Modelling the Impact of Climate Change Induced Events on the Loss Level of a Dutch Mortgage Portfolio

University of Twente
Jaap Gerrits
June 30, 2022

Faculty of Behavioral, Management and Social Sciences
Industrial Engineering and Management
Specialisation of Financial Engineering and Management

University Supervisor: B. Roorda
University Supervisor: R.A.M.G. Joosten
Company Supervisor: M. Wiersma (Zanders)
Company Supervisor: P. Klaassen (Zanders)
Company Supervisor: H. Jacobs (The Volksbank)

Preface

This thesis is the final work required for me to complete the Master of Industrial Engineering and Management with the Specialisation of Financial Engineering and Management at the University of Twente. This research was conducted in cooperation with Zanders BV and the Volksbank.

Firstly, I would like to thank Berend Roorda and Reinoud Joosten from the University of Twente for their time and feedback during this research. Secondly, from Zanders and the Volksbank I would like to thank Marije Wiersma, Pieter Klaassen, and Hans Jacobs for their support and feedback. It has all contributed greatly to the quality of this research.

Jaap Gerrits
June 2022

Management Summary

In 2021, the IPCC has published their latest report describing their current findings of the impact of human activity on climate change. They estimate that there will be an increase in hot extremes, marine heatwaves, the rise of the sea levels, heavy precipitation, and agricultural/ecological problems due to droughts. The Netherlands is also subject to these exposures. This means financial institutions that issue mortgages with the property as collateral, are also exposed to these *physical climate risks*. When an event such as a flood occurs, a large number of properties will be affected. The risk is that mortgage holders within the affected area can not pay back their debts due to these events. In case this happens the underlying property has to be sold by the bank. Due to the damages incurred, the bank might incur a loss on the difference between the mortgage loan and the selling price of the property. The current literature has very limited resources available to quantify the financial impact of these risks on mortgages in the Netherlands. This leads to main research question of this thesis:

How can we quantify the financial impact of physical climate change events on the loss distribution, in particular the expected loss, on the bank's residential mortgage portfolio in the Netherlands?

This thesis discusses two types of climate events that impact residential properties in the Netherlands: flooding and drought. Depending on the flood depth, a property can incur significant damage to its structure. If this is not repaired, a decrease in the market value of a property is inevitable. Periods of drought can impact properties where the foundation is built on wooden poles. These wooden poles are the foundation of properties built on wet terrain before 1975. They are almost always under water during the year. However, the moment the water evaporates due to prolonged periods of drought, the poles are exposed to rotting. Over time these poles are not able to carry the weight of the property. This will eventually result in subsiding of the property. Damages incurred can become very expensive as reparations to the foundation and walls is very labor and materially intensive. Again, if this is not repaired, a decrease in the market value of a property is inevitable. This research first determines a way to quantify this damage impact given the climate exposure for each property.

The location of each property in the mortgage portfolio is matched to the corresponding exposure from the data provided by the Climate Adaptation Services (2021). In order to quantify the damages for flooding, a damage function approach is used (Slager, 2017). For the pole rot data a damage class approach is used (A. Kok, 2020). Based on the likelihood of occurrence from now until 2050, the damages are priced into the market value of the property. Doing this allows the bank to calculate an Expected Loss (EL) until 2050 on the portfolio. By comparing the climate adjusted EL to the non-climate adjusted EL allows the bank to observe the contribution of these climate events to the total losses on the portfolio.

It is important to emphasize that the estimation of the impact is less accurate for pole rot than for flooding. This is due to the quality of the data. The pole rot damage data are on a *neighbourhood* level and not an individual property level (which is the case for flooding). Also, not every property built before 1975 is constructed on wooden poles. Therefore, the expected loss estimation of pole rot gives an indication of the possible losses and should not be perceived as the actual expected loss.

The results from this model show that the contribution of flooding and pole rot to the EL *for*

all exposed properties is 1.41% and 18.3% respectively. Within the portfolio a total of 21% of the properties is exposed to pole rot and 36% to flooding. Here we observe that whilst the exposure is larger for flooding, the impact is more profound with pole rot. The average property price decrease of all properties is 0.3% for flooding and 3.1% for pole rot. The literature describes an expected average decrease between 2.5% and 10% due to these exposures (Calcasa, 2019). Whilst this is not the case for the flooding, a small portion of exposed properties is within the 2.5% and 6% range, making the flood property price impact estimation true for high risk areas. For flooding the municipalities that run the largest risk for the bank on a portfolio level are Kampen and Culemborg. For pole rot these municipalities are Bergen Op Zoom and Zoetermeer. In general, it is the case that we can only observe the true impact of flooding and pole rot on the property market once these events occur. However, a wider selection of data points could improve the damage estimation on the collateral as we currently only look at the property type (Apartment/Single Home) and damage class/flood depth for pole rot and flooding respectively. These outcomes and quantification methods therefore serve as a starting point for the impact of climate events on mortgages in the Netherlands.

The impact of flooding is limited from an EL point of view whilst that of pole rot is a lot more significant. However, in both cases the absolute expected loss is not large for the bank until 2050. This indicates that the impact for *the bank* is limited. Whilst the impact on the EL is limited, it is important to not forget the Unexpected Loss (UL). The UL is a worst-case measure of the EL. This value can be *significantly* higher and is the direct measure used to determine the capital requirements for the bank. The most important future research that should be done is looking into the determination of this measure.

List of Figures

List of Tables

Contents

Abbrevations

Abbreviation	**Description**
BIS	Bank of International Settlements
CBS	Central Bureau of Statistics
DL	Direct Loss Model
EL	Expected Loss
EAD	Exposure at Default
HPI	House Price Index
IFRS	International Financial Reporting Standards
IPCC	Intergovernmental Panel on Climate Change
IRP	Insurance Risk Premium
IRB	Internal Ratings Based
GDF	Geographical Data Frames
KNMI	Koninklijk Nederlands Meteorologisch Instituut
LGC	Loss Given Cure
LGD	Loss Given Default
LGF	Loss Given Foreclosure
LTV	Loan To Value
LT	Life Time
PC	Probability of Cure
PD	Probability of Default
PF	Probability of Foreclosure
ROC	Rate of Change
SLR	Sea Level Rise
UL	Unexpected Loss
VAR	Value At Risk

1 Introduction

1.1 Problem Context

In 1990, the Intergovernmental Panel on Climate Change (IPCC) published its first document describing the effect of human activity on the environment (IPCC, 1990). In 2021, the IPCC (2021) published their latest report describing their findings of the impact of human activity on the climate. Within this report they describe various possible climate scenarios such as increase in hot extremes, marine heatwaves, sea level rise, heavy precipitation, agricultural and ecological problems due to droughts in some regions, and an increase in cyclones as well as a reduction of snow cover and permafrost (which in itself increases global warming). The global projected Sea Level Rise (SLR) is between 54 and 121 cm for 2100 (KNMI, 2021), however it is not evenly distributed for every location. The Netherlands is also exposed to some of these climate scenarios. For example, between 2006 and 2018 the sea level has risen 3.7 millimetres per year (increasing year over year) (KNMI, 2021) affecting areas that are subject to flooding even more. Furthermore, the Netherlands is also exposed to longer periods of droughts due to a decrease in the speed of the polar jet stream and the changing of the warm and cold water streams in the ocean (KNMI, 2021). Lastly, the amount and severity of storms significantly increases due to a change in temperature extremes. These changes to the climate will profoundly affect the way we live socially as well as economically. Due to the projected consequences of climate change, over 196 countries signed the Paris Climate Agreement to limit global warming below 2, preferably 1.5 degrees Celsius compared to pre-industrial levels (Horowitz, 2016). This agreement forces economies around the world to invest in technologies and business practices so global warming will not exceed the given threshold.

Banks are an important factor in the process for climate change. In order to facilitate change in economic activities they are required by regulators and society as a whole to finance new loans for companies that aim to create solutions that reduce the potential impact of climate change. However, financing such projects introduces the first climate change risk factor called "transitional risks" (Walles, 2021). The likelihood that these investments all bear fruit is not guaranteed. When a company fails to generate a marketable solution, the issued loans will probably not be paid back. This means that the bank makes a loss on this investment. Furthermore, policy and regulation are also a big part of transitional risks. Governments around the world force changes in existing businesses to make them more environmentally friendly. When these businesses do not adjust in time they run the risk of large fines. This generates potential default risks as they might not be able to payback their debt to bank due to these incurred fines.
The second climate risk banks are exposed to are called "physical risks" (Walles, 2021). Physical risks are the climate *events* that are going to play out with climate change, for example an increase in flooding or droughts. We can also make a distinction between two different types of physical risks; acute climate risks and chronic climate risks. With acute climate risks we refer to actual climate events occurring, such as storms, floods, hurricanes and cyclones (Smith, 2021). Chronic climate risks are long-term shifts in climate patterns that may cause an increase in SLR or chronic heat waves (Board et al., 2017). For banks, the exposure to physical risks occurs on assets that have an exposure to one or more climate events (i.e. flooding/drought). An example of such an asset is a mortgage with a physical property as collateral. Most banks have a mortgage portfolio that is significantly exposed to flooding or drought. Mapping these potential risks for the bank can help them improve their risk management framework and appease regulators.

The Volksbank is one of those banks that wants to investigate the effect of climate change on their mortgage portfolio. This thesis will focus on quantifying the impact of physical risks on their mortgage portfolio. Within this chapter we further discuss the core problem, research objective, research questions, and research approach.

1.2 Core Problem

Almost one third of the Dutch landmass is situated below sea level (Rijkswaterstaat, 2021a). A major portion of the Dutch population also lives within these areas. This poses a risk to the people and buildings in the area as there is higher probability that portions of the land will flood. Historically this risk has always been present and there were moments in the past where actual flooding occurred. The most known example is the North Sea Flood in 1953 leaving over 1800 people dead and a lot of properties destroyed (Rijkswaterstaat, 2021b). Since then, the Dutch government has invested heavily in protecting the Netherlands from these type of disasters. They built dikes along the coast and rivers, the enclosing dike of the IJsselmeer through the Afsluitdijk, and the Delta Works in Zeeland (Rijkswaterstaat, 2021a). Furthermore, many pumps are present to regulate water levels throughout the country. To a large extent the Netherlands seem to be well protected from flooding. However, because of the changes in the climate the current flood defences might not be enough for protecting people and properties. As mentioned, flooding is not the only climate exposure that needs to be considered. An increase in prolonged periods of drought and a change in storm intensities will also affect people and buildings over time. These developments push banks such as the Volksbank to investigate what the possible impact of climate change can be on their mortgage portfolio.

This thesis focuses on the impact of physical risks on the mortgage portfolio of the Volksbank. In particular, we are looking at the impact on the Expected Loss (EL) of the mortgage portfolio due to climate change. To make this problem more tangible, a problem cluster is made as shown in Figure 1 that analyses the potential exposure for the bank.

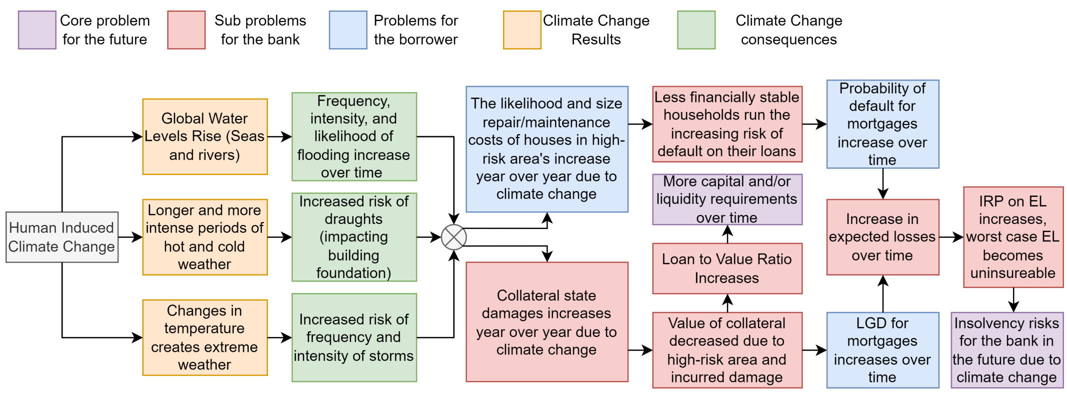


Figure 1: Core problem identification.

Figure 1 shows that there are three major risks in the Netherlands related to the future projections of climate change; flooding, droughts, and storms (KNMI, 2021). If the likelihood and intensity of all risks increase, the result will be that there are more costs associated with maintenance, repairs and increased protection for residential properties. This is set to increase as the effects of climate change becomes worse over time.

Most of the time mortgage holders can request an additional loan or pay out of their own pocket for damage repairs when a climate event occurs. However, mortgage holders can also find themselves in financial trouble due to job loss, personal circumstances, or the current macro-economic environment. When this is the case, the holder most likely does not have the cash to pay for the repairs. Also, mortgage holders in financial trouble are often not eligible for an additional loan. Combining this with the risk of the climate event, it will increase the Probability of Default (PD). Also, when a climate event would occur for this holder, the damage on the property would then remain unrepaired. This means that that the value of the collateral decreases. This in turn will increase the Loss Given Default (LGD) and Expected Loss (EL) over time. Also, the decrease in the value of the collateral will increase the Loan To Value Ratio (LTV) ratio. When this happens across a large portion of the portfolio, the capital and liquidity requirements for the bank will increase. Furthermore, as the EL increases so will the the Insurance Risk Premiums (IRP) the bank has on insuring the EL. In a worst case scenario it might even be the case that as climate projections become worse and the EL increases to such an extended that it becomes uninsurable. This means that the bank has to carry the expected loss themselves which might result in insolvency problems.

There are also additional consequences that the bank might be exposed to because of these physical climate risks. Firstly, interest payments on mortgages are on average 75% of the income for Dutch retail banks (Vijlbrief, 2020). For the Volksbank it is even 90%. If a significant portion of mortgage loans default due to physical climate risks, they lose a large portion of their income (the losses could even be higher than the interest income of the bank). Even issuing new mortgages on the seized collateral can lead to new default risks if the area is a high-risk area for climate events. This can lead to solvency issues in the future due the loss of revenue.

Secondly, there is also pressure from regulators on banks to focus on Environmental, Social, and Governance criteria within their business operations (EBA, 2020). ESG criteria are dimensions monitoring the activities of companies for their contribution to the environment and society at large. This includes the monitoring of physical and transitional risks. For example, the Dutch Central Bank (DCB) states that material climate risks should be governed in a way that is consistent with sound risk management (DNB, 2020). Furthermore, the European Central Bank (ECB) is creating various different stress tests related to physical and transitional risks for all banks under its jurisdiction (ECB, 2021). These types of statements and stress tests can lead to more regulation for banks such as additional ESG requirements and restrictions for providing loans in high risk areas further impacting the banks ability to make money.

By quantifying the financial impact of physical risks on the mortgage portfolio, banks are able to measure their potential exposure and make plans to potentially fix/mitigate these problems.

1.3 Research Objective

This research quantifies the financial impact of physical climate change events on the residential mortgage portfolio of the Volksbank. To achieve this quantification we have to define what the knowledge gap is between our goal and the literature. Before discussing this gap, we first expand on the research goal.

With the research goal we aim to merge climate data with mortgage data and create a model for estimating losses on mortgages due to climate change. For climate change exposure in the Netherlands there are two data sources; the *KNMI* (2021) and the *Klimaat Effect Atlas* (2021). The former provides a general overview whilst the latter has location specific information for the Netherlands. In turn, the mortgage data are provided by the Volksbank. Merging the most suitable climate data with the mortgage data gives us the ability to analyze the impact of climate change. We specifically aim to model the *physical climate-adjusted Loss Given Default* (LGD) for the portfolio. This can be used to measure the expected losses due to physical climate risks on the mortgage portfolio. For modelling the expected losses we also need to the Probability of Default (PD) and Exposure At Default (EAD). The results of this research provides a starting point for the bank to make plans for reducing physical risks for its balance sheet. Furthermore, it can also provide insights on how to value mortgages with a climate event exposure. It also helps clients to be aware of the potential climate risks for a certain property.

Most research with respect to climate change risk is performed in the private sector by financial institutions. The United Nations published an overview of the research done in this area (Connell et al., n.d.). For example, NatWest Group has done an assessment of flood risk to a sample of UK residential mortgages. Here they consider a sample size of mortgages at risk and analyse the results with the Loan To Value (LTV) ratio. As property values in high risk areas decrease in value, the LTV ratio will increase. However, the method used is a scoring method and not an EL approach. Furthermore, this approach only works for UK specific properties and climate risks. Also, the quantification method is not described. A similar study by ClimateWise (2019) analyses the changes in property values due to flooding on postal code level and not on an individual property level. This makes the analysis a lot less accurate and more prone to errors. Also, the paper does not describe how this can be incorporated in the risk management framework for a bank. There are two other papers by Moodys (2021) and the Society of Actuaries (2020) that do shortly touch on how this could be incorporated in the EL framework. The former does show that EL modelling approaches have been used to estimate the impact on individual mortgages within the UK (By looking at both LGD and PD). However, it also quantifies the exposure for individual properties based on a scoring variable and not on actual loss numbers. For the latter a large pool of data points (LTV ratios, insurance data, building characteristics, etc) is used to also estimate an EL through the KatRisk Model. However, both the former and latter do not describe the mathematical methodology required are for quantifying the impact. In both cases it must be procured through payment.

The gap between the literature and our research goal manifests itself in the available data, accurate damage approximation methods for the Netherlands, and a corresponding climate adjusted expected loss framework for the mortgage portfolio. We close this gap by answering our main research question which is discussed in the next section.

1.4 Research Questions

Knowing the gap in our research allows us to construct our main research question as:

How can we quantify the financial impact of physical climate change events on the loss distribution, in particular the expected loss, on the bank's residential mortgage portfolio in the Netherlands?

In order to answer this we have created a list of subquestions. Note, we make a difference between two different terms: physical climate events and physical risks. With the first term we refer to the actual events occurring and the impact thereof. With the second term we refer to the financial impact for financial institutions given the physical climate risks events.

1. What are the future risks of physical climate change events in the Netherlands?
    - Which areas can be considered high climate risk areas in the Netherlands?
    - To what degree is each high-risk area exposed to different climate events?
    - What are the projections of different physical climate events in the future for high-risk areas?
2. How large is the exposure of the bank's mortgage portfolio to the different physical climate events in the Netherlands?
    - What are the property price developments in the current climate event exposed areas for the bank in the Netherlands?
    - Which areas are considered high climate risk areas for the banks' mortgage portfolio?
3. How can we quantify different physical climate change risks in financial terms on the collateral of the mortgage portfolio?
    - How are the non-climate adjusted expected loss models currently estimated?
    - How can we model different physical climate events on different types of collateral?
    - How can we model the physical-risk-LGD given the physical climate events for the mortgages in the portfolio?
4. What is the physical risk induced expected loss projection on the mortgage portfolio given different macro-economic scenarios in the future?

1.4.1 Scope

The research questions capture the goal of the project. Nonetheless, there are limitations that affect the scope.
Firstly, the assignment focuses only on the determination of the expected loss for the mortgage portfolio given physical climate risks. This means that we do not study solutions to minimize the potential impact of the physical risks. Secondly, there will be no research done on the impact of these expected losses on the future pricing of mortgages. Thirdly, we mention in the core problem that we want to model the physical risk adjusted PD for mortgages in the portfolio. Due to the limitations of the data on this front, we keep this variable static by using the regular non-climate adjusted PD. Lastly, in case any data limitations are found, assumptions are made to simplify the problem.

1.5 Research Approach & Outline

1.5.1 Research Approach

The research approach followed the Managerial Problem Solving Method (MPSM). This method is used because there are a lot of steps within the research questions that require new knowledge and information. The way the method was applied is shown in the scheme of Appendix A. The appendix shows us the steps that have been taken to answer each research question. Each subquestion has a different colour as shown in the legend. We answer the subquestions in the sequence of the numbers. Note that there are summation nodes in the Figure. These nodes all require input steps previously completed in order to continue with the output. Also, there are validation/control points in green.

These show the steps that require validation, which means discussion with the project supervisors. The project supervisors are Marije Wiersma, Pieter Klaassen, and Hans Jacobs from Zanders and the Volksbank. From the University of Twente supervisors are Berend Roorda and Reinoud Joosten.

1.5.2 Layout of the Document

After this chapter comes Chapter 2 which consists out of the literature research for this thesis. At first, the concept of climate risk is discussed. Secondly, climate change itself is discussed in the Netherlands for the present and the future. From that point forward the relation between climate risk and credit risk is explored. Concluding from the relation between climate & credit risk, there are multiple methods discussed that can possibly quantify damages due to climate change on residential properties. The chapter ends with data research on property prices with respect to the most recent climate events in the Netherlands. This is done to observe whether a relation exists with the literature from different areas in the world and similar events in the Netherlands.

Chapter 3 discusses the data that is used within this thesis. Here we look at the climate data, the structure it has, and how it can be used for measuring climate exposure. Afterwards the mortgage data points are analysed that are required. Lastly, the data is discussed in a combined form. From that an initial analysis is made to see if there are any observations that can already be made with respect to climate risk areas for the mortgage portfolio.

Chapter 4 discusses the mathematical model that is used for quantifying climate risk. The model choice, assumptions and mathematics are discussed.

Chapter 5 will discuss the model results and discuss various scenarios that show the impact of climate change in different circumstances.

Finally, Chapter 6 will conclude the research and recommend new roads for further research.

2 Literature Review

Here we discusses the relevant literature for this thesis. We first touch on the current climate event exposures in the Netherlands from now until 2050. Then we look at the climate change predictions after 2050. Having completed the climate literature, we look at climate change and its relation to credit risk. Finally we look at analysing multiple quantification methods for estimating climate event damages and a data analysis of property price developments in current climate event exposed areas in the Netherlands.

2.1 Climate Change Risk

Financial climate change risks can be separated in two different categories: physical risks and transitional risks (Walles, 2021). Physical risks can be defined as the financial impact on business operations and properties due to the chronic changes in the climate and the increase in acute climate events. Here chronic changes in the climate, or chronic climate risks, can be defined as the subtle change of weather patterns over time in a certain region due to human induced climate change. For example, due to an increase in temperatures in the summer for longer periods there is a larger drought exposure over time. Acute climate events are events such as flooding, storms, and hurricanes. Furthermore, it can also be that chronic climate risks can lead to acute climate events. For example, due to changes in precipitation levels for certain areas there can be a significant probability of flooding even if there was almost none to begin with. Transitional risks can be defined as risks related to the process of adjustment towards a low-carbon economy due to societal, technological, and regulatory factors (BIS, 2021). As mentioned, this thesis focuses on physical risks only.

2.2 Current Climate Event Exposures in the Netherlands

The Netherlands is exposed to a variety of physical risks. The literature indicates that the major exposures are storms, droughts, and floods (KNMI, 2021). Using the data from the *Klimaat Effect Atlas*, we can determine the current climate exposures in the Netherlands. Within this sub chapter we also discuss the first subquestion: *What are the future risks of physical climate change events in the Netherlands?*.

2.2.1 Droughts

Looking at Figure 2 we observe the current and future drought risk in the Netherlands. The Figure shows the risk of droughts from low relative exposure (light colours) to very high relative exposure (dark colours). Relative exposure must not be read as an absolute impact. It is more a reflection of how an area is exposed to droughts compared to another area. The Figure shows that there is an overall increase in drought exposure in almost all areas of the Netherlands. Prolonged periods of droughts affect all forms of life; the harvest output decreases, plants die due to water shortages, animals have less food and water sources, and even humans can see their living standards decrease. Furthermore, droughts also impact residential properties that have their foundation made of wooden poles. These wooden poles were often used to build houses before 1975 on watery areas (Climate Adaptation Services, 2021). Thus, if drought periods increase and intensify, these poles will be exposed to rotting as the water evaporates. This damages the foundation of properties. Maintenance and repairs of wooden poles is very expensive and can become a problem for property owners overtime.

To determine the exposure for properties in the Netherlands we refer to Figure 3. The map on the left of Figure 3 shows the density of homes with wooden foundation within the country.

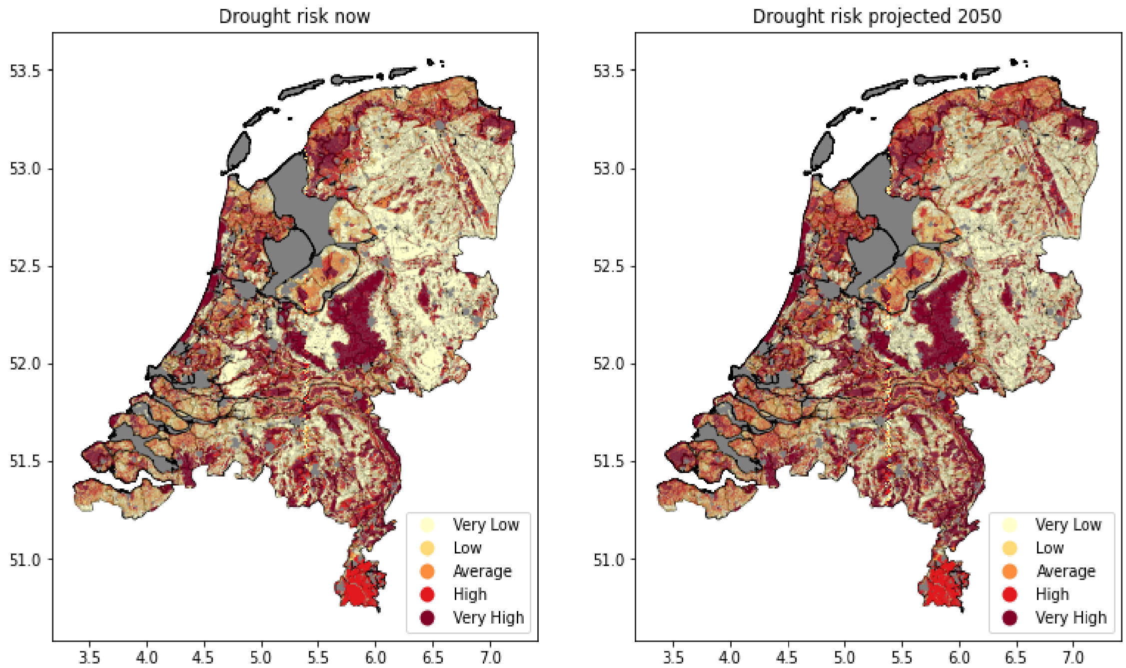


Figure 2: Present (2021) and future (2050) drought Risk in the Netherlands (Climate Adaptation Services, 2021).

The map on the right in Figure 3 shows the pole rot exposure of all municipalities in the Netherlands. Here we observe that the provinces of North Holland, South Holland, Friesland and Zeeland have the highest number of properties with wooden foundation. Comparing with the left map in Figure 3, we observe a large number of properties are also located in these areas. This is a significant financial risk for residents that live in such properties. If no improvements are made, the market value of the property can decrease over time. Furthermore, the costs of these improvements can be too large for households that already have financial problems, creating a default risk for these customers on their mortgage loans. Consequently, on a portfolio level mortgage lenders have to consider pole rot as a physical climate risk on their portfolio.

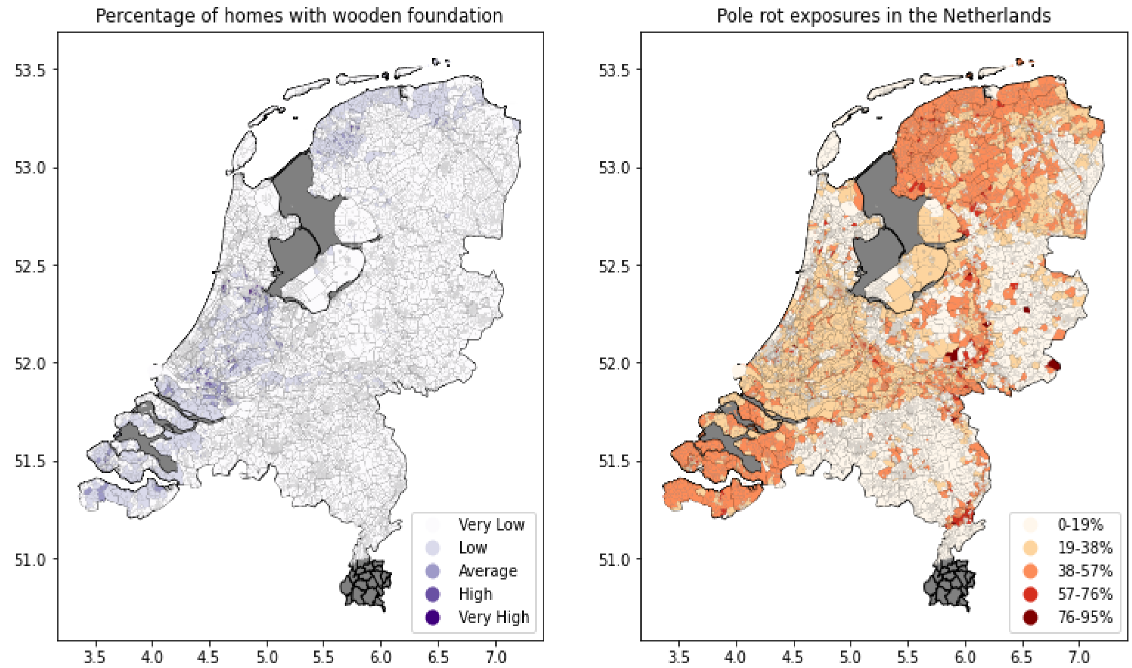


Figure 3: Properties with wooden foundation and pole rot exposure in the Netherlands (Climate Adaptation Services, 2021).

2.2.2 Storms

Storm impacts are harder to predict with respect to climate change in the Netherlands. The measurements show that at the end of the 20th century there were more storms on the North Sea (KNMI, 2020). However, since 1960 the wind speed has decreased on land and not near the coastal areas. This is attributed by the KNMI to the ever increasing number of buildings that slow down the wind. This decreases the intensity and number of storms on land. Furthermore, due to the lack of data it is hard to predict changes with respect to storms for the future. There are nonetheless some facts we know with respect to storms in the future. Firstly, the increase of temperatures on the oceans will reduce wintertime storms in all of Europe (Haarsma et al., 2013). However, this is counteracted by the increase of the height of the tropopause. If the height increases of this atmospheric level, the air will cool down slower which increases heat release and as a consequence intensifies storms. This effect is not huge with respect to climate change, but it will extend the breeding ground (and therefore intensity) of tropical hurricanes. Hurricanes tend to move from the middle of the Atlantic, to the Gulf of Mexico, to the east coast of the United States (losing most of its destructive power on the land), and finish up as a regular storm close to Europe. As the intensity of Hurricanes increases over time in the Americas, so will the storms coming from the Atlantic to Europe. Over time this will also impact the Netherlands. As a consequence, properties are more likely to experience damage. This will increase repair/maintenance costs and insurance risk premiums for the owner of the property. Luckily, because storm damages are insurable the impacted for mortgage lenders remains limited. For this research storms are excluded as there is no reliable data that can be used to quantify a potential impact.

2.2.3 Floods

One of the largest exposures the Netherlands has to climate change is the probability of flooding. As mentioned in chapter 1.1, a large portion of the Netherlands is below sea level. If a flood occurs and the protection measures fail it can result in deaths, loss of fauna, and economic damage in all forms. From the *Klimaat Effect Atlas* data we are able to show the areas in the Netherlands that run the risk of flooding with a certain height and probability in 2050. Furthermore, research has been done to determine the maximum flood depths per region with a certain probability as well. Analyzing these risks can show us the water exposure in the Netherlands. Note, whilst the probability of flooding should increase with SLR, it actually *decreases*. This is because the data assumes that more protection measures will be taken to decrease this probability (Climate Adaptation Services, 2021).

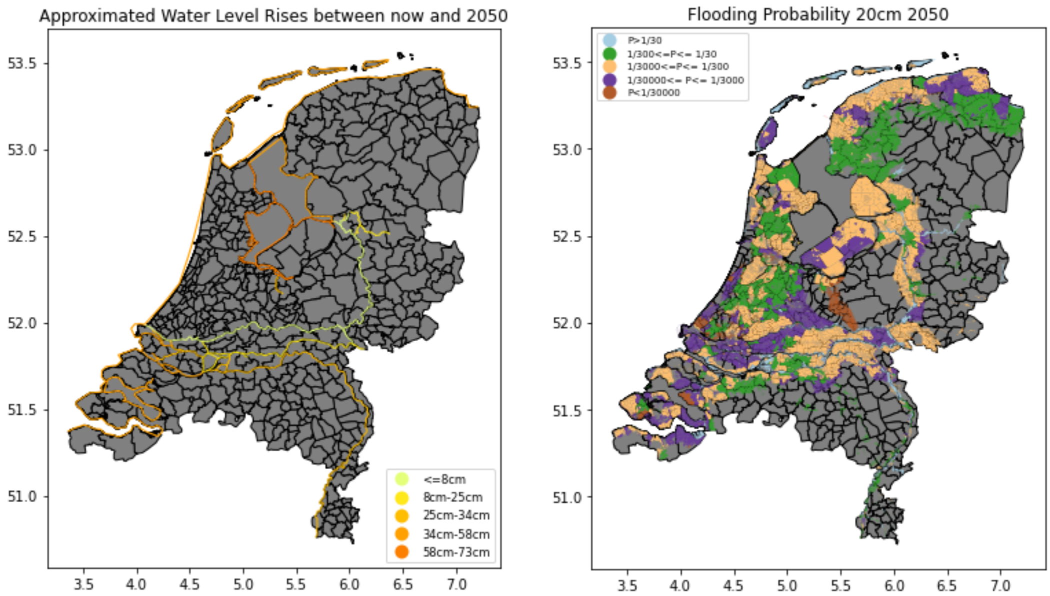


Figure 4: Exposed areas in the Netherlands to flooding and Flooding Probability of 20cm (Climate Adaptation Services, 2021)

Figure 4 shows two types of geographical maps. The first map shows us the expected rise of water levels close to the rivers in 2050. Here we see that the largest water rises can be expected around the Ijsselmeer, Zeeland, Friesland, and Groningen. Furthermore, the rivers also show significant increases in water levels over the coming decades. As part of the 2050 projections, the second picture shows us the probabilities of a 20cm flood in specified areas. The largest probabilities of flooding ($P > 1/30$), indicated in light blue is around the rivers and the Wadden Islands.
Figure 5 indicates the probabilities of 50cm floods on the left and 200cm on the right in 2050. Here we observe that there is a lot of overlap between the 20cm and 50cm map by only showing that some areas 20cm areas are not exposed to 50cm. However, the 200cm map shows that there are major hot spots for very high flooding mostly centering around the river areas and the Flevopolder. There are a large amount of properties in these areas that can incur significant damage because of this.

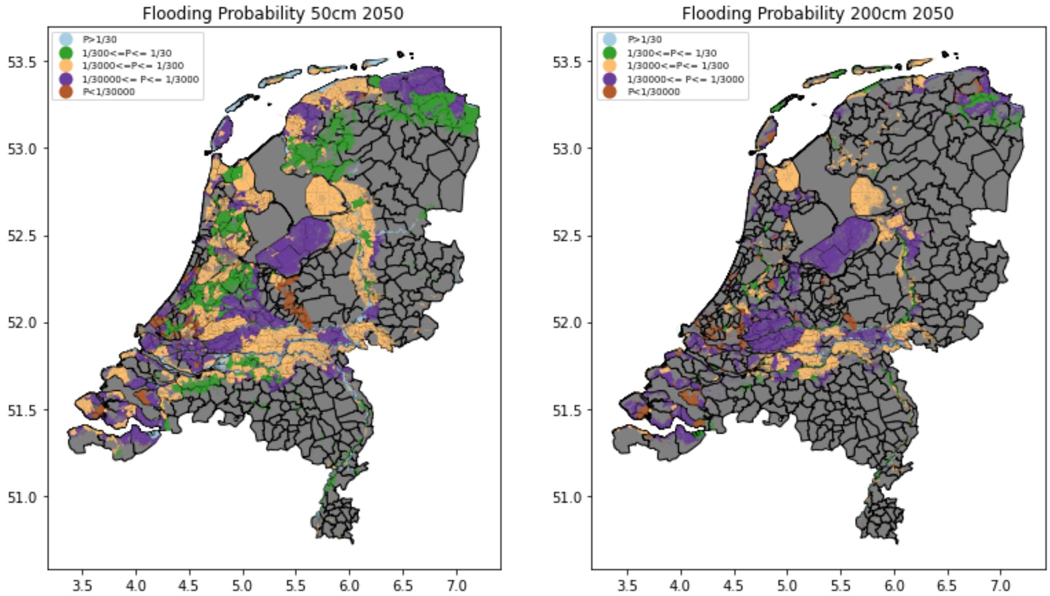


Figure 5: Flooding Probability 50cm and 200cm (Climate Adaptation Services, 2021).

Whilst these probability maps give us a good indication of the exposure in the Netherlands, they fail to capture the maximum possible exposure an area can experience. Luckily, the *Klimaat Effect Atlas* provides us with flood depth exposure with a certain probability per area in the Netherlands. This is shown in Figures 6 and 7.

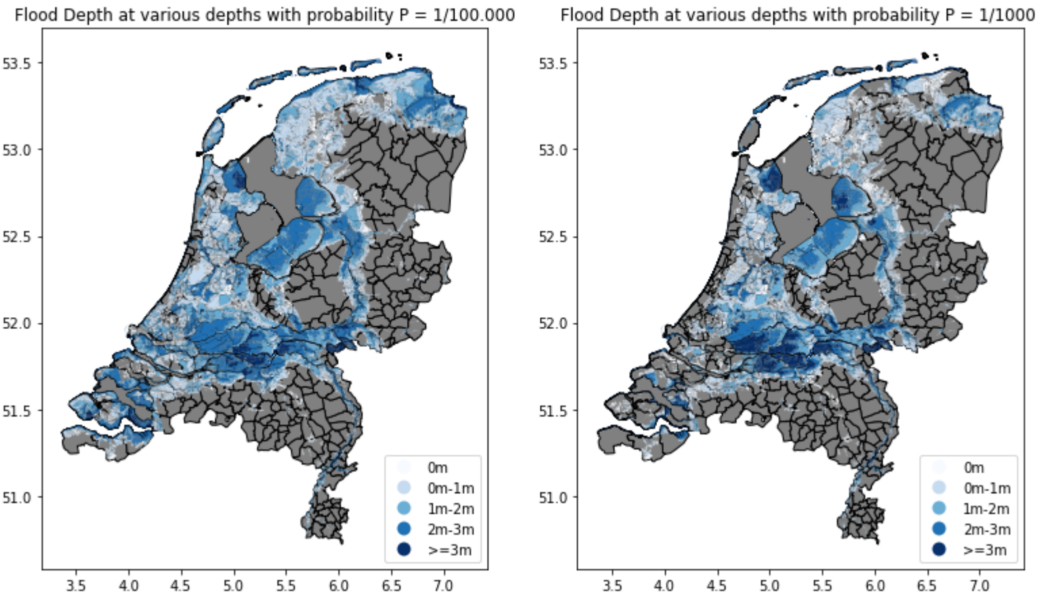


Figure 6: Flood Depth at various probabilities (Climate Adaptation Services, 2021).

Figure 6 shows the flood depths in meters for a probability of $P = 1/100.000$. Note here that the deepest flood depths are the most prominent in the middle of the country. As mentioned before, these areas are densely populated and can incur a lot of damage in case of a flood. The reason why this area runs a high risk is that it is the drain point of many rivers in Europe. When melting water or intense rainfall occurs at the sources of these rivers, it will eventually end up in these areas. It is of some comfort that most areas that are also exposed will most likely only experience floods below $1m$. Thereby limiting the impact in most areas.

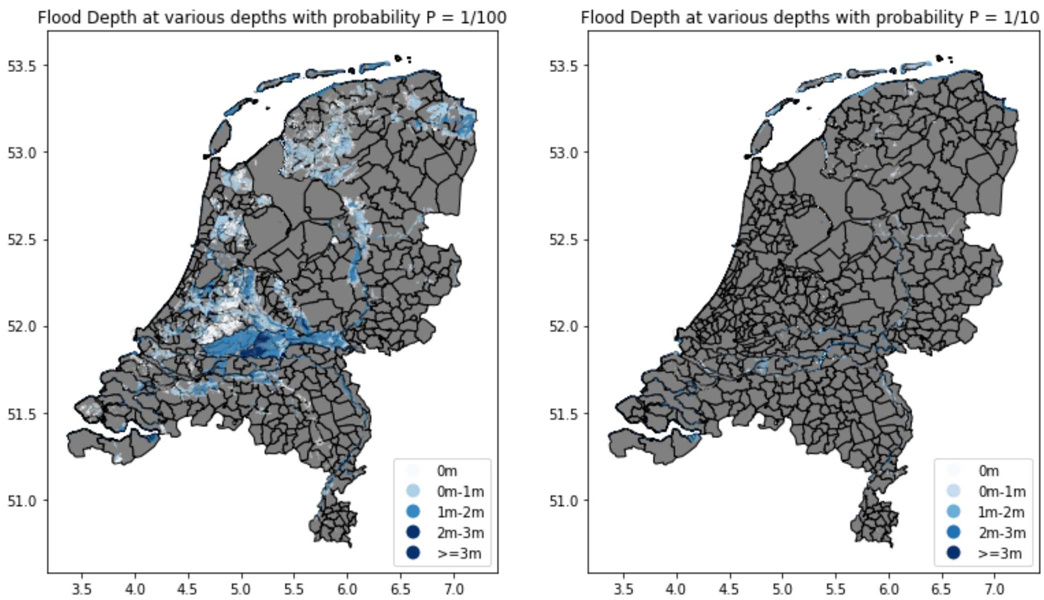


Figure 7: Flood Depth at various probabilities (Climate Adaptation Services, 2021).

Figure 7 shows the same type of results as Figure 5, but with higher probability of flood occurrence with respect to flood depth per area. It is interesting to see that even with a yearly probability of $P = 1/100$ there are areas that are dangerously exposed to very high water levels ($>= 3m$). With a flood occurrence with $P = 1/10$, we observe that this holds true for the areas directly connected to the waterways in the country. With respect to impact measurement, the results of the $P = 1/100$ is the most interesting with respect to damage analysis as there are a lot of properties in the exposed areas with a significant probability of occurrence. Again, it is however expected that these probabilities will decrease in 2050. The reason being that the government will improve the countries defense against flooding (Climate Adaptation Services, 2021).

This sub chapter answered the first two questions of the first subquestion. We found that for properties the most significant events are flooding and pole rot. This is due to SLR and increased precipitation which increase the probability of flooding. Pole rot occurs due to prolonged periods of drought which will increase over the coming years. For both events there are different areas that are exposed. For flooding its mostly in the river areas. For droughts the exposure is mostly present in the lower parts of the Netherlands (Friesland, South Holland, North Holland) where buildings historically had to be built on wooden poles due to soil characteristics. Indeed, it is the case that it only affects properties older than 1975 for pole rot risk (A. Kok, 2020).

2.3 Climate Change Predictions 2050 to 2085

For answering the first research question we still have to answer the third question, which is: *What are the projections of different physical climate events in the future for high-risk area's.*
We already talked about the projections up to 2050 in Chapter 2.2. However, the data lack information for after 2050. For this, the KNMI has estimated the possibility of four different climate scenarios up to 2085 in the Netherlands (KNMI, 2014). These scenarios are based on two variables: global temperature rise and changes in airflow. An overview of the climate scenarios are displayed in Figure 8. The Figure shows a graph with global temperature rise on the x-axis and the change in air flow on the y-axis. In the entirety of the plot four different scenarios are plotted. Note here that the squares indicate the "area" of the four scenarios. These scenarios are M_H, M_L, H_H, and H_L. The first letter indicates the temperature rise (Moderate or High) and the second letter the changes in airflow (Low and High). The more to the upper-right you go, the worse the situation will be with respect to the disruption of life due to climate change. For each of these scenarios an impact analysis is approximated on changes in absolute SLR, rate of change of SLR, precipitation, sunshine hours, evaporation, and mist hours. For our damage assessment to residential properties, the variables that can increase the probability of flooding and droughts are the most important. Figure 9 shows four different graphs. The upper two graphs display the Absolute SLR per year with respect to moderate (M_H, M_L) and high (H_H, H_L) temperature rises and changes in airflow. The same is shown for the rate of change (ROC) of sea level rise per year in the bottom two graphs.

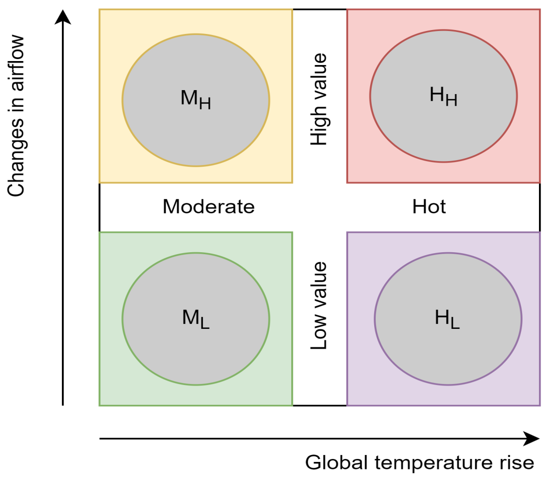


Figure 8: The four climate scenarios (KNMI, 2014).

Looking at the Absolute SLR per year we observe that in 2085 the expected sea level rise in the moderate temperature rise scenario is projected to be between 20cm and 60cm. For the high scenario this is between 40cm and 80cm. In both cases there is a significant increase in sea levels compared to today. However, the ROC in sea levels projection is a lot more uncertain than the absolute SLR. The moderate and high temperature scenarios standard error increases significantly year over year. Consequently, this variable shows to much uncertainty compared too the absolute SLR graphs.

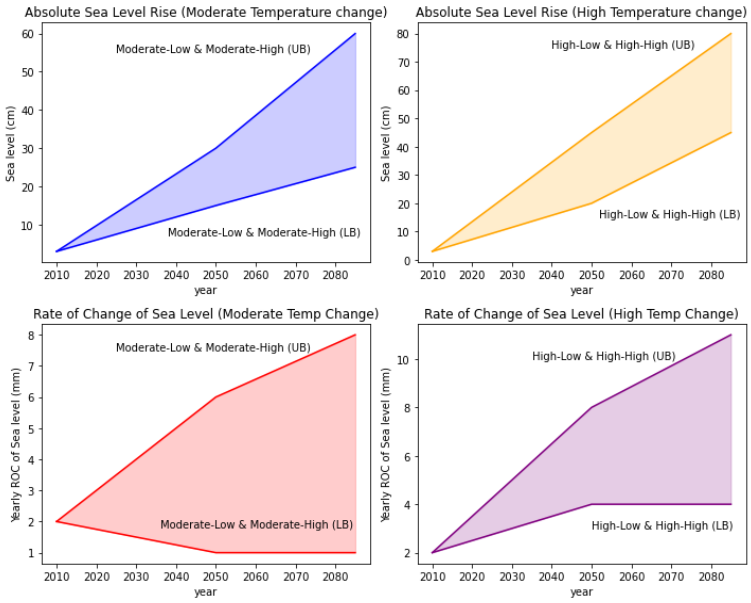


Figure 9: SLR Climate Scenario Projections 2050/2085 (KNMI, 2014).

Figure 10 shows the ROC of rainfall and the change in evaporation up to 2085. The ROC of rainfall contributes to the increased probability of flooding and the changes in evaporation in the increased probability of droughts. Whilst the general KNMI projections up to 2085 give us an indication of what can happens with the SLR and drought exposure, they will not help us with determining the impact on the mortgage portfolio. This is due to the fact that the impact of SLR, rate of change in rainfall, and average increase evaporation are not uniformly distributed (Baart et al., 2019). For example, for SLR the impact per area is different with respect to water density variations, water current, gravitational effects, and more. This means that for each area the impact is different. Consequently, we can not use these data for location specific information. This means that for this project our best indicator are the more location specific maps as given in Chapter 2.2 and as far as projections go up to 2050 and not beyond.

We have now answered the first subquestion by addressing all three points that had to be answered to gain insight in the current and future risks of physical climate change events in the Netherlands.

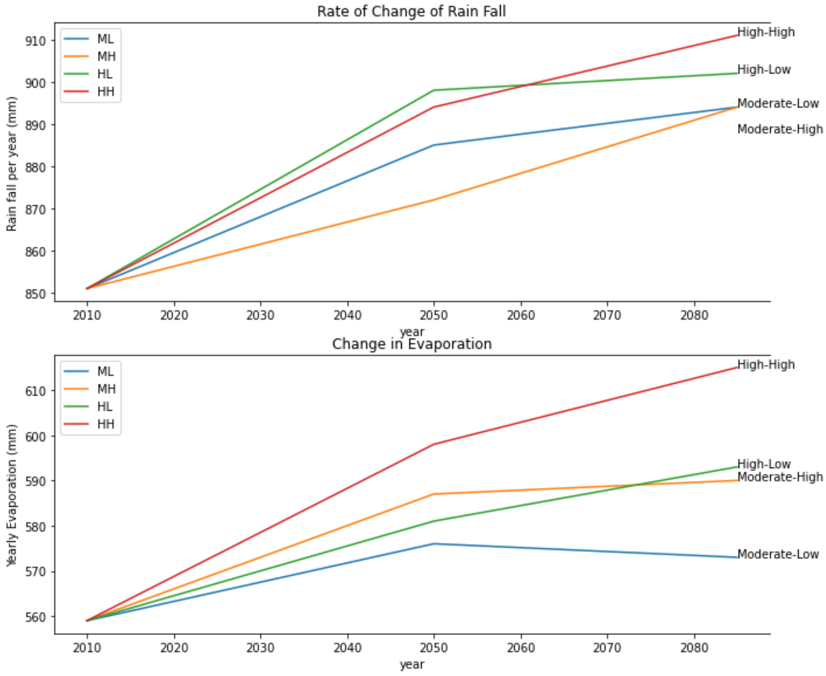


Figure 10: Precipitation & Evaporation Climate Scenario Projections 2050/2085 (KNMI, 2014).

2.4 Credit risk on Mortgages

Now that we know the physical exposures for properties in the Netherlands, we need to know what the exposure of the bank is. Just because a flood or pole rot occurs, does not mean that the bank will be affected as the residents themselves(or insurers) might pay for the damages. As long as mortgage holders pay their debts the bank does not incur a loss. Losses only occur when a borrower defaults on their loans. The uncertainty or risk of that occurring is a specific risk called credit risk. It is at this point the bank is exposed. This exposure is partially measured through the *Expected Loss*. In order to determine an expected loss model that incorporates climate risk, we have to understand how regular expected losses on mortgages are quantified. This leads to the start of our third subquestion: *How can we quantify different physical climate change risks in financial terms on the collateral of the mortgage portfolio?*. Where the first subquestion discusses this topic: *How are the non-climate adjusted expected loss models currently estimated?*.

2.4.1 Expected Loss

The expected loss calculation for a mortgage is considered a forecast of usual losses. It is a number that must always be expected as it is the nature of doing business in loan activities (Marinier, 2018). For a single mortgage the Expected Loss (EL_{it}) on mortgage i at a given time t can be calculated as:

$$EL_{it} = PD_{it} LGD_{it} EAD_{it}. \tag{1}$$

Here PD_{it} stands for the probability of default on mortgage i at time t, LGD_{it} for the Loss Given Default on mortgage i at time t, EAD_{it} the exposure at default on mortgage i at time t, and L_{it}

for the loss on mortgage i at time t. The LGD tells us the percentage loss given the EAD. EAD is the amount the borrower has borrowed to pay for the collateral. The expected loss calculation for financial institutions are based on the Internal Ratings Based (IRB) Approach. This means that expected loss calculations vary from institution to institution. For regulation a standard model is required, but that is not the IRB approach. Both the PD and LGD are estimated independently with different methods. The Volksbank also has their own approximation of the EL. It calculates two different competing expected loss models: the *regular (Rg)* and *Direct Loss (DL)* models. The combination of both of them calculate the *Expected Credit Loss* for an arbitrary mortgage i. This is shown in Figure 11.

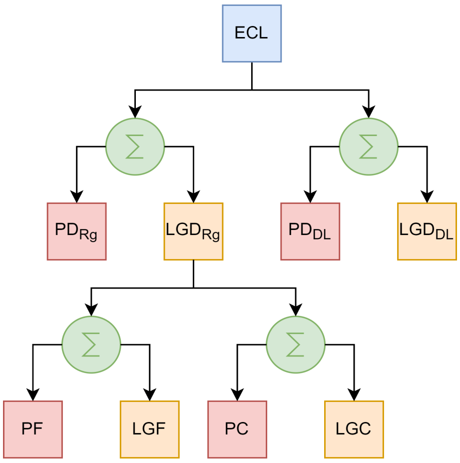


Figure 11: Expected Loss Layout Bank.

The direct loss is the portion that is immediately lost when a customer defaults. The regular PD is a combination of the Probability of Cure PC and the Probability of Foreclosure PF. Both probabilities have their own losses associated with it (LGC, LGF). The exact estimation of the probabilities is based on the financial information of the customer, current macro economic variables that determine the financial health of the customer, and historical defaults. LGDs are estimated by looking at the collateral and its characteristics (i.e: structural, environmental, social) and the macro economic variables influencing the price of the collateral. Unfortunately, the way the bank determines their expected loss is confidential. This means that the basic approach has to be used for calculating the non-climate adjusted expected loss and climate-adjusted expected loss.

This sub chapter answers the question of *How are the non-climate adjusted expected loss models currently estimated?* The literature and internal banking documents tell us how to estimate the expected loss as seen in Formula (1).

2.4.2 Unexpected Loss

For determining the credit risk exposure there is also a second part called the Unexpected Loss (UL). The UL is defined as the worst-case loss the bank could incur on the entire portfolio due to a particular loss event or risk realization (González et al., 2021). It is often calculated within the tail of the expected loss distribution. Per definition, UL is unexpected and thus a statistical measure is used to estimate it. For this thesis, unexpected losses are considered out of scope for climate change risks as there the first needs to be a firm understanding of what the actual expected losses are as there currently are no expected loss distributions available for the portfolio.

2.4.3 Climate Change and Expected Loss Models

This research determines the influence of climate change on the expected loss. Modelling climate risk is still in the beginning stages. As discussed in the research approach, there is literature from the private sector, however there are some issues with these studies that we discussed in Chapter 1.3. The methodology of determining a climate-adjusted expected loss was never discussed. Furthermore, how the damage exposure is determined is also not explained. The only observation that we do have is that once an exposure is determined it is priced in the market value of the property (Westcott et al., 2019; Magni, 2021; Evans, 2020). This shows that the literature for expected loss models is not widely available with respect to climate risk. What remains is building our own model that calculates a climate adjusted LGD and PD. Here it is the case that we do not have any default information due to climate change within the banks mortgage portfolio. Whilst this can be estimated, it is more interesting for the bank to first gain more information what these losses might be and use the current non-climate adjusted PD as a proxy for calculating the expected loss. As the PD's of the bank (PD_{reg}, PF, PC) are non-climate adjusted and we do not have any climate defaults in any of these cases available, it is better to keep the estimation of the expected loss on a more basic level as given in (2):

$$EL_{it}^{cc} = PD_{it}^{regular}\ LGD_{it}^{cc}\ EAD_{it}. \tag{2}$$

Here we redefine the climate change Expected Loss as EL_{it}^{cc} , the non-climate adjusted regular Probability of Default as $PD_{it}^{regular}$, the climate change loss given default as LGD_{it}^{cc}, and the exposure at default EAD_{it} where all variables are for mortgage i at time t (in years).
As mentioned, the LGD at a certain moment t is determined by looking at the market value of the collateral and the exposure at default. This leads us to how climate change can be quantified. There is a yearly risk of a certain climate event that can damage a property. The risk of damage decreases the market value of a property. Based on this new market value it is possible to determine a climate adjusted LGD (LGD_{it}^{cc}). If it is possible to estimate future damages it is possible to determine a climate adjusted LGD. The literature discusses various how damages due to flooding and pole rot could be calculated. This is discussed further in Chapter 2.5.

2.5 Damage Impact of Climate Events

Here we discuss the available literature that quantifies the impact of climate events on residential properties. This chapter aims to answer the second subquestion of subquestion three. Remember, this question states: *How can we model different physical climate events on different types of collateral?* We first discuss the available literature on flooding and afterwards on droughts.

2.5.1 Impact due to Flooding

The literature describes various approaches in determining the economic impact on properties due to flooding. Two different types are discussed in this thesis: Hedonic models and damage function models. Hedonic models determine the market value of property given that floods have occurred. The latter determines the maximum damage on a property type given that a certain type of flood occurs. We discuss each approach separately.

Hedonic Pricing

In general, hedonic pricing models are predictive models based on regression that can determine the market price of a property based on tangible and intangible building characteristics (Monson, 2009). Mathematically we can calculate the market price of a property i (P_i) as a function of the structural, locality/neighbourhood, and environmental characteristics (Baranzini et al., 2008). This can be written down as:

$$P_i = f(x_i; \beta) + \eta_i. \tag{3}$$

Here x_i is vector representing the structural, environmental, and neighbourhood characteristics of the property. Furthermore, β represents the vector of coefficients that are estimated. Also, η_i is the error within the model. This function can then be used to predict the price of any property i through the price prediction variable $\tilde{P}_i$:

$$\tilde{P}_i = f(x_i; \tilde{\beta}). \tag{4}$$

If information of a single property is available for several periods one could calculate the property price i adjusted for a given period with the log-linear model as:

$$\ln P_i = \beta' x_i + \beta_{T_i} T_i + \eta_i. \tag{5}$$

Here T_i is the time dummy for any other future period for property i and β_{T_i} the corresponding vector of coefficients. The adjusted price then satisfies:

$$\ln \tilde{P}_i = \tilde{\beta}' x_i + \tilde{\beta}_{T_i} T_i. \tag{6}$$

Note here that if it the property would be sold in the starting period the price would be:

$$\ln \tilde{P}_i = \tilde{\beta}' x_i. \tag{7}$$

This allows for estimating a price index between the starting period and period T_i. For flooding or hurricane damages, hedonic pricing models are adjusted with an extra variable to determine event-related damages in certain regions. By using statistical modelling (regression) w.r.t to this variable, the impact of for example flood damage can be estimated. An example of this approach is described by Ismail et al. (2016). They use the base formula approach as given in (3) and adjust it by adding the flood characteristics to the vector x_i. Their log-linear function incorporates the duration of the flood in hours with its coefficient. Using regression on historical data they found that property values have decreased due to this flood occurrence. More examples of hedonic flood and hurricane models models are also available. Zhang et al. (2019) observed a price decrease of almost 13% in their analysis. Bin et al. (2013) and Nyce et al. (2015) both adjust hedonic pricing models by incorporating flood/hurricane damages for insurance premiums. Bin et al. (2013) came to the result that house prices decreased 5.7% after hurricane Fran and 8.8% after hurricane Floyd. Fuerst et al. (2019) also used a hedonic model for a floodplane in Australia. In this case, they tried estimate future property prices by considering SLR in that area. They used a barebone model that assumed an area would be exposed to SLR if it would be below the sea level given 0.2, 0.5, 0.8, 1.0, and 1.1 meters. Furthermore, flood risk was present for an area if the flood plane would flood once in a hundred years. Fuerst et al. (2019) concluded that houses would decrease 3% in property value after flood for a certain period of time. They measured no significant results that due to SLR a property would be discounted. This seems counter intuitive which Fuerst et al. (2019) recognized and mentioned that SLR is either deliberately not factored in, purchasers are not aware of the risks,

or the risks are deemed to far ahead in the future.
The differences between these hedonic flood/hurricane pricing studies was the number of data points available of each property. The more that is known about a properties characteristic, the lower the error margin. The downside of these models is that they are based on data of a particular flood in a specific region with different property types. The model might not be accurate in other situations if these parameters are very different. It is not immediately obvious how this can be applied in the general case where a property has different characteristics and is exposed to different flood types.

Damage Functions

Damage functions are used to gain an approximated damage factor with respect to the maximum damage an asset, such as a property, can incur. If a property enters the market and the damages are not repaired, the value of the property will decrease depending on the damage impact. Consequently, if one knows the damage a property has incurred and the value of the property before the event, a new value can be approximated. However, depending on the current market situation, the perception of a value decrease with respect to the damages incurred might not always translate directly. Meaning, it might be that the market considers the damage on property *worse* then the actual repair costs required. This is something to consider when looking at this approach.

The literature makes a distinction between two types of damage functions; vulnerability and fragility functions (Lazzarin et al., 2022). Fragility functions consider a relationship between the hazard (i.e. flood), the vulnerability of the asset, and the probability of having a certain damage. Whilst vulnerability functions consider the vulnerability curve relating to a hazard for a certain area, the exposure in that area, and the assets vulnerability to damage.

A selection of fragility functions have been used to measure flood damage in various countries and situations (Thapa et al., 2020; Pita et al., 2021; Nofal et al., 2020). Thapa et al. (2020) approximated the flood damages in the Khando River (Nepal) with fragility functions. They crated five damage classes: minor, major, severe, beyond repair, and collapse. These damage classes are determined based on the mean damage ratio that was assigned to each surveyed building. The probability of reaching or exceeding a particular damage state given a certain flood depth is then calculated through the log normal distribution function. This is done for all properties with a certain damage class exposure. Using the flood data of the river and the rainfall data over a length of time, they were able to predict the damage number given the likelihood of a certain flood scenario. A similar approach is used by Pita et al. (2021) at the Paraguay river where they added extra variables for expert opinions as some information was lacking to use standard damage functions. One of the more extensive fragility approaches has been done by Nofal et al. (2020). They determined damage functions with a failure probability given a certain flood depth for all types of construction elements within in a property. This resulted in an approximated damage per property type. The key factor for fragility functions is that past flood data is available for all the exposed properties.

For vulnerability functions there is also literature available (Amadio et al., 2019; Merz et al., 2013; Huizinga, 2007; Kok et al., 2004). Huizinga (2007) created the damage functions known as JRC curves. These curves only consider a single variable (namely flood depth) to determine the maximum damage an asset type (such as a property) can incur. Amadio and Merz reported that JRC curves report significant uncertainty with respect to multivariate models that are trained with machine learning. However, both acknowledged that this is a good estimate if no other data is available. For the Netherlands, Kok and Huizinga (2004) created more specific damage functions that measure the damage on different types of properties. These functions are constantly updated and are also known as *Standard Method* functions. The most recent available methodology is from 2017 (Slager, 2017). These functions can estimate damages due to flooding only knowing the type of property (single home, apartment ground floor, apartment first floor, apartment higher floors) and flood depth. Note here that the single home function is a combination of all different types of 1 and 2 story floor homes in the Netherlands. These functions can be observed in Figure 12. By deriving the flood depth exposure for a property in a certain region, we can derive a damage factor from the graph. Based on this factor we can mathematically determine the damage incurred on a property given a certain property type as:

$$S = \sum_{i=1}^{n} a_i S_i A_i. \tag{8}$$

Where S equals total flood damage on n properties, S_i the maximum damage on property i per m^2, A_i the surface area in m^2 of the property, and a_i the damage factor on property i given a certain flood depth as shown in Figure 12. For the Netherlands this will be more accurate than the general country damage curve as mentioned in Huizinga (2007).

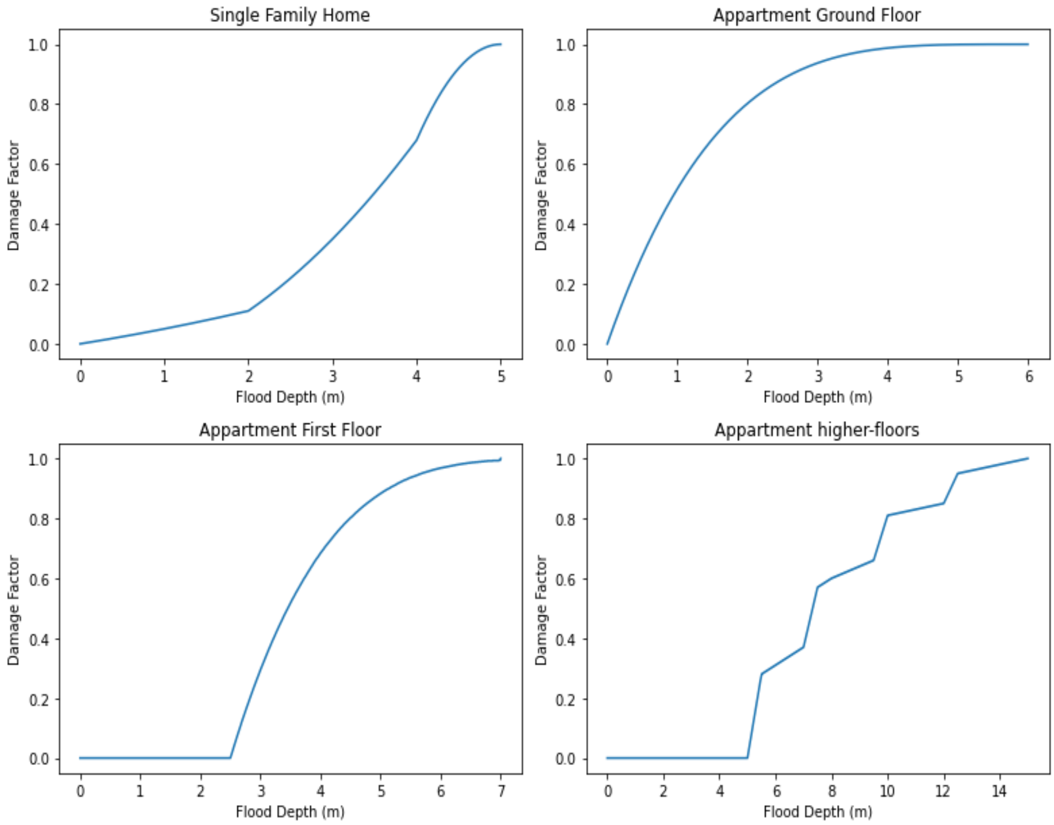


Figure 12: Property Type Damage Curves (Kok et al., 2004)

There is a second type of vulnerability damage function that is not only based on flood depth, but also on flood velocity. Lazzarin et al. (2022) described damage functions for various applications including various building types. A variable W is used to measure the intensity of the hydrodynamic conditions that produces the damage. This function is shown in (9):

$$W = (\frac{Y}{Y_W})^{\alpha}(1 + \beta F^2) \quad \text{with} \quad Y_W > 0, \alpha >= 1, \beta >= 0. \tag{9}$$

Here Y is the water depth in meters, Y_W the reference depth that scales Y, F the Froude number defined as $F = U(gY)^{\frac{-1}{2}}$, g as gravity factor, U is flood velocity, and α and β are calibration factors that measure the relative importance of static versus dynamic component W.
Then based on this function for a certain water depth and flood velocity they are able to measure the relative damage to a property which can then be inserted as a value of a_i in (8). Although velocity is included here, the paper states that the impact of low velocities are marginal as damages often are from wetting only. The impact is higher when flood depths and velocities are high. Flood velocities and probabilities can be found per area in the Netherlands from governmental institutions (Stuurgroep Water, 2018).

The literature shows us various different studies that have used hedonic pricing with/without machine learning approaches, vulnerability damage functions, and fragility damage functions. These are often adjusted to better fit the characteristics that can be observed on a case by case basis. Often the choice for a certain type of model depends on the data that is available within a project.

2.5.2 Damage due to Drought

From Chapter 2.2 we know that the impact of droughts on properties is the exposure to pole rot which results in subsidence of properties. Pole rot is an acute climate event that develops on a property over time. The literature on the quantification of pole rot in the Netherlands is severely limited (Costa et al., 2020). In other areas of the world different methods are used such as contingent valuation and expert judgement for the impact of pole rot on property values (Costa et al., 2020). However, due to different building and environmental characteristics in the Netherlands these are not usable. The only available data and damage approximation approach that can be used in the Netherlands has been created by Costa et al. (2020) and Kok et al. (2020) through the Climate Adaptation Services (2021).

The damage class model is based on observing the properties of the substrate, the ground water levels, and the building year of the property. The only properties with wooden poles are built until 1975 (S. Kok, 2021). Table 1 shows the damage classes that have been determined. Here we observe the restoration costs per m^3 and what repair works are required for each damage class.

Table 1: Damage classes for the impact of pole rot (Costa et al., 2020; A. Kok, 2020).

Damage Class	Restoration costs per EUR/m^3	Repair works per damage class
D1	3.25	Repainting
D2	15	Repainting, repairing wall cracks, rent for repair tools
D3	53	Repainting, repairing wall cracks, rent for repair tools, repair plastering work
D4	184	Repainting, repairing wall cracks, rent for repair tools, repair plastering work, repair window frames
D5	670	Repainting, repairing wall cracks, rent for repair tools, repair plastering work, repair window frames, repair foundation

The damages classes are used in Figure 3. The figure shows the damage class for all *neighbourhoods* in the country for the 2050 climate low and high exposure. If a property is in such an area it is possible to calculate the damage on a property given that it is in a certain type of neighbourhood with a specific damage class exposure as:

$$S = \sum_{i=1}^{n} A_i h_i C_i. \tag{10}$$

Here A_i is the surface area in m^2 on the collateral of mortgage i, h_i the height of the collateral of mortgage i, and C_i the damage class cost per m^3 on the collateral of mortgage i. This can be done for all properties with a building year before 1975 located in a specific damage class area. The key factor to note from this model is that it assumes that properties will *not* be fixed until 2050 and stay in the state that they are in now. The data used assumes a worst case scenario with respect to property states.

2.5.3 Conclusion Damage Impact of Climate Events

This sub chapter has answered which climate change impacts can (currently) be quantified on residential properties. We were able to look at methods that incorporate different types of property and climate event characteristics. Both flooding and pole rot have been considered. For flooding a variety of options is available in the literature, whilst the literature for pole rot is limited. We have now answered the second question of subquestion three: *How can we model different physical climate events on different types of collateral?*

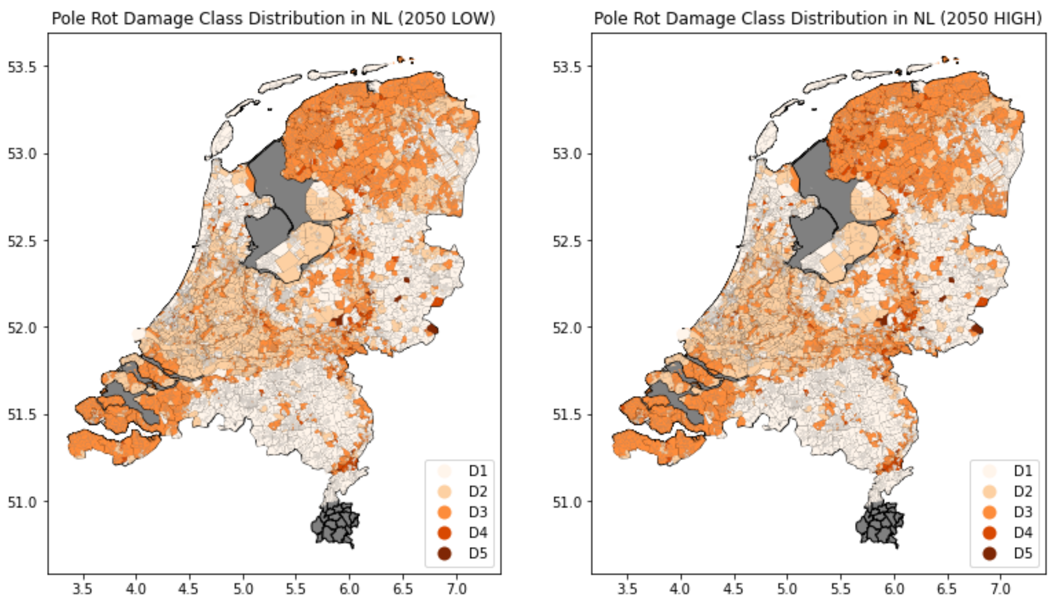


Figure 13: Risk of pole rot in 2050 (Climate Adaptation Services, 2021).

2.6 Property Market Price Developments

Now that we have our answer with respect to subquestion one and some parts of subquestion three we move on to subquestion two. Remember, subquestion two was defined as: *How large is the exposure of the banks' mortgage portfolio to the different physical climate events in the Netherlands?* We answer this subquestion with two different questions. Here we focus on the first part which states: *What are the property price developments in the current climate event exposed areas for the bank in the Netherlands?* In particular, we want to focus on the regions affected by the flooding in Limburg in the summer of 2021 and the house price developments of the earthquake areas in Northern Groningen since the 2010s.
The reason why want want to look specifically at property prices in these areas is due to the literature. As discussed in Chapter 2.5, the literature tell us that climate events around world show that property prices decrease between 3% and 13%. We want to observe whether the same trend can be found with other climate events in the Netherlands.

2.6.1 Property price development in North Groningen

Looking at Figure 14, we observe the average house price development of various municipalities in the province of Groningen from 2011 until 2021. The top graph shows the absolute property price changes and the bottom graph the percentage change of property prices for each municipality with respect to the change in the dutch average of each year. The black line in the top graph shows us the average property price developments of the country. The data is retrieved from an external party that indexes the house price of the entire country every six months within the database of the bank.

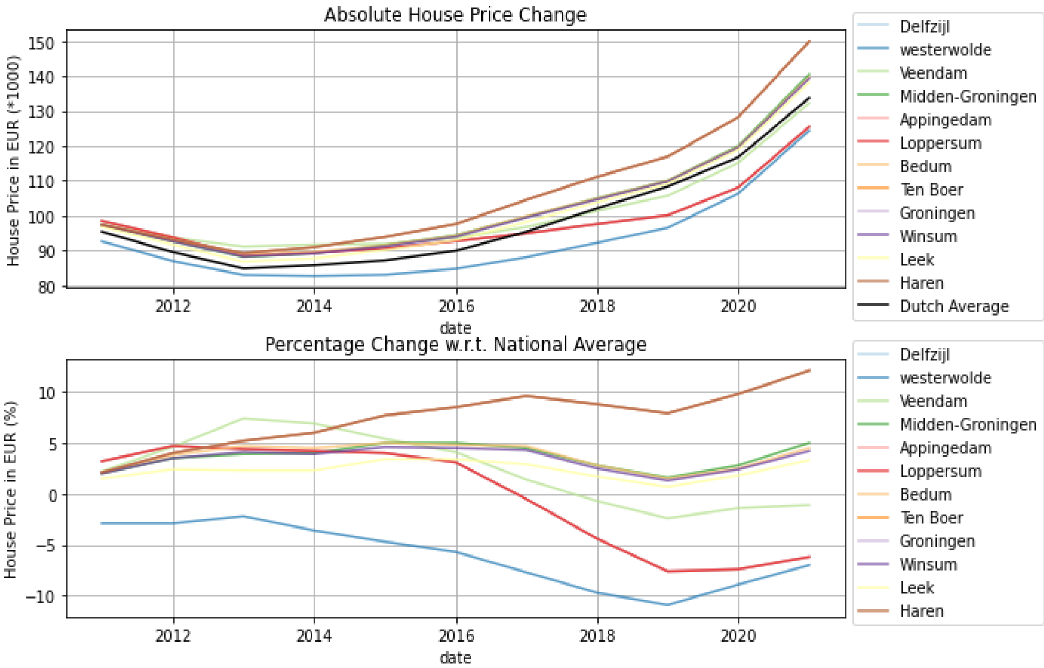


Figure 14: House price developments in municipalities of North Groningen

From the absolute house price change graph we observe that most municipalities are in line with the national average. Within the percentage change graph we do observe some small deviations between the municipalities and the average. There are multiple explanations possible for different property prices for each municipality. For example, how close most properties are located to a major city, the average physical state of each property, the property types, and other macro-economic variables such as aging and limited economic opportunities within the region. Because of these different factors it is not always easy to pinpoint the exact cause of an increase or decrease in property prices. We do observe that the influence of media reporting over the years for *some* municipalities has influenced the value of their properties.

At the start of the 2010s the property market was still recovering from the financial and euro crisis. The years that followed show that the prices increased significantly as demand started to pick up. The earthquakes started to occur from 2003 up to 2011. Every year on average the impact increased slightly. The first major earthquake occurred in 2012 and received large scale media attention. The epicenter was in Huizinge which is located in Loppersum. After this event the damages were shown repeatedly on the news until today (Nationale Ombudsman, 2021). Looking at the percentage change graph, we observe that property prices started to decline for a selection of municipalities. In particular Loppersum, Veendam, and Westerwolde started deviating downwards from the national average. However, almost all municipalities were significantly affected by the earthquakes and not every region experienced property price decreases. Here we observe that the media plays a large role. The municipalities that got reported on the most are Veendam and mostly Loppersum. This pattern is observed in the percentage decrease map of Figure 14. Loppersum decreased approximately 6% over the years and Veendam 2%. Westerwolde is also below the national average, but there are other factors at play here such as location and economic opportunities that influence the property prices.

From 2020 on wards we observe that almost all property prices start to increase. This is mostly attributed to the COVID-19 pandemic housing boom. However, it is still the case that the impacted regions remain significantly below the national average due to remaining exposure.

2.6.2 Property price development in Limburg

The price development of properties in Groningen shows to some degree that the market has priced in the danger of earthquakes within certain municipalities. However, this is mostly for the regions that have had the largest media exposure. Other municipalities that are also at risk do not show significant market value decreases. Flooding is different for many individuals in the Netherlands as they are better able to identify areas that are exposed to it. When flooding occurs it often happens at key points where the water has the largest chance of either leaving a river or breaking a barrier as earlier discussed in Chapter 2.2. Most individuals will not buy properties outside the dykes. This is often already reflected in the price of those properties and insurance premiums on the property. This is something to consider when we are looking at the property price developments after the flooding of 2021. Looking at Figure 15, we observe the absolute property price changes and the percentage change of property prices per municipality in Limburg with respect to the Dutch national average over the last ten years.

The coloured time series show the municipalities that have flooded or ran the most risk of flooding. There is not much to observe from this graph with respect to the price development after the flood. When we translate this graph to the percentage change of each municipality with respect to the national average per year, we do observe differences between them. However, it is currently impossible to attribute any property price decreases to flooding. The flooding occurred in the summer of 2021 whilst the data shows only one extra period of property prices. Within this period we see that almost all property prices decreased with respect to the national average. This can be due to the flooding, but also because of the demand in other areas of the Netherlands or other macro-economic factors. A larger period of time is required to observe if any price developments could be attributed to flooding.

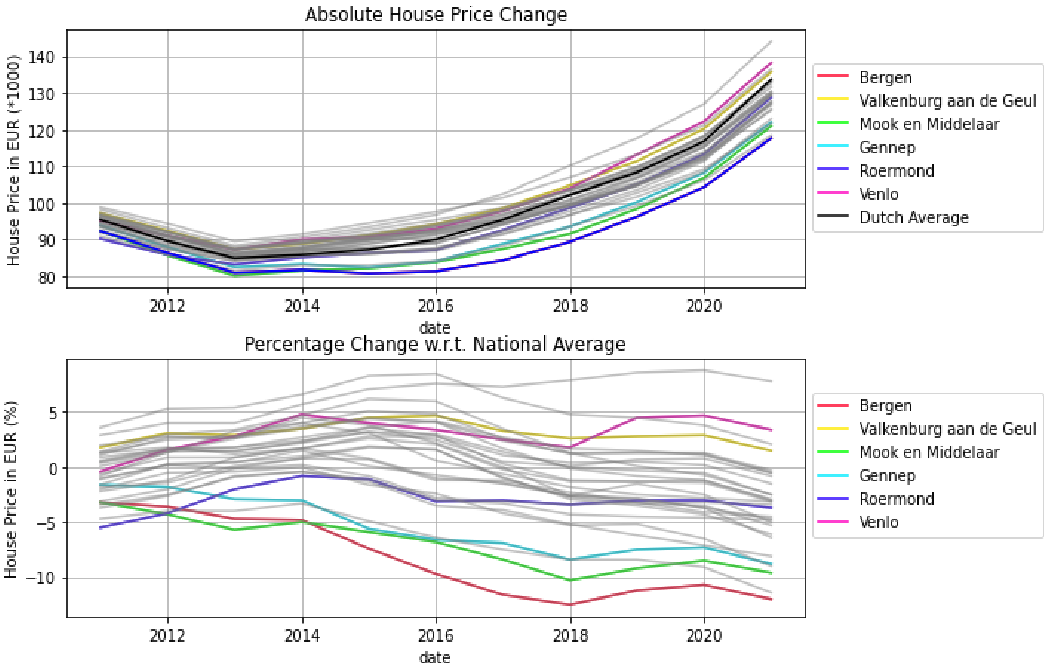


Figure 15: House price developments within municipalities of Limburg

2.6.3 Conclusion Property price Development

As mentioned, in the literature the impact of flooding on property price developments has been shown through various hedonic models. Indeed, Bin et al. (2013) and Zhang et al. (2019) reported property price decreases between 5.7%-8.8% and 13.3% for their respective regions. A study from Cambridge University (Zhang and Leonard, 2019) indicated that house prices recover after 5 or 6 years to the original house price after the flood occurrence. The same result was also found by Bin et al. (2013). However, if floods become regular in a certain area it can lead to systemic long-term discounting of property prices (Fuerst and Warren-Myers, 2019). For the Netherlands an estimation has been made that climate change induced flooding can result in a total value decrease of properties between 2.5% and 10% (Calcasa, 2019; Reeken, 2022). Whilst our data for Limburg does not provide evidence for this, our data for Groningen do. For the municipalities in Groningen there is a systemic long-term discounting for the affected regions with media attention: Loppersum (−6%) and Veendam (−2%). Even though flooding is different from earthquakes, we do observe that if a systemic climate risk is present property prices will drop within the same range as presented by the literature.

With this we have answered our second question for subquestion two: *What are the property price developments in the current climate event exposed areas for the bank in the Netherlands?* We can conclude that the data are in line with the literature and that there already is a certain risk exposure to climate events. Whilst there is nothing to conclude about the Limburg floods, based on the earthquakes in Groningen (where an eartquake can be seen as a climate event) an impact is measured on property prices due to these possible systemic long term climate risks. If more systemic flooding would occur due to climate change the same can happen in Limburg with its property prices.

3 Data Review

This chapter discusses the data used in this research. A portion of this chapter is used to discuss the particularities of this data and another portion focuses on the second question of subquestion two: *How large is the exposure of the banks' mortgage portfolio to the different physical climate events in the Netherlands?*

3.1 Climate Data Structure

The climate data from the *Klimaat Effect Atlas* have been obtained in the form of *Geographic Data Files*. These files can be transformed to *Geographic Data Frames (GDF)* within the *Python* programming language through the *Geopandas* package. This section discusses the way the data are presented and how they are used to link climate exposure to individual properties.

3.1.1 Geographical Data Frame Structure

Before we analyse the various climate data frames we first discuss the structure behind geographical dataframes. Secondly, we show how the data are transformed into usable data sets. One of the key GDF's that we use is displayed in Table 2.

Table 2: GeoDataFrame of the Netherlands.

Index	NAME_1	NAME_2	TYPE_1	TYPE_2	Geometry
0	Drenthe	Aa en Hunze	Province	Municipality	POLYGON((...,...,...))
1	Drenthe	Assen	Province	Municipality	POLYGON((...,...,...))
...	...	...	...	...	...
490	Zuid Holland	Zwijndrecht	Province	Municipality	POLYGON((...,...,...))

Table 2 shows the entries for the Netherlands on a municipality level. The two columns of interest here are: *geometry* and *NAME_2*.The geometry column has geographic coordinates of the municipality stored in them. Depending on the shape of the municipality it is stored either in a polygon or a multipolygon. A multipolygon is different from a polygon in it being a collection of multiple individual polygons of various possible shapes and sizes. The coordinate system that creates the size of the polygon is called the *EPSG:4326*. To show an example of how a plot would look like, we have plotted the Netherlands with its municipalities in Figure 16. In here, the municipalities of *Aa en Hunze*(Green), *Assen*(red), and *Zwijndrecht*(blue) are highlighted. These are the entries as shown in Table 2. The x and y axis show the geographical position of each location based on the coordinate system.

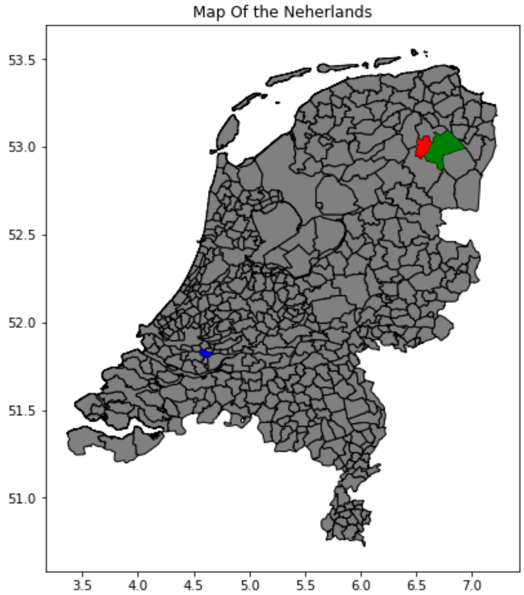


Figure 16: Map of the Netherlands with highlighted regions.

The climate data from the Climate Adaptation Services (2021) are also delivered in GDF form. Using this standard map of the Netherlands we are able to map climate exposures and mortgage data on top of it with its precise location using the geometry columns. In this way we can identify areas of interest.

3.1.2 GeoDataFrame of the Flood Depth Exposure

Now that we know the basics we are able to discuss the climate data set that we are going to use. A sample of the data frame belonging to the Flood Depth exposure is displayed in Table 3. This dataframe has already been combined with the dataframe of the Netherlands as shown in Chapter 3.1.1.

Table 3: GeoDataFrame of Flood Depth at various probabilities

Index	DN	Geometry	NAME_1	NAME_2	TYPE_1	TYPE_2
116	1	POLYGON((...,...,...))	Friesland	Schiermonnikoog	Province	Municipality
117	1	POLYGON((...,...,...))	Friesland	Schiermonnikoog	Province	Municipality
...		...	...	...	...	...
479961	0	POLYGON((...,...,...))	Limburg	Vaals	Province	Municipality

The plotting of these polygons results directly in Figures 6 and 7 shown in Chapter 2.2. The key column here is the *DN* column. This indicates the maximum flood depth that can be reached on certain coordinate points of the geometry. The *NAME_1* and *NAME_2* columns indicate in what province and municipality this point is located. Note that it is possible that a certain flood depth is outside a city and municipality as it is on a coordinate level. In this case the *NAME_1* and *NAME_2* entries will be empty. These tables all look the same for every probability of occurrence of flood depth level as indicated in the Figures 6 and 7.

3.1.3 GeoDataFrame of Pole Rot Exposure

The GDF that is used for Pole Rot, as displayed in Figure 13, is shown in Table 4. This GDF is on a *neighbourhood* (column: buurtnaam) level. This means that the geometry is based on this column. This Table is used for both the *low* and *high* 2050 climate exposures. For the low climate exposure we have the *damage class* column called *mild_cc__2* and for the high climate exposure the *sterke_cc_* column. Because we only have our damage classes in integer variables each damage class entry is rounded to the nearest integer for every neighbourhood.

Table 4: GeoDataFrame of Pole Rot Risk (HIGH & LOW) in 2050

Index	buurtnaam	gemeente code	gemeente naam	mild_cc __2	sterke _cc_	Geometry
0	Oude Binnenstad en Nieuwstad	GM0216	Culemborg	3.1225	3.1217	MULTI-POLYGON((...,...,...))
1	Oude Buitenwijken	GM0216	Culemborg	1.995	2.008	MULTI-POLYGON((...,...,...))
...	...		...	...		...
13415	Konwerderzand	GM1900	sudwest-Friesland	0	0	MULTI-POLYGON((...,...,...))

3.2 Mortgage Data Structure

In this section we discuss the mortgage data provided by the Volksbank. We aim to create an overview of what the relevant data points of the mortgages are with respect to climate change.

3.2.1 Data Points for Impact Analysis

The bank has a lot of different data points for various different goals and purposes. The mortgage data are no exception and contains a lot information from which customer and collateral data are monitored. The banks internal models are based upon this data structure. With respect to climate change it is important that we obtain as much information about the collateral as possible. After all, a model choice can only be made if the required data points are available. Table 5 shows us a list of 23 data points that show customer and collateral data that can be used for our model.

Table 5: Data Points Of Mortgage Data.

Index	Data Points Required	Explanation
1	Customer ID	Identification number of the customer at the bank
2	Collateral ID	Identification number of the collateral within the portfolio
3	Land ID	Country Identification number
4	Collateral Type ID	Identifcation ID of the type of collateral (Appartment, Single Home)
6	Active ID	Is the Customer ID still a customer (y/n)
7	Customer Type	Private or corporate client(y/n)
8	Postal Code	Collateral location information
9	Street Name	Collateral location information
10	House Number	Collateral location information
11	City/Town	Collateral location information
12	Province ID	Collateral location information
13	Region/Municipality ID	Collateral location information
14	Building Year Collateral	Year in which the collateral was built
15	Surface area in square meters	Total area in m^2 of the property or the average m^2 of properties in that region
16	Market Value Collateral Indexed To the Gauge Date	Most recent market value of the property index till gauge date
17	Principle Amount	Principle amount borrowed at the start of the loan
18	Average interest paid by borrower	Interest that is being paid on average year over year since loan origination
19	PD Regular	Probability of Default that is currently calculated
20	Initial Exposure	Height of the mortgage at start date
21	EAD Regular	Exposure at Default that is currently calculated
22	Loan Type	Type Mortgage: Annuity, interest-only-linear
23	Time To Maturity of Mortgage	Time it takes till the mortgage is not on the balance sheet anymore

3.2.2 GeoDataFrame of Mortgage Data & Climate Data

In order to make the mortgage data compatible with the climate data we have to transform the active collateral data in the portfolio to geographical coordinates. We do this through a process called geocoding. Through various requests through Python we can map the property addresses to geographical coordinates and save them in a GDF. The new GDFs are a combination of all the information of Table 5 with Table 3 for flood risk and Table 4 for pole rot. The final GDF for flood risk is displayed in Table 6 below.

Table 6: Merged Flood & Mortgage Data Structure.

Index	Address	Customer/ Collateral ID	Market Value	...	Time to Maturity	Flood Depth	geometry
0	Streetname, housenumber, city, postal code	XXXXXXX	300000	...	26	2	POINT((...,...))
1	Streetname, housenumber, city, postal code	XXXXXXX	175000	...	13	2	POINT((...,...))
...	...	...	...	...	...	...	POINT((...,...))
260699	Streetname, housenumber, city, postal code	XXXXXXX		...	28	5	POINT((...,...))

The final GDF for pole rot risk is shown in Table 7 below. This dataframe is available for both the 2050 High and low risk scenarios. Note, a damage class of 0 means that there is no damage due to pole rot for the particular property in 2050.

Table 7: Merged Pole Rot & Mortgage Data Structure.

Index	Address	Customer/ Collateral ID	Market Value	...	Time to Maturity	Damage Class 2050	Geometry
0	Streetname, housenumber, city, postal code	XXXXXXX	300000	...	26	3	POINT-((...,...))
1	Streetname, housenumber, city, postal code	XXXXXXX	175000	...	13	0	POINT-((...,...))
...	...	...	...	...	...	...	POINT-((...,...))
260699	Streetname, housenumber, city, postal code	XXXXXXX		...	28	2	POINT-((...,...))

3.3 Physical Risk Exposure on the Mortgage Portfolio

Now that we have mapped the climate and mortgage data for both flood and pole rot risk we can answer the second question from subquestion two: *Which areas are considered high climate risk areas for the banks mortgage portfolio?*. We discuss each climate exposure separately.

3.3.1 Flood Risk

Appendix B shows every mortgage that has a certain flood depth exposure to it. We observe that most properties in the portfolio at least have some exposure to a significant flood depth. As expected, we observe that there are only a few mortgages that have a significant flood depth ($> 3m$). There are however two problems with this representation. Firstly, we only observe the flood depth and not the corresponding probability of occurrence. Secondly, we see a lot of mortgages but we do not know which areas have the largest exposure. Figure 17 shows the bar plot of the number of properties in certain municipalities that are exposed to 5 and above 6 meter flood depths. Also, Appendix B further shows us the bar plots of the 1m to 4m flood depths.

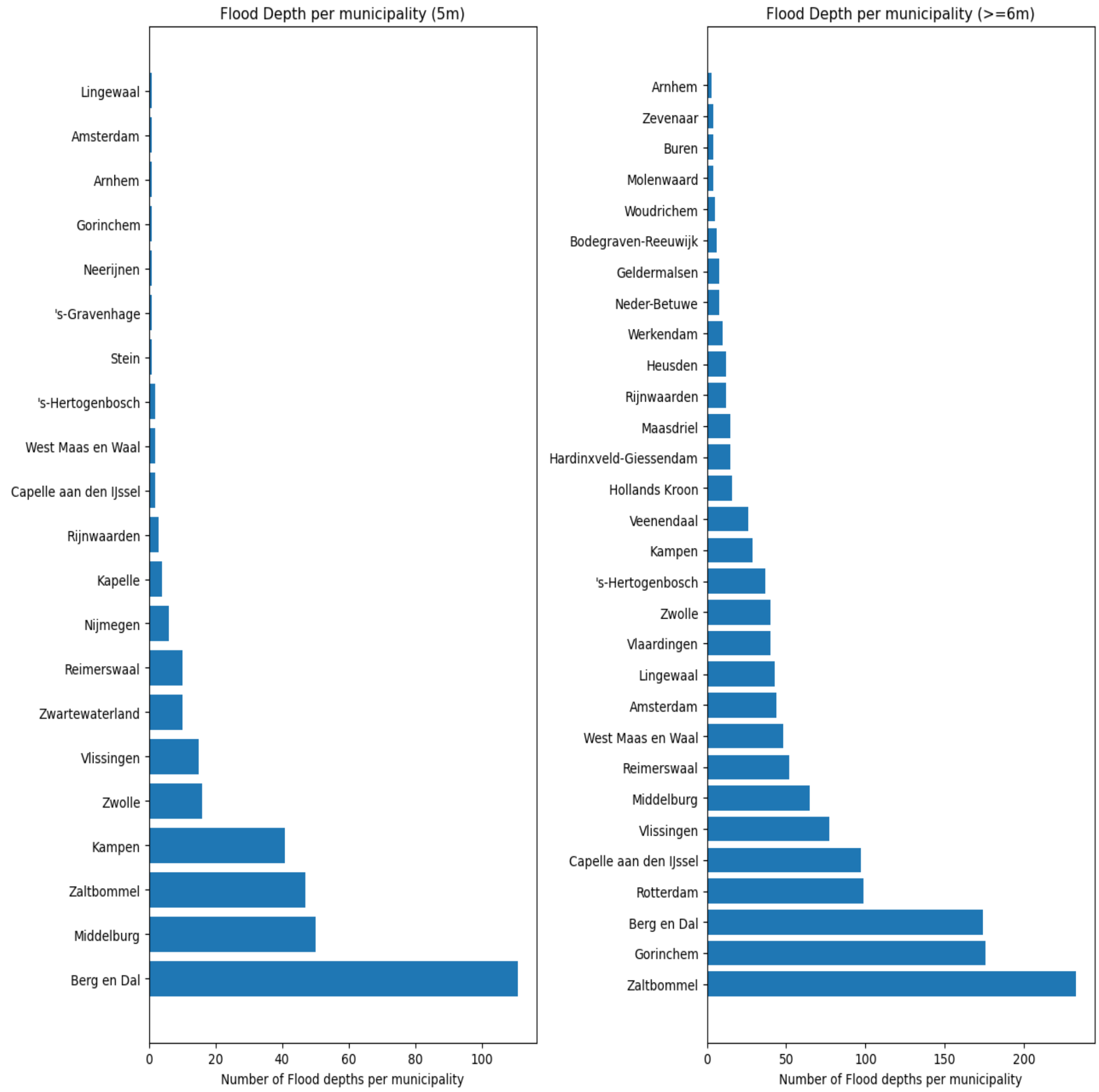


Figure 17: Bar Plot Flood Depth of 5m and larger than 6m.

Indeed, Figure 17 shows that there is a significant portion of properties in some municipalities that have a large flood depth exposure. Interestingly but not unsurprisingly, a large portion of these areas have direct connection to the Dutch rivers, we observe that the municipalities of Zaltbommel (Province of Zuid-Holland), Berg en Dal (Province of Limburg), Zwolle/Kampen (Province of Overijssel) have the largest exposure. This also because the banks portfolio in these municipalities has historically been large. Whilst this maps tells the bank what areas have the exposure to the largest flood depths, it does not tell us anything about the losses for the bank as this is a combination of flood maps as given in Figures 6 and 7 and the properties within the portfolio. In order to gain further insight we have to start modelling the expected losses.

3.3.2 Pole Rot Risk

Pole rot is also a climate exposure on the banks portfolio. Recall that Figure 13 shows the pole rot exposure of properties within the Netherlands. Note that damage class exposure is on a *neighbourhood* level. This means it is not as accurate as flood depth exposure which can observe the risk on an *individual* property level. Appendix G shows us the pole rot exposure map in the Netherlands for each individual property. In total 21% of the total portfolio is exposed to pole rot. To further analyse the potential risks we want to sort the properties in terms of damage class exposure. This can be seen in Figure 18.

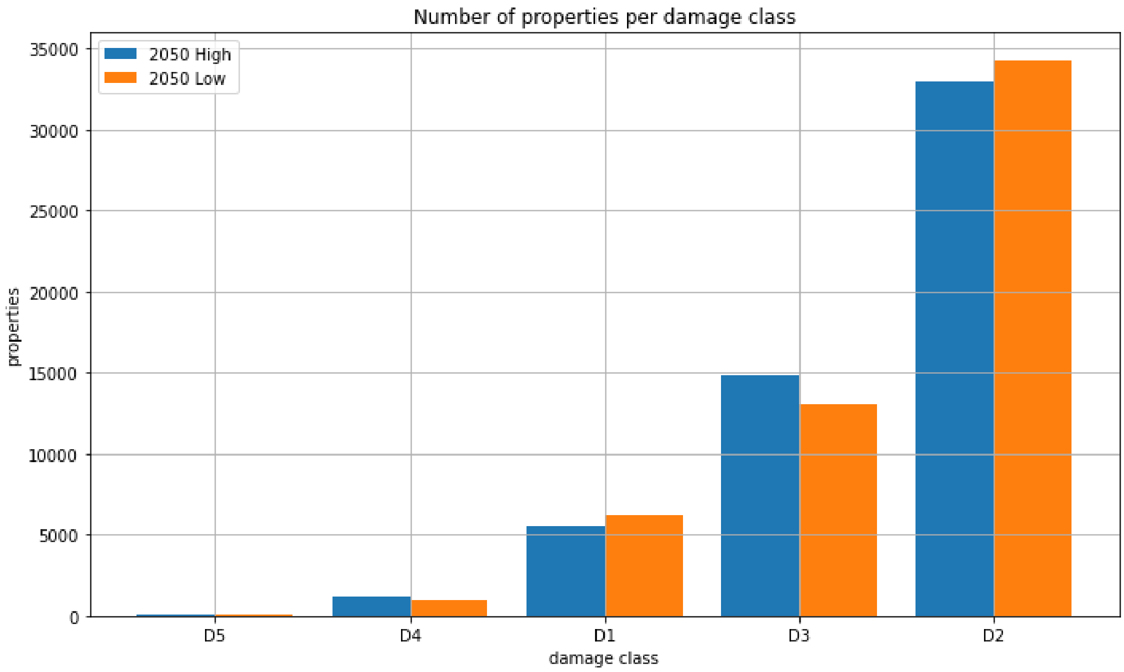


Figure 18: Number of properties per damage class in the 2050 High and Low climate exposures.

We observe that the largest exposure is in the D3 damage class which accounts for the total reparation costs of 53 EUR/m^3 in 2050. Furthermore, we observe that there are limited number of properties exposed to the D4 and D5 damage classes. We also deconstructed the number of properties within these classes to their respective municipalities as given in Figure 19.

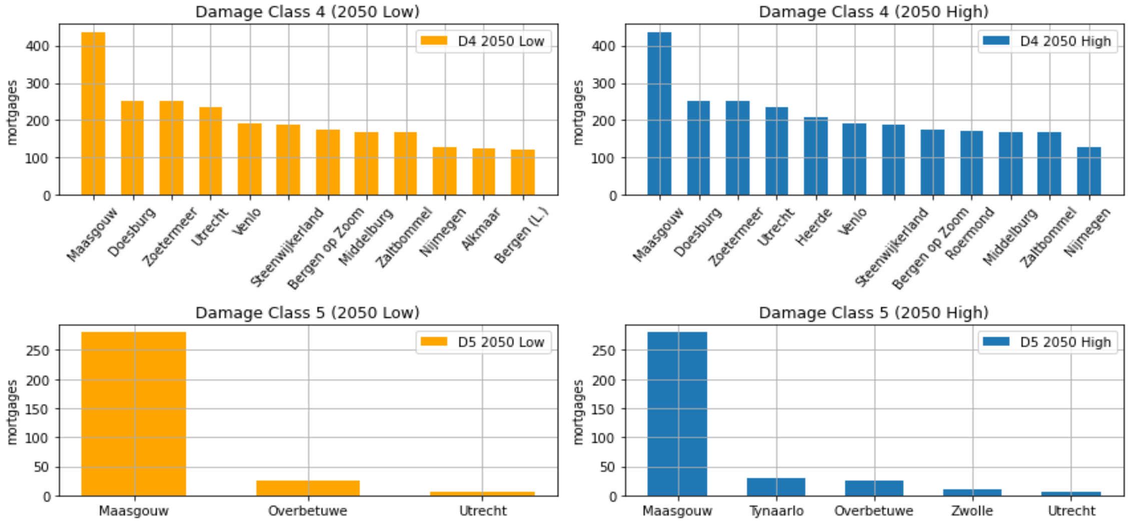


Figure 19: Number of properties in D4/D5 in the 2050 High and Low climate exposures)

Looking at D4 (showing the top 12 municipalities), we find that the largest exposure can be observed in Maasgouw which is in the province of Limburg. Maasgouw is a municipality that lies next to the Maas. It is also an area that is significantly exposed to flood risk. Historically the Volksbank has a lot of properties in the south of the Netherlands which partially explains the large exposure. The other municipalities are mostly located in the provinces of Utrecht, North Holland, and South Holland. The differences in the 2050 low and high climate exposure scenarios do not seem large for the D4 class.
For D5 we observe that in the 2050 low scenario only the municipalities of Maasgouw, Overbetuwe and Utrecht are found which are all in the river areas. Interestingly, the 2050 high scenario shows that two more municipalities join with a D5 exposure: Tynaarlo and Zwolle. Luckily, the number of properties in this damage class are low compared to D4 and D3.
Again the same conclusion can be made as with flooding: To measure the impact for the bank we have to look at the expected loss.

3.3.3 Conclusion Portfolio Climate Exposure

Our second question of subquestion 2 stated: *Which areas are considered "high climate risk areas" for the banks mortgage portfolio?* We analysed both the flood and pole rot exposure for the bank where we found that the exposure is largely in line with the original exposure maps as given in Chapter 2.2. We were able to count the number of properties exposed in each area to assess the locations of interest for the bank. We have now answered subquestion 2 which stated: *How large is the exposure of the banks' mortgage portfolio to the different physical climate events in the Netherlands?* We found from our first question that there already are systemic decreases in property price developments in the Netherlands due to 'climate events'. From our second question we found that the climate exposures for both pole rot and flooding on the mortgage portfolio are 21% and 36% respectively when looking at the *number* of mortgages.

4 Mathematical Model

We are now able to formulate a mathematical model that will help us determine the climate-adjusted expected loss model. In this chapter we first discuss the model choice and assumptions before we continue with the actual model. This chapter also answers the entirety of subquestion 3 which stated: *How can we quantify different physical climate change risks in financial terms on the collateral of the mortgage portfolio?*.

4.1 Model Choice

Based on the literature of chapter 2.5 we can determine a model that quantifies the damage exposure of properties within the mortgage portfolio with respect to flooding and pole rot.

For flooding we have two quantification methods as given in Chapter 2.5: The hedonic pricing approach and damage function approach. The hedonic pricing method is insufficient as we do not have all the data available for every property and past flood data for all regions in the Netherlands. For example, the method posed by Bin et al. (2013) requires distances of houses to local urban areas, the number of bedrooms, what type of bricks used, whether it has a fire place, size of the acreage, in what flood plane the property is, prices before and after most recent floods and much more. Our data set only provides the *estimated* flood depth on a property, the surface area of the property, property type (i.e. apartment/single family home), and building year. As we lack these data points and past flood data for the Netherlands this method is excluded.
The damage function approach is split into two different model types: vulnerability and fragility functions. The fragility functions from Thapa (2020), Pita (2021), and Nofal et al. (2020) are a good match if there are enough data points available. However, for this to function properly we require past flood data to classify different damage classes. Again, we do not have this flood data, thus we are not able to use this method effectively.
The *current* best approach for our situation in the Netherlands is using the damage functions from Slager (2017). We have all the data-points that are required for applying this method: flood depth on a property, square meter of the property, and most importantly property type (i.e. apartment or single family home). This allows for the full usage of data points we have for the collateral. Also, this method has been updated and refined over the years for the Netherlands by the institutions that built them.

For pole rot there is only one model discussed in Chapter 2.5.2. This model is directly compatible with the data from the Climate Adaptation Services (2021) as seen in Figure 13. The damage class method is the closest estimation of possible damages for the mortgage portfolio we currently have. The damage class assignment is on a *neighbourhood* level.

4.2 Model Assumptions

Our mathematical model for both flooding and pole rot is built upon a selection of assumptions and limitations. We discuss them in the list below.

1. Climate risks are currently *not* priced in the market value of a property.

2. Due to current data limitations, the size of the collateral is the average municipality property size from the Central Bureau of Statistics.

3. The pricing in of damages depends on the life time of a property. This because there is a certain probability of an event occurring each year. Thus, to consider all possible damage occurrences over time, we have to take a look at the life time of the property. The lifetime of an individual property is not easily identifiable. With the right amount of maintenance properties can last up to multiple decades (even 100+ years), but due to other external factors it might be only 20 years. To make our life easier we price in flood risk until 2050 as our climate data is available to that date. However, it is not obvious if this is *enough*, *too much*, or *too little*:
   - **Too Little:** We only calculate a yearly expected damage for 20 years. The ideal property value is determined based on the actual exposures until the end of its life, the priced in damages might be to little.
   - **Too Much:** The risk of climate events also exists after 2050, most likely for the entire lifetime of the property. However, if this is the case and the probability of flooding or a climate exposure is high, it means that the priced in value of the property should already be very low. This is not how the market works as we clearly see that market values increases even if the property is in a high risk area (Chapter 2.6).

4.3 Model

Now that we know the underlying assumptions we can move to the mathematical notation of the model for both flooding and pole rot. In Table 8 the model abbreviations of the iterators are described. Note that FD means "Flood Depth" and iterator s is directly related to each map in Figures 6 and 7.

Table 8: Model Abbreviations: iterators.

iterator	Meaning	Range	Range explained
i	Mortgage i	i = 0, 1, ..., m	
c	Pole rot scenario c	c = 0, 1	c = {Low Exposure 2050, — High Exposure 2050}
k	Mortgage type k	k = 0, 1, 2	k = {linear mortgage, — interest-only mortgage, annuity mortgage}
j	IFRS scenario j	j = 0, 1, 2	j = {base scenario, up scenario, down scenario}
s	Flood depth scenario s	s = 0, 1, 2, 3	s = {FD map $P = 1/10$, FD map $P = 1/100$, FD map $P = 1/1000$, FD map $P = 1/100000$}
t	Time t in years	t = 0, 1, 2, ...	
τ	Time τ in months	τ = 0, 1, 2, ...	
θ	Month to year iterator θ	θ = 0, 12, 24, ..., 360	

In Table 9 the model parameters are shown in which we use the iterators of Table 8. Within the model explanation we touch on how each value is retrieved.

Table 9: Model Abbreviations: parameters

Parameter	Meaning	Extra
β	Execution factor in case of foreclosure	15%
A_i	Surface area in m^2 on collateral of mortgage i	
$a_i(f_{is})$	Damage factor on mortgage i as a function of f_{is}	
C_{ic}	Pole rot damage class exposure on mortgage i in scenario c	
D_i^{flood}	Sum of discounted flood damage on mortgage i	Function of t
$D_{ic}^{Pole\ Rot}$	Sum of discounted pole rot damage on mortgage i	Function of t
d_{is}^{flood}	Flood damage on the collateral of mortgage i for scenario s	
$d_{ic}^{Pole\ Rot}$	Pole rot damage on the collateral of mortgage i for scenario c	
f_{is}	Flood depth on mortgage i given flood depth scenario s	
G_i	Full monthly payment on mortgage i given annuity type	
h_i	Height of collateral i in meters	
HPI_{jt}	House Price Index in IFRS scenario j at time t	
I	Inflation factor for damages i	2%
l_{itk}	Amount paid on mortgage i at time t given mortgage type k	
$M_{i\tau}$	Principal annuity payment in month τ for mortgage i	
p_s	Probability of flood depth for scenario s	
r	Dutch risk free rate	1.4%
r_i^{year}	Yearly Interest rate on mortgage i	
r_i^{month}	Monthly Interest rate on mortgage i	
S	Maximum damage on collateral for one square meter	€1000
T_i^{loan}	Time to maturity of loan on mortgage i	
T_i^{total}	Total duration of mortgage i	
$T^{PriceIn}$	Max time time that is priced in for climate scenarios	28 years
v_{it}	Market value of mortgage i at time t	
$v_i^{initial}$	Market Value of mortgage i within 2021	
w_{itc}	Pole rot damage on mortgage i at time t given climate scenario c	
Y_i	Total principal amount of mortgage i	

This leads us to the first formula that determines the flood damage for each property in the portfolio given as:

$$d_{is}^{flood} = a_i\left(f_{is}\right) A_i S \quad \text{where} \quad a_i\left(f_{is}\right) \in \{0,1\}. \tag{11}$$

Where $a_i(f_{is})$ is the damage factor on mortgage i where the damage factor is based on the property type of the mortgage as seen in Figure 12. It is a function of f_{is} which indicates the flood depth for mortgage i in scenario s. Note here that scenario s indicates to what scenario **map** it belongs to (i.e. Figures 6 and 7). Also, the variable S is the maximum damage per square meter which is set to €1000 (Slager, 2017). The parameter A_i is the surface area of the property belonging to mortgage i. The data of the bank only shows if a property is an apartment or a single family home. It does not indicate on what floor it is located. Therefore, we assume that all apartment types are located on the ground floor for a worst-case assessment.
In case of pole rot our damage function on a single property is different. Remember that the pole rot data has the average damage class for each neighbourhood in 2050 (Figure 13). Calculating the damage on a property for a given pole rot damage class can be done with:

$$d_{ic}^{Pole\ Rot} = A_i h_i C_{ic}. \tag{12}$$

In here A_i is the surface area of the collateral of mortgage i in m^2, h_i the height of the collateral, and C_{ic} the damage class exposure on mortgage i given that we calculate it for the 2050 low or high climate scenarios c.

In order to price the damage into the value of the property, we need to know the discounted climate event expected damage (D_i) over a certain period of time. For flooding we can define it as:

$$D_i^{flood} = \sum_{s=0}^{3} \sum_{t=1}^{T^{PriceIn}} \frac{\lambda_s I^t E\left[d_{is}^{flood}\right]}{(1+r)^t} \quad \text{where} \quad E\left[d_{is}^{flood}\right] = p_s a_i \left(f_{is}\right) A_i S \quad \forall i. \tag{13}$$

Here p_s is the probability from scenario map s (Figures 6 and 7) and r is the discount factor based on the Dutch 20-year government bond rate. Note that we sum in (13) over all periods t up to $T^{PriceIn}$. In our case we sum from 2022 to 2050, thus: $T^{PriceIn} = 28$. We also account for 2% annual inflation I^t in damages costs. The 2% is the inflation target from the European Central Bank over time. Lastly, we observe the binary variable λ_s. The condition for this variable can be found in (14):

$$\lambda_s = \begin{cases} 1, & \text{if } f_{is} \neq 0 \text{ then pick } s \text{ where } \min(p_s) \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

The variable λ_s is used to give the appropriate probability of flooding to a property. Each flood probability scenario from Figures 6 and 7 are assigned to a property such that if a flood depth exists for a property in more than one flood scenario map, only **one** scenario map is assigned. The one that is assigned must always be the highest probability so that the highest exposure for the property is used. This is done because the relation between these scenario maps is unknown. Furthermore, the Climate Adaptation Services (2021) estimates that the probability of flooding will decrease over the coming years as protection measures are improved. In our case, we keep the probability of flooding constant due to data limitations.

For pole rot we discount the damages incurred at each time t until 2050. Pole rot damage is different than flood damage. Flood damage is an instant form of damage whilst pole rot occurs over time. Pole rot damage remains low until a tipping point is reached (A. Kok, 2020). Once reached, the damage will grow exponentially. The pole rot data shows the total damage exposure depending on the damage class for a certain area in 2050. This damage is the cumulative damage from now until 2050. Our damage calculation is the cumulative damage development from 2022 to 2050. We assume that the damage is 0 in 2022 and exponentially develops until the cumulative damage class for the collateral of an arbitrary exposed mortgage i in 2050 is reached. Again, the damage cost grows year-over year with 2% such that inflation is incorporated.
The damage for pole rot on mortgage i in year t given pole rot scenario c is defined as w_{itc}. Note that scenario c indicates if it is the 2050 climate low or high scenario exposure. This yearly damage will be discounted as:

$$D_{ic}^{Pole\ Rot} = \sum_{t=1}^{T^{PriceIn}} \frac{I^t w_{itc}}{(1+r)^t}. \tag{15}$$

Once the expected damage on a property is known, the value of the property with expected flood or pole rot damage priced in at $t = 0$ can now be determined as:

$$v_{i0}^{flood} = v_{i0} - D_i^{flood}, \tag{16}$$

$$v_{ic0}^{Pole\ rot} = v_{i0} - D_{ic}^{Pole\ Rot}. \tag{17}$$

Where v_{i0} is the current non-climate adjusted market value of the property for mortgage i as provided by the Volksbank. Note, that for pole rot we can calculate two possible property values: for the low or high climate scenario indicated with c.

From this point forward the **formula's are the same for both flood and pole rot risk**. We now use **cc** which stands for Climate Change as the indicator for a climate adjusted parameter. Furthermore, the iterator c, which indicates if pole rot exposure is calculated for the high or low scenario, is excluded from notation but the calculation remains the same for $c = 1$ or $c = 2$.

Looking ahead from 2022 up to 2050, we can index the value of the property with the House Price Index as given in (18). However, if we want to look at the additional expected loss of a climate event we also have to calculate the regular market value of a property as given in:

$$v_{itj}^{cc} = v_{i0}^{cc} \Delta HPI_{jt} \quad \text{where} \quad t \in T^{PriceIn}, \tag{18}$$

$$v_{itj}^{regular} = v_{i0}^{regular} \Delta HPI_{jt} \quad \text{where} \quad t \in T^{PriceIn}. \tag{19}$$

Note here that HPI_{jt} is the House Price Index of IFRS scenario j at time t. Also, $v_{i0}^{regular}$ is the non damage adjusted market value of the property. IFRS stands for the *International Financial Reporting Standard*. In total there are three IFRS scenarios: the base, up, and down. Financial regulators require that banks use these scenarios within their risk management framework for measuring their exposure in different situations. Each scenario also has a House Price Index. This is an index that forecasts the rise or fall in property prices for a long period of time. It also is inflation adjusted. Appendix E shows the graph of each of these scenarios.

Now that we can calculate the value of all the properties in the portfolio for all mortgages, the next step is to calculate an Exposure At Default (EAD) for all mortgages i at time t depending on the mortgage type k (linear, annuity or interest-only mortgages). This exposure is the amount outstanding of the *principal* for every mortgage loan at time t. This is calculated as given in (20):

$$EAD_{it} = EAD_{i,t-1} - l_{itk} \ \forall t \ \wedge \ t = 0. \tag{20}$$

Here l_{itk} is the amount of the principle paid back on mortgage i in year t for mortgage type k. The amount depends on the mortgage type k. Let's first discuss the mortgage types below:

- Linear Mortgage ($k = 0$)
  - The amount of principal paid per month is constant until mortgage maturity.
  - Interest is paid on the remaining exposure of the month before.
- Interest-only Mortgage ($k = 1$)

  - From the issue date until one month before maturity only the interest is paid on the mortgage.
  - At maturity the principal of the loan is paid off.

- Annuity Mortgage ($k = 2$)
  - An *equal* amount is paid every month until maturity. However, it is a varying combination of both the amount of principal and interest payments.
  - At $t = 0$ the amount paid per month is the lowest with respect to the principal and the highest with respect to the interest on the loan. Every month a payment is done, more is paid on the principal and less on the interest compared to the previous month. This occurs whilst the amount paid per month remains the same until maturity.

A key assumption in this model is that prepayments are **not** included for all mortgage types. With this information we are able to construct the l_{itk} formula for each different mortgage type for the payment per year:

$$l_{itk} = \begin{cases} \frac{Y_i}{T_i^{total}}, & k = 0 \\ 0, & k = 1, \forall t \ \wedge \ t \neq T_i^{total} \\ Y_i, & k = 1, \ t = T_i^{total} \\ J_{it}, & k = 2 \end{cases} \tag{21}$$

Here $k = 0$ indicates a linear mortgage where the yearly contribution is determined by dividing the principal of the loan Y_i by the total duration of the loan T_i^{total}. Looking at $k = 1$ indicating an interest-only mortgage, for all years until $t = T_i^{total} - 1$, nothing is paid to the reduction of the principle. When $t = T_i^{total}$, the total principle is paid off.
The annuity mortgage type ($k = 2$) is different with respect to its yearly payments. As indicated earlier, the amount of principle and interest paid every month changes over the life time of the mortgage, but the total payment per month always stays the same. First we calculate the equal amount that has to be paid every month as:

$$G_i = \frac{Y_i r_i^{month}}{1 - (1 + r_i^{month})^{(-12T_i^{total})}}. \tag{22}$$

Here Y_i is the total principle amount borrowed, r_i^{month} is the monthly interest paid on the mortgage, and T_i^{total} the total duration of the loan in years. The monthly interest is determined as:

$$r_i^{month} = (1 + r_i^{year})^{\frac{1}{12}} - 1. \tag{23}$$

Here G_i is also known as the *PMT* formula which stands for payments. The monthly payments of the principle, also known as the *Principle Payments* (PPMT), can then be determined as:

$$M_{i\tau} = -(1 + r_i^{month})^{(\tau-1)}(Y_i r_i^{month} - G_i). \tag{24}$$

Here τ is the time in months. We indicate the monthly payments to the principle on mortgage i at time τ as $M_{i\tau}$. Because the climate data are in years we transform this to yearly payments for each mortgage as:

$$J_{it} = \sum_{\tau=\theta}^{\theta+12} M_{i\tau} \text{ where } t \in T_i^{loan} - 1, \ \theta \in \{0, 12, ..., 360\}. \tag{25}$$

When time in years t increases with 1, θ increases with 12. Note, θ starts at 0 (at $\tau = 0$ the payment is 0 as well). Also, when the last year of mortgage payments only consists out of 6 months, only those will be added. Using this formula allows us to correctly show the EAD development of annuity mortgages.

With these formulas we are now able to calculate the *regular* LGD ($LGD_{itj}^{regular}$) and the *climate adjusted* LGD (LGD_{itj}^{cc}) for mortgage i at each period t for IFRS scenario j as:

$$LGD_{itj}^{regular} = \frac{\max\left(EAD_{it} - (1-\beta)v_{itj}^{regular}, 0\right)}{EAD_{i0}} \quad \text{where } t \in T_i^{loan}, \tag{26}$$

$$LGD_{itj}^{cc} = \frac{\max\left(EAD_{it} - (1-\beta)v_{itj}^{cc}, 0\right)}{EAD_{i0}} \quad \text{where } t \in T_i^{loan}. \tag{27}$$

Where β is the execution factor. Note here that the execution factor is the historical execution factor in case a property is sold by the bank due to a foreclosure (after default) of a mortgage. This factor is the % decrease of the property price. Banks do not want the collateral on their balance sheet as it is a liability. Therefore they want to sell it as soon as possible. Because of that it is often below the market value of the property, hence the execution factor. Here we use the execution factor as calculated by the Volksbank.
Once we have calculated the EAD_{it} and LGD_{itj}^{cc} for every mortgage i at period t and IFRS scenario j, we can determine the regular and climate change adjusted expected loss for mortgage i in every period t as given in (28) and (29):

$$EL_{itj}^{regular} = \frac{PD_{it}^{regular} LGD_{itj}^{regular} EAD_{it}}{(1+r)^t} \quad \text{where } t \in T_i^{loan}, \tag{28}$$

$$EL_{itj}^{cc} = \frac{PD_{it}^{regular} LGD_{itj}^{cc} EAD_{it}}{(1+r)^t} \quad \text{where } t \in T_i^{loan}. \tag{29}$$

Here it is again the case that the value is discounted over time. In order to get the *life time* (LT) expected loss for each different IFRS scenario over all periods for a *single* mortgage i we can use (30) and (31):

$$EL_{ij}^{regularLT} = \sum_{t=1}^{T_i^{loan}} E\left[L_{itj}^{regular}\right], \tag{30}$$

$$EL_{ij}^{ccLT} = \sum_{t=1}^{T_i^{loan}} EL_{itj}^{cc}. \tag{31}$$

Using this we can now determine a delta expected loss such that we can see the total contribution of climate change events on an arbitrary mortgage i in IFRS scenario j as given in (32):

$$\Delta EL_{ij} = EL_{ij}^{ccLT} - EL_{ij}^{regularLT}. \tag{32}$$

Then for the whole mortgage portfolio (PF) we can calculate the total expected loss for every scenario j for the regular scenario and due to a climate change event up to 2050 as given in (33) and (34):

$$EL_j^{regularPF} = \sum_{i=1}^{m} EL_{ij}^{regularLT} \quad \forall j, \tag{33}$$

$$EL_j^{ccPF} = \sum_{i=1}^{m} EL_{ij}^{ccLT} \quad \forall j. \tag{34}$$

Directly from this we can determine a delta expected loss on a portfolio level to see the contribution of climate change events as given in (35).

$$\Delta EL_j^{PF} = EL_j^{ccPF} - EL_j^{regularPF} \quad \forall j \tag{35}$$

Applying this model can help us gain insight to see which mortgages in certain areas are exposed with respect to pole rot and flood risk. This model calculates the current expected loss based upon the assumptions as discussed in Chapter 4.2.

Note that we have now answered the last subquestion of subquestion three where it was defined as: *How can we model the physical-risk-LGD given the physical climate events for the mortgages in the portfolio?* The model explains that it is indeed possible.

4.4 Model Conclusions

This section answered subquestion 3 which stated: *How can we quantify different physical climate change risks in financial terms on the collateral of the mortgage portfolio?* We looked at both flooding and pole rot. For flooding we found a model that could be used (i.e. damage function approach) and for pole rot also a damage class approach was found. We were able to use our credit risk information about calculating the expected loss on single mortgages and the portfolio as a whole. The result of this model is discussed in Chapter 5.

5 Results

In this chapter we discuss the model results. We aim to find answer to the final subquestion which states:

What is the physical risk induced expected loss projection on the mortgage portfolio given different macro-economic scenarios in the future?

We separate the results from flooding and pole rot. The results show the contribution of flood risk and pole rot risk to the total expected loss. We consider the expected loss under the IFRS HPI base, up, and down scenarios.

Lastly, we also discuss how prices develop over the portfolio for all properties affected by flooding and pole rot. This can give us a closer insight if it is inline with our observations in Groningen and from the literature as indicated in Chapter 2.6.

5.1 Flood Risk

For flood risk on the mortgage portfolio we first look at the three base scenarios (HPI Base, HPI, UP, HPI Down). We analyse the losses on a portfolio level and look at the individual municipalities at risk for the bank. Afterwards we discuss various different scenarios to stress test our results.

5.1.1 Initial Model Results

Table 10 shows us the absolute *contribution of flood risk* to the total expected loss for all mortgages that are exposed to flooding. This value is calculated according to Formula (35), also known as the delta Expected Loss (ΔEL) on the portfolio. The table shows the total contribution and the contribution of the portfolio of mortgage types to flood risk (i.e linear, annuity, interest-only). Note, the portfolio mortgage type results sum up to total number in the first column.

Table 10: IFRS Flood Induced Expected Loss.

	ΔEL Total Mortgage Portfolio	ΔEL Linear Mortgage Portfolio	ΔEL Annuity Mortgage Portfolio	ΔEL Interest-only Mortgage Portfolio
HPI Base	€ 385.786	€ 36.143	€ 42.921	€ 306.721
HPI Up	€ 375.151	€ 30.002	€ 30.950	€ 314.198
HPI Down	€ 430.986	€ 43.673	€ 81.844	€ 305.468

The losses incurred for the bank seem small in absolute terms. There are multiple reasons that explain this result. Firstly, a lot of mortgages have an EAD that is significantly lower than the market value of the property. Even if a mortgage has been issued in recent years, the market values have risen significantly due to the current housing price boom. Consequently, even if a significant damage due to flooding is expected, it is often offset by the high market valuation. Secondly, many properties are not in high probability exposure areas. Significant market value decreases due to flood risk only occur for properties in the $p = 1/10$ and $p = 1/100$ flood depth maps (Figures 6 and 7). There are only a limited number of properties exposed to very high probabilities and high flood depths. Again, here it is often the case that these properties have very low $EADs$ compared to the market value of the property. Furthermore, one of our model assumptions is that the flood depth probability remains constant over time. In reality, this probability should be *decreasing* up to 2050 according to the assumptions of the Climate Adaptation services (2021). This would result in lower losses. However, this might be offset by another assumption which says that the Area A_i is an estimation for the average property surface area in m^2. There are quite some homes that have larger surface areas which are located in high risk locations.

For the effect on a portfolio level of these absolute losses we refer to Table 11. Here we see the percentage contribution of flood risk on the expected loss of all properties exposed.

Table 11: Percentage Contribution of Flooding to the Expected Loss

	Percentage of Total Losses (All Mortgage Types)	Percentage of Total Losses (Linear Mortgage Type)	Percentage of Total Losses (Annuity Mortgage Type)	Percentage of Total Losses (Interest-only Mortgage Type)
HPI Base	1,44%	0,13%	0,16%	1,15%
HPI Up	1,53%	0,12%	0,13%	1,28%
HPI Down	1,36%	0,14%	0,26%	0,96%

The contribution of flood risk is only 1.41% in the base and up scenarios to the total expected loss of all exposed properties. However, we observe that the total contribution decreases in the HPI down scenario. Furthermore, the contribution of interest-only mortgages decreases, whilst the contribution of linear and annuity mortgages increases. To see why this change happens we perform an extra scenario (scenario 2), which will be discussed in Chapter 5.1.2.

The losses that we do observe are explainable through customers that have just received their mortgage loan. This makes sense as they have not made any significant payments to their debt yet and the market value of the property almost equals the exposure at default. Consequently, within the first three to five years most losses are incurred on these mortgages if the flood risk is priced in the current market value of the property. After five years it is almost always the case that the flood adjusted market value of the property is higher than the customers EAD at that time.

When we look closer at the results and the different mortgage types we observe a couple of factors. Firstly, on average for all scenarios, linear mortgages are 16% of the total number of mortgages, annuity mortgages 50%, and interest-only mortgages 34%. The largest exposure is observed with interest only mortgages at 80%, whilst it has the second largest percentage of mortgages. This is because the principal payment is paid in full at the maturity date of the mortgage. During the lifetime of the mortgage only interest is paid. This means that the EAD remains high until maturity, hence making the losses larger for these types of loans. The annuity mortgage type is the largest percentage of mortgages that is exposed due to flooding, but is 11% of the percentage of delta expected losses. The amount paid of principal every month increases month over month. As time goes on, more of the principal is paid. This decreases the EAD faster over time. This is the reason why losses are limited compared to the interest-only mortgages. The smallest portion of the portfolio is the linear mortgage type. Remember, linear mortgage payments are a constant amount of the principal every month and an interest on the left over exposure from the previous month. Interestingly, compared to the annuity mortgage type it has only 16% of the number of mortgages in the portfolio, but it has approximately 9% of the losses. There are a variety of factors that contribute to these findings, e.g, the height of the EAD, the market value of the underlying properties and the flood exposure. The real takeaway from the mortgage type analysis is that the exposure is significantly higher for interest only mortgages. The other two types are less exposed.

Having discussed the results on a portfolio level, it is interesting to take a closer look at the losses on a municipality level. Figure 20 shows two different geographical maps. For both pictures we observe the number of properties with a delta expected loss. Remember, this ΔEL is the contribution of flood risk to the expected loss on a mortgage. We observe that the left map shows the **number** of properties with an $EL > 0$ and on the right with an $EL > 200$ (Appendix C shows us the maps and bar chart of maps with $EL > 500$ and $EL > 1000$).

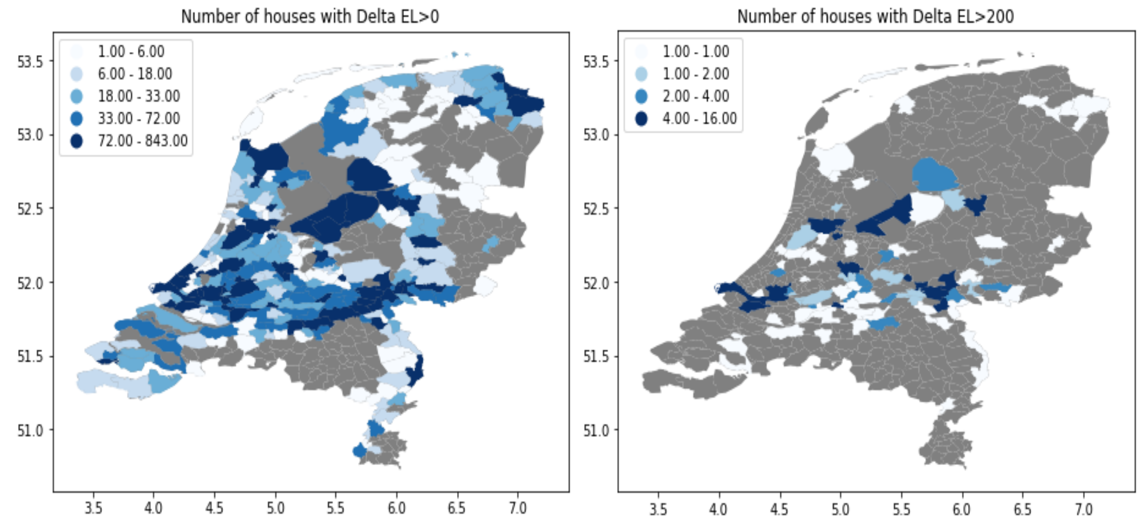


Figure 20: Municipalities with highest number of losses on average.

The $\Delta EL > 0$ map shows that the number of properties exposed for the bank on a municipality level is very similar to the regular climate exposure map as shown in Figure 7. The $\Delta EL > 200$ map excludes the low loss category from which we can see that only a select number of municipalities have a significant contribution to the expected loss. We observe that the exposure for the areas with $EL > 200$ is around the municipalities connected to the IJssel, Maas, Rijn, Waal, and at the intersections of these rivers. These are also the areas that have the larger flood depth possibilities (Figure 6). Appendix C gives us a deeper analysis by looking at the areas that have the largest ΔEL. These Figures show that only a limited number of properties is exposed to a significant loss. The good thing is that from a risk management perspective the bank can consider possible solutions on an individual mortgage basis. By creating awareness under customers the bank can help them take the necessary precautions.

To explore the contribution of each municipality further, we would like to see the percentage contribution of each municipality to the ΔEL. This can be seen in Figure 21 (see Appendix C for the geographical map). This percentage overview shows which areas for the bank require the most attention. If a flood occurs, these areas pose the largest risk on the expected loss metric. Here we see that the regions of Culemborg, Amsterdam, and Veenendaal have the largest exposure. Interestingly we observe that Culemborg has the largest exposure in the HPI base scenario with 12.5%, making this a location of interest.

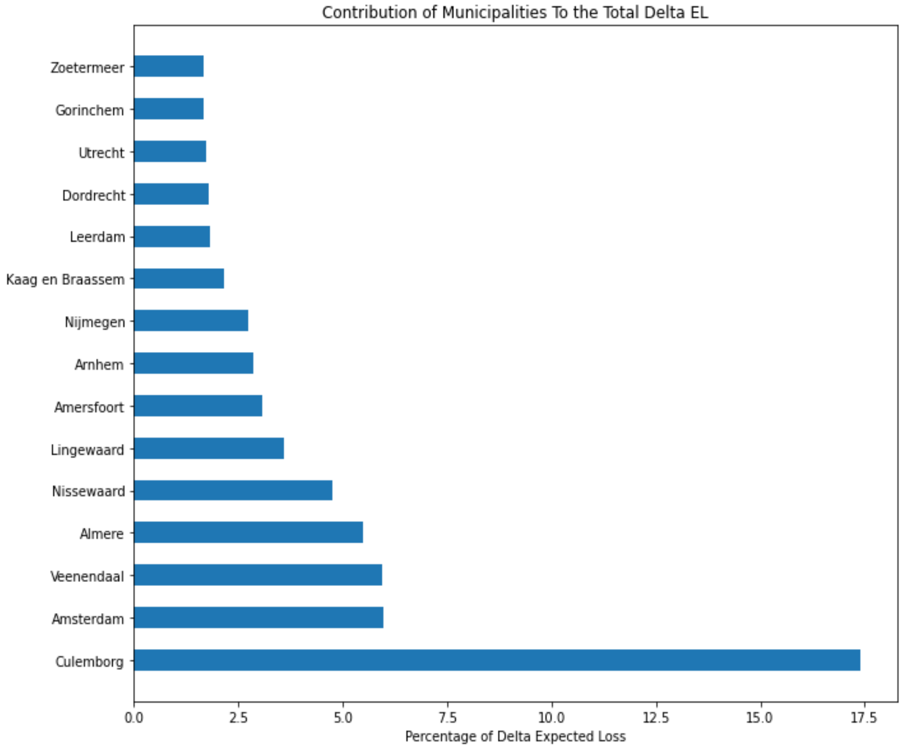


Figure 21: Percentage contribution of each municipality to the ΔEL.

With respect to the absolute expected loss we observe that the impact is limited. There are a couple of factors that make the EL less severe. Firstly, the property market has very high valuations due to demand which do not reflect regular market conditions. Secondly, the HPI forecast only considers property prices going up (even the downturn scenario only considers 1 year of 1% decrease and increases afterwards). In recession situations, there are longer periods of year over year decreasing property prices. Finally, the probability of occurrence is low which means that damages are also low. However, when a flood does occur it is often the case that a larger area is hit and the damages become *real*. This loss is not captured by the EL, but by the *Unexpected Loss* (UL). The UL considers the tail risk probability of occurrence (in our case a high probability of flooding) and calculates the corresponding loss. This increases losses significantly. The UL has a direct impact on the capital requirements for the bank.
In our scenario analysis we address the first point by adjusting the market value of the property (Scenario 1 below). The second point will be addressed by creating a recession type HPI and will be combined with scenario one as well (Scenario 2 below). The third point will not be addressed as it is outside the scope of this project.

5.1.2 Scenario Analysis

This section discusses two different scenarios that stress the expected loss on a portfolio level for the bank. The results should show the contribution of flooding to the EL on a portfolio level through changes in the initial property values (scenario 1) and a change in the HPI (scenario 2).

5.1.2.1 Scenario 1: Property Market Value Shock Shocking the market value of the property requires an adjustment to the *price in* formula of the mathematical model. The function that has to be adjusted is:

$$v_{i0}^{flood} = v_{i0} - D_i^{flood} \quad \forall i, \tag{36}$$

which will be adjusted with a factor $1 - \phi$. This will change the function too:

$$v_{i0}^{flood} = (1 - \phi)v_{i0} - D_i^{flood} \quad \forall i \quad \text{where} \quad \phi \in \{0, 1\}. \tag{37}$$

Once this parameter is set, the regular model calculation continues with function (18) and a ΔEL is calculated. This will be done until a ΔEL is calculated for every percentage decrease of the initial property value (i.e. ϕ goes from 0 to 0.2 with steps of 0.01). The corresponding graph can then be plotted as given in Figure 22. Note that for Scenario 1, the HPI down scenario is used.

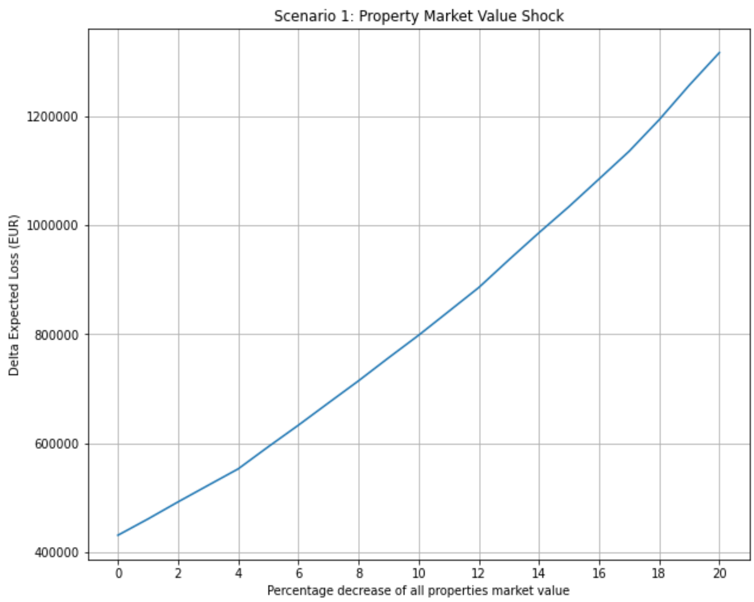


Figure 22: Scenario 1.

Here we observe that the delta expected loss on the portfolio increases almost linearly for each percentage decrease in the initial market value of all properties in the portfolio. An interesting observation is that the delta expected loss almost triples in absolute losses in case of a 20% percent decrease in property values. The almost linear relation is a consequence of a couple of factors. Firstly, a decrease in property values within the portfolio results in an increase in the number of mortgages that now have an EAD higher than the underlying property value. This means that for a couple of years their $EL > 0$. The flood risk exposure of these properties is often very low but can be different from each other which creates non-linearity. Secondly, the way the exposure develops is different for each mortgage type. On a portfolio level this creates slight non-linearity but evens out with a large data set. The relatively stable increase in flood risk exposure is favourable for the bank as it means that the total contribution of flood risk stays relatively the same over time. From this we can conclude that shocking the initial property value will not significantly increase the EL for the bank.

5.1.2.2 Scenario 2: House Price Index Shock One of the reasons why the EL due to flooding is low is because of the development of the HPI over time. To show the effect of the HPI we refer to Figure 23. Note here that y-axis is the multiplication factor of the initial market value of a property as shown in (18).

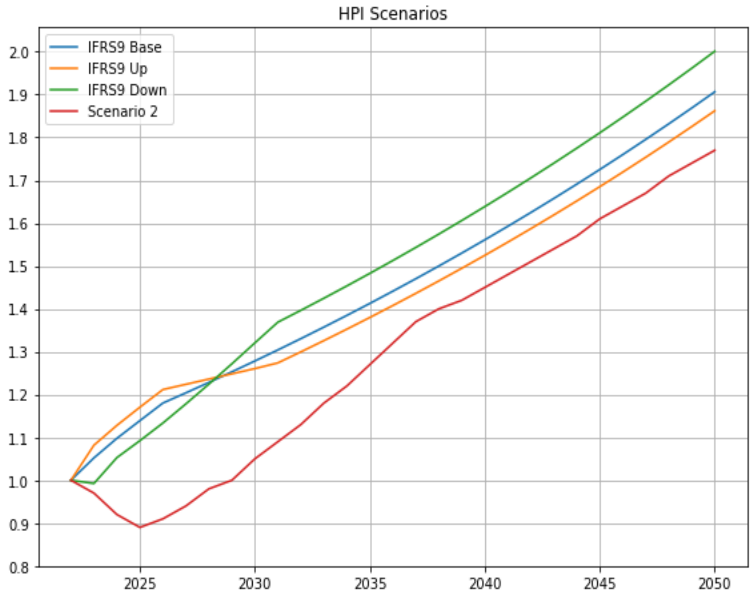


Figure 23: Scenario 2.

The figure shows four different HPI scenarios. The blue, orange, and green lines are the IFRS scenarios that are used in the results of Chapter 5.1.1. The red line is the House Price Index Shock. This shock is made to stress the housing market for a significant period of time. The price decreases until 2025 and makes a recovery afterwards. The result of this model scenario is shown in Table 12.

Table 12: Scenario 2: Results.

	ΔEL Total mortgage portfolio	ΔEL Linear mortgage portfolio	ΔEL Annuity mortgage portfolio	ΔEL Interest-only mortgage portfolio
HPI Scenario 2 Percentage	1.13%	0.09%	0.29%	0.75%
HPI Scenario 2	€ 943.970	€ 76.234	€ 239.858	€ 627.877

With the alternative HPI scenario we observe that the losses more then double (119%) compared to the IFRS HPI base scenario as shown in Table 11. We also observe that the contribution to the percentage of total losses decreases slightly compared to Table 10. Looking closer at the percentages, the contribution of interest-only and linear mortgages decreases compared to the IFRS down scenario. Whilst the contribution of annuity mortgages increases. This can be explained by the fact that the number of mortgages with an annuity mortgage type has increased. This means that there are more annuity mortgages with an exposure to flood risk that now have a market value that is lower than the exposure for the first couple of years. Also, there are no major changes in the way the EL develops compared to the initial HPI indices. Flood risk is still not a large contributor to the total expected mortgage losses.

To see the contribution of each municipality to the delta expected loss with Scenario 2 we refer to the bar chart in Figure 24. Two different patterns emerge with respect to Figure 21. Firstly, the total contribution of Culemborg decreases, whilst the contribution of other municipalities increase. Secondly, the largest exposure is now observed in Kampen instead of Culemborg. The first point is a result of the fact that as property prices decrease across the board, there are a larger number of properties in other municipalities that now have flood exposure. This decreases the total contribution of the initial large exposure areas. The second point is that the municipality of Kampen has a larger exposure once property prices decrease. This makes it a problematic area with respect to flood risk.

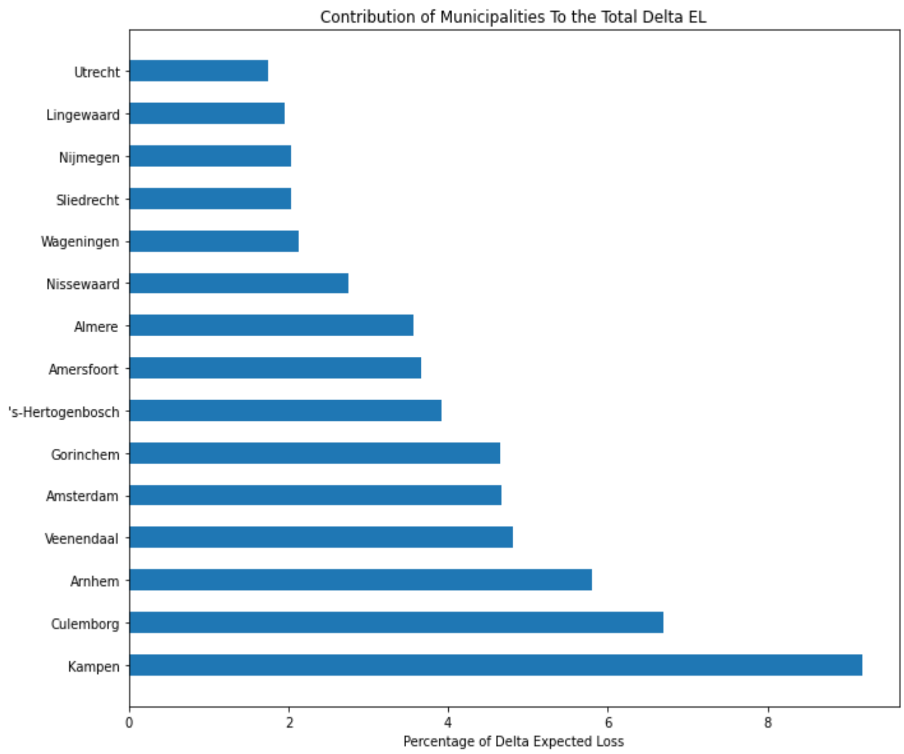


Figure 24: Scenario 2: Percentage Delta Expected Losses for the top 15 municipalities.

The original IFRS HPI scenarios show that the percentage contribution of flooding to the total losses decreases 0.31% for HPI Scenario 2 index compared to the base scenario. This is due to the decrease in property values. To see whether this trend holds we combine Scenario 1 and 2 and see how the percentage contribution of flood risk changes to the total losses on the portfolio and the different mortgage types. Figure 25 shows how for each percentage decrease in the initial market value of the property, the contribution of flood risk on the total portfolio decreases. The linear (green), annuity (orange), and interest-only (red) lines sum up to the total portfolio contribution (blue). As the total contribution decreases, so does the interest-only contribution. However, we do observe that the contribution of linear and annuity mortgage types stays relatively constant. This means that their contribution actually increases but keeps stable as a percentage. Overall we can conclude that the regular LGD contributes more than the flood-adjusted LGD.

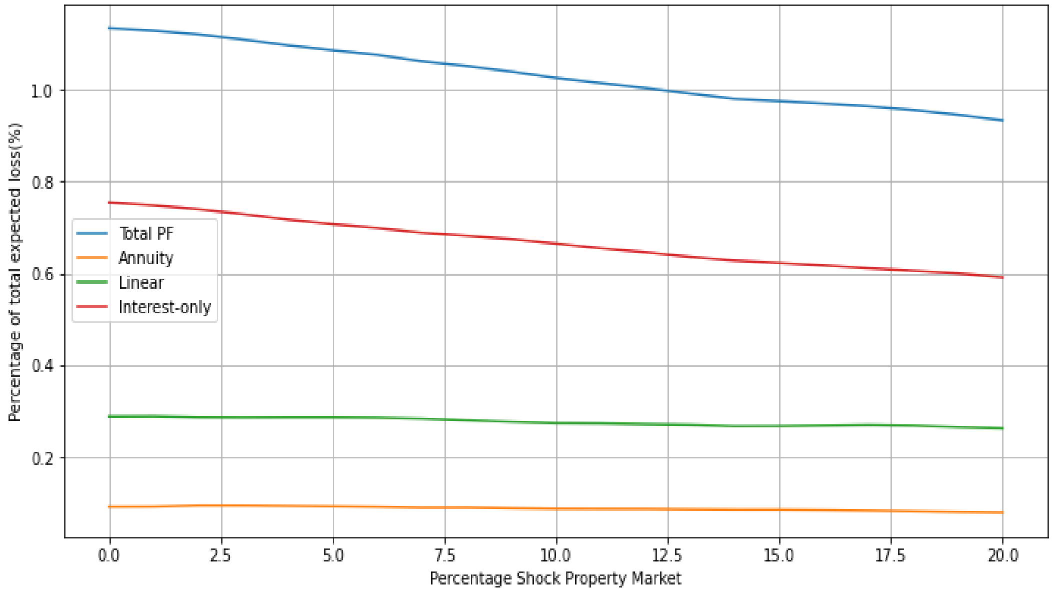


Figure 25: Scenarios 1+2: Contribution of flood risk to the total portfolio.

As Scenario 1 also included an analysis of the absolute losses with percentage decreases in the initial market value of all the properties, we refer to Appendix F for this result. Here we observe that the same linear relation still exists only with higher absolute values compared to HPI of Scenario 2. Here the same applies as before, shocking the initial property value will not significantly increase the EL due to flood risk for the bank. It remains as the percentage contribution as given in Figure 25.

5.2 Pole Rot Model Results

Pole rot also generates interesting results that are discussed here. Again, we first look at the base IFRS House Price Index results and afterwards we look at various different scenarios to observe how the losses can develop.

5.2.1 Initial Model Results

Looking at Table 13, we can see the absolute expected loss caused *only* by pole rot. This is referred to as the Delta (Δ) Expected Loss. Note, the first column is the sum of total losses from the linear,

annuity, and interest-only mortgage portfolio.
Our first observation is that the losses are significantly higher than with flooding. Most of the losses are on the interest-only mortgage portfolio.

Table 13: IFRS Pole Rot Induced Expected Loss.

	ΔEL Total Mortgage Portfolio	ΔEL Linear Mortgage Portfolio	ΔEL Annuity Mortgage Portfolio	ΔEL Interest-only Mortgage Portfolio
HPI Base	€ 3.754.436	€ 207.979	€ 431.028	€ 3.115.428
HPI Up	€ 3.620.682	€ 178.632	€ 338.429	€ 3.103.619
HPI Down	€ 3.949.407	€ 263.523	€ 613.373	€ 3.072.509

To see the impact of pole rot on the total losses of all properties with an exposure to pole rot (including non-climate adjusted losses), we refer to Table 14. Here we see the percentage contribution to the total expected loss for each of the IFRS HPI scenarios for the total portfolio (column 1) and all individual mortgage type portfolios (column 2,3,4). Here we observe that the total contribution of pole rot is 18.3% in the Base scenario, 19.0% in the Up scenario and 16.8% in the Down scenario. Compared to flood risk this is a significant portion of the total losses.

Table 14: Percentage Contribution of Pole Rot to the Expected Loss.

	Percentage of Total Losses (All Mortgage Types)	Percentage of Total Losses (Linear Mortgage Type)	Percentage of Total Losses (Annuity Mortgage Type)	Percentage of Total Losses (Interest-only Mortgage Type)
HPI Base	18,3%	1,0%	2,1%	15,2%
HPI Up	19,0%	0,9%	1,8%	16,3%
HPI Down	16,8%	1,1%	2,6%	13,0%

From these results we observe that pole rot is a larger problem than flood risk until 2050 within our model. There are more properties exposed to high pole rot damage than large flood damage. The exposure is more widespread with large portions of land having significant damage class exposures. When we look at flood damage it is the case that the probability of occurrence determines the damage. In general, most properties in the Netherlands are not in a high probability of a certain flood depth area. Which means that the probability of large losses occurring is limited only to a small region.

Now that we know the additional loss due to pole rot, it is interesting to observe what the contribution of each municipality is to this number. For this we refer to Figure 26. Note, we consider the HPI base scenario for this assessment. Here we observe the 15 municipalities with the largest contribution to the additional expected loss caused by pole rot. The top contributing factor to the losses is Zoetermeer with almost 13%. The number two (Steenwijkerland) and number three (het Bildt) contribute 7% and 5% respectively. The same applies here as with flooding but to a lesser degree: mostly it is only a couple of properties that contribute to this percentage. For further information for the entire Netherlands we refer to Appendix H for all municipalities which are shown with a geographical map. Note that these results are in line with Figure 13.

When we look back at our damage exposure graph in Figure 19 we saw that Maasgouw had the largest exposure for possible damages. However, we see it only contributes 4% to the calculated delta expected loss. This is due to the fact that the EAD of all these mortgages is lower for this municipality. This again shows that just because there is an exposure of pole rot (or flood depth), it does not mean that the bank is at risk. This only occurs when the exposure is significantly higher than the climate-adjusted market value of the property.

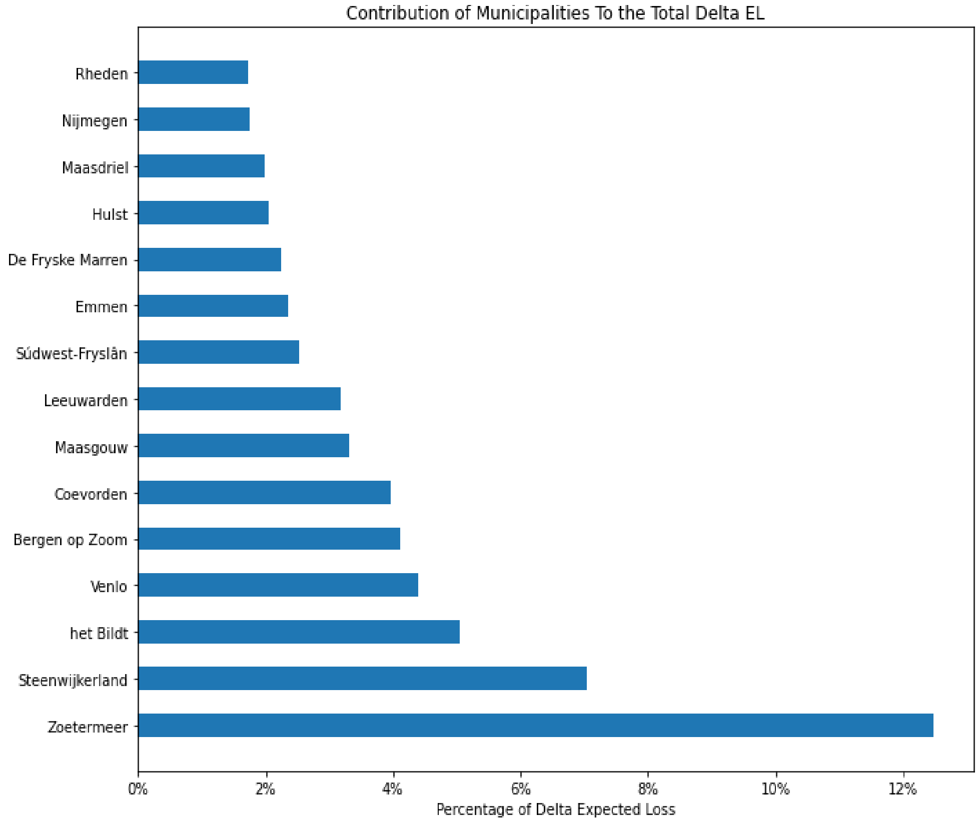


Figure 26: Percentage of losses contributed to the **Total Δ Expected Loss** by the top 15 municipalities.

A very important fact to consider is that pole rot is measured on a neighbourhood level and not on an individual property level. This means that whether or not a property is exposed to the degree of pole rot as given in the data is not certain. Furthermore, the data from the Climate Adaptation Services (2021) estimated that only a selection of properties is built on wooden poles within each neighbourhood based on the building style before 1975. This is also not entirely certain as it might very well be that only a small portion of properties with a building year of below 1975 is built on wooden poles. This means that the pole rot damage is conservative estimate with a large degree of uncertainty compared to our flood damage assessment.

With flooding we talked about the Unexpected Losses (UL) which are often greater with a higher order of magnitude compared to the EL. This affects a banks capital requirements. As the projected damages are already high with the EL, this can have a significant impact on the portfolio. However, as we just mentioned there is a lot of uncertainty with this data. This means that when we calculate the UL it might not represent the actual situation. Further research is required to make these findings more solid.

Just as with flooding we aim to see what happens in different property market situations. For this we perform the same scenario analysis as before.

5.2.2 Scenario Analysis

In this section we discuss our stress testing results of the market value of the property. Again, we first discuss the regular property market value shock in Scenario 1 and afterwards we discuss the House Price Index shock in Scenario 2.

5.2.2.1 Scenario 1: Property Market Value Shock This analysis adjusts the initial property value with a factor $(1 - \phi)$ such that it will decrease from 1% to 20%. What happens is that we adjust the following equation:

$$v_{ic0}^{Pole\ rot} = v_{i0} - D_{ic}^{Pole\ Rot} \quad \forall i, c \tag{38}$$

To:

$$v_{ic0}^{Pole\ rot} = (1 - \phi)v_{i0} - D_{ic}^{Pole\ Rot} \quad \forall i, c \quad \text{where} \quad \phi \in \{0, 1\} \tag{39}$$

After doing this adjustment, the regular model will continue from equation (18) on wards. We do this 20 times and then we get the result as given in Figure 27. On the x-axis we have the changes in ϕ (change in phi from 0 to 0.2 with steps of 0.01) and on the y-axis the delta expected loss that results from a percentage point change in ϕ.

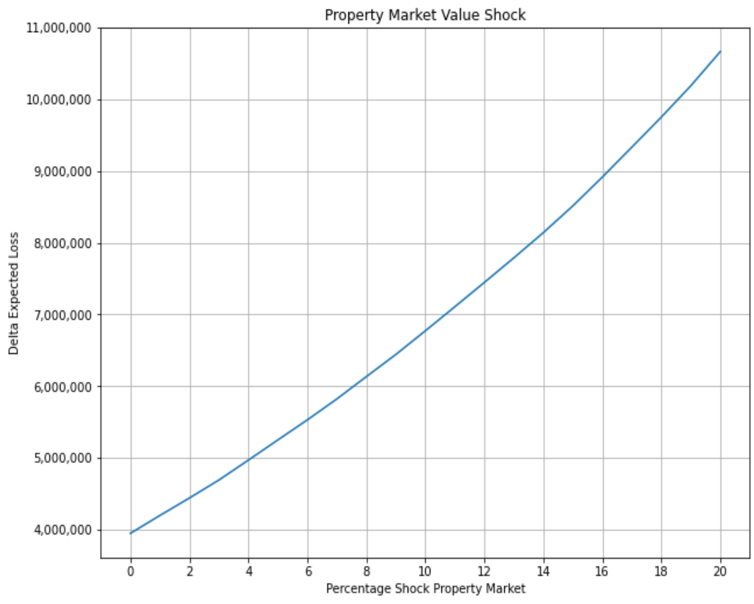


Figure 27: Scenario 1.

This graph shows us that there is a relatively linear increase in the delta expected losses if the value of the underlying decreases. The non-linearity can be explained by multiple factors. First, what has to be understood is that when we price in the initial exposures (i.e. $phi = 0$), the largest exposures are already priced in. As *phi* increases (and the market value decreases), the increase in expected loss comes from properties that now have both a market value lower then their exposure and through the properties where now the market value has decreased significantly such that the price in of pole rot now has an impact. With every percentage point decrease, the price in value on the properties increases almost linearly. However, the exposure of each customer is different due to the different mortgage types. As can be imagined, the interest-only mortgages do not have principal payments and thus their exposure remains high. This slightly increases the losses in a non-linear fashion. This (almost) linear increase in delta expected losses results that over time a decrease in the overall contribution of pole rot on the portfolio decreases. This will be shown more clearly in Scenario 2.

5.2.2.2 Scenario 2: House Price Index Shock The second scenario uses the same HPI Scenario 2 as seen in Figure 23. The results are shown in Table 15. In Appendix I we see Scenario 2 and the absolute property price development of Scenario 1.

Table 15: Scenario 2: Pole Rot Results.

	ΔEL Total mortgage portfolio	ΔEL Linear mortgage portfolio	ΔEL Annuity mortgage portfolio	ΔEL Interest-only mortgage portfolio
HPI Scenario 2 Percentage	13.3%	0.8%	2.7%	9.8%
HPI Scenario 2	€7.416.596	€465.709	€ 1.478.486	€ 5.472.399

Comparing these results to Tables 13 and 14 we observe that the absolute losses are an increase of 95% compared to the original base scenario. Furthermore, we also observe that the total contribution decreases with 5% compared to the base scenario. As property values go down, the impact of regular losses increases faster than those of pole rot. Just as with flood exposure, as market values decrease, more mortgages with small exposures arrive in the expected loss territory.

Figure 28 shows the bar plot of the percentage contribution for Scenario 2 of each municipality. The largest changes with respect to Figure 26 occurs at the top. We now observe that Bergen op Zoom contributes 7% to the total expected loss and Zoetermeer decreased to only 6%. Furthermore, most other municipalities increased in their contribution compared to before. This shows that as property prices decrease, so does the contribution of each municipality. Also, Bergen Op Zoom is particularly sensitive to decreases in property prices compared to the other municipalities. This means that the bank has to keep a closer look on the mortgages within that area.

Looking at the contribution of each mortgage type and the total losses to the delta expected loss we refer to Figure 29. This is a combination of Scenarios 1 and 2 where on the x-axis the percentage property shock (ϕ) is shown and a corresponding percentage contribution of each mortgage type is determined on the y-axis.

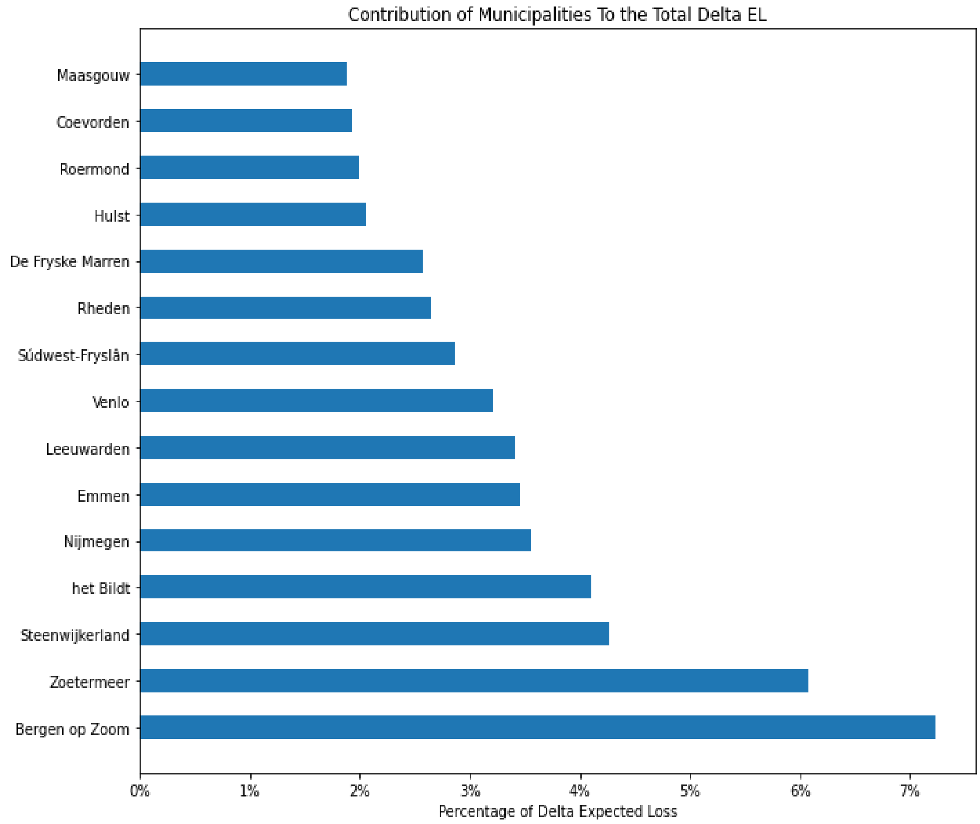


Figure 28: Scenario 2: Percentage of losses contributed to the **Total Δ Expected Loss** by the top 15 municipalities.

A pattern again emerges that the contribution of pole rot drops with market value decreases of properties. Interestingly, we do observe that again the drop is high for interest-only mortgages and stable for other mortgage types. Note that the percentage of the number of mortgages in all shock situations stays the same! This means that the total exposure of the linear and annuity mortgages contribution increases and interest-only mortgages decreases as the market decreases in sentiment.

For pole rot the impact on the expected loss is high, however it is expected that the UL will be a lot higher. The UL impacts the capital requirements for the bank. However, as mentioned the accuracy is low with respect to the actual exposure. Because of this, caution is advised in taking these numbers as actual expected losses.

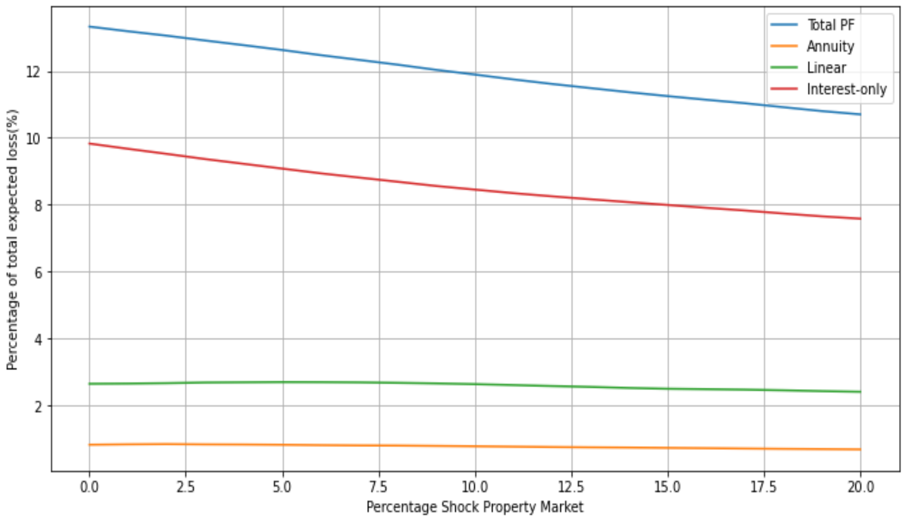


Figure 29: Scenario 1+2: Contribution of pole rot to the total Delta Expected Loss.

5.3 Impact on Property Prices

Now that we know the impact on the expected loss for the mortgages exposed to flooding and pole rot, we also want to observe the impact on property prices given these two events. Our mathematical model makes changes to the current market value of the property. One way that we can confirm the validity of the model is to look at the average property price decreases in the Netherlands. We have data available from Groningen and the literature (Chapter 2.6). Remember, the average property price decrease in Groningen due to earthquakes is estimated to be between 2% and 6%. From the literature a decrease between 2.5% and 10% is expected (Calcasa, 2019). Note, that Calcasa (2019) considers these percentages when an area is perceived in having high climate exposure.

We analyse the property price differences for both flooding and pole rot in percentages with the initial property market value ($v_{i,t=0}$) and the value with the event priced in ($v^{cc}_{i,t=0}$). Figures 30 and 31 show us the property price developments for both flooding and pole rot for all properties that are exposed to flood risk.

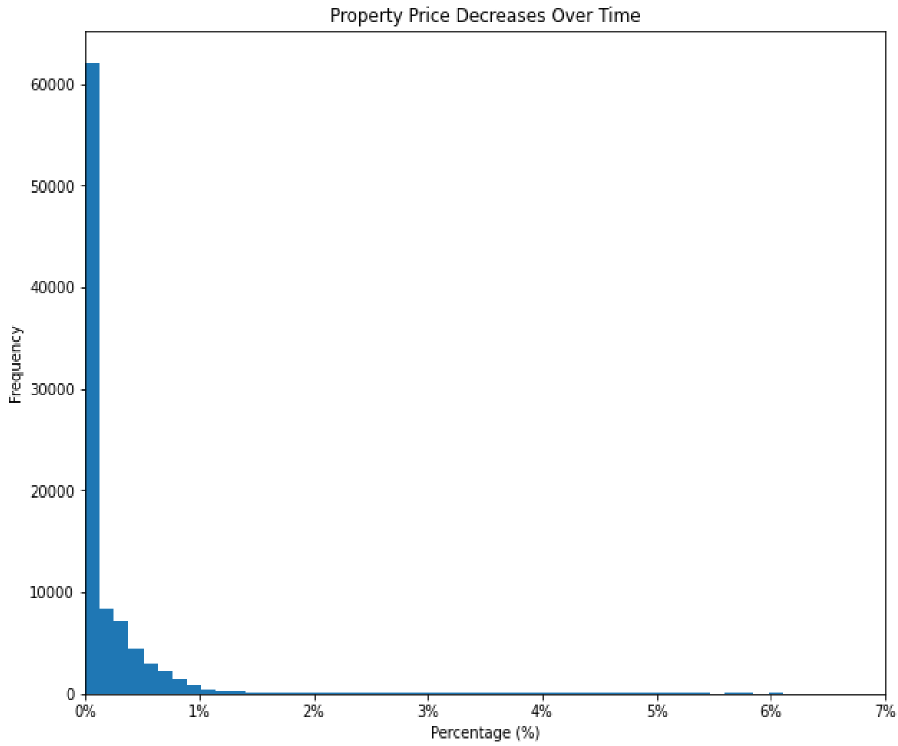


Figure 30: Percentage property price development for flooding.

Looking at the property price developments with respect to flooding we observe that most property exposures are within the 0%-2% range. There is a limited numer of properties exposed between the 2% and 7% range. On average we find that the property price decreases with only 0.3%. This decrease is for all properties that are exposed in all probability maps. It seems that this is not in line with our observations in Groningen and from the estimations of Calcasa (2019). However, the areas with the high probability exposure have the decreases in the tail of the distribution (between 2% and 7%) which is inline with the literature and our observations.

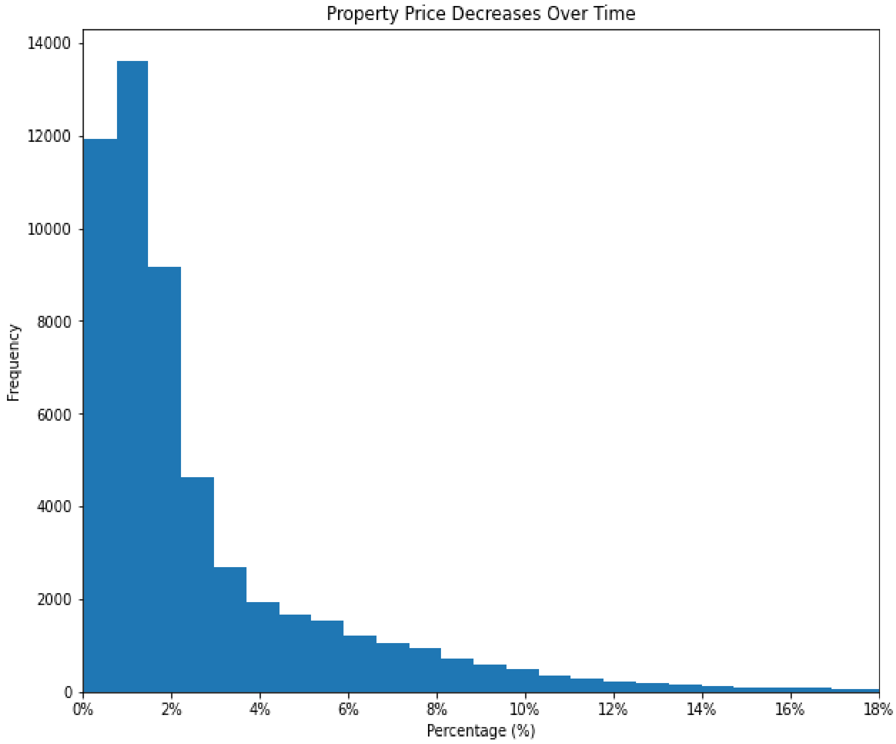


Figure 31: Percentage property price development for pole rot.

The percentage developments for pole rot are shown in Figure 31. Here we see that, whilst the number of properties is less than for flooding, the percentage decrease is significantly higher. The largest bulk of properties is within the 0% and 4% range. However, a significant number of properties is within the 2% and higher category. For a very small selection of properties there can even be 18% decrease in property value. On average the property price decrease is 3.1%. This is due to the large amount of properties below the 2% range. For the areas with the largest exposure we can conclude (between 2% and 10% with some outliers upwards) that it is in line with what we observe in Groningen and the estimations of Calcasa (2019).

The property price decreases for flooding and pole rot show mixed results for property price decreases. For flooding we observe that only a small number of properties is exposed to large price decrease, but on average it is below the expected decrease of Calcasa (2019). For earthquakes we do find that it is in line with the literature, but a large number is still within the 0% and 2% range. As mentioned in Chapter 2.6 and by Calcasa (2019), the perception of climate exposure is important. Once it is known by the market that an area is exposed, property prices will decrease across that region. This can already be observed for the municipality of Loppersum in Groningen. As time goes on we do expect that the property values will reflect the climate exposure once more events occur over that triggers a change in market sentiment.

6 Conclusion

This chapter discusses the results and draws a conclusion. Afterwards we recommend the next steps for further research.

6.1 Discussion

At the start of the research we aimed to find an answer to the question:

How can we quantify the financial impact of physical climate change events on the loss distribution, in particular the expected loss, on the bank's residential mortgage portfolio in the Netherlands?

The result of this question was answered through four subquestions. We first identified what the climate risks are. Afterwards we looked at what the exposure is for the bank with respect to these risks. Then we looked at how these exposures can be quantified in financial terms. The last step was looking at what the eventual loss projection is on the portfolio.

Here we briefly summarize the result of these subquestions. We researched two different physical climate event exposures that could have an impact on the mortgage portfolio of the Volksbank: flooding and pole rot. The former is caused by an increase in SLR and the higher likelihood of longer periods of (intense) precipitation. The latter is caused by a higher likelihood of longer periods of drought. These climate events could damage the underlying property of the mortgage, hence decreasing its value. The degree to which each underlying property is exposed depends on the probability of flooding and the exposure in 2050 with respect to a certain damage class for pole rot. The location of each property in the portfolio is matched to the corresponding flood or pole rot exposure from the data provided by the Climate Adaptation Services (2021). In order to quantify the damages for flooding, a damage function approach is used (Slager, 2017). For the damages of pole rot, a damage class approach is used (A. Kok, 2020). Based on the likelihood of occurrence from now until 2050 and the property characteristics, the damages are priced into the market value of the property. Doing this allows the bank to calculate a climate-adjusted expected loss until 2050 on their mortgage portfolio. By comparing the *climate adjusted* expected loss to the *non-climate adjusted* expected loss allows the bank to observe the contribution of these climate events to the total credit losses of the bank.

With respect to flooding, a total of 36% of all properties within the portfolio is exposed. However, our results show that the expected loss contribution in 2050 is limited on a portfolio level, but can be catastrophic for a small percentage of mortgage holders. The impact is limited because the total contribution of flooding to the expected loss on *exposed mortgages* is only 1.44% in the base HPI scenario (absolute losses equal €385.786,-). Our lowest scenario (Scenario 2) shows that the contribution even decreases to 1.13%. From the base scenario we observed that the largest exposure is in the municipality of Culemborg with a contribution to the flood adjusted expected loss of 17.5%. However, as property prices decrease in Scenario 2, the contribution of Culemborg decreases to 7% as largest exposed municipality becomes Kampen at 9%. This means that the largest exposures with respect to flooding is in Kampen in a down turn scenario for the property market. Nonetheless, both areas must be analyzed accordingly. From an expected loss point of view it seems that other risks, such as the current macro-economic environment, are more important. Note however that the bank measures its potential credit losses through the expected and Unexpected Loss (UL). It could be that flooding would have more impact on the UL than the calculated impact on the EL. The impact on the UL is outside the scope of this thesis.

For pole rot, 21% of the properties in the total portfolio is exposed to pole rot. For the bank pole rot is a larger problem than flooding. It is 18.3% of the total expected loss of the properties exposed to pole rot in the base scenario. Also, in terms of absolute losses it is almost 10 times higher than flooding. However, as property values decrease the contribution becomes lower and reduces to 13.3% for Scenario 2. The main municipalities at risk in the base scenario is Zoetermeer with 12% contribution to the expected loss. However, in scenario 2 when property prices decrease significantly, Bergen Op Zoom contributes more than 7% and Zoetermeer decreases to 6%. This shows that the municipality of high interest is Bergen Op Zoom as it quickly adds to the losses as property prices decrease. Sadly, there is one catch with pole rot risk. The damage calculations for pole rot are less accurate than for flood risk, as the damage class for a property is linked to the average exposure on a *neighbourhood* level and not on the individual property level. Also, it is assumed that all properties before 1975 are on wooden poles in these exposed areas. However, this does not have to be the case as the data did not verify this. Users of this model must therefore be careful with the loss calculation of pole rot. The flood damage calculations do not have this problem as the accuracy of the climate data is on an individual property basis.

When we look at property price developments with the 28 year priced in climate events, we see an average decrease of 0.3% for flooding and 3.1% for pole rot. Whilst the average is low, a significant number of property price decreases is between 2% and 10% for pole rot. However, for flooding there are only a couple of properties between the 2% and 7% range. The literature describes a decrease between 2.5% and 10% for exposed areas (Calcasa, 2019). When we consider high-risk areas for flooding, our results agree with the literature, but our average does not. For pole rot there does seem overlap between the literature and the result. In general, it is the case that we can only observe the true impact of flooding and pole rot on the property market once these events occur. This would allow for a more accurate estimation of these property prices as historic data would then be available.

With the model limitations and results in mind, this thesis managed to answer the main research question by quantifying the financial impact of both flooding and pole rot with respect to the expected loss on the banks residential mortgage portfolio. The next Section indicates future research that will add to the research done in this thesis.

6.2 Limitations & Future Research

Credit risk in combination with climate exposure for financial institutions for both physical and transitional risks is still in its early stages. More research should be done that would improve/add towards the results in this thesis.

First looking at the model presented in this thesis, the first steps for improvement is to eliminate some assumptions that have been discussed in Chapter 4.2. The ones that can be eliminated require the right data sets which have to be obtained through various institutions. Firstly, there are data available through *Kadaster* that would enable mapping the correct surface area to each individual property. Secondly, Kadaster also provides updated data on which floor each apartment is located. Thirdly, *HKV Consultants* have data that map a more accurate probability of flooding to each individual property given the maximum flood depth. Fourthly, due to the inaccuracy of pole rot exposures, a key step that the bank can take is to do an assessment around its customers for the state of the collateral with respect to pole rot. Our estimation indicates that the damages can be significant, but because the accuracy is not as large as with flooding; more data and analysis are required to quantify these risks. Fifthly, the model does not incorporate prepayments on mortgages. For our loss estimation this means that payments are only done at the moment they are due. In reality a large portion of customers chooses to pay more to lower their exposure. If this is included this would decrease the expected loss. However, if physical events occur, mortgage holders might also be more likely to stop prepaying as they require the money for repairs. This should be considered whilst implementing prepayment structures. Lastly, the impact of flooding seems low with only 0.3% average property price decrease. It is interesting to investigate Assumption 3 in Chapter 4.2. This assumption prices in flood risk until 2050. By pricing in for a longer period of time the results might be more in line with he literature and our data research of Groningen.

Additional research can be done on methods to quantify the impact of physical climate risk on the PD for mortgages in the Netherlands. This would increase the accuracy of the expected loss estimations. A climate adjusted PD could increase the expected loss as an additional risk is observed. The non-climate adjusted PD is determined based on defaults that occurred historically and their corresponding data points (i.e. credit rating, financial situation, macro economic environment, etc). The challenge is to link these climate events to a possible increase in this probability as no representative event has yet occurred that can verify this.

Also, there are more modelling approaches that could be used if the right data are available for determining the market value of a property. If the properties in the portfolio are analysed closer (i.e number of rooms, bathrooms, location, distance to nearest city center, energy label, etc) a comparison can be made with hedonic pricing model for before and after a flood for their value. If these data is gathered for a representative sample of all areas in the Netherlands, a better estimation could be possible. The literature as described in Chapter 2.5 describes multiple studies that used this approach.

Furthermore, there is also transitional risks for mortgages. Properties with lower energy labels can possibly reduce in value or the value increase is lower over time. This could also impact possible losses for the bank in the future.

Lastly, this thesis has discussed the impact of flooding and pole rot. However, there are two other climate events that also could have an impact: forest fires and storms. The prediction of the frequency and intensity of these events are a lot harder to quantify (Climate Adaptation Services, 2021). As data becomes available these methods should be further explored.

References

Amadio, M., Scorzini, A. R., Carisi, F., Essenfelder, A. H., Domeneghetti, A., Mysiak, J., & Castellarin, A. (2019). Testing empirical and synthetic flood damage models: The case of Italy. *Natural Hazards and Earth System Sciences*, *19*(3), 661–678.

Baart, F., Rongen, G., Hijma, M., Kooi, H., de Winter, R., & Nicolai, R. (2019). Zeespiegelmonitor 2018. de stand van zaken rond de zeespiegelstijging langs de Nederlandse kust.

Baranzini, A., Ramirez, J., Schaerer, C., & Thalmann, P. (2008). Hedonic methods in housing markets: Pricing environmental amenities and segregation.

Bin, O., & Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management*, *65*(3), 361–376.

BIS. (2021). Climate-related risk drivers and their transmission channels.

Board, F. S. et al. (2017). Recommendations of the task force on climate-related financial disclosures.

Calcasa. (2019). Angst voor natuurramp: Woningen potentieel 200 miljard minder waard.

Climate Adaptation Services. (2021). Klimaat Effect Atlas.

Connell, R., Hamaker-Taylor, R., Khosa, B., Firth, J., Rycerz, A., Turner, S., Owain, E., Lu, X., Bater, R., Haworth, A. et al. (n.d.). Charting a new climate.

Costa, A. L., Kok, S., & Korff, M. (2020). Systematic assessment of damage to buildings due to groundwater lowering-induced subsidence: Methodology for large scale application in the netherlands. *Proceedings of the International Association of Hydrological Sciences*, *382*, 577–582.

DNB. (2020). Integration of climate-related risk considerations into banks' risk management.

EBA. (2020). Mapping climate risk: Main findings from the eu-wide pilot exercise.

ECB. (2021). Climate risk stress test 2022.

Evans. (2020). Residential flood risk in the United States: Quantifying flood losses, mortgage risk and sea level rise.

Fuerst, F., & Warren-Myers, G. (2019). Sea level rise and house price capitalisation. *Available at SSRN 3359289*.

González, M. R., Ureña, A. P., & Fernández-Aguado, P. G. (2021). Regulatory estimates for defaulted exposures: A case study of Spanish mortgages. *Mathematics*, *9*(9), 997.

Haarsma, R. J., Hazeleger, W., Severijns, C., De Vries, H., Sterl, A., Bintanja, R., Van Oldenborgh, G. J., & van den Brink, H. W. (2013). More hurricanes to hit western europe due to global warming. *Geophysical Research Letters*, *40*(9), 1783–1788.

Horowitz, C. A. (2016). Paris agreement. *International Legal Materials*, *55*(4), 740–755.

Huizinga, J. (2007). Flood damage functions for EU member states.

IPCC. (1990). First ipcc assessment report (far).

IPCC. (2021). Ar6 climate change 2021: The physical science basis.

Ismail, N. H., Karim, M., & Basri, B. H. (2016). Flood and land property values. *Asian Social Science*, *12*(5), 84–93.

KNMI. (2014). Klimaatscenario's 2014.

KNMI. (2020). Waarnemingen klimaatveranderingen.

KNMI. (2021). Knmi klimaat signaal 21.

Kok, A. (2020). Impact droogte op funderingen.

Kok, Huizinga, Vrouwenvelder, & Barendregt. (2004). Standard method 2004 damage and casualties caused by flooding.

Kok, S. (2021). Technische toelichting risicokaarten funderingen.

Lazzarin, T., Viero, D. P., Molinari, D., Ballio, F., & Defina, A. (2022). Flood damage functions based on a single physics-and data-based impact parameter that jointly accounts for water depth and velocity. *Journal of Hydrology*, 127485.

Magni, L. (2021). Climate hazard modelling: Impact of floods on credit risk for the UK mortgages.

Marinier, C. (2018). Equity-at-risk and transfer pricing: Annualised expected loss versus cumulative expected loss.

Merz, B., Kreibich, H., & Lall, U. (2013). Multi-variate flood damage assessment: A tree-based data-mining approach. *Natural Hazards and Earth System Sciences*, *13*(1), 53–64.

Monson, M. (2009). Valuation using hedonic pricing models.

Nationale Ombudsman. (2021). Schadeproblematiek gaswinning in Noord-Nederland is nationale crisis.

Nofal, O. M., van de Lindt, J. W., & Do, T. Q. (2020). Multi-variate and single-variable flood fragility and loss approaches for buildings. *Reliability Engineering & System Safety*, *202*.

Nyce, C., Dumm, R. E., Sirmans, G. S., & Smersh, G. (2015). The capitalization of insurance premiums in house prices. *Journal of Risk and Insurance*, *82*(4), 891–919.

Pita, G. L., Albornoz, B. S., & Zaracho, J. I. (2021). Flood depth-damage and fragility functions derived with structured expert judgment. *Journal of Hydrology*, *603*, 126982.

Reeken, P. (2022). Is flood risk already affecting house prices? lessons learned from an impact assessment study in the netherlands.

Rijkswaterstaat. (2021a). Actueel hoogtebestand Nederland.

Rijkswaterstaat. (2021b). Watersnoodramp 1953.

Slager, W. (2017). Standaardmethode 2017 schade en slachtoffers als gevolg van overstromingen.

Smith, P. (2021). The climate risk landscape.

Stuurgroep Water. (2018). Overstromingsrisico's in Nederland.

Thapa, S., Shrestha, A., Lamichhane, S., Adhikari, R., & Gautam, D. (2020). Catchment-scale flood hazard mapping and flood vulnerability analysis of residential buildings: The case of Khando river in eastern nepal. *Journal of Hydrology: Regional Studies*, *30*, 100704.

Vijlbrief, E. (2020). Balance sheet management at retail banks.

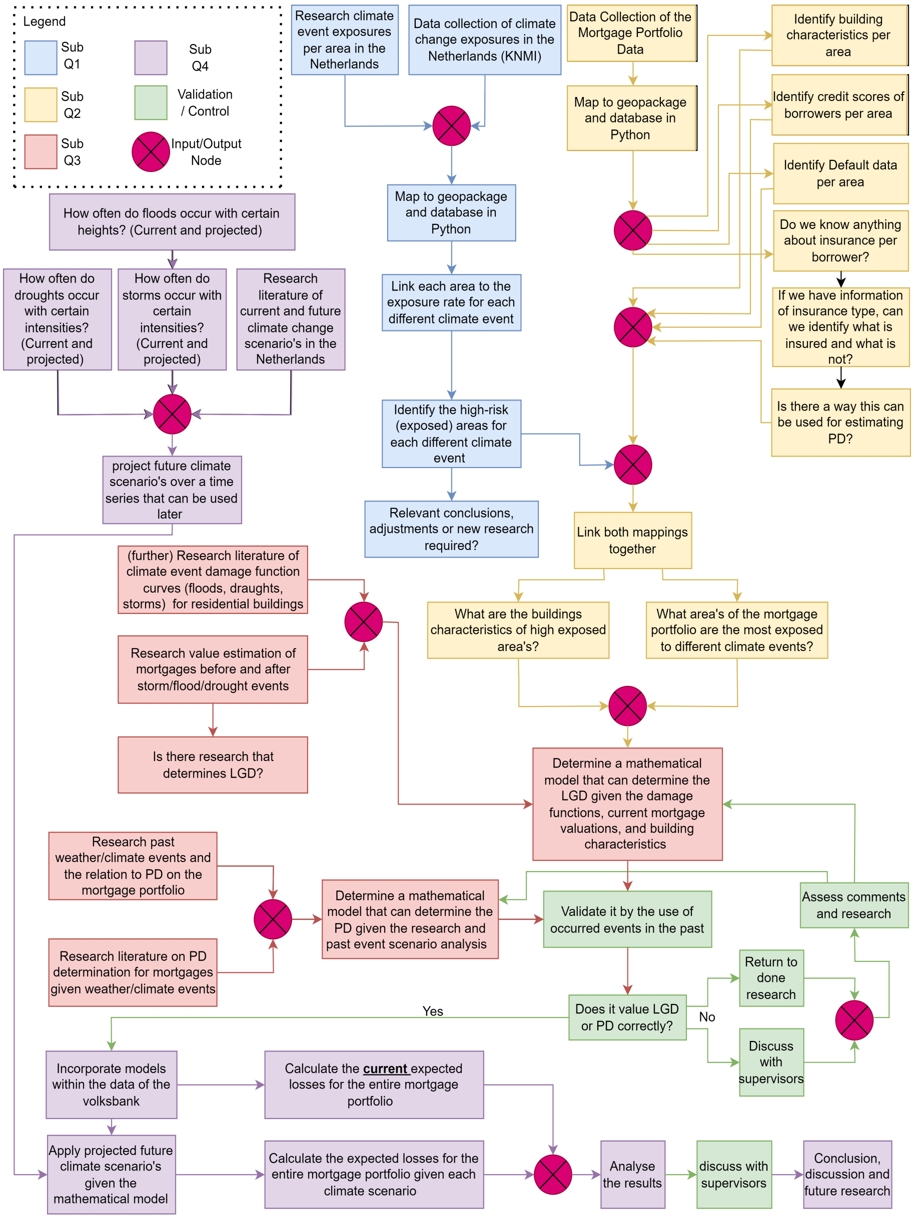
Walles, R. (2021). How can climate related financial risk be quantified for a mortgage portfolio in the u.s.?

Westcott, M., Ward, J., Surminski, S., Sayers, P., & Bresch, D. N. (2019). Physical risk framework: Understanding the impacts of climate change on real estate lending and investment portfolios.

Zhang, L., & Leonard, T. (2019). Flood hazards impact on neighborhood house prices. *The Journal of Real Estate Finance and Economics*, *58*(4), 656–674.

A Appendix A

Plan of Approach scheme as described in section 1.5.



B Appendix B

Figure 32 shows all the properties in the mortgage portfolio that are exposed to a certain flood depth. It start with all properties with a maximum of 1m flood depth in the top left and ends with all properties with a flood depth of 6 meter and higher in the bottom right.

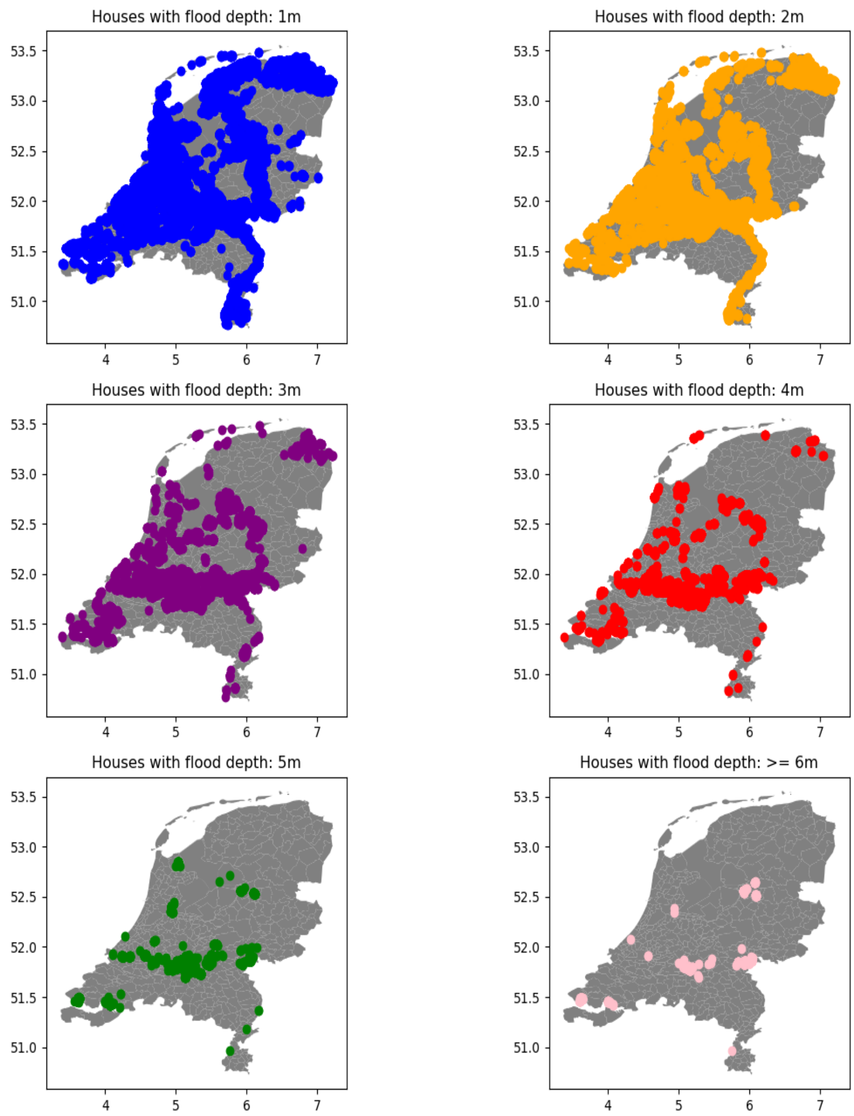


Figure 32: Flood Depth Map of all properties on the portfolio

Figure 33 shows the bar chart with the number of properties exposed for each municipality given 1m, 2m, 3m, and 4m flood depths.

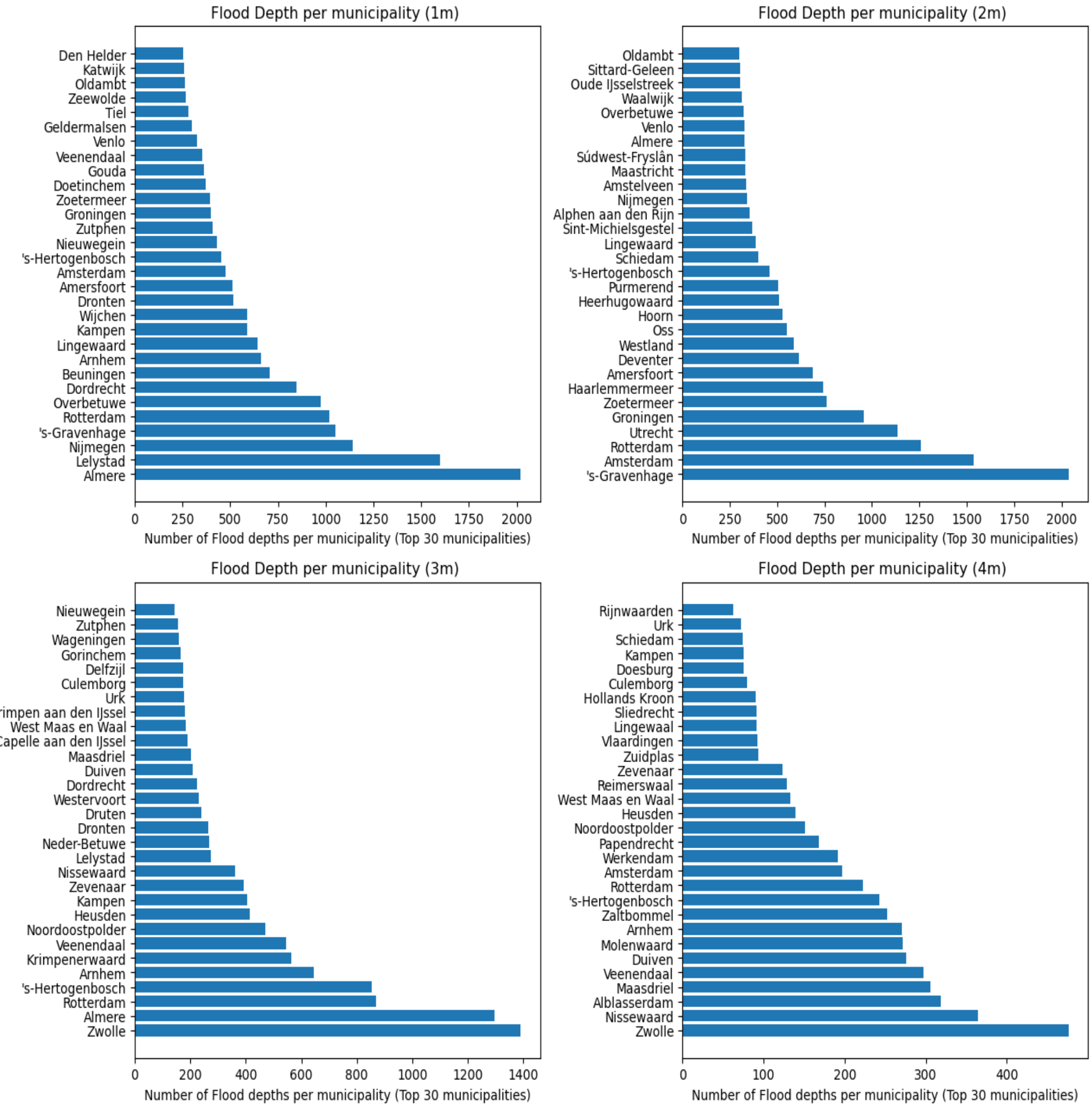


Figure 33: Bar Plot Netherlands 1

C Appendix C

Figure 34 shows two maps with the number of properties with an $EL > 500$ and $EL > 1000$ in each municipality for the IFRS HPI base scenario.

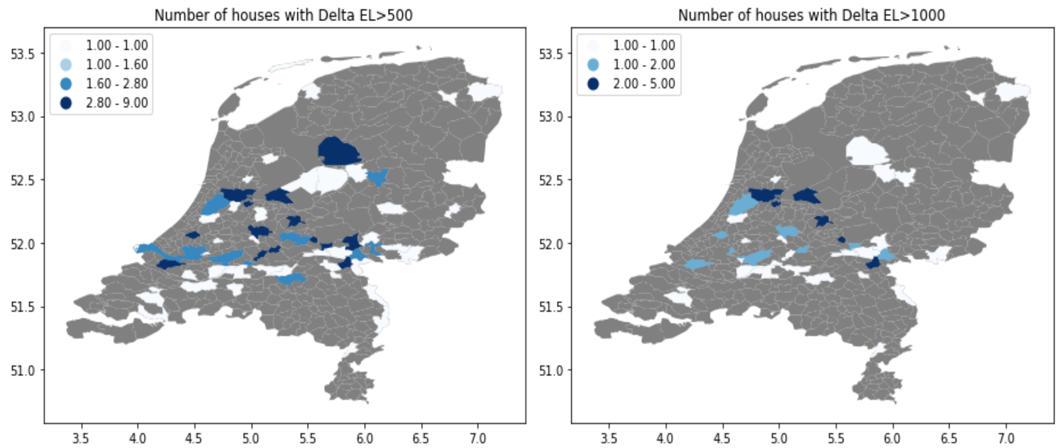


Figure 34: Map of number of properties with EL 500 and EL 1000

Figure 35 is the direct geographical map of Figure 21. Note here that the dark blue point is Culemborg.

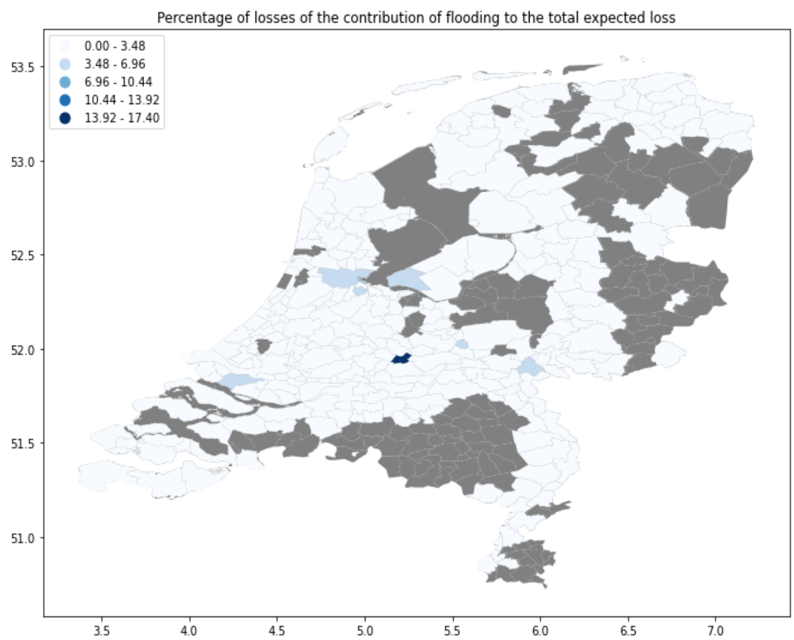


Figure 35: Contribution Map

Figure 36 shows the bar chart with the top 10 municipalities.

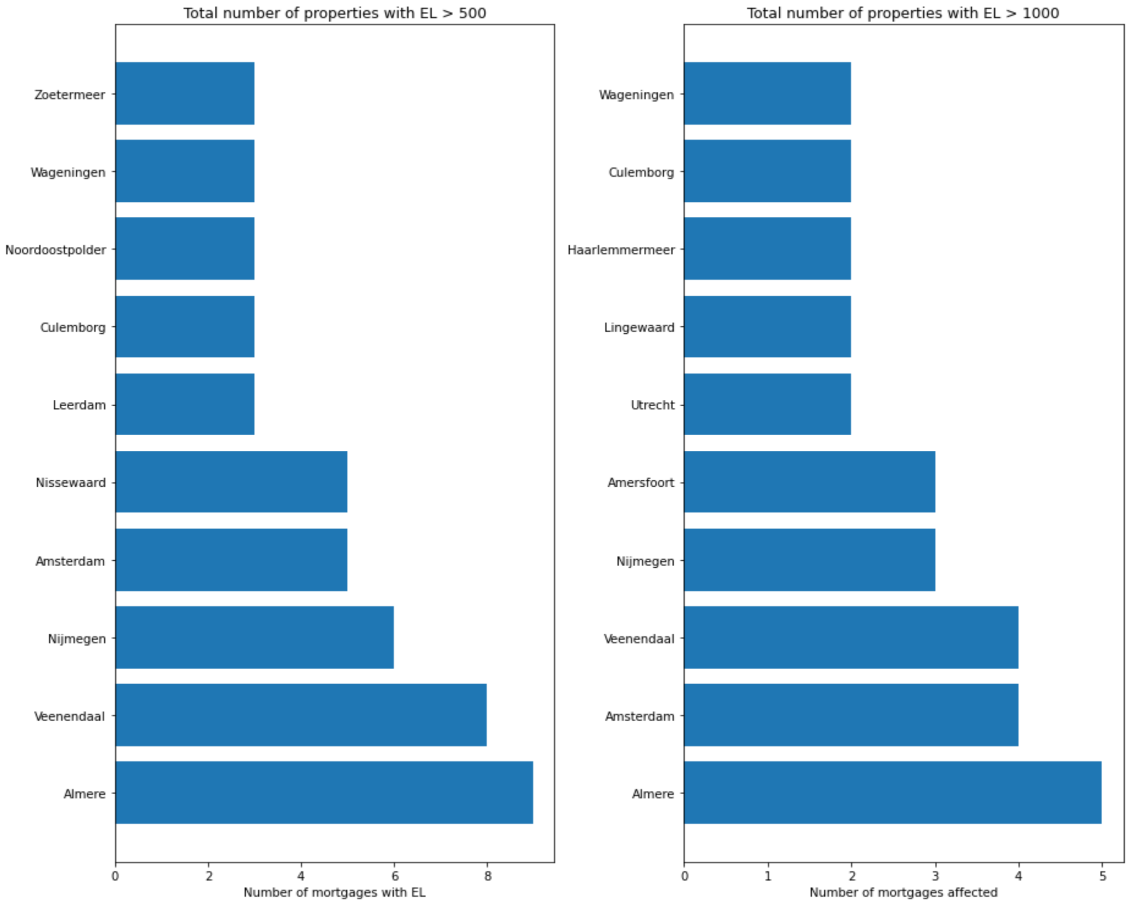


Figure 36: Bar Plot of municipalities with total number of houses with an $EL > 500$, $EL > 1000$
.

It can be seen that there are only 53 properties exposed with an $EL > 500$ and only 29 properties with an $EL > 1000$.

D Appendix D

Four maps showing the number of properties with a delta expected loss above 0, 200, 500 and 1000 (the contribution of flood risk to the toal losses). Note that this is for scenario 2: HPI shock.

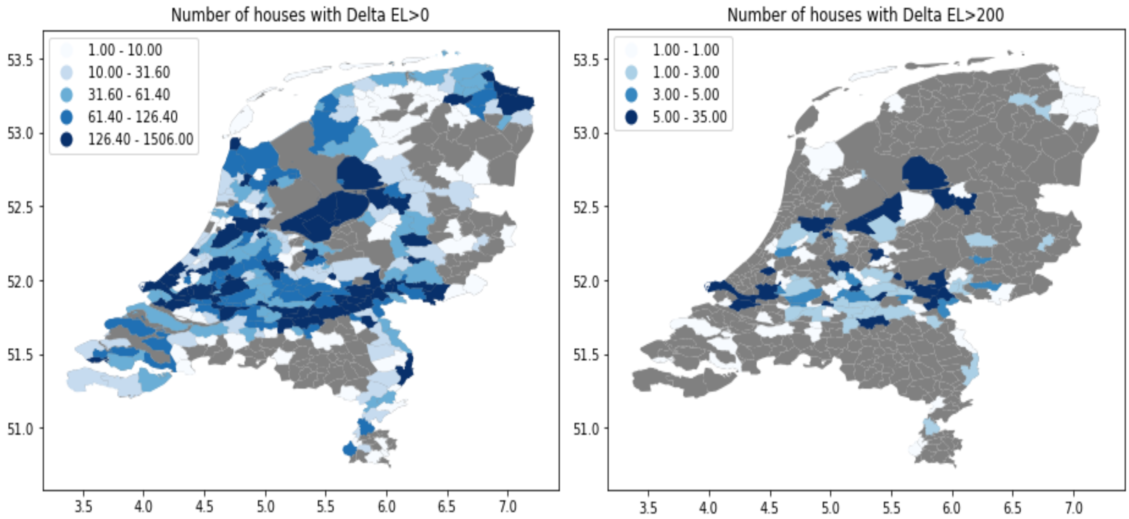


Figure 37: Scenario 2: Map of number of properties with EL 0 and EL 200

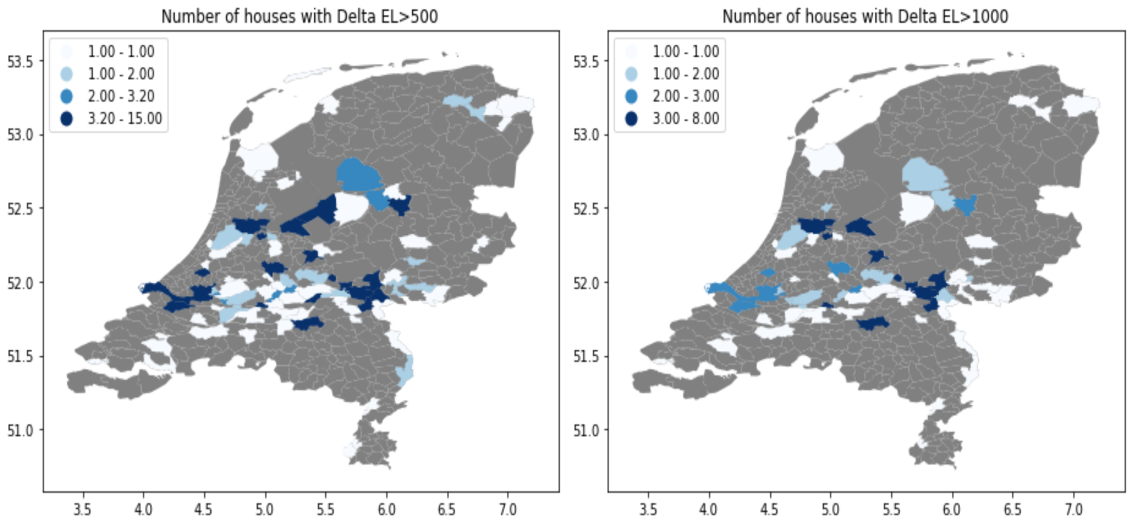


Figure 38: Scenario 2: Map of number of properties with EL 500 and EL 1000

E Appendix E

The graph below shows us the IFRS House Price Index base, down, and up scenarios from within the Volksbank. Note here that the general trend is upwards from the moment this HPI was published.

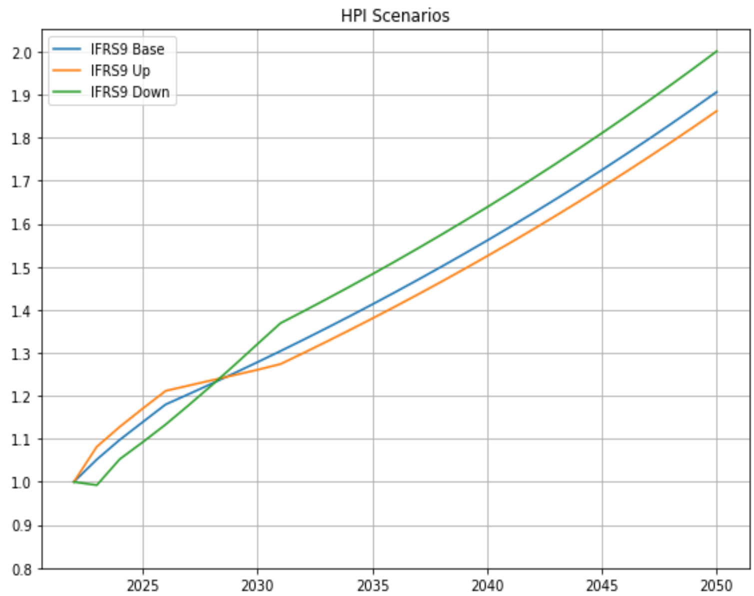


Figure 39: HPI base, up, down

F Appendix F

This Figure shows the total delta expected loss for flooding given the Scenario 2 HPI for every percentage decrease of the property values. This means that if the x-axis is at 2%, the non-climate adjusted market value of all properties is decreased by 2%. From that point forward the HPI is used to calculate the delta expected loss. We observe that it is the case that the relation is linear just as with the IFRS base, up, and down scenarios.

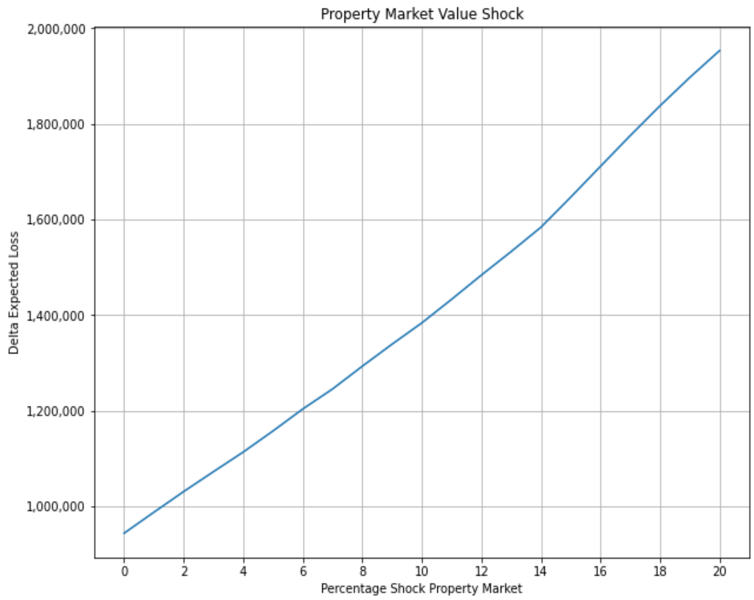


Figure 40: Scenario 1 and 2 combined

G Appendix G

The Figure below shows us the total exposure of the bank to pole rot with respect to the damage classes. Note here approximately 21% of the total portfolio is exposed to pole rot.

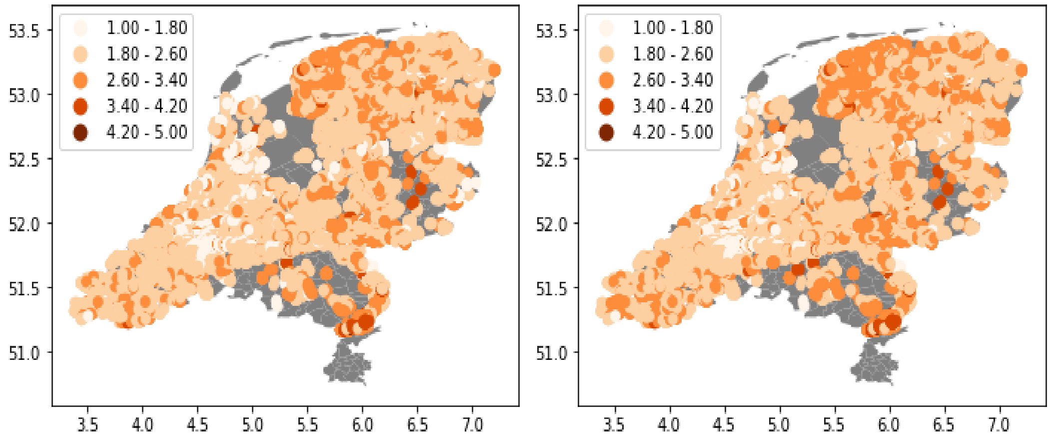


Figure 41: Portfolio Pole Rot exposure

H Appendix H

This appendix shows the map of the percentage contribution to the total expected loss of areas that are affected by pole rot. An interesting observation is that the areas with the relatively large exposure according to Figure 13 are not the largest contributor to the total expected loss. This is due to the nature and number of properties within the portfolio.

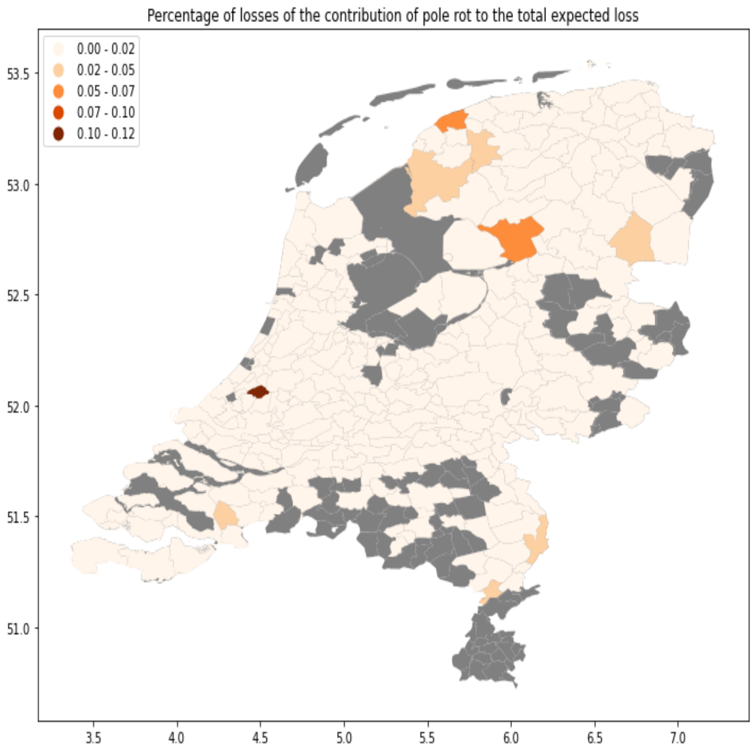


Figure 42: Pole Rot Contribution Map

I Appendix I

This Figure shows the total delta expected loss for pole rot given the Scenario 2 HPI for every percentage decrease of the property values. This means that if the x-axis is at 2%, the non-climate adjusted market value of all properties is decreased by 2%. From that point forward the HPI is used to calculate the delta expected loss. We observe that it is the case that the relation is linear just as with the IFRS base, up, and down scenarios.

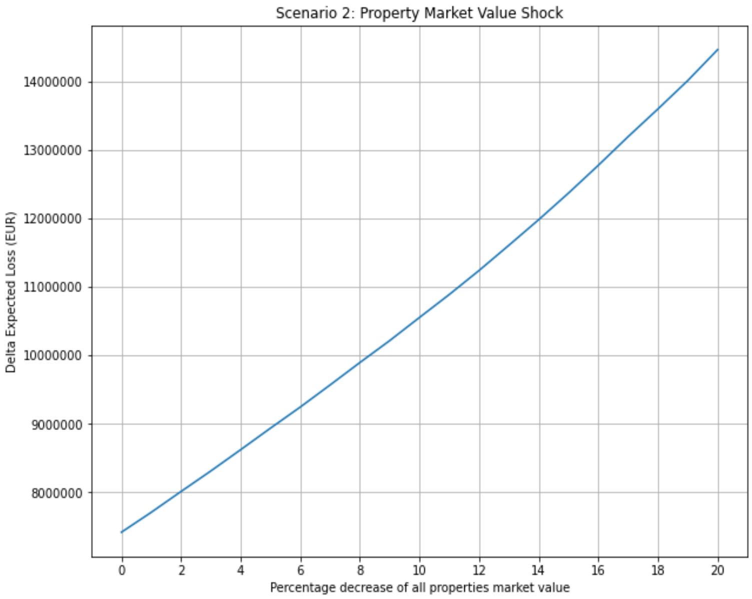


Figure 43: Pole Rot: Scenario 1+2 Percentage Decrease