Investigating Flood Risk Insurance Feasibility in the Netherlands: A Case Study for the Province of Limburg in the Current Climate

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Abstract

This research aims to quantify the feasibility of flood risk insurance in the Netherlands, employing a case study centered on the province of Limburg and utilizing data reflective of the current climate. The research provides an extensive integration of diverse publicly available data sources that are refined to operate at the neighborhood level. Premium estimates are derived based on a voluntary flood insurance model, while also considering the potential implementation of a mandatory flood insurance program. Furthermore, the study incorporates an evaluation of flood damage mitigation (FDM) measures by using a variety of depth-damage curves that provide indications of the expected damage to residences. Estimation yields ambiguous results, with substantial variations stemming from the use of different data sets and the inclusion of FDM measures. Due to limitations in the data used, this study cannot provide conclusive insights into the feasibility of flood risk insurance. Nonetheless, the findings of this research offer valuable insights into its potential.

Keywords: Flood risk, Climate change, Voluntary flood insurance model, Mandatory flood insurance, Flood damage mitigation, Limburg, Netherlands

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Contents

1 Introduction

Due to socio-economic developments, the damage caused by flooding has increased considerably over the last decades, which has caused intensified concerns among European nations (Kundzewicz et al., 2018). Consequently, non-stationarity in extreme precipitation and high river discharge due to climate change has become an active research area. For instance, Kundzewicz et al. (2018) examined observed and projected changes in flood hazard in Europe. Also, Hudson et al. (2019) aimed to evaluate the ability of flood insurance arrangements in Europe to cope with trends in flood risk. The subject is also high on research agendas in individual EU member countries. In the Netherlands, for instance, Botzen and Van Den Bergh (2008) as well as Aerts and Botzen (2011) discussed the role insurance can play in adapting to climate change impacts and flooding.

The risk of flooding is difficult to insure due to low-probability high-impact events (Kron, 2009). Also, flood insurance differs widely in scope and form across Europe (Surminski et al., 2015). Currently, the Netherlands is largely uninsured against the risks of flooding. Companies and citizens may have stronger expectations that the government will compensate flood damage due to the limited availability of voluntary insurance contracts (Seifert et al., 2013). The flood disaster of 1953 can be attributed as a potential cause of this limited availability. Due to the severity of damages caused by this event the risks were considered to be too large to be insured on the private market. Therefore, many insurers cancelled their flood insurance policies (Seifert et al., 2013). In 1955, there even came a binding contract drafted by the predecessor of the Dutch Association of Insurers that forbade its members to insure flood risk. More than thirty years later, in 1998, this contract was dissolved and it rather became an advice to insurers to not insure flood risk. In the same year, the Disaster Damage Compensation Act (WTS) was enacted, which could be evoked in the event of a flood. With this act, individuals and companies can be eligible for a compensation from the government in case of a freshwater flood, earthquake or other major accident [Dutch Association of Insurers, 2020][1]. Nonetheless, this compensation is never complete and the decision to provide compensation as well as the extent of damage relief provided depends on political will (Botzen and Van Den Bergh, 2008).

When examining flood insurance policies across different countries, significant variations become evident. Germany's approach to flood damage compensation bears similarities to that of the Netherlands. Like the Dutch Disaster Damage Compensation Act (WTS), Germany allows for the possibility of public flood damage compensation (Hudson et al., 2019). However, flood insurance is primarily voluntary and offered, packaged with other natural disasters, as supplement to the home contents or building insurance. Flood maps are used to identify exposure zones, each representing different levels of flood risk, and the level of insurance depends on the zone a residence is located in. Nonetheless, due to the possibility of a public flood damage compensation, the market

[1]The Dutch Association of Insurers is the interest group of non-life and life insurers in the Netherlands who represent the interests of private insurance companies operating in the Netherlands.

penetration[2] of voluntary flood insurance is relatively low (Seifert et al., 2013). In the United States, the National Flood Insurance Program (NFIP), administered by the Federal Emergency Management Agency (FEMA), also offers voluntary flood insurance. Premiums are calculated based on factors like property location, flood risk, and coverage, similar to the system in Germany. However, properties in high-risk flood zones, referred to as Special Flood Hazard Areas (SFHAs), are obligated to take flood insurance, resulting in increased market participation. Conversely, in France and Belgium, there is a solidarity public structure by which flood insurance is provided as part of other insurance contracts. As a consequence, the market penetration for flood insurance in these nations is nearly universal, approximating 100% coverage (Botzen and Van Den Bergh, 2008). Furthermore, premium rates in these regions are not contingent upon individual flood risk assessments, with all households remitting the same premium level. Government support is extended to insurers; however, there is no provision for public compensation for flood damage. Lastly, the United-Kingdom, operates a public-private partnership (PPP) market. Flood insurance purchase is connected to mortgage lender or rental conditions, premiums are partially risk based and there is a governmental reinsurance scheme[3] to support insurers.

Because of the increase in the risk of flooding in the future due to climate change and the shortcomings of the WTS, in recent years, the government and insurance companies have discussed the possibility of introducing a new flood insurance system. In this way, the government intends to transfer the responsibility of compensation in case of a natural disaster to the private market where possible (Jongejan and Barrieu, 2008; Kok, 2005; Water Adviescommissie, 2006). According to Botzen et al. (2009), this will provide a better financial security for individuals and will also provide an incentive for households to limit their risk. In 2018, the Dutch Association of Insurers has written a report in which they advice to insure local floods in the buildings and contents policy. At the end of 2020, the association also wrote a Position Paper with solution directions in order to better compensate damage because of local precipitation as well as damage caused by the overflowing or beating of (a dike along) a canal, stream or small river. However, damage resulting from flooding in the main waterways is excluded as well as compensation for households in outer dike areas.

This thesis aims to evaluate the feasibility of voluntary flood risk insurance in the Netherlands by using a composite of publicly accessible data sets. These data sets encompass details related to flood probabilities, inundation depths, geographical delineations of neighborhoods and municipalities, residential properties, and average WOZ-values. The extensive scope of some of these data sets renders a nationwide study across the entire Netherlands computationally unfeasible. As a consequence of the flood disaster that occurred in Limburg during the summer of 2021 and the

[2]Defined as the ratio of insurance premiums to GDP

[3]In 2016, the UK government introduced the Flood Re scheme. Flood Re is a joint initiative between the government and the insurance industry. It is a reinsurance program that provides a backstop for flood risk. Under this scheme, insurance companies can pass on the flood risk component of their policies to Flood Re at a fixed premium. This helps stabilize flood insurance prices and ensures that homeowners in high-risk flood areas can obtain affordable coverage.

notably elevated risk of flooding prevalent in this geographical region, this research is deliberately constrained to the province of Limburg. All data sets have been refined to operate at the neighborhood level. Consequently, the resultant premium estimates are also delineated per neighborhood. What sets this research apart is its extensive integration of diverse publicly available data sources, representing a unique and previously unexplored endeavor conducted at this level of data granularity. It is essential to acknowledge that the process of sourcing, transforming, and integrating these data sets is labor-intensive and time-consuming, by which it constitutes the primary focus of this research. The main challenge in this thesis revolves around the limited quality of some of the data sets under investigation, complicating the precise computation of premium estimates. Nevertheless, this thesis provides a substantial and valuable addition to the existing academic literature in this field.

Section 2 of this thesis offers a comprehensive overview of existing literature with respect to flood risk insurance. In Section 3, the fundamental components involved in conducting a flood risk assessment are described. Section 4 delves deeply into the complexity of the acquired data for this research. That section encompasses insights into the data sources utilized and the comprehensive data transformation process. Ultimately, all data is carefully aggregated back to the neighborhood level specifically within the province of Limburg. Section 5 introduces the model employed for the calculation of premium estimates, based on the data sets derived from the data transformations delineated in Section 4. Moreover, Section 5 expounds upon the methodology behind fitting a distribution and explains how the premium estimate distribution is altered upon the implementation of a flat-rate premium and a historical simulation technique. Section 6 showcases the premium estimates that have emerged through the distinct data sets and adjustments applied within the model. Consequently, Section 7 provides the concluding remarks and prospects for potential future research initiatives.

2 A literature review on flood risk

Flooding is, in many parts of the world, the leading cause of losses from natural phenomena and responsible for more damage than other types of natural hazard such as earthquakes, wildfires or drought (Tsakiris, 2014; Kron, 2005). Munich (1999)[4] found that roughly half of all fatalities due to nature's forces and a third of the economic losses can be attributed to flooding. Due to climate change, precipitation increases and sea levels rise, by which flood damages have become more severe over recent decades (Solomon et al., 2007; Aerts et al., 2009). Precipitation has caused river flood hazards in Western and Central Europe and the UK to rise by 11% per decade from 1960 to 2010 (Douville et al., 2021; Ranasinghe et al., 2021). According to Blöschl et al. (2020), the most recent three decades had the highest number of floods over the past 500 years with increases in summer[5]. Kron (2005) stated that over the past ten years, losses due to the consequences of flooding ran up to more than US$ 250 billion globally. In countries where the occurrence of flooding is a more frequent event, the population has learned to be prepared and take preventive measures against the risk of flooding. In other countries, where floods are not so common, the event of a flood catches individuals completely by surprise. Due to the lack of preventive measures in these areas, losses increase drastically. Moreover, due to urbanization and socio-economic growth, the exposure to natural disasters and damage from these weather-related events is expected to increase in the future (Paudel et al., 2015). More and more people are living in flood-prone areas, unaware of the risk this poses. As a result, especially low-lying countries like the Netherlands are forced to create adaption policies due to climate change and sea level rise (Klijn et al., 2012).

The unprecedented events of extreme precipitation and flooding in July 2021, underscore the importance of effective flood management strategies. The province of Limburg, located in the south-eastern part of the Netherlands was hit hard and large areas were substantially flooded. The measured amounts of precipitation and river discharges had never been this heavy before. River discharges from the Meuse nearby Eijsden, which is a village in the south of Limburg, were the highest ever measured (Rongen et al., 2021). A flood event of such magnitude is estimated to occur only once every 100 to 1,000 years. On behalf of the Flood protection expertise network (ENW), Rongen et al. (2021) wrote a report in which the first facts and interpretations were published shortly after the flood event. In this report, the total damage was estimated between 350 and 600 million euros. For Belgium and Germany, the situation was more catastrophic due to even more precipitation and faster-flowing rivers. In total, the flooding led to billions worth of damage and hundreds of deaths.

In the Netherlands, primary flood defences protect against the risk of flooding. However, they must be reinforced in order to prevent increasing flood risk in the future. At this moment, over half of the dikes do not yet meet the safety standard that all Dutch dikes must meet by 2050

[4]Munich Reinsurance Company (Munich RE): leading global provider of reinsurance, primary insurance and insurance-related risk solutions

[5]Because a warmer atmosphere can hold more water vapor, heavy rainfall events are expected to become more intense during the summer, increasing the risk of floods.

[Rijkswaterstaat, 2023]. The primary water defenses include about 3,500 kilometers of dikes, along with the locks and pumping stations that must protect the Netherlands from flooding. According to the Dutch flood protection program (HWBP), 1,500 kilometers of these dikes must be reinforced to meet the 2050 standard. Of this, 174 kilometers have now been completed and more than 500 kilometers are expected to be reinforced by 2028. The National Delta Program [2023] states that the Netherlands must be climate-proof and water-robust by the year 2050, which means that water safety, freshwater supply and spatial planning must be in order. It is only with these measures in place that the country can continue to cope well with the consequences of climate change. The main objective of the Delta Decision on Flood Risk Management is that the probability of death from flooding for everyone behind the dikes should not exceed 1 in 100,000 per year (or 0.001%) by 2050 at the latest. This is the so-called "basic protection level".

On a broader scale, the European Union enacted a new Flood Directive (2007/60/EC)[6] in response to more severe flooding in Central Europe during the last two decades. With this flood directive, the EU measures to manage the risks floods pose to human health, the environment, the economy and cultural heritage[7]. It emphasizes the importance of a transition from traditional flood defence strategies to a flood risk management approach at the basin scale in Europe (Tsakiris, 2014; De Moel et al., 2009). In order to comply with this flood risk management approach, member states are urged to map flood hazards and risks. The flood hazard maps must cover the geographical areas which could be flooded according to high, medium and low probability scenarios. For each scenario, the flood extent, water depth and if possible the flow velocity must be shown. Also, the maps must provide the indicative number of inhabitants and the economic activities in the area that are potentially affected. The flood maps are often developed by governmental organizations and primarily used for emergency planning, spatial planning, and awareness raising (De Moel et al., 2009). For the Netherlands, the LIWO (National Water and Flood Information System) has developed a collection of maps that present the probabilities and possible inundation depths of flood events in the Netherlands under current climate conditions. Additionally, the LIWO provides maps that include flood probabilities representing the standard for the year 2050. In this scenario, it is assumed that all reinforcement tasks of the HWBP are finished. Consequently, it is anticipated that by the year 2050, the probabilities of flooding will be substantially lower when compared to the current situation.

When considering the province of Limburg, it is noteworthy that a significant portion of this region lacks the protective coverage of dike infrastructure. Consequently, the improvements resulting from dike reinforcements do not enhance the situation in Limburg as opposed to the majority of other Dutch regions. Research by Bisschop et al. (2015) showed that the economic risk in outer dike areas is about seven times greater when compared to inner dike areas, which emphasizes the

[6]Directive 2007/60/EC of the European Parliament and of the Council of 23 October 2007 on the assessment and management of flood risks

[7]Statement from https://environment.ec.europa.eu/topics/water/floods_en, an official website of the European Union

vulnerability in these outer dike areas to flood related risks. Furthermore, in the aftermath of the 2021 floods, deficiencies within the Dutch Disaster Damage Compensation Act (WTS) came to light. Within the frameworks of the WTS, efforts were made to be as generous as possible regarding the allowance for damage expenses. However, as was written in the process evaluation by Helmond et al. (2023), the ambitions around generosity were not in line with the legal possibilities within the frameworks of the WTS. Among those impacted by the floods, there was uncertainty regarding the extent of reimbursement and relief entitlements, often falling short of their expectations. Furthermore, two years later, there are still pending compensation applications.

Flood insurance markets may need reform to offer sufficient and affordable financial protection for households and incentives for risk reduction (Hudson et al., 2019). Aerts et al. (2009) have examined whether long-term insurance contracts with a duration of 5, 10 or 15 years could serve as a solution for covering flood risk and accommodating increasing flood losses in the Netherlands. They have taken into account that the uncertainty of how future risk will develop as a consequence of climate and socio-economic change may complicate insurers' rate-setting of long term contracts. The research focused on 53 dike-ring areas, and included a range of climate-change scenarios for which the dynamics of insurers' funds have been explored. The estimation results for the current risk-based flood insurance premiums revealed large regional differences. Also, it showed a great incentive for short-term insurance contracts due to the uncertainty about the true trend of climate and socio-economic change. Seifert et al. (2013) investigated how characteristics of flood risk influence household flood insurance demand based on household surveys undertaken in Germany and the Netherlands. They showed that although flood risks are not generally covered in property insurance policies in the Netherlands, many Dutch homeowners have a positive willingness to pay (WTP) for flood insurance. A flood insurance policy would provide more clarity to households regarding the level of compensation they could expect in the event of a flood. Additionally, such policies could serve as incentives for households to implement measures aimed at minimizing flood-related damages, such as elevating their homes or adopting flood-adapted interior fittings (Priest, 1996; Aerts et al., 2009). These factors collectively suggest there may be viable opportunities for the introduction and expansion of flood insurance coverage within the Netherlands.

3 Flood risk assessment

Generally, risk is defined as the exposure to danger, harm, or loss. In case of flood risk, this is defined as the product of flood hazard and the negative consequences of flooding. The negative consequences of flooding depend on the elements that are present at the location involved (exposure) and the lack of resistance for those elements to the flooding (vulnerability) (Foudi and Osés-Eraso, 2014). Consequently, a comprehensive flood risk analysis comprises three fundamental components: hazard, exposure, and vulnerability.

3.1 Hazard

The hazard is defined as a threatening natural event including its probability of occurrence (Kron, 2005). Flood hazard thus provides information about the severity of the flood and the associated flood probability. The flood severity is mainly characterized by the flood extent and the inundation depth, but also parameters such as the flow velocity, duration and spatial dynamics can be used (De Moel et al., 2009). The flood probability shows how likely a location is to experience a particular flood in one year, it is an approximation denoting a larger probability for a more probable flood. The flood probabilities can be translated to return periods which is a measure of frequency denoting the inter arrival time in years between two flood events occurring of the same magnitude (Foudi and Osés-Eraso, 2014). The return period is the inverse of the annual probability, and vice versa. Hence when the return period is denoted with r and the annual flood probability with p, this becomes $r = \frac{1}{p}$. To accurately asses flood risk, hydraulic studies collect information on flood events of different return periods and describe their characteristics. This is essential when estimating the consequences of flooding, described by the exposure and vulnerability.

3.2 Exposure

The exposure includes all the values at risk in case of a flood, encompassing the buildings, items and humans within the affected area (Kron, 2005). The extent of the exposure is dependent on the spatial dynamics of the area under consideration. Notably, urban areas tend to experience more pronounced flood impacts compared to rural regions. Due to socio-economic developments and spatial planning policies, wealth and exposure have increased considerably in flood-prone areas (Re, 2005). For insurers, exposure to flood risk is influenced by a multitude of factors, including the number of policies issued in flood-prone areas, the value of assets insured, and the accuracy of their risk assessment models. To gauge current exposure levels and project future risks, flood hazard maps serve as valuable tools in the assessment process.

3.3 Vulnerability

The vulnerability is defined as the lack of resistance to damaging/destructive forces (Kron, 2005). Hence, it captures the potential damage, often expressed as a monetary value, to all elements that are exposed to the risk of flooding. An element at risk of being harmed is more vulnerable the more it is exposed to a hazard and the more it is susceptible to its forces and impacts (Messner and Meyer, 2006). Hence, when the inundation depth of a flood rises, the damage to an element will increase as well. Also, the difference in buildings leads to different estimates of potential damage. Residential buildings will probably have less damage when compared to industrial or commerce buildings when hit by a comparable flood. The reason for this is that industrial or commerce buildings often contain more expensive equipment or inventory, which is often placed on the ground floor. The susceptibility in case of a flood event is also dependent on the extent to which preventive flood protection measures are undertaken. Taking these measures, such as placing sandbags or draining systems, can mitigate the total loss.

Many works have been published that analyse flood vulnerability based on various different methods or models (Rehman et al., 2019). The accuracy of the models often depends on the availability of sufficient and adequate data. When this is not the case, for example when there are few historical records on flood damages, only a more general approach can be applied.

To give an indication of the possible damage to residences that are exposed to the risk of flooding and therefore define the vulnerability, so called depth-damage curves are often used. Depth-damage curves relate the damage to a building to the severity of the flood expressed in inundation depths. For every depth level, a corresponding damage factor is computed. This factor signifies a percentage that, when multiplied by the value of a property, provides an estimate of the potential damage. Many practitioners embrace these depth-damage curves for their simplicity and wide applicability (Huizinga et al., 2017; Gerl et al., 2016; Molinari et al., 2020). Depth-damage functions are key components upon which loss assessments are based and are accepted worldwide as the standard method in estimating flood loss (Apel et al., 2009). Even though flood damage cannot fully be explained by the depth-damage relationship, other hazard indicators such as flow velocity and inundation duration are often excluded from multivariate regression models, as detailed data from flood events are scarce (Poussin et al., 2015; Van Ootegem et al., 2015; Zhai et al., 2005).

Huizinga et al. (2017) have developed a globally consistent database of depth-damage curves depicting fractional damage as a function of water depth. Given that the data set utilized by Huizinga et al. (2017) encompasses both riverine and coastal flooding, the developed damage functions are not restricted to a particular flood type. Rather, they can be employed for evaluating the damage caused by a generic flood event. In the figure below, the curves are presented for several countries in Europe, including the Netherlands. The x-axis shows the depth in meters to a specific residence and the y-axis shows the corresponding damage factor which is a percentage of the sum insured. From the curve of the Netherlands it can be concluded that the damage to a residence that is flooded by 3 meters is on average a bit more than 20% of the sum insured.

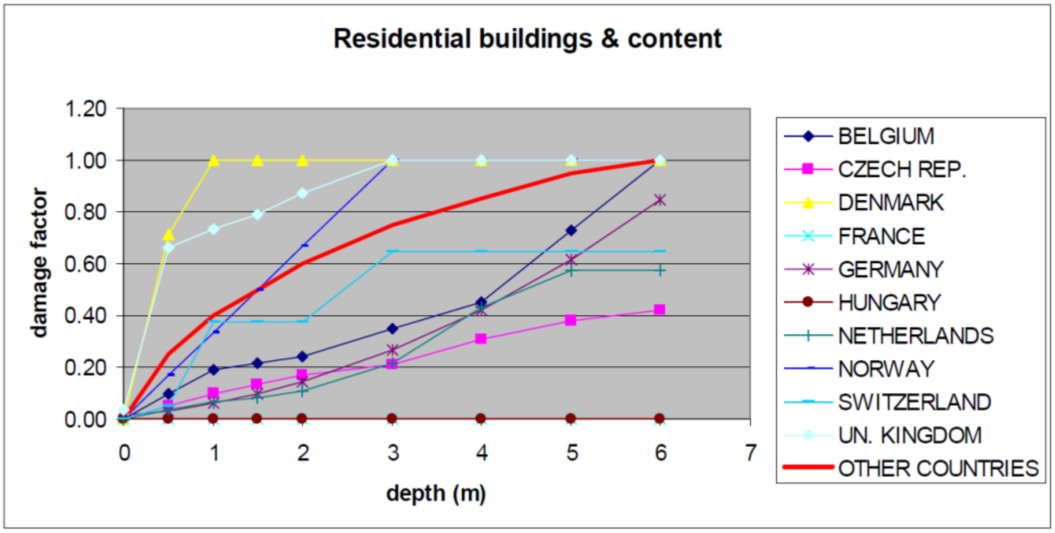


Figure 1: Calibrated depth-damage curves, obtained from Huizinga et al. (2017)

In the Netherlands, flood damage models are less frequently calibrated. The current estimates from the Dutch damage model, known as the SSM-2017[8], draws upon flood damage records originating from the coastal flood of 1953 as well as from the 1953 and 1955 fluvial floods. However, while there is a significant amount of data available for coastal flooding due to events like the 1953 flood disaster, the availability of detailed historical flood damage data for fluvial flood events is more limited. Consequently, the current estimates, primarily informed by the 1953 coastal flood, are characterized by the considerably greater inundation depths. Also, the comparatively less sturdy construction of houses at that time, making them prone to complete collapse, leads to a steep increase in expected damage when the inundation depths rise. This phenomenon causes the damage functions of the SSM-2017 to exhibit an exponential trend (De Bruijn et al., 2015; Slager and Wagenaar, 2017).

As of recently, a research by Endendijk et al. (2023) was published that used a unique data set with experienced damages after the flood event in Limburg in July 2021. The data set is obtained by conducting a survey amongst households that were affected by the 2021 flood event. They were asked about the depth level at their residence, the damage in monetary values and whether they took flood damage mitigation (FDM) measures. The research used an instrumental-variable estimation to measure the effect of the implementation of FDM measures on the household level and whether these measures are truly effective. This paper is highly valuable to our study as

[8]The SSM-2017 (Damage and Victim Module 2017) is the successor to the HIS-SSM. SSM-2017 enables the computation of diverse flood outcomes for every simulation of a potential flood scenario in the Netherlands. These outcomes encompass estimations such as the impact on vulnerable structures and inhabitants, the potential extent of damage, and the likelihood of casualties.

it examines the same research area. Additionally, the outcomes derived from the IV-regression serve as inputs for constructing depth-damage curves, specifically in the context of fluvial flooding. Figure 2 shows the bi-variate depth-damage curves as they are obtained by Endendijk et al. (2023). As evident from the graphs, all curves except for the SSM-2017 curve exhibit a root function, causing them to flatten as inundation depth increases. The red curve corresponds to the scenario where no FDM measures are implemented. Notably, this curve surpasses the blue and green curves, representing scenarios in which households adopted FDM measures. The contrast highlights the significant reduction in flood damage achieved through these measures. The black and purple curves, utilized by Federal Emergency Management Agency, (FEMA) (2023) for the US flood model and Thieken et al. (2005) for Germany, respectively, do not differentiate between scenarios with or without FDM measures. Consequently, these curves depict an average. Endendijk et al. (2023) also separate damage to building structures from damage to household contents, contrary to Huizinga et al. (2017).

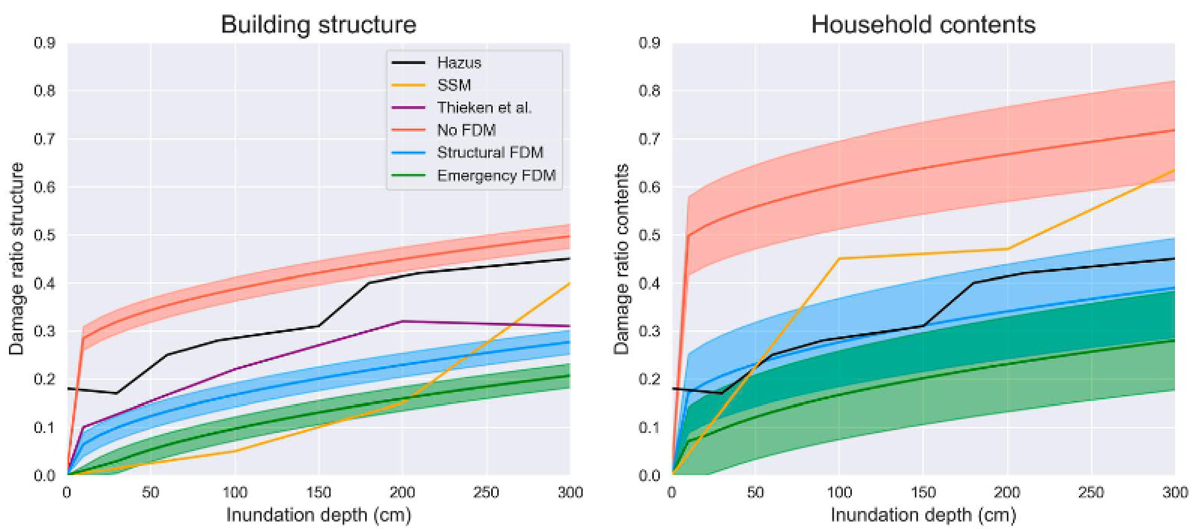


Figure 2: Calibrated depth-damage curves, obtained from Endendijk et al. (2023)

4 Data

To address the research question regarding the possibility of flood risk insurance in the Netherlands and to determine appropriate premiums to cover expected damages, data from various sources is essential. It's important to remember that flood risk analysis involves considering three primary components: hazard, exposure, and vulnerability. This section outlines the data acquisition process aimed at defining these components. Table 1 offers an overview of the data sets employed in this thesis, all of which will be discussed in this section.

Data Set	Data Type	Granularity	Export Format	Information
Maximum Inundation Depth Maps	Geospatial	25 meters	Geometric Raster Files	Four map layers: • Large probability (1 in 10 years) • Medium probability (1 in 100 years) • Small probability (1 in 1,000 years) • Extremely small probability (1 in 100,000 years)
Site-specific flood probability Maps	Geospatial	5 meters	Geometric Raster Files	Four map layers: • Depth > 0 cm • Depth > 20 cm • Depth > 50 cm • Depth > 200 cm
CBS Data Set	Geospatial	N/A	Geometric Shapefile	Detailed neighborhood and municipality information
BAG Data Set	Tabular	N/A	Tabular/Database	Addresses in the Netherlands (updated January 2023)
WOZ Data Set	Tabular	N/A	Tabular/Database	Average WOZ-values per neighborhood

Table 1: Summary of Data Sets

4.1 Flood hazard maps

The research is based on a collection of map layers obtained from the LIWO[9] (National Water and Flood Information System) of the Netherlands. These map layers include information on flood risk scenarios and serve as a means for crisis management[10] concerning flood risk in the Netherlands. The LIWO serves as a publicly available resource for professionals involved in flood preparedness within the Netherlands, involving crisis management and spatial adaptation. Additionally, it offers valuable insights to individuals interested in understanding the potential impact of climate change

[9] https://basisinformatie-overstromingen.nl/#/maps

[10] crisis management is divided into two phases: preparation and response. In the context of flooding, preparation entails mitigating risks through the reinforcement of dikes and primary flood defenses. On the other hand, response pertains to addressing the aftermath and potential consequences of a flood event.

in their local areas. The flood maps presented by the LIWO originated from a national database in which different authorities have made information available for national use. A total of eight map layers depict information on the probabilities of flooding and the maximum inundation depth.

4.1.1 Maximum inundation depth

Four of the eight map layers give an indication of the maximum inundation depth for floods occurring with varying probabilities. More specific, they show for a flood event possibly occurring with a large, medium, small or extremely small probability, meaning that they occur with return periods of 1 in 10, 100, 1,000 or 100,000 years respectively, the corresponding maximum level of inundation in different areas of the Netherlands. Each map layer encompasses four distinct flooding scenarios, illustrating the inundation resulting from breaches in either primary or non-primary flood defenses, inundation in outer dike areas and inundation from the regional water system. In the context of the province of Limburg, flood risk is most pronounced in the outer dike regions. Intense precipitation events have the potential to trigger river overflow, and with the absence of flood defenses in these areas, inundation depths can escalate significantly. Additionally, given Limburg's reliance on secondary water defenses and regional water systems, any shortcomings in either of these protective mechanisms, as witnessed during the summer of 2021 when the regional water systems were overwhelmed by heightened runoff, can also lead to substantial inundation depths in the vicinity of these water sources.

The maps indicating the inundation depths are presented for the current climate and will be the premise in all flood risk calculations in this thesis. It is essential to note that these values represent the maximum inundation depths rather than the expected inundation depths. Consequently, when calculating premium estimates in subsequent stages, an adjustment factor will be applied to account for this distinction. Figure 3 shows an example of two of the four map layers. In this figure, the inundation depths are depicted for a flood event with a large probability, corresponding to a return period of 1 in 10 years, and for a flood event with an extremely small probability, denoting a return period of 1 in 100,000 years. The 1 in 100,000 years probability is used to analyse the worst-case scenarios for planning and preparedness. It represents an extreme event that, while highly unlikely in a specific year, will have catastrophic consequences if it were to occur. Appendix section (A.1) contains the two additional map layers depicting inundation depths for floods with medium and small probabilities.

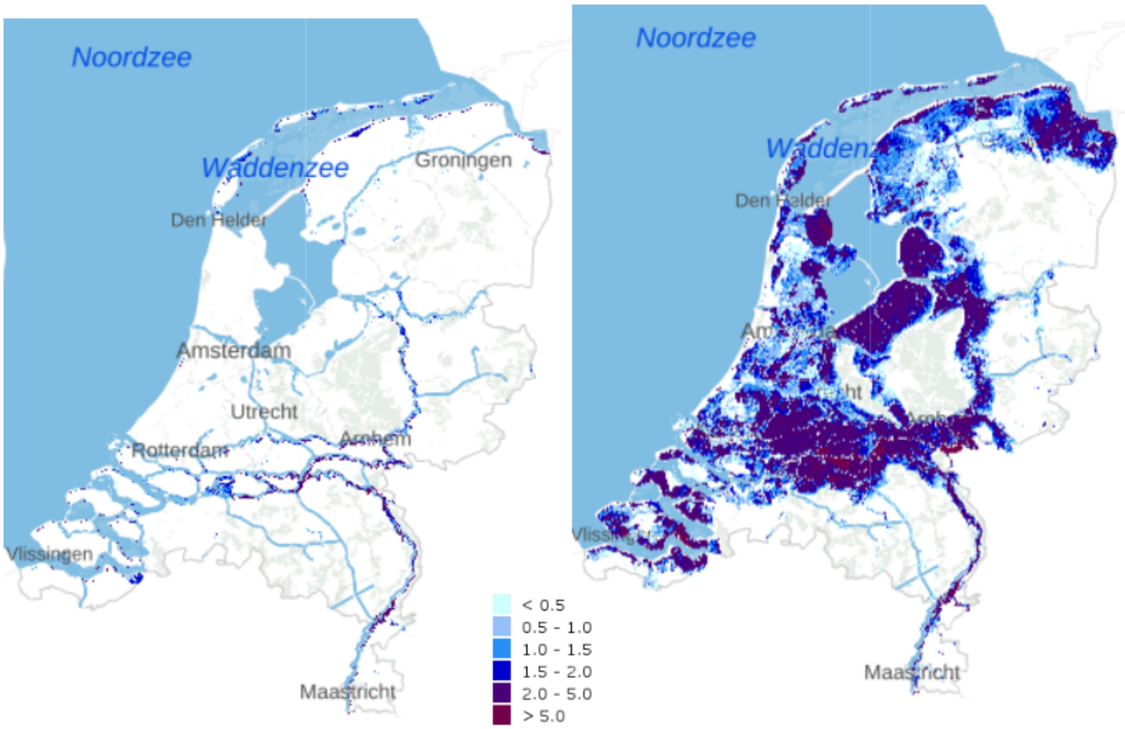


Figure 3: Map layers obtained from the LIWO containing maximum flood depth levels occurring with large probability (left) and extremely small probability (right). The legend indicates the maximum water depth in meters.

The four map layers including the maximum inundation depths for the four probability levels can be exported as raster files. They have a grid resolution of 25 meters which implies that the depth levels are accurate to an area of 25 x 25 meters.

4.1.2 Site-specific flood probability

The other four maps illustrate the likelihood of flooding for different levels of inundation. More specific, they show the probability of a flood occurring in a certain area with an inundation depth of more than 0, 20, 50 or 200 centimeters. The colors in the map layers represent the different probability intervals. The four maps are presented for the year 2022 as well as for the year 2050. The 2022 maps are used in this thesis as they relate to the current situation at the beginning of the reinforcement of the dikes and primary flood defenses, offering the most up-to-date assessment of flood risks available. The map layers for the year 2050 reflect the standard that has to be met at that time. It is for this reason that the probabilities of flooding in the year 2050 are expected to be much lower than they are in the year 2022. Figure 4 shows an example of the map layers for the year 2022. In this figure the probabilities of a flood occurring of more than 0 cm and more that 200 cm are presented. The intervals listed in the legend below the pictures are referred to in the data as categories 1 through 5. The categories are shown in Table 2. Appendix section (A.1) contains the two additional map layers depicting the probabilities of a flood occurring of more than 20 cm and 50 cm.

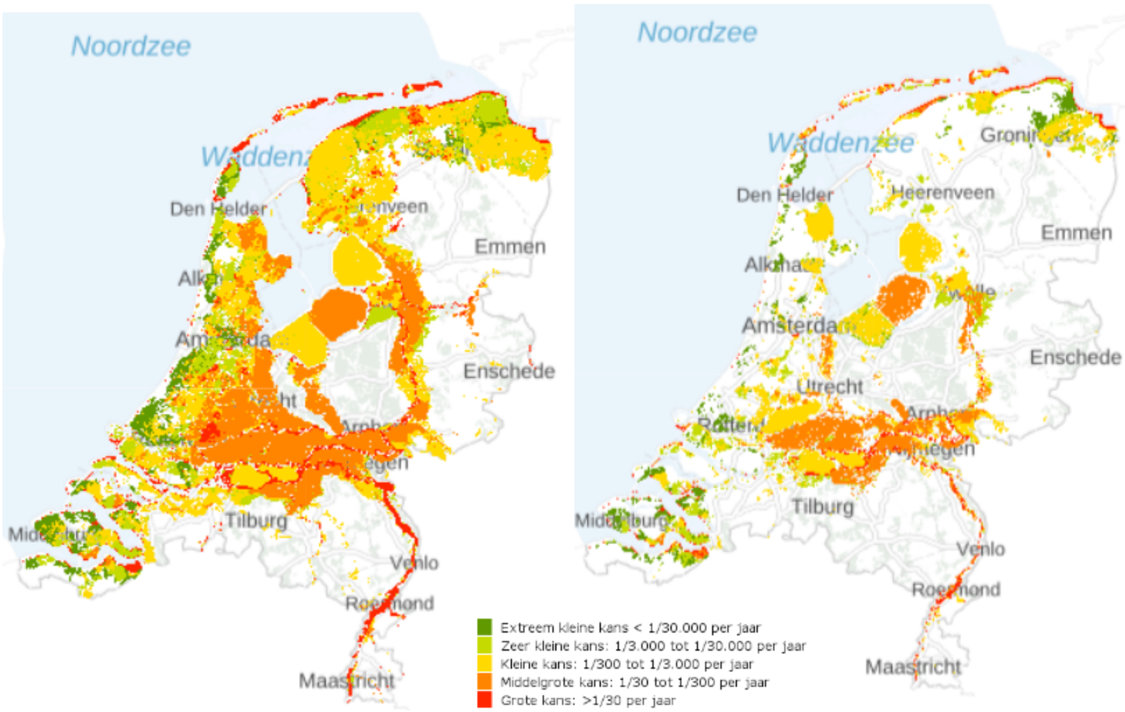


Figure 4: Map layers obtained from the LIWO containing site-specific flood probabilities with depths greater than 0 cm (left) and 200 cm (right). The legend indicates the flood probabilities based on five intervals.

Category	interval
1	$<$ 1/30.000 per year
2	1/3.000 til 1/30.000 per year
3	1/300 til 1/3.000 per year
4	1/30 til 1/300 per year
5	$>$ 1/30 per year

Table 2: Clarification of the categories as they are defined within the dataset underlying the map layers housing site-specific flood probabilities acquired from the LIWO.

The maps including the site-specific flood probabilities can also be exported as raster files. These maps provide a finer level of detail, with a granularity of 5 meters, compared to the maps that display maximum inundation depths. However, since these map layers are based on interval values, they provide a less accurate representation of the possible flood probabilities and corresponding depths, despite the higher granularity. As a result, calculations based on these maps will primarily serve as a means of comparing results against those obtained from the maps featuring maximum inundation depths.

4.2 Demographic and housing data

To accurately identify and quantify the number of houses at risk of flooding in specific neighborhoods, along with the corresponding inundation depths, the integration of various data sets is required. In addition to the flood probability and inundation depth data, data sets from the Central Bureau of Statistics (CBS) and the Dutch Cadaster are essential.

The CBS data set is obtained from the National Georegister (NGR)[11] and provides detailed information about neighborhoods and districts in the Netherlands. It includes multipolygons representing the borders of these areas, as well as key demographic and geographic data such as population size, number of households, and land and water areas in hectares. Complementing this, the Dutch Cadaster data set, specifically the Basic Registration of Addresses and Buildings (BAG) data set[12], is utilized. The BAG data set, last updated in January, contains information on all residential objects in the country.

Furthermore, a data set is obtained that includes the average WOZ-value for each neighborhood[13], which represents the value of immovable property. By combining these data sets with the flood probability and inundation depth data, it becomes feasible to accurately assess the risk of flooding for specific neighborhoods and determine the corresponding inundation depths.

4.3 Data transformation

In order to merge the data sets and effectively utilize the data from all the maps, a coordinate-based merging approach is employed. It is important to note that certain data sets have different coordinate reference systems, necessitating the transformation of all coordinates to RD-coordinates. RD-coordinates are commonly used in the geodetic coordinate system in the Netherlands, serving as the foundation for geographical indications, files, geographic information systems (GIS) and land registry maps.

Given the extensive volume of data obtained from the eight aforementioned maps in conjunction with the CBS, BAG and WOZ data, working with the entire data set of the Netherlands is highly time-consuming and computationally complex. This is particularly evident when considering the granularity of the maps including the site specific flood probabilities. To illustrate, for the province of Limburg alone, these maps consist of over 250 million rows each. To focus the research on an

[11] Wijk- en Buurtkaart 2022 versie 1 (EPSG:28992) Geopackage - wijkenbuurten_2022_v1.gpkg
[12] BAG 2.0 Extract
[13] The WOZ data is obtained from https://openinfo.nl in personal correspondence. The data provided by Openinfo is retrieved from original data providers and enriched by adding geo locations and regional levels.

area of interest, the recent floods in the province of Limburg during the summer of 2021 limit the scope of the study to this particular province. The initial analyses will combine all the aforementioned data at the neighborhood level.

To extract addresses within the province of Limburg, the BAG data set proves valuable as it includes information on the municipality and province for each address. By identifying the addresses located in the province of Limburg, the corresponding municipalities can be determined. From the CBS data set, all neighborhoods falling within these municipalities are also extracted. Consequently, a data set is formed that encompasses the multipolygons of coordinates denoting the borders of each neighborhood, along with their respective municipalities. The geographic coordinates extracted from the raster files are then assigned to their corresponding neighborhoods, and the associated values are averaged. Moreover, to evaluate the level of exposure, the number of households within each neighborhood is tallied. The next section gives a detailed explanation of this process.

4.4 Data process in detail

Extracting the coordinates that belong to the province of Limburg is done by using a geographic information system like QGIS. A geographic information system (GIS) is a computer system for capturing, storing, querying, analysing, and displaying geospatial data (Chang, 2016). This data contains information that describes objects, events or other features with a location on or near the surface of the earth.

4.4.1 Set-up of the example

Upon importing the map layers acquired from the LIWO into QGIS, the segment encompassing all data within the province of Limburg can be isolated. As depicted in Figure 5, this extraction is showcased for two out of the eight maps. From the four maps presenting an estimation of the maximum inundation depth, the left segment of Figure 5 illustrates the extraction of the map layer indicating the maximum flood depth with a large probability, corresponding to a return period of 10 years. Similarly, from the four map layers displaying site-specific flood probabilities, the extraction of the map layer encompassing site-specific flood probabilities with depths surpassing 0 cm is displayed on the right side of Figure 5. Throughout this section, these two map layers are used as an example in order to provide an explanation of the data process in detail. These extracted map layers will be respectively referred to as the depth map (on the left) and the probability map (on the right).

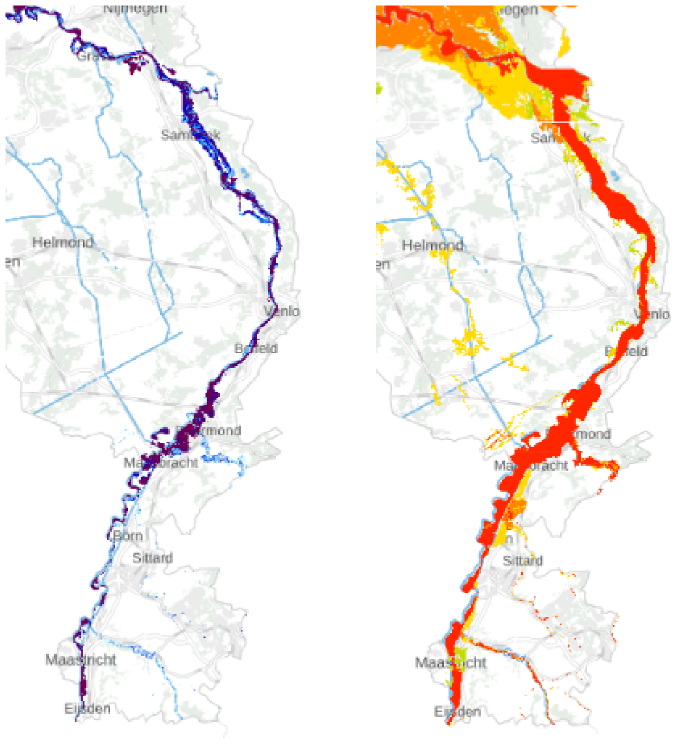


Figure 5: Extracted part of the map layers presenting the maximum flood depth with large probability (left) and the site-specific flood probability with depth greater than 0 cm (right)

The data behind these map layers consists of a x and y column representing the longitude and latitude of the coordinates and a third column including the depths or probabilities, depending on the map layer in question. By transforming the data into a Geodataframe, the x and y columns are combined into a geometry column and it becomes possible to perform spatial operations. As mentioned in Section 4.1.2, the probability map has a grid resolution of 5 meters. The grid resolution is defined as the distance between two coordinates in the map. An accuracy of 5 x 5 meters means that the map has a relatively high granularity and provides a detailed image of the flood probabilities. The downside of this map is however, that the values in the map represent probability intervals which are much less accurate (This issue will be addressed in Section 4.7). Due to the high granularity of the probability map, the obtained Geodataframe is extremely large with over 250 million rows. In comparison, the depth map has a grid resolution of 25 meters by which it has a lower granularity and thus provides a less detailed view of the flood depths corresponding to the different probabilities. The upside however, is that these depth values are not categorized but displayed in real numbers, by which they still provide a better reflection of the flood risk.

4.4.2 Allocation process

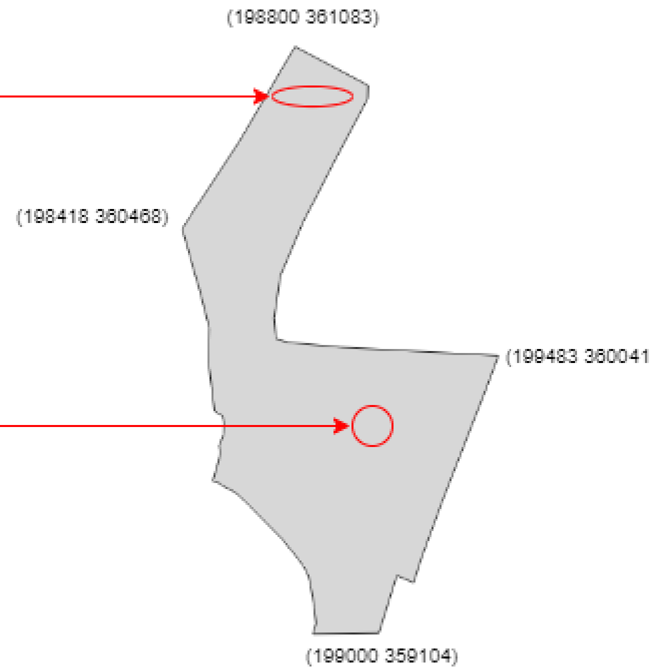
As described in Section 4.2, data from the CBS is used in order to assign the probabilities and depths to their corresponding neighborhood and municipality. To obtain all neighborhoods that are within the province of Limburg, first the BAG data set from the Dutch Kadaster is needed. This data set contains all addresses in the Netherlands (last updated in January 2023), and for each address it also includes the municipality and province it is located in. Consequently, extracting addresses situated in Limburg is straightforward. Based on the municipalities extracted from the BAG data set, it is feasible to subsequently retrieve all neighborhoods from the CBS data set that are situated within any of these municipalities. Each neighborhood is represented by a location polygon, containing an array of coordinates representing the geometric vertices of the neighborhood. Some neighborhoods might encompass multiple polygons if they are non-contiguous. Moreover, there are residences in Limburg that do not fall within a specific neighborhood but rather in the outskirts of a municipality. The polygons corresponding to these areas are also incorporated. In total, this entails 922 location polygons within the confines of the Limburg province. Given that Limburg features several neighborhoods sharing the same name but located in distinct municipalities, it is important to consistently present neighborhoods alongside their respective municipalities. Failing to do so could lead to the misallocation or overwriting of values.

Figure 6 provides a graphical representation of the process through which values from the probability map and the depth map are allocated to their respective neighborhoods. The presented example centers on the neighborhood of Asselt, which has been randomly selected. At the upper part of the figure, a table showcases the entry for the Asselt neighborhood, accompanied by its corresponding municipality. The third column of the table contains the location polygon outlining the Asselt neighborhood. Given that Asselt's location polygon comprises numerous vertices, only a select number of coordinate points are displayed in the table. The shaded region on the right-hand side of the figure portrays the shape of Asselt as visualized after the CBS data is imported into QGIS. Additionally, the coordinates extracted from the geometry cell in the table are depicted in the figure, aligned with their respective vertices.

On the left-hand side of the figure, a subset of five coordinates sourced from the depth map, alongside another subset of five coordinates from the probability map, is showcased. It should be noted that these five points are merely a small representation of the multitude of points encompassing the entirety of Limburg. By tracing the path outlined by the red arrows, it becomes evident that these selected points fall within the boundaries of the Asselt neighborhood. This alignment is further confirmed upon comparing the coordinates in the tables and evaluating their compatibility with the extent of the location polygon. To validate the accuracy of the process, Table 3 and Table 4 display the assignment of the appropriate neighborhood and municipality to each row present within the geometrical data frames.

Index	Neighborhood	Municipality	Geometry (coordinates)
⋮	⋮	⋮	⋮
323	Asselt	Roermond	POLYGON ((198418 360467, ..., 198800 361083, ..., 199483 360041, ..., 199000 359104, ..., 198418 360467))
⋮	⋮	⋮	⋮

Index	Geometry (longitude latitude)	Depth large probability (m)
⋮	⋮	⋮
3914609	POINT (198775 361025)	2.00
3914610	POINT (198800 361025)	2.15
3914611	POINT (198825 361025)	2.23
3914612	POINT (198850 361025)	1.97
3914613	POINT (198875 361025)	1.05
⋮	⋮	⋮



Index	Geometry (longitude latitude)	Probability > 0 cm
⋮	⋮	⋮
144553825	POINT (199000 359800)	5
144553826	POINT (199005 359800)	5
144553827	POINT (199010 359800)	5
144553828	POINT (199015 359800)	5
144553829	POINT (199020 359800)	5
⋮	⋮	⋮

Figure 6: Example of the data allocation process for neighborhood Asselt in municipality Roermond

Index	Geometry (longitude latitude)	Depth large probability (m)	Neighborhood	Municipality
⋮	⋮	⋮	⋮	⋮
3914609	POINT (198775 361025)	2.00	Asselt	Roermond
3914610	POINT (198800 361025)	2.15	Asselt	Roermond
3914611	POINT (198825 361025)	2.23	Asselt	Roermond
3914612	POINT (198850 361025)	1.97	Asselt	Roermond
3914613	POINT (198875 361025)	1.05	Asselt	Roermond
⋮	⋮	⋮	⋮	⋮

Table 3: Extraction of the dataset including flood depths with a large probability

Index	Geometry (longitude latitude)	Probability $>$ 0 cm	Neighborhood	Municipality
⋮	⋮	⋮	⋮	⋮
144553825	POINT (199000 359800)	5	Asselt	Roermond
144553826	POINT (199005 359800)	5	Asselt	Roermond
144553827	POINT (199010 359800)	5	Asselt	Roermond
144553828	POINT (199015 359800)	5	Asselt	Roermond
144553829	POINT (199020 359800)	5	Asselt	Roermond
⋮	⋮	⋮	⋮	⋮

Table 4: Extraction of the dataset including flood probabilities for a flood $>$ 0 cm

4.4.3 Averaging of allocated values per neighborhood

Upon the successful allocation of the appropriate neighborhood and municipality to each set of coordinates, the process continues with the computation of average depth values for each neighborhood. In the case of Asselt, a total of 1476 coordinates were linked to this neighborhood from the depth map. This aggregation leads to an average depth of 0.46 meters, in case of a flood with large probability occurs. Although this might seem low in comparison to the depth map sample exhibited in Table 3, it is important to recognize that the primary flood risk in Asselt is concentrated in the northwestern region of the neighborhood, precisely where the provided sample coordinates are positioned. This association becomes clearly evident when integrating the CBS data layer with the depth map.

The probability map contributed 36970 coordinates to the neighborhood of Asselt. Subsequent to averaging, the probability values are rounded to the nearest integer, effectively representing the most frequent category within the neighborhood. In the case of Asselt, this value amounts to 5, signifying that the probability of a flood occurrence surpassing 0 cm in a given year exceeds 1/30. This conclusion can also be confirmed by combining the CBS data layer and the probability map.

The combination of the CBS data layer with both the depth map (on the left) and the probability map (on the right) is visually demonstrated in Figure 7.

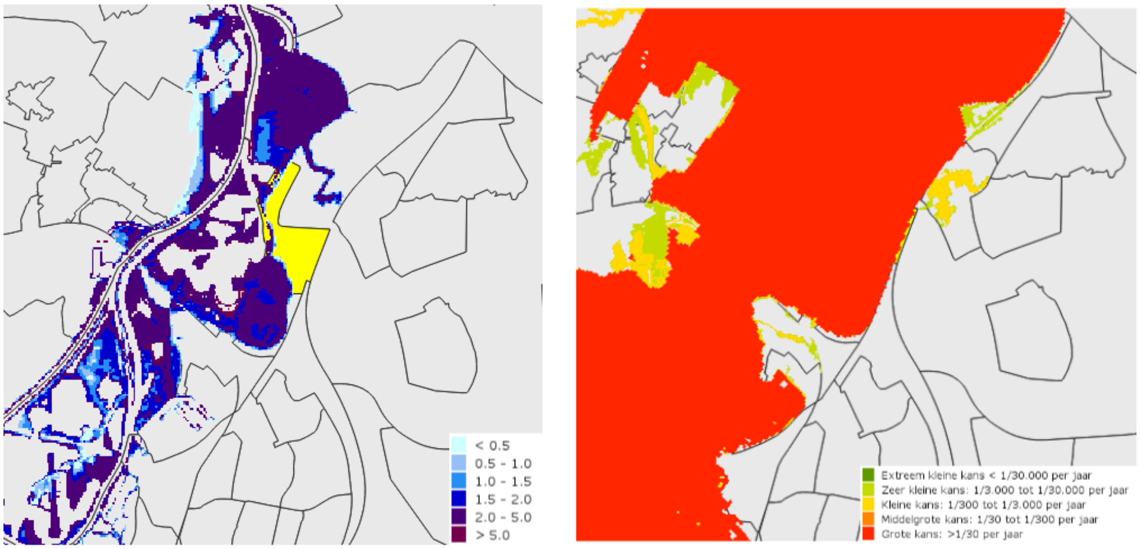


Figure 7: Combination of the CBS map layer with the map layer containing depth levels for a flood with large probability (left) and with the map layer containing the site-specific flood probability with depth greater than 0 cm (right), zoomed in on Asselt

4.4.4 Outlying areas

The process of determining average flood risk values extends to encompass the outlying areas as well. However, these regions lack specific neighborhood designations and are identified as "scattered houses" followed by the name of an adjacent neighborhood. It's worth noting that certain areas might not possess such a neighborhood name if they do not border any particular neighborhood. Moreover, these outlying areas often consist of multiple polygons, which are not necessarily contiguous.

An example is depicted in Figure 8. The map highlights four polygons marked in yellow, corresponding to the outlying areas of the Eijsden-Margraten municipality, situated in the southwestern region of Limburg. It's evident that one polygon does not share a border with the others, and the cumulative area of the outlying region is notably extensive. By way of comparison, the inner grey zones illustrate the neighborhoods within the same municipality, which are considerably smaller in size.

Since the map is combined with the depth map, it can be noted that only a part of the leftmost polygon has a risk of flooding. Consequently, computing average depth values across the entire area would inaccurately represent the actual risk. Additionally, average WOZ-values can be obtained for each of the four polygons individually, and can vary by more than a tonne.

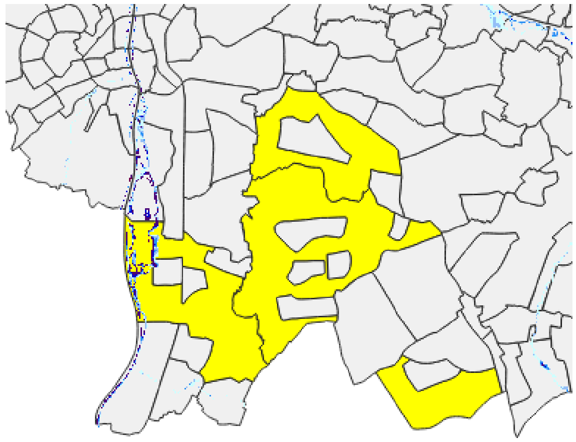


Figure 8: Outlying areas with scatterd houses in the municipality of Eijsden-Margraten

Over the whole data set of Limburg, there are only four cases of these extensive outlying areas. However, due to their size and location, it is important to take them into account properly. The polygons that make up these outlying areas will therefore be included separately. In the example presented in Figure 8, the scattered houses in Eijsden-Margraten are thus assigned to the northern, center, western or south-eastern part. The values obtained from the depth and probability maps are assigned to the corresponding parts and subsequently averaged. Table 5 shows the average values from the depth map for the different polygons. As mentioned before, only a part of the leftmost polygon has a risk of flooding. Hence, only this polygon has a positive average depth probability.

Index	Neighborhood	Municipality	Average depth large probability (m)
757	Scattered houses - Center	Eijsden-Margraten	0.0
759	Scattered houses - North	Eijsden-Margraten	0.0
766	Scattered houses - West	Eijsden-Margraten	0.11
770	Scattered houses - South East	Eijsden-Margraten	0.0

Table 5: Averaged depth values for outlying areas in Eijsden-Margraten, retrieved from the depth map

4.5 Neighborhood-level data

The procedure of associating coordinates with their respective polygons is performed for all coordinates extracted from the depth and probability map. All coordinates falling within the same polygon(s) attributed to a specific neighborhood are averaged, resulting in an average depth value and the most prevalent category from the probability map for each neighborhood. Notably, the depth and probability map represent only a subset of the eight maps acquired from the LIWO data set. Similarly, the process of calculating average depths per neighborhood can be extended to map layers depicting depths for flood scenarios with medium, small, and extremely small probabilities. Likewise, the process of computing the most common probability category per neighborhood can be extended to map layers depicting probabilities for floods with depths of more than 20 cm, 50 cm and 200 cm.

The data covers a total of 910 distinct neighborhoods in Limburg province. Among these, 501 neighborhoods (approximately 55%) exhibit no positive probability of experiencing flooding of one centimeter or more during a flood event, even with a probability as low as 1/100,000. Conversely, the remaining 409 neighborhoods (approximately 45%) display a positive probability of flooding for instances of flood events with a probability of 1/100,000 or higher. Considering the map layers that include probabilities for various flood depth levels, 493 of the 910 neighborhoods (approximately 54%) indicate zero probability of flooding, even by one centimeter. Conversely, the other 417 neighborhoods (approximately 46%) present a likelihood of flooding, at least to a minimal degree of one centimeter.

It is important to acknowledge that during the process of determining the most prevalent probability category, the rounding procedure can potentially result in situations where a neighborhood is assigned to category 0 (indicating zero probability of flooding), even if certain parts of the neighborhood may possess a positive flood probability. Consequently, instances might arise where the calculated average probability falls within the range of 0 to 0.5, yet is still categorized as 1, representing a very low probability of flooding.

In Table 6 the average depth per neighborhoods for the four probability levels is presented for the twenty neighborhoods with the highest depth levels. Table 7 shows the most common probability category corresponding to the four depth levels. Display is limited to the twenty neighborhoods with the highest probability rankings.

Neighborhood	Municipality	Depths under corresponding return periods			
		1/10	1/100	1/1000	1/100000
Verspreide huizen Illikhoven en Visserweert	Echt-Susteren	1.50	2.62	2.93	3.03
Itteren	Maastricht	1.40	1.92	2.27	2.76
Molenbossen	Venlo	1.34	1.94	2.42	2.73
Geulle	Meerssen	1.26	2.27	2.48	2.96
Oud-Bergen Buitengebied	Bergen (L.)	1.10	1.72	2.27	2.83
Maasplassen	Roermond	1.07	1.68	2.00	2.24
Grevenbicht	Sittard-Geleen	0.98	1.63	1.98	2.17
Aijen Buitengebied	Bergen (L.)	0.80	1.35	1.81	2.43
Rijkel	Beesel	0.78	1.19	1.48	1.77
Middelaar Katerbosch en Heikant	Mook en Middelaar	0.75	1.35	1.73	2.90
Meers	Stein	0.74	1.98	2.25	2.42
Noord	Gennep	0.74	1.09	1.33	2.12
Maasveld I	Venlo	0.73	1.12	2.06	2.48
Buitengebied Melick	Roerdalen	0.68	1.18	2.02	2.02
Laak	Maasgouw	0.67	1.21	1.34	1.77
Panoven-Maaskemp	Gennep	0.67	1.16	1.63	2.23
Maaswaard	Venlo	0.66	0.92	1.61	2.02
Maasveld II	Venlo	0.65	0.96	1.75	2.19
Boschpoort	Maastricht	0.64	0.97	1.43	1.62
Eiland-Brandt	Maasgouw	0.61	1.49	1.60	1.70
⋮	⋮	⋮	⋮	⋮	⋮

Table 6: Averaged maximum depth levels per neighborhood for the twenty neighborhoods with the highest depth levels

Neighborhood	Municipality	Probability categories under corresponding depth levels			
		> 0 cm	> 20 cm	> 50 cm	> 200 cm
Maasplassen	Roermond	5	5	5	5
Oud-Bergen Buitengebied	Bergen (L.)	5	5	5	4
Aijen Buitengebied	Bergen (L.)	5	5	5	3
Verspreide huizen Linnerveld en Weerd	Maasgouw	5	5	5	3
Eiland-Brandt	Maasgouw	5	4	4	3
Heugem	Maastricht	5	4	4	3
Maasveld I	Venlo	5	4	4	3
Meers	Stein	5	4	4	3
Middelaar Katerbosch en Heikant	Mook en Middelaar	5	4	4	3
Ool	Roermond	5	4	4	3
Panoven-Maaskemp	Gennep	5	4	4	3
Rijkel	Beesel	5	4	4	3
Stevensweert waaronder Bilt	Maasgouw	5	4	4	3
Voorstad	Roermond	5	4	4	3
Wessem	Maasgouw	5	4	4	3
Buitengebied Aasterberg	Echt-Susteren	5	4	4	2
Geulle	Meerssen	5	4	4	2
Grevenbicht	Sittard-Geleen	5	4	4	2
Itteren	Maastricht	5	4	4	2
Kazerneterrein	Venlo	5	4	4	2
⋮	⋮	⋮	⋮	⋮	⋮

Table 7: Most common probability categories for the twenty neighborhoods with the highest probabilities.

4.6 Uniformly distributed intervals

As indicated previously and as evident from Table 6, the flood probabilities presented in the table are categorized into different probability intervals, clarified in Table 2. Additionally, the depth levels in Table 6 are denoted as threshold values, such as > 0 cm, > 20 cm, > 50 cm, and > 200 cm. To utilize these values effectively in subsequent calculations, a more precise estimation is required, taking into account both the probability intervals and depth thresholds.

To address the depth levels, we consider them as intervals, similar to the probability categories. However, there is a challenge with the highest threshold value, "> 200 cm," as it lacks an upper bound. To transform it into an interval, we must establish an assumption regarding the maximum depth level. An analysis of the data supporting Table 6 reveals that only 25 neighborhoods have an extremely low probability of experiencing flooding exceeding 200 cm. Consequently, it is crucial not to choose an excessively high upper bound, as it may yield unrealistic results in further calculations. Based on the data, the maximum average depth level, as depicted in Table 6, slightly exceeds 300 cm for scattered houses around the neighborhoods Illikhoven and Vissersweert, corresponding to a flood probability of 1/100,000 per year. To provide a conservative estimate, we set the upper bound on the depth level to 400 cm. If X would be a random variable representing the depth in centimeters, then:

- $X > 0\,\text{cm}$: Represents the interval $(0, 20]\,\text{cm}$, which includes values greater than 0 up to and including 20 centimeters.
- $X > 20\,\text{cm}$: Represents the interval $(20, 50]\,\text{cm}$, which includes values greater than 20 up to and including 50 centimeters.
- $X > 50\,\text{cm}$: Represents the interval $(50, 200]\,\text{cm}$, which includes values greater than 50 up to and including 200 centimeters.
- $X > 200\,\text{cm}$: Represents the interval $(200, 400]\,\text{cm}$, which includes values greater than 200 up to and including 400 centimeters.

Considering the probability and depth intervals, it is assumed that within these respective intervals, values are uniformly distributed. This means that between the bounds of the interval, often denoted by a and b describing the minimum and maximum value respectively, all values have constant probability. The mean of the continuous uniform distribution is denoted by $\frac{1}{2}(a + b)$. Considering the intervals for the depth levels as just described above in the four bullet points, the means are 10 cm, 35 cm, 125 cm and 300 cm.

Instead of the category values in Table 7, the mean of the corresponding intervals is calculated and used as an approximation of the probability. However, as was the case concerning the depth thresholds, the probability categories 1 and 5 lack a lower or upper bound. For category 1, it is straightforwardly assumed that the lower bound is 0, as probability values cannot be negative. Determining the upper bound for category 5 is however not so obvious. Setting the upper bound equal to 1 would imply that there is a flood of more that 0 cm every single year, which is a very unrealistic assumption. Considering the fact that the the intervals from category 1 up to category 5 increase by a factor 10 each time, the most logical value for the upper bound would be 1/3, even though this upper bound is still relatively high for most locations. Nonetheless, the top five neighborhoods in Table 6 have an average depth level of more than 1 meter with a probability of 1/10. For this reason, it is possible that with a probability of 1/3 per year, the depth levels in those neighborhoods may still exceed 0 cm. Hence, the upper bound for category 5 is defined as a probability of 1/3 per year. Table 8 shows the new values after the threshold values are changed to the means of the depth intervals and the probability categories are changed to the means of the corresponding probability intervals.

Neighborhood	Municipality	Probabilities under corresponding depth levels			
		10 cm	35 cm	125 cm	300 cm
Maasplassen	Roermond	11/60	11/60	11/60	11/60
Oud-Bergen Buitengebied	Bergen (L.)	11/60	11/60	11/60	11/600
Aijen Buitengebied	Bergen (L.)	11/60	11/60	11/60	11/6000
Verspreide huizen Linnerveld en Weerd	Maasgouw	11/60	11/60	11/60	11/6000
Eiland-Brandt	Maasgouw	11/60	11/600	11/600	11/6000
Heugem	Maastricht	11/60	11/600	11/600	11/6000
Maasveld I	Venlo	11/60	11/600	11/600	11/6000
Meers	Stein	11/60	11/600	11/600	11/6000
Middelaar Katerbosch en Heikant	Mook en Middelaar	11/60	11/600	11/600	11/6000
Ool	Roermond	11/60	11/600	11/600	11/6000
Panoven-Maaskemp	Gennep	11/60	11/600	11/600	11/6000
Rijkel	Beesel	11/60	11/600	11/600	11/6000
Stevensweert waaronder Bilt	Maasgouw	11/60	11/600	11/600	11/6000
Voorstad	Roermond	11/60	11/600	11/600	11/6000
Wessem	Maasgouw	11/60	11/600	11/600	11/6000
Buitengebied Aasterberg	Echt-Susteren	11/60	11/600	11/600	11/60000
Geulle	Meerssen	11/60	11/600	11/600	11/60000
Grevenbicht	Sittard-Geleen	11/60	11/600	11/600	11/60000
Itteren	Maastricht	11/60	11/600	11/600	11/60000
Kazerneterrein	Venlo	11/60	11/600	11/600	11/60000
⋮	⋮	⋮	⋮	⋮	⋮

Table 8: Flood probabilities from the map layers including the site-specific flood probabilities based on uniformly distributed intervals

5 Methodology

Determining an appropriate premium for flood insurance presents a complex challenge. This section outlines various approaches for estimating premiums using the data collected in Section 4. In Section 5.1, premium levels for each neighborhood within the framework of a voluntary flood insurance program are calculated. The premium estimates must be sufficient to cover the anticipated damage for each neighborhood individually, as determined by the previously acquired depth levels and probabilities (Tables 6 and 7). To identify the underlying data patterns more effectively, a distribution fitting process is employed on the discrete data behind Table 6 that includes the average maximum depth levels per neighborhood. Subsequently, premium estimates are calculated based on the newly acquired probability levels, derived from the fitted distribution. The consideration of mandatory flood insurance becomes relevant due to concerns related to adverse selection[14] or the possibility of excessively high premiums. Therefore, Section 5.3 explores a more solidarity-oriented flood insurance model, featuring a flat-rate premium structure that allocates flood risk not only across households with positive flood risk but across all households in the province of Limburg. Lastly, in Section 5.4 the premium estimates are calculated based on a simulation approach that evaluates a one year flooding scenario that accounts for the fact that not all neighborhoods will experience flooding during a flood event.

As described in the preceding section, the values associated with geographical coordinates from each flood risk map layer are attributed to the neighborhoods within the province of Limburg. This process yields data sets encompassing 910 distinct neighborhoods, upon which all subsequent calculations in this section are based. As the map layers illustrating the site-specific flood probabilities with inundation depths exceeding 0, 20, 50, or 200 centimeters initially employ both probability and depth intervals (Figure 4), the accuracy of the data behind these map layers is rather low. Conversely, the map layers depicting the maximum inundation depths based on four probability levels offer greater accuracy and thus serve as a premise for all subsequent calculations. The data set containing the site-specific flood probabilities will be exclusively utilized in the subsequent section, particularly for computing premium estimates within the framework of the voluntary flood insurance model. The results derived from this data set will solely serve as a comparison to the primary model.

The estimation of the expected damage relies on the depth-damage curves elucidated in Section 3. Besides the curves from Huizinga et al. (2017), the curves from Endendijk et al. (2023) (Figure 2) have proven to be especially relevant to this research due to their close alignment with the data at hand. Furthermore, the distinction that is made by Endendijk et al. (2023) between damage to building structures and damage to household contents represents a significant enhancement to this thesis. Given that this research exclusively relies on the WOZ-value of residences as a measure of

[14] Adverse selection refers to the tendency of high-risk individuals obtaining insurance or when one negotiating party has valuable information another lacks (asymmetric information). For flood insurance, this occurs when especially individuals in areas with high flood risk purchase insurance and the insurance company has difficulties with charging appropriate premiums to higher or lower risk individuals due to asymmetric information.

exposure, it is more fitting to employ damage curves that specifically represent the damage-factor associated with building structures.

As a consequence, all premium calculations incorporate the obtained depth-damage curves from Endendijk et al. (2023). The calculations encompass the depth-damage curve assuming no FDM measures (denoted in red), as well as two variations considering either structural (blue) or emergency (green) FDM measures. Also, an average curve is computed, which does not differentiate between the adoption of FDM measures. For comparative purposes, the premiums are also estimated based on the depth-damage curve for the Netherlands from Huizinga et al. (2017) (Figure 1).

5.1 Voluntary flood insurance model

In order to determine a first estimate of the premium for flood insurance, a formula based on the Climate Risk Insurance Model (CRIM) from Aerts and Botzen (2011) is used. Aerts and Botzen (2011) calculated a premium for each dike ring area in the Netherlands including different climate change scenario's. In this thesis, the model is used as a starting point in order to determine an estimate of the premium for each neighborhood in the province of Limburg. The formula in order to determine the premium in the CRIM is as follows:

$$\text{premium}_{it} = \frac{l \cdot h \cdot \text{total expected damage}_{it}}{\text{total houses}_{it}} \cdot \text{flood probability}_{it} \tag{1}$$

Where i represents a dike-ring area, with a total of $I = 53$ and t is the time in years. In this equation, l represents the premium loading factor. When $l > 1$, a surcharge is added to the premium in order to cover administrative or transaction costs and an economic return for insurance companies. For now, the loading factor is assumed to be equal to 1 by which the premiums are actuarially fair. h signifies the proportion of the overall anticipated damage attributed to residential properties. When this proportion is divided by the total number of houses, it yields an estimation of the expected damage to an individual residence.

Given the absence of empirical data on the total expected amount of damage after a flood event for each neighborhood in Limburg, the methodology employed for calculating the expected damage for each household should be adapted. In contrast to the approach taken in the Climate Risk Insurance Model from Aerts and Botzen (2011), the method in this thesis computes the damage incurred by an individual residence by employing depth-damage functions applied to the average WOZ-value for each neighborhood. This adjustment in the calculation of expected damage results in a modified CRIM formula, which is expressed as follows:

$$\text{premium}_i = l \cdot \text{WOZ-value}_i \cdot \sum_d \text{flood probability}_{i,d} \cdot \text{damage factor}(d) \tag{2}$$

In this equation i represents a neighborhood with a total of $I = 910$. The time element is left out because the data is only based on the current climate. The damage factors are determined for the averaged maximum depth levels per neighborhood as obtained from Table 6. From the depth-damage curves from Endendijk et al. (2023) and Huizinga et al. (2017), the damage factors corresponding to each depth level can be retrieved. In Equation (2), the product of the damage factor and the WOZ-value signifies the expected damage per residence within a given neighborhood in the event of a flood with depth level d. By subsequently multiplying the expected damage with the probability of such a flood event and adding the results for each neighborhood, an estimation of the annual premium is found.

Specifying Equation (2) to the generated data set that includes the average maximum depth levels per neighborhood for four probability levels, leads to Equation (3). In Equation (3), the dependent variable $PE(i)$ signifies the premium estimate for neighborhood i. The vector $p(j)$ is a column vector that delineates the four probabilities associated with the specified depth levels. To be explicit, $p(j) = [0.1, 0.01, 0.001, 0.0001]'$. The matrix $DF(j, i)$ is used to represent the calculated damage factors derived from the corresponding depth-damage curve for each depth level of each neighborhood. Given that four distinct depth-damage curves are utilized in the computations, the calculations are executed four times, each time incorporating different damage factors in matrix $DF(j, i)$. Lastly, $W(i)$ is a column vector containing the average WOZ-values for each neighborhood.

$$PE(i) = W(i) \cdot \sum_{j=1}^{N=4} p(j) \cdot DF(j, i) \tag{3}$$

When applying Equation (2) to the generated data set containing probabilities determined by uniformly distributed intervals, it yields Equation 4. It is noteworthy that this equation bears similarities to Equation (3). Nevertheless, in this scenario, four specific depth levels are established, each with corresponding probabilities. The column vector $DF(j)$ contains four distinct damage factors, each associated with the defined depth levels. These damage factors are contingent upon the use of different depth-damage curves. As a result, the calculation is carried out four times to determine premium estimates based on these various depth-damage curves. $p(j, i)$ denotes a matrix that contains the probabilities that correspond to each of the damage factors for each neighborhood.

$$PE(i) = W(i) \cdot \sum_{j=1}^{N=4} DF(j) \cdot p(j, i) \tag{4}$$

5.2 Distribution fitting

The equations for determining the premium estimates as described in the previous section, consider the discrete depth and probability values as denoted in Table 6. In order to better represent the underlying data and to predict the probability of the magnitude of a flood in a certain interval, a distribution is fitted to the data. The principle behind fitting distributions to data is to find the type of distribution and the value of the parameters that give the highest probability of producing the observed data (Vose, 2010).

To see which distribution best fits the data, a visual comparison is a good start. However Vose (2010) also states that, particularly for small data sets, the data pattern will not usually look like the same pattern one would see when the data set was large. Also, it is important to consider the properties of the fitted distribution in terms of range and skewness. Based on the discrete data from Table 6, a lognormal distribution is considered to potentially fit the data well. Since a random variable that is log-normally distributed only takes on positive real values, it aligns well with the context of flood risk analysis where negative depth levels are nonexistent. Additionally, the observed pattern in the data, where lower depth levels have a higher probability of occurring, while higher depth levels have a lower probability of occurring, corresponds to the behavior of a lognormal distribution. The lognormal distribution is known for concentrating a significant portion of its probability mass at smaller values and gradually extending to larger values in the right tail.

The lognormal distribution is calibrated to the data set using a least-squares fit under two mild assumptions. The first assumptions is that the zero values in the data set are replaced by very small depth values of 0.0001. The reason for this is that the lognormal distribution only takes on positive values. Increasing the zero values to 0.0001 has little to no effect on the final premium estimates. The second assumption is that the maximum flood depth is set to 4 meters.

The main objective of the calibration process is to estimate the parameters μ and σ for the standard normal cumulative distribution function (CDF) that provide the best fit to the given data set. The algorithm iterates over the columns of matrix $D(j, i)$, that contains the depth levels for each neighborhood i corresponding to the probabilities in vector $p(j)$, as previously defined. Distribution fitting is restricted to neighborhoods with a positive flood risk. Consequently, the total number of neighborhoods considered in this calculation amounts to $I = 409$.

For each neighborhood, a goal function is defined to quantify the discrepancy between the empirical data and the standard normal CDF. The optimization aims to minimize the squared differences between the CDF values for the data and the desired probabilities denoted by the vector $\mathbf{p} = [0.1, 0.01, 0.001, 0.0001]'$. To initiate the optimization process, the algorithm provides an initial guess for the parameters μ and σ of the standard normal CDF, and sets a lower bound for σ to prevent negative values.

The goal function computes the cumulative distribution function (CDF) values for two sets of adjacent data points extracted from the data set $D(j, i)$. The parameters $x(1)$ and $x(2)$ represent the μ and σ of the standard normal CDF, respectively. By taking the difference between the

CDF values of these two sets, the algorithm determines the change in CDF values. Furthermore, it quantifies the extent to which the CDF values of neighboring data points match the desired probabilities by subtracting the initial probabilities in vector $p(j)$. The goal function then squares these differences and sums them up to provide an overall measure of the discrepancy between the empirical data and the standard normal CDF for that specific neighborhood. The calibration process aims to find the values of μ and σ that minimize this discrepancy for each neighborhood in the data set D.

$$x_i = \sum_{j=1}^{N=4} \left(\left(\Phi\left(\frac{(\ln(D(j+1,i)) - x(1))}{x(2)} \right) - \Phi\left(\frac{(\ln(D(j,i)) - x(1))}{x(2)} \right) - p(j) \right)^2 \right) \tag{5}$$

In which $\Phi(\cdot)$ is equal to the standard normal cumulative distribution function

$$\Phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \tag{6}$$

Inserting the optimized values for μ and σ into equation (7) returns a matrix including the flood probabilities based on the fitted distributions. In contrast to the probabilities denoted earlier by $p(j)$, these probabilities are now specified for each neighborhood separately and stored in matrix $P(j,i)$.

$$P(j,i) = \Phi\left(\frac{(\ln(D(j+1,i)) - \mu_i}{\sigma_i} \right) - \Phi\left(\frac{(\ln(D(j,i)) - \mu_i}{\sigma_i} \right) \tag{7}$$

To calculate the premium estimates based on the fitted distribution, matrix $P(j,i)$ is multiplied element-wise with matrix $DF(j,i)$ containing the damage factors corresponding to the depth values in matrix $D(j,i)$. Then, for each neighborhood, the entries are multiplied with column vector $W(i)$ containing the average WOZ-values for each neighborhood.

$$PE(i) = W(i) \cdot \sum_{j=1}^{N=4} P(j,i) \cdot DF(j,i) \tag{8}$$

5.3 Flat-rate premium

When insurance against flood risk becomes voluntary, the problem of adverse selection potentially arises. Possibly, only the households that face a higher risk of being flooded will purchase flood insurance, and to fight this adverse selection, insurance companies will try to reduce exposure to large claims by limiting coverage or raising premiums. Based on the principle of solidarity, the introduction of a flat-rate premium for households that live in areas with no flood risk, would contribute to the success of a flood arrangement compensating flood damage. Individuals who live in those low-risk areas will also benefit from flood insurance if it ensures that indirect damage such as the disruption of economic activities is quickly recovered (Aerts and Botzen, 2011; Bockarjova, 2007). Introducing a flat-rate premium for households in low-risk areas serves to augment the overall capital pool designated for flood damage coverage. This additional premium income can be used to take the burden off the households in high-risk areas by reducing their premium estimates. In the context of calculating premium estimates following the introduction of a flat-rate premium, neighborhoods are categorized into two groups: those with pre-existing premium estimates exceeding the flat rate (denoted by n_1), and those with premium estimates equal to or less than the flat-rate premium (denoted by n_2). These two subsets encompass the entire set of neighborhoods, where $n_1 + n_2 = N = 910$. To effectively redistribute the surplus premium income, the disparities between the flat rate and the premium estimates of neighborhoods within the n_2 category are aggregated. The resulting sum is then multiplied by the corresponding number of households in each neighborhood ($h(i)$), yielding the total amount (T) available for redistribution among neighborhoods with higher premium estimates (n_1). The calculation of T is depicted in Equation (9) in which FR denotes the flat-rate and $PE(i)$ the premium estimate before redistribution for neighorhood i:

$$T = \sum_{i=1}^{n_2} (\mathrm{FR} - PE(i)) \cdot h(i) \tag{9}$$

To ensure a fair and proportionate deduction, the concept of a deduction ratio (R) is introduced for each neighborhood within the n_1 category. This ratio represents the share of the total deduction (T) that is assigned to a specific neighborhood. Equation (10) shows the computation of this deduction ratio:

$$R(i) = \frac{PE(i) \cdot h(i)}{\sum_{i=1}^{n_1} PE(i) \cdot h(i)} \tag{10}$$

The initial premium estimate for a neighborhood ($PE(i)$) is now lowered by deducting the product of the deduction ratio ($R(i)$) and the total deduction (T), followed by normalization relative to the number of households ($h(i)$) in the respective neighborhood. The equation is captured by:

$$PE(i) = PE(i) - \frac{R(i) \cdot T}{h(i)} \tag{11}$$

It is possible that the deduction process may lead to premium estimates falling below the designated flat rate. In such cases, a new division is made between the neighborhoods exceeding the flat rate and those with premium estimates equal to or below it. This initiates a renewed cycle of redistributing the surplus premium income, continuing the iterative process as necessary.

5.4 Historical simulation

The premium estimates derived from the preceding model frameworks may exhibit a degree of disparity with reality, as not all neighborhoods that have a positive risk of flooding are inundated during a flood event. Consequently, there exists the potential for the aggregate premium income to surpass the damage in monetary values incurred by such a flood event. To address this problem and to further expand the solidarity principle described in the previous section, a simulation technique is applied. This historical simulation technique is used to calculate the expected damage for one year in the future based on the known probability and depth levels of Table 6, and distributes the total amount amongst all households in the province of Limburg.

Utilizing the probabilities from Table 6, it is possible to construct an array comprising 100,000 entries for each neighborhood. All entries within this array have an equal probability of occurrence. However, the cardinality of entries assuming specific depth values is contingent upon the associated probabilities corresponding to those particular depth levels, as indicated by the table. Hence, for each neighborhood, only one of the 100,000 entries attains the highest depth value as is obtained from the last column of Table 6. 100 entries mirror the depth level linked with a probability of 1/1,000, 1,000 entries contain the depth level aligned with a probability of 1/100, and 10,000 entries corresponds to the depth level associated with a probability of 1/10. The residual subset of entries, indicating the absence of inundation, is characterized by zero values, representing cases where flooding is not present.

The historical simulation involves the generation of an extensive set of samples from the previously outlined array for each distinct neighborhood. When extracting a random value, in approximately 90% of the cases, the resultant outcome is anticipated to be zero. However, certain scenarios yield positive depth values. For this reason, only a few neighborhoods obtain a positive depth value in each iteration. For each extracted depth value, the corresponding damage factor is determined and multiplied with the average WOZ-value of the corresponding neighborhood. This process is conducted for all extracted depth values, leading to a definition of anticipated damages specific to each individual neighborhood within the simulated scenario. The summation of these expected damages yields the aggregate projection of one-year total expected damage for one iteration. By iteratively sampling multiple instances from the arrays, the technique effectively predicts the potential occurrence of a flooding event in the forthcoming year, along with its corresponding expected damage. Subsequently, with a substantial number of iterations, the computed average of all outcomes serves as the projection for the total expected damage over a one-year time frame. Algorithm 1 shows some pseudo-code that describes the historical simulation that is applied to the constructed arrays.

Algorithm 1: Historical simulation

Data: EstimatedIterations

Result: averageTotalExpectedDamage

```
Initialize an array with 100,000 entries based on probabilities;
totalExpectedDamagesList ← [];
for iteration ← 1 to EstimatedIterations do
    totalExpectedDamage ← 0;
    extractedDepthValues ← [];
    for neighborhood in distinctNeighborhoods do
        randomValue ← randomly select a value from the array;
        add randomValue to extractedDepthValues;
    end
    for depthValue in extractedDepthValues do
        damageFactor ← calculate_damage_factor(depthValue);
        neighborhoodWOZValue ← get_average_WOZ_value(neighborhood);
        anticipatedDamage ← damageFactor × neighborhoodWOZValue;
        totalExpectedDamage ← totalExpectedDamage + anticipatedDamage;
    end
    add totalExpectedDamage to totalExpectedDamagesList;
end
averageTotalExpectedDamage ← sum of totalExpectedDamagesList / EstimatedIterations;
```

Result: averageTotalExpectedDamage

6 Results

The premium estimates in this section are obtained after applying the models from the previous section to the generated data sets including the average maximum depth levels per neighborhood and the site-specific flood probabilities based on uniformly distributed intervals, as presented in Section 4. In the equations, four different depth-damage curves are used in order to calculate the premium estimates. the curve for the Netherlands from Huizinga et al. (2017) (Figure 1) is utilized as well as the curves from Endendijk et al. (2023) (Figure 2) that consider no FDM measures, structural FDM measures and emergency FDM measures. Moreover, a premium estimate is calculated based on an average of the three curves from Endendijk et al. (2023) referring to the case where no differentiation is made between the adoption of FDM measures. Each table in this section, including premium estimates, presents the estimations for the twenty neighborhoods with the highest estimated values.

Section 6.1 presents premium estimates for the data set comprising average maximum depth levels per neighborhood after applying the voluntary flood insurance model. Section 6.2 discusses the results when applying the model to the data set containing site-specific flood probabilities, offering a comparison with the outcomes in Section 6.1. Sections 6.3, 6.4 and 6.5 delve further into results based on the data set with average maximum depth levels per neighborhood. Section 6.3 covers premium estimates following the fitting of a lognormal distribution. Section 6.4 introduces flat-rate premiums, and Section 6.5 outlines results derived from the application of a historical simulation.

6.1 Primary premium estimates

For each depth level in the data set that is behind Table 6, the damage-factors are determined based on the four different depth-damage curves. Table 9 shows an example of how the depth levels are transformed to the damage factors, subject to the depth-damage curve (denoted in red) from Figure 2 that does not include FDM measures. The last column includes the average WOZ-values per neighborhood.

Neighborhood	Municipality	Damage factors				WOZ-value
		1/10	1/100	1/1000	1/100000	
Maasplassen	Roermond	0.394	0.431	0.450	0.464	486000
Genooy	Venlo	0.332	0.378	0.417	0.437	494000
Panoven-Maaskemp	Gennep	0.357	0.400	0.428	0.464	450000
Gebied Patersweg	Venlo	0.319	0.376	0.398	0.412	491000
Looierheide	Gennep	0.305	0.343	0.370	0.385	493000
Meuleveld	Venlo	0.345	0.378	0.390	0.397	436000
Noord	Gennep	0.364	0.395	0.410	0.457	390000
Verspreide huizen ten zuiden van Baarlo	Peel en Maas	0.289	0.318	0.342	0.356	485000
Verspreide huizen Hout-Blerick	Venlo	0.289	0.343	0.358	0.395	478000
Ool	Roermond	0.316	0.351	0.471	0.493	439000
Hasselt en Het Vorst	Venlo	0.306	0.372	0.417	0.436	446000
Bloemenstraat-Zwarteweg	Gennep	0.293	0.309	0.349	0.432	468000
Geulle	Meerssen	0.405	0.466	0.479	0.498	334000
Hout en Oijen	Peel en Maas	0.308	0.370	0.397	0.417	430000
Middelaar Katerbosch en Heikant	Mook en Middelaar	0.365	0.411	0.434	0.496	364000
Buitengebied Vlodrop	Roerdalen	0.280	0.294	0.324	0.324	477000
Verspreide huizen Kesseleik	Peel en Maas	0.290	0.304	0.311	0.318	460000
Heijensebos	Gennep	0.304	0.333	0.356	0.380	427000
Verspreide huizen Buggenum	Leudal	0.313	0.394	0.417	0.438	405000
Verspreide huizen Swalmen	Roermond	0.314	0.341	0.352	0.363	410000
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 9: Damage factors and WOZ-values per neighborhood for the twenty neighborhoods with the highest premium estimates. Damage factors are based on the depth-damage curve from Figure 2 that considers no FDM measures (red curve).

Applying Equation (3), as denoted in the previous section, to the data set containing the averaged maximum depth levels per neighborhood, yields the premium estimates presented in Table 10. The first three columns present the estimates based on taking no FDM measures, structural FDM measure and emergency FDM measures obtained from the depth-damage curves of Endendijk et al. (2023). The premium estimates in the fourth column are based on an average curve which does not differentiate between the adoption of FDM measures. Lastly, the fifth column encompasses premium estimates based on the depth-damage curve specific to the Netherlands, as obtained from Huizinga et al. (2017).

Neighborhood	Municipality	Premium no FDM	Premium structural FDM	Premium emergency FDM	Premium average curve	Premium (Huizinga et al., 2017)
Maasplassen	Roermond	21473.32	9604.11	5849.86	12309.10	4604.46
Genooy	Venlo	18467.86	6470.60	2699.21	9212.56	2609.51
Panoven-Maaskemp	Gennep	18070.66	7080.65	3585.09	9578.80	3153.49
Gebied Patersweg	Venlo	17683.26	5867.35	2227.32	8592.64	2146.17
Looierheide	Gennep	16932.43	5176.49	1629.73	7912.88	1617.68
Meuleveld	Venlo	16866.94	6218.86	2830.83	8638.88	2666.52
Noord	Gennep	15885.07	6360.40	3329.87	8525.11	2865.76
Verspreide huizen ten zuiden van Baarlo	Peel en Maas	15718.61	4305.17	967.70	6997.16	967.30
Verspreide huizen Hout-Blerick	Venlo	15619.69	4353.28	1046.29	7006.42	1037.19
Ool	Roermond	15607.71	5061.41	1832.66	7500.59	1800.39
Hasselt en Het Vorst	Venlo	15487.12	4848.87	1637.22	7324.40	1566.84
Bloemenstraat-Zwarteweg	Gennep	15307.13	4271.09	1027.97	6868.73	1026.16
Geulle	Meerssen	15258.06	7079.59	4520.92	8952.86	3562.70
Hout en Oijen	Peel en Maas	15001.05	4729.83	1618.76	7116.55	1557.64
Middelaar Katerbosch en Heikant	Mook en Middelaar	14946.60	6056.91	3230.06	8077.86	2751.63
Buitengebied Vlodrop	Roerdalen	14918.15	3783.00	590.62	6430.59	590.62
Verspreide huizen Kesseleik	Peel en Maas	14894.74	4071.73	908.42	6624.96	908.42
Heijensebos	Gennep	14553.83	4387.17	1330.70	6757.23	1327.85
Verspreide huizen Buggenum	Leudal	14456.95	4745.53	1778.00	6993.49	1680.34
Verspreide huizen Swalmen	Roermond	14409.12	4575.01	1568.01	6850.71	1564.70
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 10: Premium estimates per neighborhood for the twenty neighborhoods with the highest premium estimates based on the map layers including the maximum depth levels. The estimates are based on the four different depth-damage curves including an average of the three curves from Endendijk et al. (2023) by which no differentiation is implied between FDM measure adoption.

Given that the depth values provided in Table 6 signify the maximum inundation depths in the event of a flood, determining insurance premiums based on these values might result in unrealistically high costs for policyholders. To align these premiums with more realistic scenarios, an adjustment is necessary. It is assumed that by reducing the premium values by 50%, they will better correspond to the average flood depth levels that can be expected during flood events. The adjusted premium estimates, reflecting this correction, are presented in Table 11.

Neighborhood	Municipality	Premium no FDM corrected	Premium structural FDM corrected	Premium emergency FDM corrected	Average Premium corrected	Premium (Huizinga et al., 2017) corrected
Maasplassen	Roermond	10736.66	4802.06	2924.93	6154.55	2302.23
Genooy	Venlo	9233.93	3235.30	1349.60	4606.28	1304.76
Panoven-Maaskemp	Gennep	9035.33	3540.32	1792.54	4789.40	1576.74
Gebied Patersweg	Venlo	8841.63	2933.68	1113.66	4296.32	1073.08
Looierheide	Gennep	8466.22	2588.24	814.86	3956.44	808.84
Meuleveld	Venlo	8433.47	3109.43	1415.42	4319.44	1333.26
Noord	Gennep	7942.54	3180.20	1664.94	4262.56	1432.88
Verspreide huizen ten zuiden van Baarlo	Peel en Maas	7859.30	2152.58	483.85	3498.58	483.65
Verspreide huizen Hout-Blerick	Venlo	7809.84	2176.64	523.14	3503.21	518.60
Ool	Roermond	7803.86	2530.70	916.33	3750.30	900.20
Hasselt en Het Vorst	Venlo	7743.56	2424.44	818.61	3662.20	783.42
Bloemenstraat-Zwarteweg	Gennep	7653.56	2135.54	513.98	3434.36	513.08
Geulle	Meerssen	7629.03	3539.80	2260.46	4476.43	1781.35
Hout en Oijen	Peel en Maas	7500.52	2364.92	809.38	3558.27	778.82
Middelaar Katerbosch en Heikant	Mook en Middelaar	7473.30	3028.46	1615.03	4038.93	1375.82
Buitengebied Vlodrop	Roerdalen	7459.08	1891.50	295.31	3215.30	295.31
Verspreide huizen Kesseleik	Peel en Maas	7447.37	2035.86	454.21	3312.48	454.21
Heijensebos	Gennep	7276.92	2193.58	665.35	3378.62	663.92
Verspreide huizen Buggenum	Leudal	7228.48	2372.76	889.00	3496.75	840.17
Verspreide huizen Swalmen	Roermond	7204.56	2287.50	784.00	3425.35	782.35
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 11: Corrected premium estimates per neighborhood for the twenty neighborhoods with the highest premium estimates based on the map layers including the maximum depth levels. The estimates are based on the four different depth-damage curves including an average of the three curves from Endendijk et al. (2023) by which no differentiation is implied between FDM measure adoption.

The corrected premium estimates represent the annual premium that households residing in the specific neighborhoods should pay to safeguard their residences against the expected damage. Table 11 reveals a notable dependence of these premium estimates on the choice of depth-damage curves. Comparatively, it appears that the curve for the Netherlands sourced from Huizinga et al. (2017) tends to underestimate the extent of damage, particularly considering that it includes damage to household contents. Moreover, it is evident that the implementation of FDM measures significantly reduces the projected damage, which is reflected in the premium outcomes.

6.2 Premium estimates based on uniformly distributed intervals

Table 12 shows the flood probabilities based on uniformly distributed intervals. This table closely resembles Table 8, with the difference being that in this table, the headers represent the damage factors. The damage factors correspond to the depth levels based on the depth-damage curve (denoted in red) from Figure 2 that does not include FDM measures. The last column of the table presents the average WOZ-values for each neighborhood.

Neighborhood	Municipality	Probabilities				WOZ-value
		0.28	0.3175	0.405	0.5	
Maasplassen	Roermond	11/60	11/60	11/60	11/60	486000
Oud-Bergen Buitengebied	Bergen (L.)	11/60	11/60	11/60	11/600	251000
Aijen Buitengebied	Bergen (L.)	11/60	11/60	11/60	11/6000	278000
Verspreide huizen Linnerveld en Weerd	Maasgouw	11/60	11/60	11/60	11/6000	262000
Panoven-Maaskemp	Gennep	11/60	11/600	11/600	11/6000	450000
Ool	Roermond	11/60	11/600	11/600	11/6000	439000
Middelaar Katerbosch en Heikant	Mook en Middelaar	11/60	11/600	11/600	11/6000	364000
Eiland-Brandt	Maasgouw	11/60	11/600	11/600	11/6000	345000
Voorstad	Roermond	11/60	11/600	11/600	11/6000	335000
Rijkel	Beesel	11/60	11/600	11/600	11/6000	331000
Geulle	Meerssen	11/60	11/600	11/600	11/60000	334000
Maasveld II	Venlo	11/60	11/600	11/600	11/60000	326000
Kazerneterrein	Venlo	11/60	11/600	11/600	11/60000	312000
Genooy	Venlo	11/600	11/600	11/600	11/60000	494000
Maasband	Stein	11/60	11/600	11/600	11/60000	289000
Itteren	Maastricht	11/60	11/600	11/600	11/60000	285000
Stevensweert waaronder Bilt	Maasgouw	11/60	11/600	11/600	11/6000	262000
Maasveld I	Venlo	11/60	11/600	11/600	11/6000	256000
Well-West	Bergen (L.)	11/60	11/600	11/600	11/60000	275000
Kern Arcen	Venlo	11/60	11/600	11/600	11/60000	272000
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 12: Site specific flood probabilities per neighborhood for the twenty neighborhoods with the highest premium estimates, based on uniformly distributed intervals. The headers show the damage-factors based on the depth-damage curve from Figure 2 that considers no FDM measures (red curve).

Table 13 presents premium estimates derived from applying Equation (4) to the generated data set incorporating site-specific flood probabilities determined through uniformly distributed intervals. Due to the lack of preciseness in the data, the results exhibit significant variability, including large outliers. Especially when considering the premium estimates based on the depth-damage curves proposed by Endendijk et al. (2023), the values are observed to be more than tenfold higher than those obtained based on the data set containing average maximum depth levels per neighborhood (Table 11). This substantial discrepancy is primarily attributed to the excessive weighting placed on the highest depth level, resulting in values that are highly unrealistic due to their extreme magnitude.

Upon reviewing Table 7, it is notable that the neighborhood Maasplassen is unique in receiving the highest category value for the most extreme depth level. Assuming uniformly distributed intervals, this designation corresponds to a probability of 11 out of 60 for experiencing a flood with an inundation depth of three meters as could be observed from Table 8. In the context of return periods, this suggests that such an extreme flood event could potentially occur approximately every six years. This particular scenario, as derived from the data set containing site-specific flood probabilities, yields premium estimates of exceptionally high magnitudes. It also underscores a critical limitation intrinsic to this data set, as the likelihood of such a scenario materializing is considered highly improbable.

Neighborhood	Municipality	Premium no FDM	Premium structural FDM	Premium emergency FDM	Average Premium	Premium (Huizinga et al., 2017)
Maasplassen	Roermond	133872.75	56689.88	32967.00	74509.88	31630.50
Oud-Bergen Buitengebied	Bergen (L.)	48432.54	17681.90	8329.02	24814.49	7224.62
Aijen Buitengebied	Bergen (L.)	51348.92	18299.58	8261.70	25970.06	6992.63
Verspreide huizen Linnerveld en Weerd	Maasgouw	48393.58	17246.37	7786.20	24475.38	6590.17
Panoven-Maaskemp	Gennep	29473.12	8367.56	2235.75	13358.81	2037.75
Ool	Roermond	28752.67	8163.02	2181.10	13032.26	1987.94
Middelaar Katerbosch en Heikant	Mook en Middelaar	23840.48	6768.43	1808.47	10805.80	1648.31
Eiland-Brandt	Maasgouw	22596.06	6415.13	1714.08	10241.76	1562.28
Voorstad	Roermond	21941.10	6229.19	1664.39	9944.89	1516.99
Rijkel	Beesel	21679.12	6154.81	1644.52	9826.15	1498.88
Geulle	Meerssen	21600.06	6056.28	1543.69	9733.34	1391.22
Maasveld II	Venlo	21082.69	5911.22	1506.72	9500.21	1357.90
Kazerneterrein	Venlo	20177.30	5657.37	1442.01	9092.23	1299.58
Genooy	Venlo	9124.59	3251.80	1468.09	4614.82	1242.57
Maasband	Stein	18689.87	5240.32	1335.71	8421.97	1203.78
Itteren	Maastricht	18431.19	5167.79	1317.22	8305.40	1187.12
Stevensweert waaronder Bilt	Maasgouw	17159.91	4871.78	1301.70	7777.80	1186.42
Maasveld I	Venlo	16766.93	4760.21	1271.89	7599.68	1159.25
Well-West	Bergen (L.)	17784.48	4986.46	1271.00	8013.98	1145.47
Kern Arcen	Venlo	17590.47	4932.06	1257.14	7926.56	1132.97
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 13: Premium estimates per neighborhood for the twenty neighborhoods with the highest premium estimates based on the map layers including site-specific flood probabilities. The probabilities are obtained using uniformly distributed intervals and the estimates are based on the four different depth-damage curves including an average of the three curves from Endendijk et al. (2023) by which no differentiation is implied between FDM measure adoption.

Table 14 provides summary statistics for the premium estimates based on the averaged depth levels (Table 11) and those based on the site specific flood probabilities (Table 12). While the calculated means of the premium estimates of the two different data sets are somewhat close to each other, the median for the estimates based on the data set including the site-specific flood probabilities is considerable lower. This difference is further illustrated in Figure 9, which presents a comparison of the premium estimate distributions when no distinction is made between the adoption of FDM measures. It's worth highlighting that within the data set featuring probability intervals, despite the generation of exceptionally high premium estimates for select neighborhoods, more than half of the neighborhoods with positive flood probabilities are categorized within the lowest probability range, resulting in considerably low premium outcomes. This is immediately apparent from the substantial peak just above the zero value in the right graph of Figure 9. In contrast, the distribution of the premium estimates based on the averaged maximum depth levels shows a more gradual increase, as can be observed from the left graph of Figure 9. Appendix section (A.2) contains the four other graphs illustrating the comparisons of premium estimates based on no FDM measures, structural FDM measures, emergency FDM measures and the depth-damage curve from Huizinga et al. (2017).

Averaged maximum depth levels	Mean	Median	St. Dev.
Premium no FDM	2191.04	914.08	2497.22
Premium structural FDM	667.53	270.72	836.02
Premium emergency FDM	215.11	47.1	386.29
Average premium	1024.56	418.91	1212.66
Premium Huizinga et al. (2017)	197.80	47.1	334.63
Site-specific flood probabilities	Mean	Median	St. Dev.
Premium no FDM	3133.36	8.69	9617.42
Premium structural FDM	929.95	3.68	3488.98
Premium emergency FDM	286.56	2.04	1780.48
Average premium	1449.96	4.84	4894.44
Premium Huizinga et al. (2017)	264.18	1.98	1679.33

Table 14: Summary statistics for premium estimates per neighborhood based on different data sets and different depth-damage curves. The upper part of the table refers to the data set including the averaged maximum depth levels per neighborhood. The lower part of the table refers to the data set containing the site-specific flood probabilities.

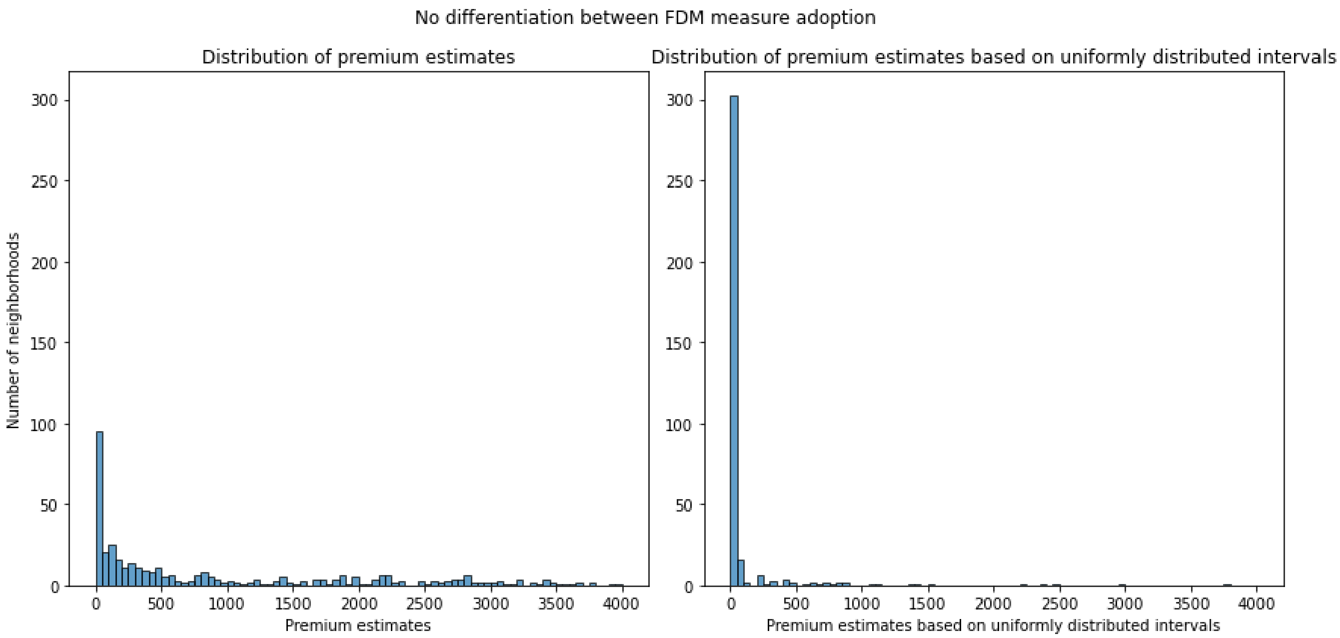


Figure 9: Distribution of primary premium outcomes (left) compared to the distribution of the outcomes based on the uniformly distributed intervals (right), considering no differentiation between FDM measure adoption

6.3 Premium estimates based on fitted lognormal distributions

Table 15 presents the premium estimates obtained after calibrating the lognormal distribution to the data set including the averaged maximum depth levels per neighborhood. Just as the primary premium estimates, a correction of 50% is applied to the results. The outcomes based on the calibrated lognormal distributions generally align closely with the primary premium estimates. Figure 10 presents a visual representation of this comparison for the average depth-damage curve that assumes no differentiation between the adoption of FDM measures. It is evident that, in certain instances, the fit provided by the lognormal distribution appears to be less accurate, resulting in substantial disparities between the premium estimates derived from both models. Notably, these differences are particularly pronounced in the lower estimate range. This phenomenon can be attributed to the lognormal distribution's diminished accuracy when dealing with depth levels that approach zero. Figure 11 shows the distributions of the premium estimates based on the initial discrete probabilities (on the left) and the premium estimates based on the probabilties obtained from the fitted lognormal distribution (on the right). Also from these graphs it can be observed that the differences between the two models tend to increase, particularly within the lower estimate range. All graphs containing the comparisons based on the other four depth-damage curves can be found in the appendix under section (A.3). Due to the higher prevalence of neighborhoods featuring lower premium estimates in the lognormal distribution-based model, the resulting median of the estimated premiums is observed to be lower compared to the median obtained from the primary premium estimates as can be observed from Table 16.

Neighborhood	Municipality	Premium no FDM corrected	Premium structural FDM corrected	Premium emergency FDM corrected	Average Premium corrected	Premium (Huizinga et al., 2017) corrected
Maasplassen	Roermond	10929.82	4904.96	3006.14	6280.31	2365.50
Geulle	Meerssen	7509.94	3485.16	2219.98	4405.03	1769.64
Panoven-Maaskemp	Gennep	9085.08	3565.48	1810.63	4820.40	1590.54
Verspreide huizen Illikhoven en Visserweert	Echt-Susteren	6191.86	2993.04	1982.17	3722.36	1583.82
Itteren	Maastricht	6666.10	3153.24	2050.95	3956.76	1578.94
Noord	Gennep	8002.20	3208.99	1683.93	4298.37	1447.44
Middelaar Katerbosch en Heikant	Mook en Middelaar	7539.12	3064.64	1643.74	4082.50	1396.81
Meuleveld	Venlo	8536.58	3160.77	1450.28	4382.54	1359.14
Genooy	Venlo	9238.60	3238.29	1352.52	4609.80	1306.50
Rijkel	Beesel	6909.63	2823.54	1524.04	3752.40	1287.75
Oud-Bergen Buitengebied	Bergen (L.)	5604.65	2523.28	1550.46	3226.13	1220.90
Gebied Patersweg	Venlo	8992.85	3012.98	1170.16	4392.00	1114.44
Grevenbicht	Sittard-Geleen	5268.18	2323.36	1393.91	2995.15	1107.56
Aijen Buitengebied	Bergen (L.)	5826.06	2405.96	1319.88	3183.97	1105.78
Maasveld II	Venlo	6419.42	2472.99	1217.34	3369.92	1089.17
Eiland-Brandt	Maasgouw	6429.90	2445.72	1180.18	3351.93	1071.13
Laak	Maasgouw	6014.17	2348.37	1182.81	3181.78	1044.27
Asselt	Roermond	6951.30	2457.59	1039.48	3482.79	1006.46
Maaswaard	Venlo	5722.46	2212.78	1096.06	3010.43	976.70
Meers	Stein	4974.62	2021.44	1092.44	2696.17	938.49
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 15: Corrected premium estimates per neighborhood for the twenty neighborhoods with the highest premium estimates based on the fitted lognormal distribution to the averaged maximum depth levels per neighborhood. The premium estimates are presented for the four different depth-damage curves including an average of the three curves from Endendijk et al. (2023) by which no differentiation is implied between FDM measure adoption.

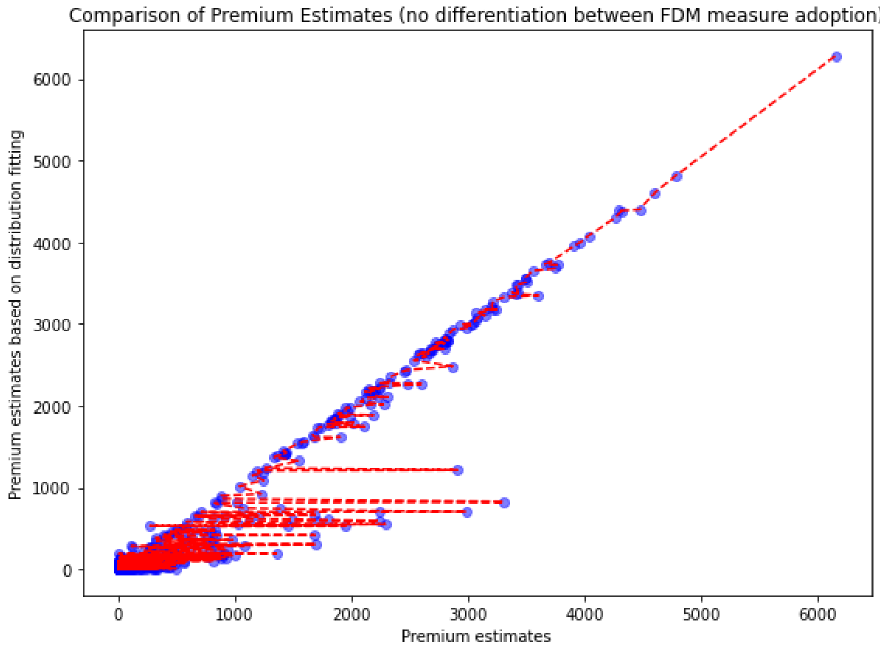


Figure 10: Comparison of the primary premium estimates with the premium estimates based on the fitted lognormal distribution, considering no differentiation between FDM measure adoption

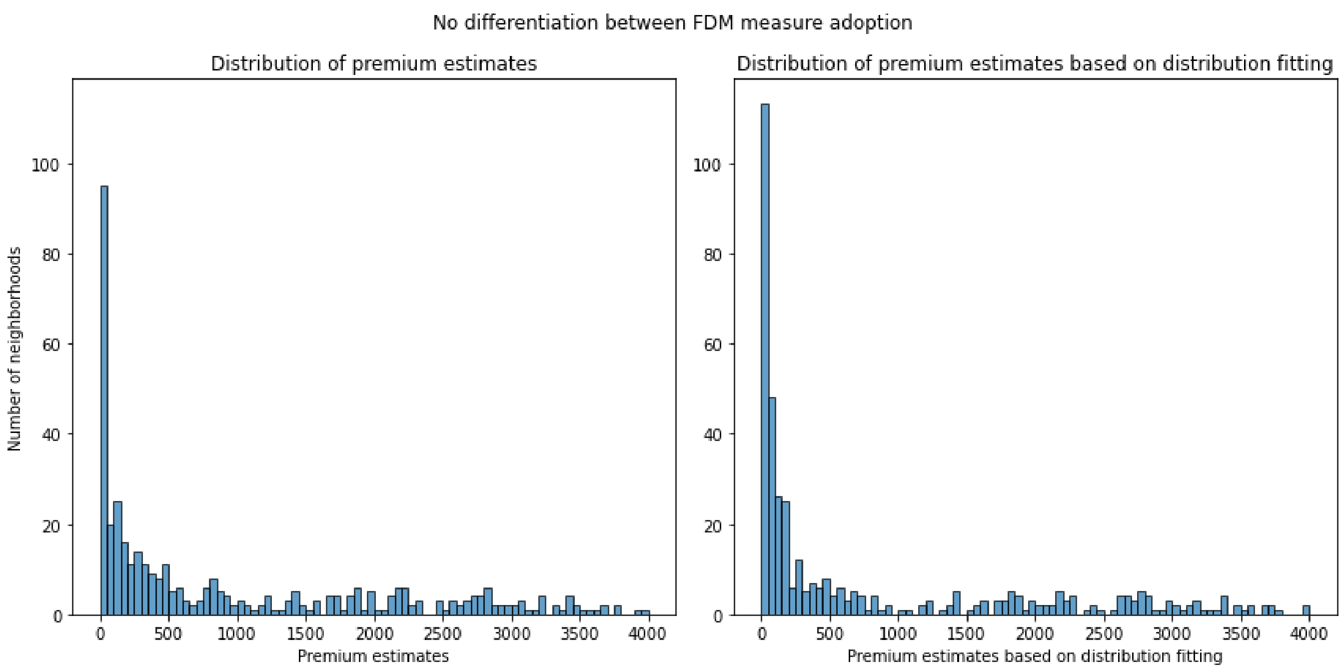


Figure 11: Distribution of primary premium estimates (left) compared to the distribution of the outcomes based on the fitted lognormal distribution (right), considering no differentiation between FDM measure adoption

Averaged maximum depth levels	Mean	Median	St. Dev.
Premium no FDM	2191.04	914.08	2497.22
Premium structural FDM	667.53	270.72	836.02
Premium emergency FDM	215.11	47.1	386.29
Average premium	1024.56	418.91	1212.66
Premium Huizinga et al. (2017)	197.80	47.1	334.63
Fitted lognormal distributions	Mean	Median	St. Dev.
Premium no FDM	1875.86	420.90	2499.37
Premium structural FDM	585.32	109.26	843.82
Premium emergency FDM	199.60	24.38	388.59
Average premium	886.93	183.31	1219.89
Premium Huizinga et al. (2017)	183.62	23.70	337.11

Table 16: Summary statistics for premium estimates per neighborhood based on different depth-damage curves. The upper part of the table refers to estimates based on averaged maximum depth levels per neighborhood. The lower part of the table refers to estimates based on the calibrated lognormal distributions

To check whether the lognormal distribution is a good fit for the underlying data, the Mean Squared Error (MSE) is calculated. The MSE is a common metric used to assess the goodness of fit between a model and the observed data. It quantifies the average squared difference between the predicted values and the actual values. Equation (12) denotes the formula for the MSE that compares the probabilities generated from the lognormal distribution ($P(j,i)$) to the target probabilities ($p(j)$) that correspond to the averaged maximum depth levels per neighborhood.

$$MSE(i) = \frac{1}{4}\sum_{j=1}^{N=4}(P(j,i) - p(j))^2 \tag{12}$$

Table 17 presents statistics derived from the Mean Squared Error (MSE) calculations conducted for each neighborhood. In general, the computed MSE values are relatively low, ranging from a maximum of 0.0027 to a minimum value of 1.4948e-08. However, when interpreting these MSE statistics, it is crucial to consider the magnitudes of the probabilities being compared. In situations involving exceedingly small probabilities, even a seemingly modest MSE value may not necessarily indicate a satisfactory fit, as the disparities between these small probabilities can still be considerable in practical terms. The observed pattern in the MSE outcomes aligns with the observations made in Figures 10 and 11. Higher MSE values are typically associated with neighborhoods featuring average or lower premium estimates. This implies that, for these neighborhoods, the lognormal distribution provides a slightly less accurate fit to the data. Conversely, lower MSE values for neighborhoods with higher premium estimates suggest that the fitted lognormal distribution effectively captures the variability and characteristics of the higher depth values, indicating a good fit. This potentially indicates that the tail behavior of the fitted distribution corresponds well with that of the observed data for these neighborhoods.

	Mean	Median	St. Dev.	Maximum	Minimum
MSE	0.0011	2.5277e-05	0.0012	0.0027	1.4948e-08

Table 17: Summary statistics of the Mean Squared Error applied to the probabilities generated form the fitted lognormal distribution and the target probabilities that correspond to the averaged maximum depth levels per neighborhood.

6.4 Premium estimates including a flat-rate

As the previous sections have shown, there exists a wide variability in premium estimates with certain neighborhoods displaying exceptionally high values. To investigate the potential impact of contributions from low-risk regions on the overall capital pool allocated for flood damage coverage, a uniform flat-rate premium of €50 is introduced. Table 18 presents the premium estimates following the implementation of the €50 flat rate. The resulting estimates show substantial reductions in comparison to those presented in Table 11. Notably, this adjustment ensures that all households within the 910 neighborhoods are subject to a minimum premium estimate of €50, significantly mitigating the premium estimates for high-risk neighborhoods.

Another factor contributing to the substantial reduction in premium estimates within high-risk regions is the inherent demographic disparity. Typically, these high-risk areas exhibit lower population densities in comparison to their low-risk counterparts. Consequently, the introduction of flood insurance contributions from all households in low-risk neighborhoods exerts a more pronounced downward effect on the per-household contribution in high-risk regions.

Neighborhood	Municipality	Premium no FDM	Premium structural FDM	Premium emergency FDM	Average Premium	Premium (Huizinga et al., 2017)
Maasplassen	Roermond	10310.69	4109.04	1086.28	5168.67	751.23
Genooy	Venlo	8867.58	2768.39	501.23	4045.73	581.27
Panoven-Maaskemp	Gennep	8676.86	3029.39	665.73	4123.99	521.16
Gebied Patersweg	Venlo	8490.84	2510.30	413.60	3804.91	514.50
Looierheide	Gennep	8130.33	2214.71	302.63	3549.22	507.05
Meuleveld	Venlo	8098.88	2660.68	525.67	3761.74	467.56
Noord	Gennep	7627.42	2721.24	618.34	3655.67	448.94
Verspreide huizen ten zuiden van Baarlo	Peel en Maas	7547.49	1841.92	179.70	3189.70	435.05
Verspreide huizen Hout-Blerick	Venlo	7499.99	1862.51	194.29	3185.60	425.75
Ool	Roermond	7494.24	2165.48	340.31	3333.34	412.97
Hasselt en Het Vorst	Venlo	7436.34	2074.55	304.02	3271.64	394.26
Bloemenstraat-Zwarteweg	Gennep	7349.91	1827.34	190.89	3122.71	382.17
Geulle	Meerssen	7326.35	3028.94	839.51	3731.60	361.05
Hout en Oijen	Peel en Maas	7202.94	2023.62	300.59	3175.72	355.74
Middelaar Katerbosch en Heikant	Mook en Middelaar	7176.80	2591.40	599.80	3456.00	352.39
Buitengebied Vlodrop	Roerdalen	7163.14	1618.52	109.67	2963.78	350.15
Verspreide huizen Kesseleik	Peel en Maas	7151.90	1742.05	168.69	3020.88	348.29
Heijensebos	Gennep	6988.21	1877.01	247.10	3037.44	323.60
Verspreide huizen Buggenum	Leudal	6941.69	2030.33	330.16	3100.73	319.12
Verspreide huizen Swalmen	Roermond	6918.72	1957.37	291.17	3055.75	316.36
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 18: Premium estimates per neighborhood for the twenty neighborhoods with the highest premium estimates, after introducing a flat rate premium of €50, based on the map layers including the average maximum flood depths and four different depth-damage curves including an average of the three curves from Endendijk et al. (2023) by which no differentiation is implied between the adoption of FDM measures.

6.5 Historical simulation

The historical simulation is employed to estimate the one-year expected damage resulting from flood occurrences, using a range of simulated scenarios. By employing numerous scenarios, the cumulative anticipated damage reflects the fact that not all neighborhoods will experience flooding during a flood event. Consequently, the total damage projected through this simulation is considerably lower than the sum of individually calculated expected damages for all neighborhoods.

Based on a significant number of iterations (100,000), an approximation of the one-year expected damage is presented. Summary statistics for the expected damage outcomes associated with each of the depth-damage relations are presented in Table 19. It is noteworthy that these computations also account for a 50% correction factor due to the utilization of maximum depth values.

Maximum Flood Depth Model	Mean	Median	St. Dev.	95% CI
Expected one-year damage no FDM	896565.43	888976.53	194994.51	(895356.84, 897774.02)
Expected one-year damage structural FDM	273147.85	270136.81	63727.73	(272752.86, 273542.84)
Expected one-year damage emergency FDM	88024.26	85852..20	27805.89	(87851.92, 88196.61)
Average expected one-year damage	419245.85	415268.36	93777.16	(418664.61, 419827.08)
Expected one-year damage Huizinga et al. (2017)	80935.11	79312.89	24006.60	(80786.31, 81083.90)

Table 19: Summary statistics for the one-year expected damage estimates based on the historical simulation and the four different depth-damage curves including an average of the three curves from Endendijk et al. (2023) by which no differentiation is implied between the adoption of FDM measures.

On the basis of these one-year expected damage estimates, the insurance premium can be determined. The technical premium required to cover the anticipated damages is calculated by distributing the monetary damage equally across all households in the province of Limburg. These outcomes are showcased in the initial column of Table 20. Because of the many iterations and the small probability of drawing positive flood depths, the overall anticipated damage for all neighborhoods, and thus the premium estimates, remain substantially low.

To introduce a form of risk stratification in the results, reflecting a scenario where households in flood-prone neighborhoods contribute more the insurers fund, an alternative approach is taken. The premium estimates are computed by dividing the anticipated one-year damage solely among households with a positive flood risk. This yields the premium estimates illustrated in the second column of Table 20.

Assuming that households with no flood risk pay the premium as indicated in the first column of the table, and households facing a positive flood risk pay the premium outlined in the second column, an equitable distribution of premiums that captures risk disparity is achieved. This revised structure renders the insurance fund no longer actuarially fair but rather incorporates an additional reserve.

	All households	Households with positive flood risk
Premium no FDM	1.67	3.53
Premium structural FDM	0.51	1.08
Premium emergency FDM	0.16	0.35
Average premium	0.78	1.65
Premium Huizinga et al. (2017)	0.15	0.32

Table 20: Premium estimates based on the historical simulation and different depth-damage curves. The first column considers the case in which all households are insured while the second column includes the estimates based on the case in which only the households with positive flood risk are insured

6.6 General interpretation of the Results

The premium estimates for household voluntary flood insurance rely on data from the current climate, which encompasses averaged maximum depth levels for different neighborhoods within Limburg province. The flood insurance premiums range from €0 per year for 501 out of the 910 neighborhoods to over €10,000 per year for the neighborhood Maasplassen, if assumed that households in this area do not implement FDM measures. It is apparent that premium estimates vary considerably and are influenced by multiple factors. A key determinant of premium levels is the adoption of FDM measures, which leads to a notable reduction, often halving the premium estimates or more.

The data set including the site-specific flood probabilities for each neighborhoods based on uniformly distributed intervals, yields premium estimates that are unrealistic. These premium estimates underscore the inherent limitations of this data set, primarily resulting from its reliance on broad interval values, resulting in a fairly rough estimate of flood risks and inundation depths.

The principle of solidarity presents a promising approach to flood risk insurance. The implementation of a flat-rate premium, requiring all households in Limburg province to contribute at least €50, serves as a means to ease the financial burden on households located in high-risk flood zones. Although the flat-rate premium helps significantly in reducing the overall premium estimates, it relies on the unrealistic assumption that all neighborhoods would experience flooding simultaneously during a flood event. Since flood insurance is no longer voluntary in this case, the total amount of premium income would exceed the expected one year damage. As a result, the premium estimates generated through the simulation technique in are deemed to offer greater reliability, as they are rooted in real-world flood occurrence scenarios. Furthermore, by spreading the expected damage across all neighborhoods, the premium per household remains affordable, reaching a maximum of just €3.53 per year.

7 Conclusions

The hypothesis regarding the feasibility of flood risk insurance in the Netherlands has not been proven within the scope of this thesis. The findings presented here provide a good first impression on the possibilities, but to substantiate this hypothesis, it would necessitate the utilization of more intricate and comprehensive data sets, along with a more precise evaluation of anticipated damages. Given the limitations of the data sets employed in this research, it is imperative to refrain from drawing definitive conclusions regarding the feasibility of flood insurance.

Conducting the research at the neighborhood level, thereby focusing on relatively small and specific geographical areas, represents an innovative approach within the existing literature. This methodology prevents the dispersion of higher flood risks across a larger region, enhancing the precision of overall premium estimates. By pinpointing risk assessments to smaller areas, this research offered valuable insights into the costs associated with voluntary flood insurance.

The establishment of a voluntary flood insurance program for the Netherlands could be feasible if modeled after the National Flood Insurance Program (NFIP) administered by the Federal Emergency Management Agency (FEMA) in the United States. The National Flood Insurance Program is a voluntary flood insurance program in which the cost of an annual flood insurance policy are dependent on factors that include the location of the insured property, the property's flood risk zone, the coverage amount, and whether the property is in a Special Flood Hazard Area (SFHA) among others. On average, NFIP flood insurance premiums can range from a few hundred dollars to over a thousand dollars annually. Premiums are typically higher for properties located in high-risk flood zones (SFHAs) as opposed to those in low to moderate-risk zones. Properties in SFHAs are usually required by mortgage lenders to have flood insurance. Also, FEMA incentivizes communities to go beyond the minimum floodplain management standards required for participation in the NFIP through a program known as the Community Rating System (CRS). Under the CRS, policyholders in participating communities can enjoy significant discounts ranging from 5% to 45% on their flood insurance premiums. These discounts are determined by the community's efforts on taking flood damage mitigation measures. The National Research Council conducted an assessment, finding that the CRS program, on average, provided an 11.4% discount on premiums for policies within the NFIP. Importantly, the discounts offered through the CRS program are cross-subsidized across the NFIP. This means that while one community benefits from reduced premiums, the costs are spread out, with premium rates increasing slightly in all participating communities within the NFIP to offset the discounts (Horn, 2021).

Based on the analyses carried out on neighborhood level, it becomes evident that within these neighborhoods, the variations in flood risks are comparatively limited. This leads to more pronounced disparities in estimated insurance premiums among different neighborhoods. In contrast, the premium estimates for the 53 dike ring areas discussed in the study conducted by Aerts and Botzen (2011) appear lower. This discrepancy is primarily attributed to the uneven distribution of flood risks within these larger geographical units.

The distribution of flood risks across larger regions necessitates the implementation of a mandatory flood insurance program. Through mandatory flood insurance, risk distribution becomes feasible, resulting in reduced premium estimates as the expected damage can be collectively shared. This approach enhances affordability, making flood insurance more accessible to a broader population. As this research is primarily centered on a case study within the province of Limburg, where fluvial flood risks are relatively high, extending this approach to encompass the entire Netherlands offers greater potential for the collective sharing of flood risk.

In the pursuit of advancing future research in the context of a mandatory flood insurance program, a significant area of improvement lies in refining the simulation methodology. The simulation approach employed within this thesis operates under the assumption of independence among flood occurrences in distinct neighborhoods. Nevertheless, reality demonstrates that there exists a noticeable degree of dependence among flooding events within specific geographical regions. Consequently, to enhance the reliability of the simulation process and the accuracy of one-year flood risk scenario estimations, it is essential to systematically incorporate and model these inherent correlations between flooding incidents.

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A Figures

A.1 Map layers

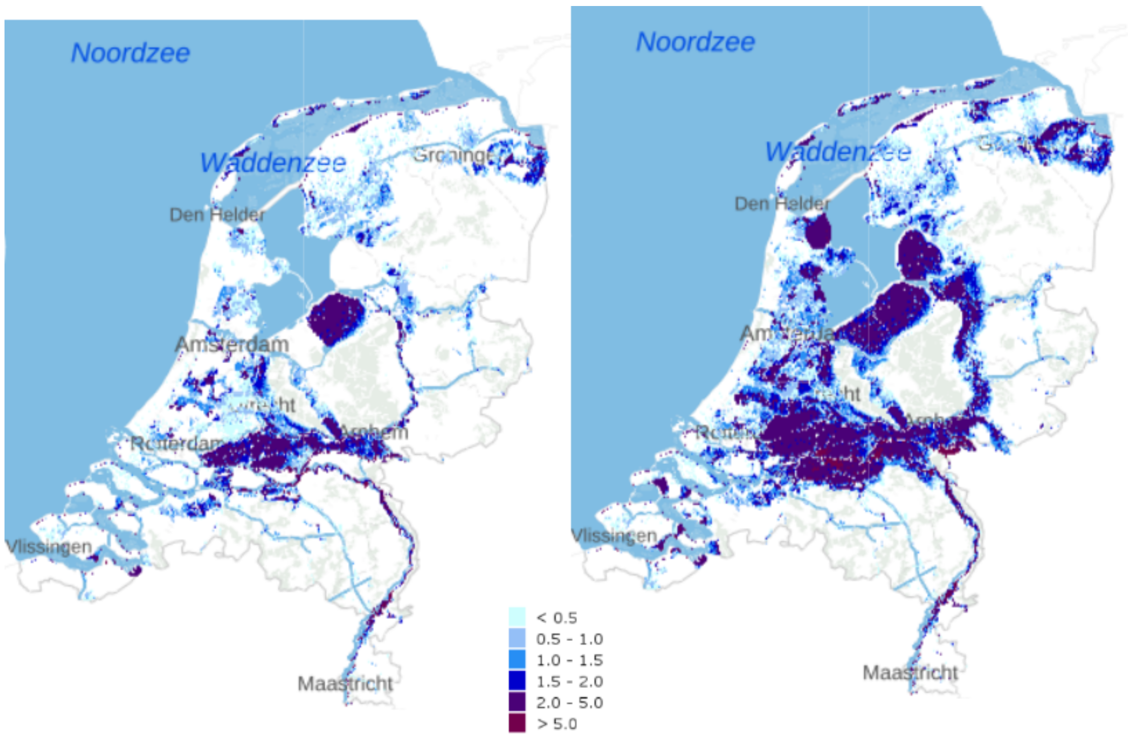

Figure 12: Map layers obtained from the LIWO containing maximum flood depth levels occurring with medium probability (left) and small probability (right). The legend indicates the maximum water depth in meters.

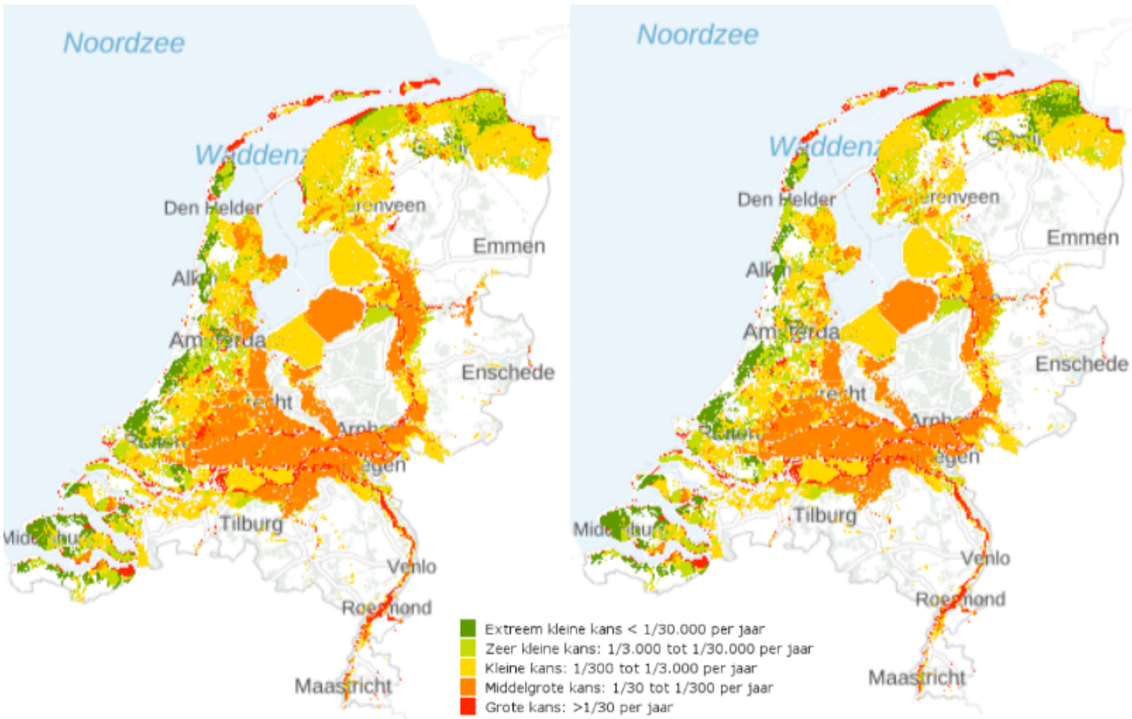

Figure 13: Map layers obtained from the LIWO containing site-specific flood probabilities with depths greater than 20 cm (left) and 50 cm (right). The legend indicates the flood probabilities based on five intervals.

A.2 Uniformly distributed intervals

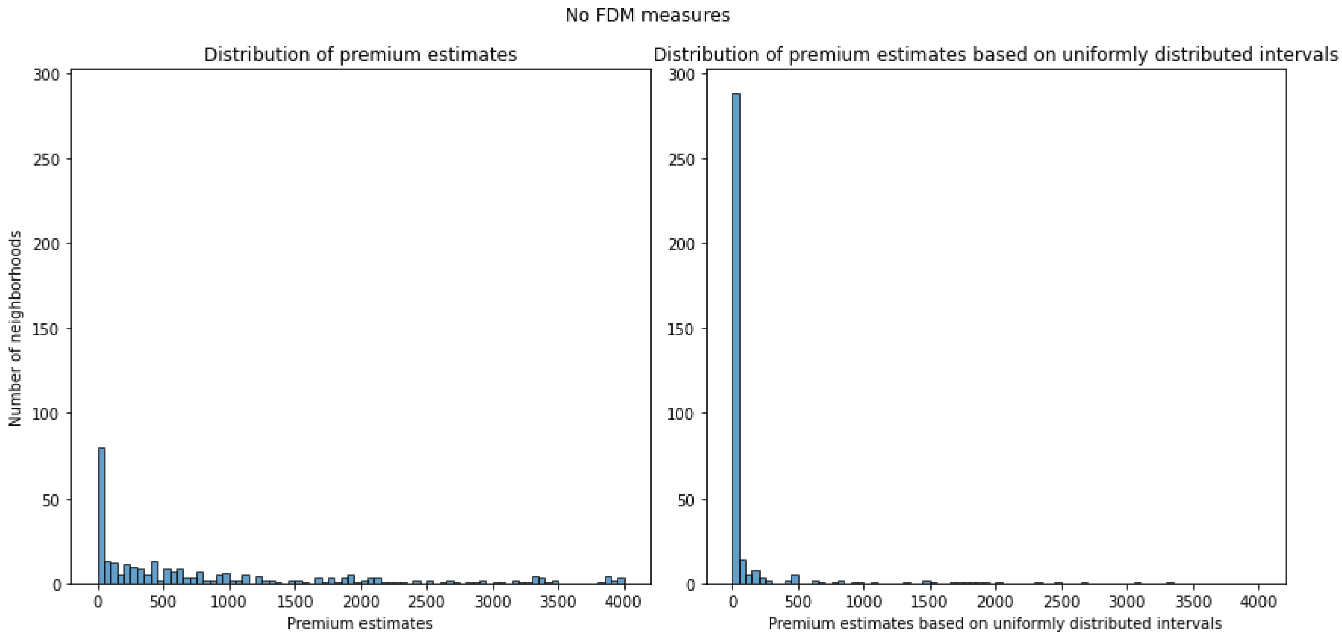

Figure 14: Distribution of primary premium outcomes compared to the distribution of the outcomes based on the uniformly distributed intervals, considering no FDM measures undertaken

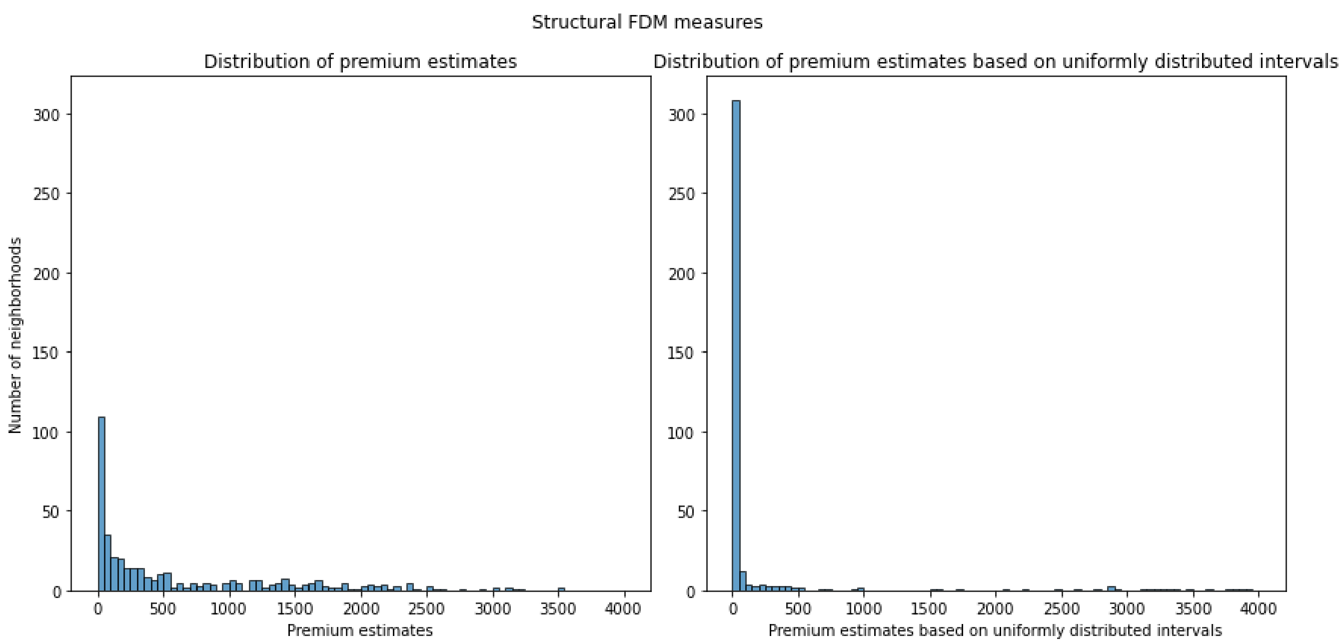

Figure 15: Distribution of primary premium outcomes compared to the distribution of the outcomes based on the uniformly distributed intervals, considering structural FDM measures undertaken

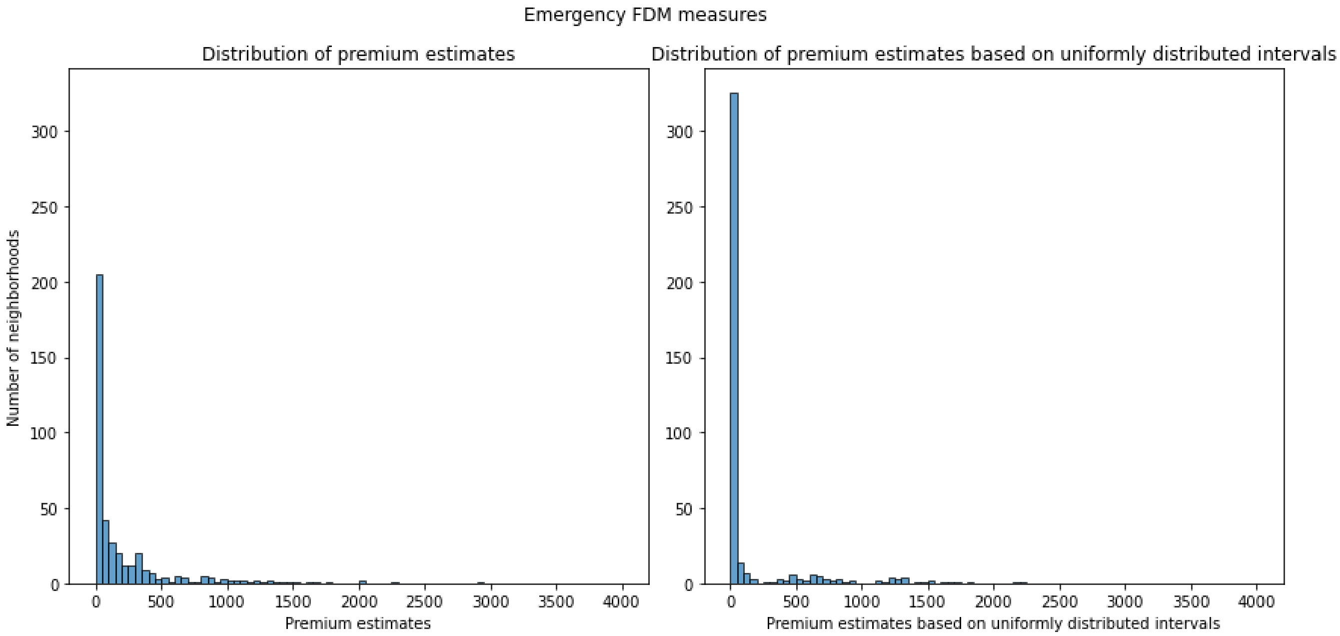

Figure 16: Distribution of primary premium outcomes compared to the distribution of the outcomes based on the uniformly distributed intervals, considering emergency FDM measures undertaken

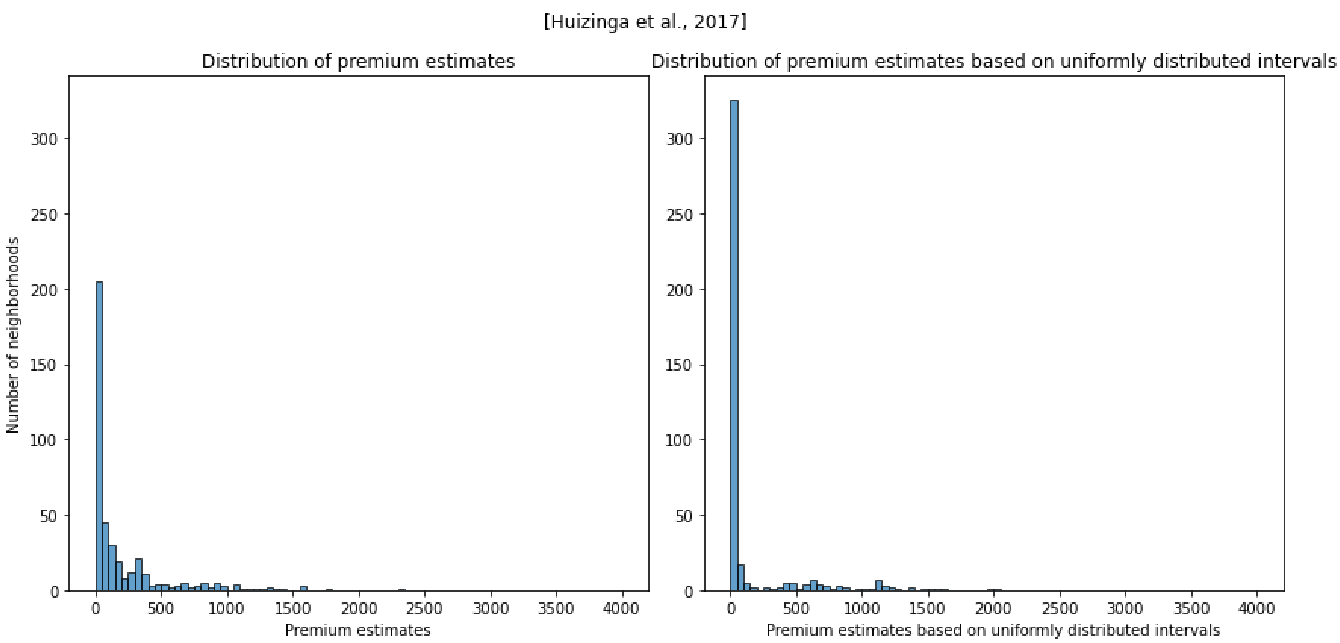

Figure 17: Distribution of primary premium outcomes compared to the distribution of the outcomes based on the uniformly distributed intervals, considering the depth-damage curve for the Netherlands from Huizinga et al. (2017)

A.3 Fitted lognormal distributions

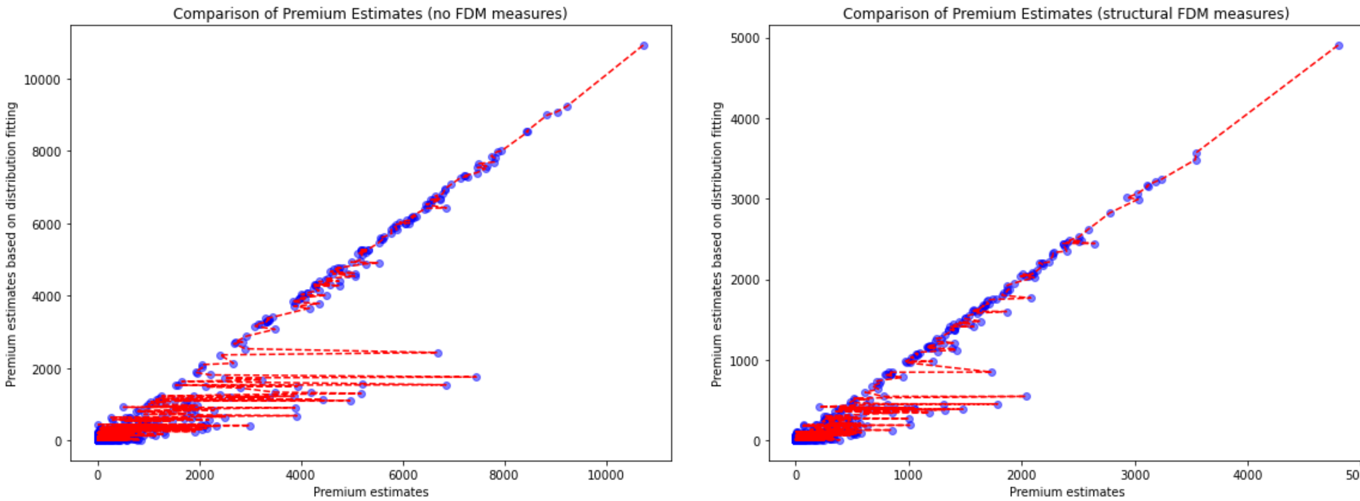

Figure 18: Comparison of the primary premium estimates with the premium estimates based on the fitted lognormal distributions, considering no FDM measures undertaken (left) and structural FDM measures undertaken (right)

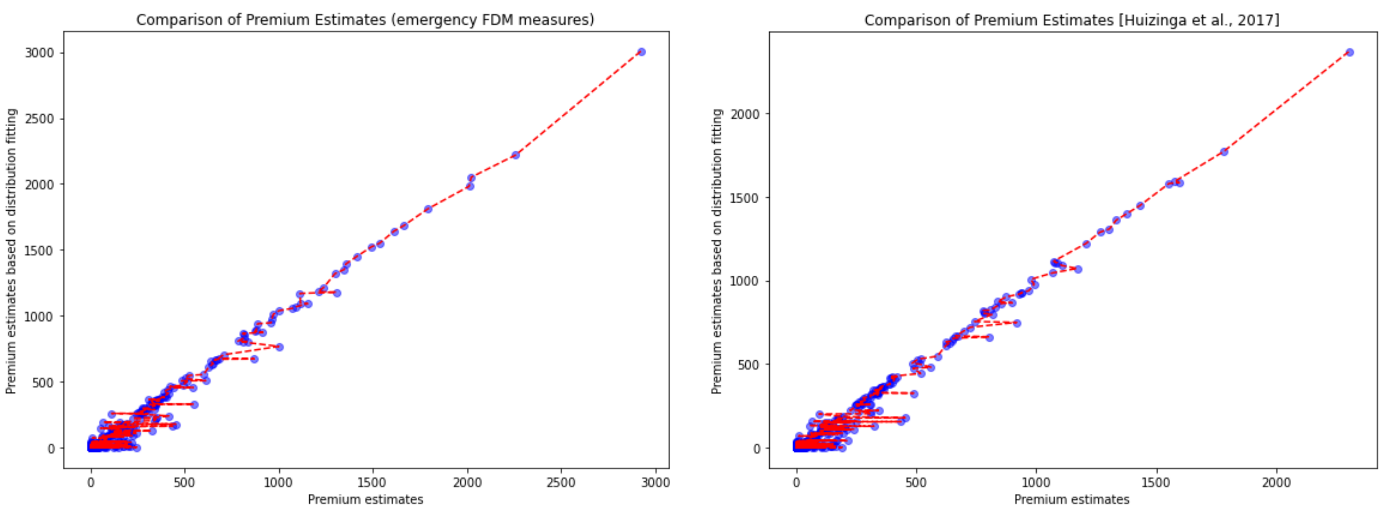

Figure 19: Comparison of the primary premium estimates with the premium estimates based on the fitted lognormal distributions, considering emergency FDM measures undertaken (left) and the depth-damage curve for the Netherlands from Huizinga et al. (2017) (right)

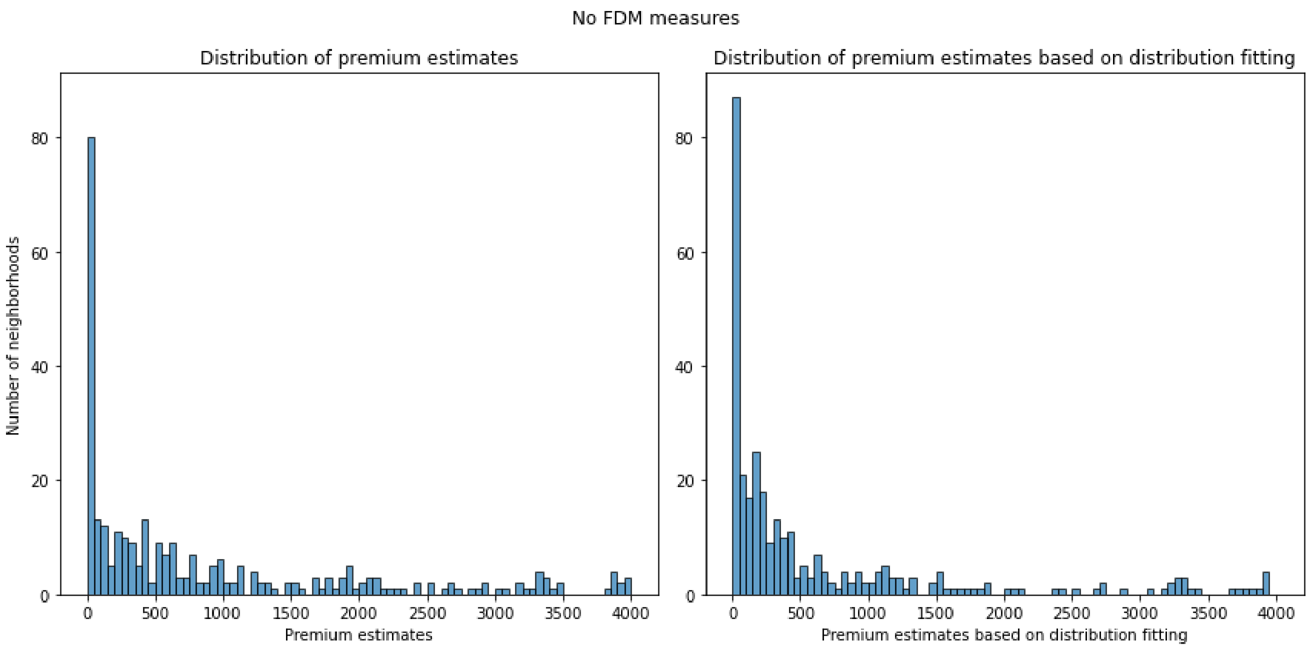

Figure 20: Distribution of the primary premium outcomes compared to the distribution of the outcomes based on the fitted lognormal distributions, considering no FDM measures undertaken

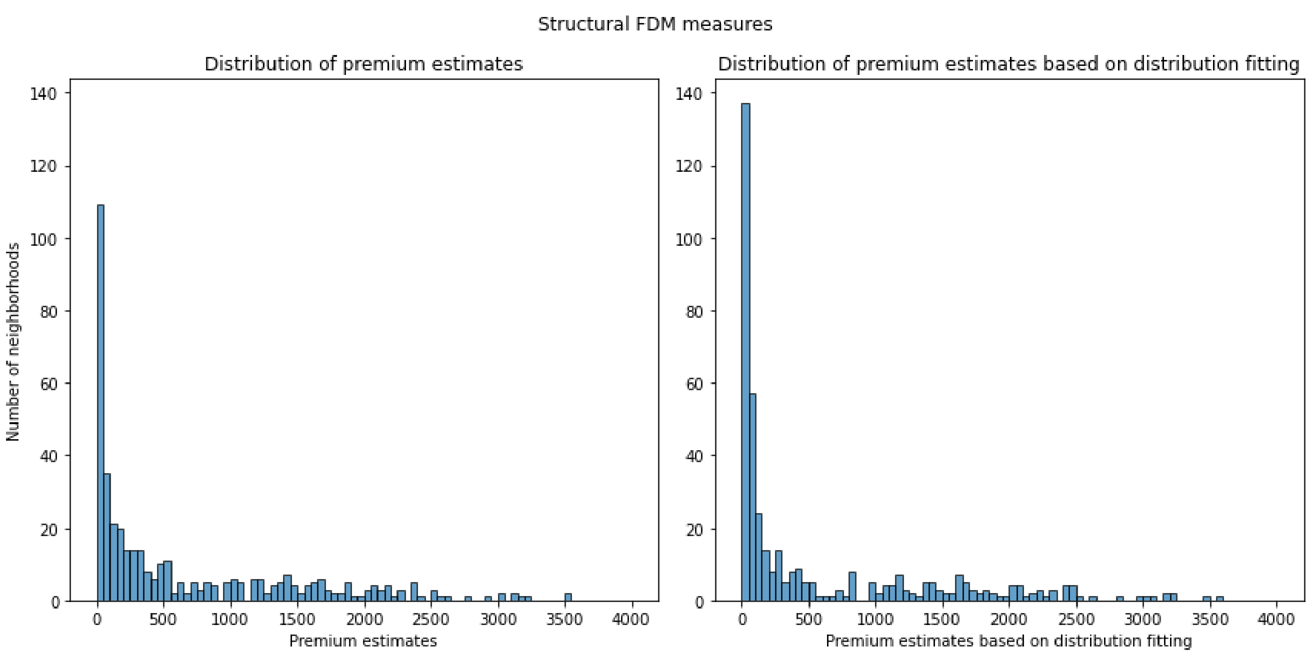

Figure 21: Distribution of the primary premium outcomes compared to the distribution of the outcomes based on the fitted lognormal distributions, considering structural FDM measures undertaken

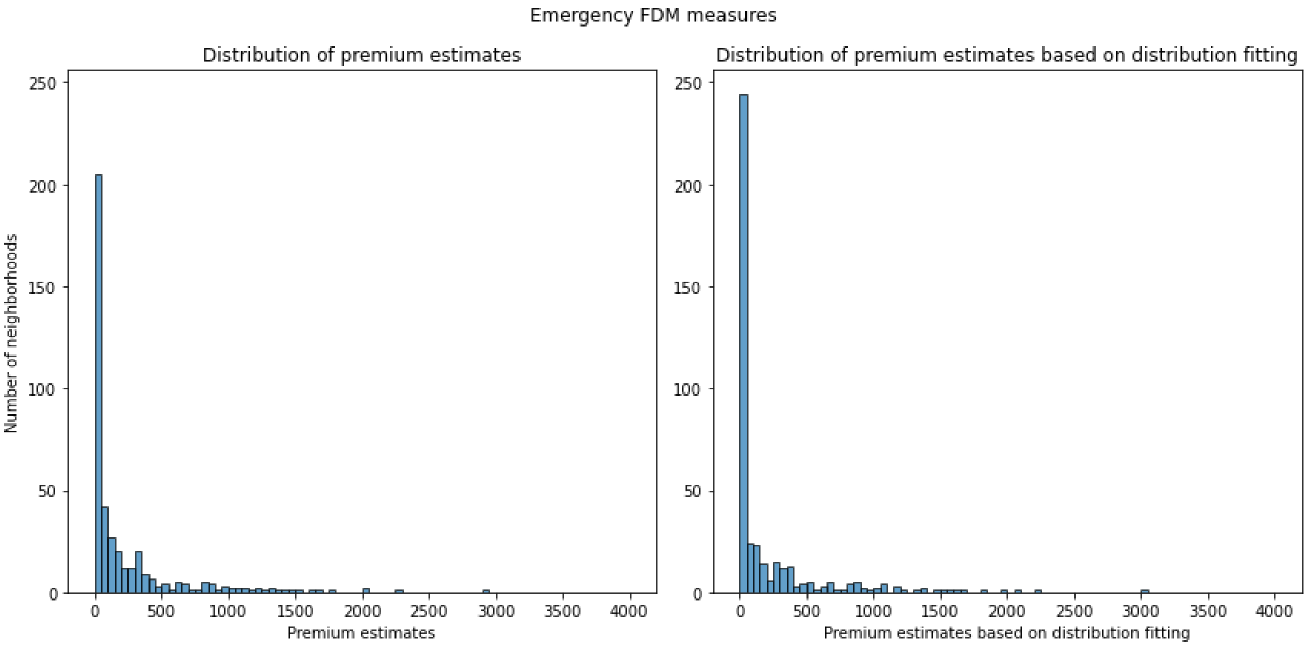

Figure 22: Distribution of the primary premium outcomes compared to the distribution of the outcomes based on the fitted lognormal distributions, considering emergency FDM measures undertaken

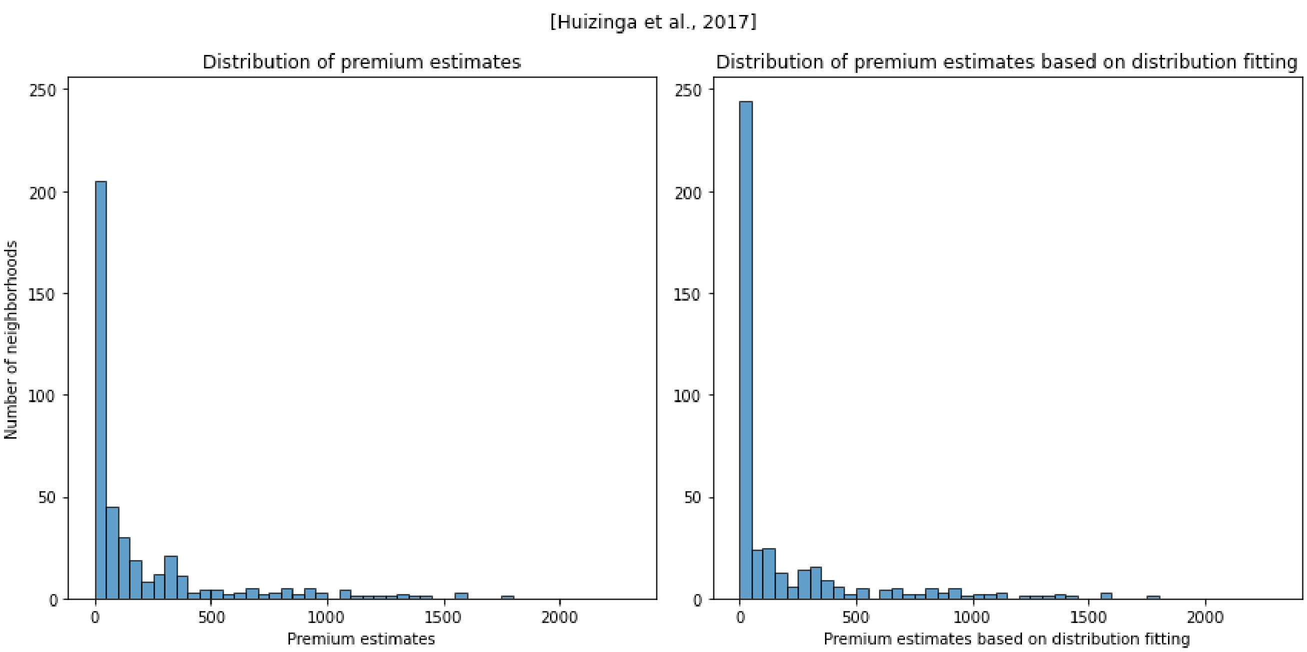

Figure 23: Distribution of the primary premium outcomes compared to the distribution of the outcomes based on the fitted lognormal distributions, considering the depth-damage curve for the Netherlands from Huizinga et al. (2017)