the corresponding bank.

The PD multiplier provides a system-wide measure of how flood-induced changes in collateral values propagate into increased probabilities of default. This multiplier also plays an important role in the final quantification of the financial impact as a result of flood scenarios, which will become clear in the next part.

3. CET1 ratio Impact

To assess how flood scenarios could impact the financial health of banks, it is essential to examine their regulatory capital. A key metric in this regard is the Common Equity Tier 1 (CET1) ratio, which as discussed earlier, measures a bank's core equity capital relative to its risk-weighted assets (RWA), recall equation (8). A lower CET1 ratio signals a weaker capital position, potentially increasing financial vulnerability.

The denominator of the CET1 ratio, RWA, essentially quantifies the riskiness of a bank's assets. The RWA is computed as the product of Exposure at Default (EAD), a constant regulatory factor of 12.5% and the capital requirement factor K. This aligns with the Basel regulatory framework, as discussed in Section 3. Recall that the capital requirement factor K depends on both bank-specific and scenario-specific values of Loss Given Default (LGD) and Probability of Default (PD).

[5] The National Mortgage Guarantee (NHG, or Nationale Hypotheek Garantie) is a Dutch government-backed scheme that provides a safety net to both lenders and borrowers in case of payment difficulties due to circumstances beyond the borrower's control.

As discussed, the occurrence of a flood can change the LGD and PD for exposed loans. To capture this, the concept of scenario-specific RWA (RWA^S) is introduced, representing the RWA that would result if a particular flood scenario S occurs. To quantify the relative change in RWA due to a flood scenario, a scenario-specific RWA multiplier (m^S_{RW}) is defined as follows

$$
\begin{aligned}
m^S_{RW} &= \frac{\sum_b \sum_i w_b w_i RWA^S_{i,b}}{\sum_b \sum_i w_b w_i RWA_{i,b}} \\
&= \frac{\sum_b \sum_i w_b w_i K^S_{i,b}}{\sum_b \sum_i w_b w_i K_{i,b}},
\end{aligned}
$$

where $RWA^S_{i,b}$ denotes the RWA for loan i of bank b under flood scenario S, and $RWA_{i,b}$ represents the initial RWA. Similarly, $K^S_{i,b}$ and $K_{i,b}$ denote the scenario-specific and initial capital requirement factors, respectively. The weights w_b and w_i account for the relative importance of each bank and loan. Essentially, this multiplier quantifies the average relative change in RWA across all banks and their real estate loan portfolios under scenario S.

Since the capital requirement factor K depends on the LGD and PD, the previously calculated scenario-specific multipliers for LGD (m^S_{LGD}) and PD (m^S_{PD}) are the key drivers behind variations in K and, consequently, in RWA. More specifically, for residential mortgages, the scenario-specific capital requirement factor is given by

$$
K^S = LGD \cdot m^S_{LGD} \cdot \Phi\left(\frac{\Phi^{-1}(PD \cdot m^S_{PD})}{\sqrt{1-\rho}} + \sqrt{\frac{\rho}{1-\rho}} \cdot \Phi^{-1}(0.999)\right) - PD \cdot m^S_{PD} \cdot LGD \cdot m^S_{LGD}, \quad (22)
$$

where Φ is the cumulative standard normal distribution function, and ρ represents the asset correlation parameter as defined in the Basel framework. A higher LGD and/or PD under scenario S leads to a higher K^S, which in turn increases RWA^S, resulting in an RWA multiplier greater than one.

Finally, the impact of these scenario-induced RWA changes on the CET1 ratio is examined. The formula is given by:

$$
\Delta CET1\ ratio^S = \frac{CET1}{RWA} - \frac{CET1 - \Delta EL^S}{RWA + \Delta RWA^S} \quad (23)
$$

where ΔEL^S represents the difference between the expected loss under the flood scenario and the starting-point expected loss and ΔRWA^S denotes the scenario-specific change in risk-weighted assets. CET1 represents a bank's core capital, previously denoted as CET1-capital in Equation (8), but abbreviated as CET1 in this formula for conciseness. To better understand this formula, its derivation is as follows

$$
\begin{aligned}
\Delta CET1\ ratio^S = CET1\ ratio^0 - CET1 ratio^S &= \frac{CET1}{RWA} - \frac{CET1^S}{RWA^S} && (24)\\
= \frac{CET1}{RWA} - \frac{CET1 - \Delta EL^S}{RWA \cdot m^S_{RW}} &= \frac{CET1}{RWA} - \frac{CET1 - \Delta EL^S}{RWA + \Delta RWA^S}. && (25)
\end{aligned}
$$

This derivation clarifies how the CET1 ratio is affected by both expected credit losses (ΔEL^S) and changes in risk-weighted assets (ΔRWA^S). The first term, $\frac{CET1}{RWA}$, represents the initial CET1 ratio in the absence of a flood scenario, while the second term incorporates the effects of flood scenario S. Specifically, a higher ΔEL^S leads to a reduction in CET1 capital, and a higher ΔRWA^S increases the denominator, amplifying the decline in the CET1 ratio. Alternatively, the final expression in the denominator can also be conveniently rewritten as $RWA^S = RWA \cdot m^S_{RW}$, utilizing the previously defined scenario-specific RWA multiplier.

In summary, the entire methodology essentially builds up to this final dependency, the flood-scenario-specific CET1 ratio (23). It begins with the construction of a parameter that represents the general impact of flooding on collateral values, ϕ_p^S (12). This fraction is then incorporated into the scenario-specific Loan-to-Value ratio, LTV_i^S (14). The adjusted loan-to-value subsequently influences both the LGD and PD modeling each in its own way, ultimately resulting in the scenario-specific multipliers m_{LGD}^S (19) and m_{PD}^S (21), respectively. In the final step these multipliers are used, in line with Basel regulatory formulas, to compute the capital requirement K^S (22), which feeds into the adjusted risk-weighted assets RWA^S, and finally determines the overall impact on the $CET1\ ratio^S$.

It is also important to acknowledge certain limitations of the methodology. First, the model does not incorporate potential mitigating factors, such as insurance payouts, government relief schemes, or other compensatory mechanisms that may reduce actual credit losses. Second, the approach is based on scenario analysis and does not attempt to estimate the probability of the flood event occurring. As a result, it does not quantify the full expected impact, but rather the conditional impact under the assumption that a specific flood scenario takes place.

The objective of this section was to provide a detailed overview of how a Dutch state-of-the-art, publicly available flood risk integration methodology is structured. From the initial construction of the flood-induced collateral depreciation parameter to the final impact assessment on the CET1 capital requirements, it is clear that numerous assumptions are made throughout the entire process. Many of these assumptions could benefit from further investigation, ensuring that the overall modeling approach remains as precise, robust and comprehensive as possible.

Concluding Remarks

This literature study has laid the theoretical foundation for the next phases of the thesis project. It has explored key components of credit risk modelling, reviewed relevant regulatory developments and examined flood risk as a specific case of physical climate risk. By bringing together insights from these domains, it provides the necessary background to begin evaluating the assumptions underlying ABN AMRO's current flood risk integration.

While this report was written independently from ABN AMRO's internal data and modelling practices, it provides a structured overview of state-of-the-art, publicly available modeling approaches relevant to this research. The methods and insights discussed—particularly in the context of scenario-based flood impact studies—serve as a conceptual and methodological reference point. While the approach discussed is insightful, it also has limitations, such as the omission of mitigating factors and the focus on scenario-based impacts without considering flood probabilities. These very limitations also contribute to the ability to objectively analyze how ABN AMRO has incorporated climate risks into its models. In other words, they provide a useful basis for properly answering the research sub-questions: understanding how flood risk can be incorporated into credit risk models (SQ1), identifying ABN AMRO's underlying assumptions (SQ2), and evaluating their calculated impact (SQ3).

In the next phase of this research, the focus will shift to identifying, implementing, assessing and quantifying the assumptions underlying ABN AMRO's internal model quantification method. This will ultimately support the development of practical, data-driven recommendations for flood risk integration.

Appendix

Exposure Class	Relevance / Impact	Climate Risk Type	Example Hypothesis	Climate Data & Metrics	Example Credit Risk Models	Examples
Mortgages (Residential Real Estate - RRE)	• Floods/subsidence • Higher insurance costs	Physical + Transition	*Flood risk integration improves PD models for mortgage loans in high-risk areas.*	• Flood maps • Subsidence models • Energy efficiency data	• Scoring models: Logistic regression (PD), ML algorithms (NN) • Risk Models: Monte Carlo Simulations, VaR Models	A home in a low-lying area is classified as high-risk by new flood maps. As a result, insurers demand higher premiums and some banks refuse to refinance. > Credit risk impact: The value of collateral drops, and the risk of default increases as households are unable to bear the higher housing costs.
Commercial Real Estate (CRE)	Depreciation due to floods, storms, heat waves.	Physical	*Integration of storm and heat forecasts improves valuation models for commercial real estate.*	• Climate hazard indices • Storm and heat forecasts	• Moody's KMV model (option-based) • Merton model (default probability based on business value)	An office building in the center of a city suffers damage during a heat wave due to cooling system overload, leading to increased operating costs and temporary closure. > Credit risk impact: Property values drop and the likelihood of tenant payment problems increases.
Agricultural loans	Reduced crop yields due to drought, extreme rainfall.	Physical	*Use of drought and rainfall data improves default predictions for agricultural loans.*	• Drought indices • Rainfall forecasts • Soil moisture data	• Logistic regression • Credit scores (agriculture-specific)	A farmer loses a large portion of the crop due to a prolonged drought, despite irrigation. > Credit risk impact: Decreased yield reduces repayment capacity, increasing the probability of default.
Car loans	• Damage from floods, storms • Stricter emission rules	Physical + Transition	*Integration of emissions regulations and storm risks improves predictions of future defaults on auto loans.*	• Regional flood risks • Storm risks • Trends in emission regulations	• Credit Scores (Consumer Auto Loans) • Decision trees	A consumer owns a diesel car that depreciates faster due to new emissions taxes and limited access environmental zones in cities. > Credit risk impact: The residual value of the vehicle is lower than expected, which can lead to a higher loss provision in case of default.
SME loans	Loss of income from operations/cash flow due to • Disasters (e.g., flood, storm) • Regulatory Compliance	Physical + Transition	*Integration of regional climate data quantifies business risks from floods and storms.*	• Frequency data of regional disasters • Regulatory compliance levels	• Credit scores (SMB specific) • Hybrid models (macroeconomic and climate risk data)	A small bakery in a city that is badly hit by floods is losing customers and has extra costs to repair (items in) the store. This results in a temporary or long-term drop in income. > Credit risk impact: The risk of default rises as the company's revenue decreases, while loan repayments remain the same.
Business loans (High-Carbon)	Higher costs due to • CO2 taxes • Stricter regulations	Transition	*Integration of CO_2 emission predictions improves risk models for companies in carbon-intensive sectors.*	• CO_2 emissions data • Energy consumption profiles	• Moody's EDF model • Reduced-form models (firm-specific risk factors)	A cement manufacturer must meet stricter emission standards, leading to expensive investments in cleaner technologies or penalties for non-compliance. This significantly reduces profit margins. > Credit risk impact: The financial health of the company deteriorates, increasing the risk of default.
Municipal Bonds	Decrease in debt repayment due to disasters such as floods/droughts.	Physical	*Integration of drought and flood data improves risk assessment of municipal bonds.*	• Regional flood maps • Drought risk indices • Scarcity projections for water	• Reduced-form models (credit risk municipal bonds) • Macroeconomic risk models	A municipality in a coastal area is hit by a major flood. The costs of repair and infrastructure reconstruction are rising, while tax revenues are falling as businesses and residents leave. > Credit risk impact: The municipality has fewer resources to repay its bond debt, increasing the risk of default.
Renewable Energy Projects	Variability in performance due to weather conditions.	Physical	*Integration of drought and storm forecasts improves financing models for renewable energy projects.*	• Drought and storm forecasts • Site-specific climate data	• Project financing models (renewable energy specific) • Monte Carlo simulations (project risk assessment)	A wind farm produces less electricity due to unexpectedly low wind speeds, which leads to lower revenues. Additional damage from storms causes high repair costs and longer downtime. > Credit risk impact: Lower revenues and higher maintenance costs increase the risk of default by the wind turbine company.

References

[1] W. J. W. Botzen, J. C. J. M. van den Bergh and L. M. Bouwer, *Climate change and increased risk for the insurance sector: a global perspective and an assessment for the Netherlands*. Springer Nature, (2009), https://doi.org/10.1007/s11069-009-9404-1.

[2] S. Hauswirth, *Hydrological Droughts in the Netherlands: from Simulations to Projections*. Utrecht Studies in Earth Sciences, volume 305, (2024), https://dspace.library.uu.nl/handle/1874/437427.

[3] Smith, Adam B. and Katz, Richard W., *U.S. Billion-dollar weather and climate disasters: Data sources, trends, accuracy and biases*. Natural Hazards, (2013), https://doi.org/10.1007/s11069-013-0566-5.

[4] Asian Development Bank, *Climate-Related Disasters in Asia and the Pacific*. Asian Development Bank, 2013.

[5] L. Jiang, T. Gerkema, D. Idier, A.B.A. Slangen and K. Soetaert, *Effects of sea-level rise on tides and sediment dynamics in a Dutch tidal bay*. Ocean Sci., (2020), https://doi.org/10.5194/os-16-307-2020.

[6]

[7] European Banking Authority, *Final Guidelines on the Management of ESG Risks*. European Banking Authority, 2025.

[8] Bank for International Settlements, *IRB approach: risk weight functions*. Bank for International Settlements, 2023.

[9] European Central Bank, I, *Guide on climate-related and environmental risks: Supervisory expectations relating to risk management and disclosure*. European Central Bank, 2020.

[10] M.-S. Tsai and L.-C. Chen, *The calculation of capital requirement using Extreme Value Theory*. Economic Modelling, (2011), https://doi.org/10.1016/j.econmod.2010.08.010.

[11] Francesco G. Caloia and Kees van Ginkel and David-Jan Jansen, *Floods and financial stability: Scenario-based evidence from below sea level*. Tinbergen Institute Discussion Paper, 2023.

[12] KPMG AG Wirtschaftsprüfungsgesellschaft, *Climate and Environmental Risks in Credit Risk Models: Market Survey 2024*. KPMG, 2024.

[13] European Central Bank, *ECB Banking Supervision Newsletter – May 2024*. European Central Bank, 2024.

[14] R. Vermeulen, E. Schets, M. Lohuis, B. Kölbl, D.-J. Jansen and W. Heeringa, *The heat is on: A framework for measuring financial stress under disruptive energy transition scenarios*. Ecological Economics, (2021), https://doi.org/10.1016/j.ecolecon.2021.107205.

[15] W. Salet, *Public Norms in Practices of Transitional Planning - The Case of Energy Transition in The Netherlands*. Sustainability, (2021), https://doi.org/10.3390/su13084454.

[16] European Banking Authority (EBA), *Report on the Role of Environmental and Social Risks in the Prudential Framework*. European Banking Authority, 2023.

[17] European Central Bank, *Supervisory Guide on Internal Models*. European Central Bank, 2024.

[18] McNeil, Alexander J. and Frey, Rudiger and Embrechts, Paul, *Quantitative Risk Management: Concepts, Techniques and Tools*. Princeton University Press, 2005.

[19] Bank of England, *Modelling Credit Risk*. Bank of England, 2025.

[20] Basel Committee on Banking Supervision, *An Explanatory Note on the Basel II IRB Risk Weight Functions*. Bank for International Settlements, (2005), http://www.bis.org/publ/bcbsca.htm.

[21] Basel Committee on Banking Supervision, II, *Basel II: International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version*. Bank for International Settlements, 2006.

[22] Bank for International Settlements, *History of the Basel Committee and Its Membership*. Bank for International Settlements, 2014.

[23] European Central Bank, *The Single Supervisory Mechanism (SSM) Explained*. European Central Bank, 2020.

[24] De Nederlandsche Bank (DNB), *Toezicht op financiële instellingen*. De Nederlandsche Bank, 2024.

[25] Basel Committee on Banking Supervision, I, *International Convergence of Capital Measurement and Capital Standards*. Bank for International Settlements, 1988.

[26] Bank of England, *Modelling Credit Risk*. Bank of England, 2015.

[27] Basel Committee on Banking Supervision, II, *International Convergence of Capital Measurement and Capital Standards: A Revised Framework*. Bank for International Settlements, 2004.

[28] Basel Committee on Banking Supervision, III, *Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems*. Bank for International Settlements, 2011.

[29] Basel Committee on Banking Supervision, IV, *Basel III: Finalising post-crisis reforms*. Bank for International Settlements, 2017.

[30] Basel Committee on Banking Supervision, *Calculation of RWA for Credit Risk – Standardised Approach: Individual Exposures (CRE20)*. Bank for International Settlements, 2025.

[31] BDO, *Final EBA Guidelines on ESG Risk Management – Implications for Governance and Risk Management*. BDO, 2025.

[32] Informatiepunt Leefomgeving (IPLO), *Crisismanagement water*. Informatiepunt Leefomgeving (IPLO), Accessed: 2023.

[33] Rijkswaterstaat, *Landelijk Informatiesysteem Water en Overstromingen (LIWO)*. Rijkswaterstaat, 2025.

[34] Kymo Slager and Dennis Wagenaar, *Standaardmethode 2017: Schade en slachtoffers als gevolg van overstromingen*. Deltares, 2017.