Geo-information Science and Remote Sensing

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AN INDICATOR BASED APPROACH TO QUANTIFY RIVER FLOOD RISK FOR THE MAAS RIVER IN LIMBURG

combining hazard, vulnerability, and exposure

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Abstract

Traditional Dutch flood risk management (FRM) policies are mainly oriented towards building flood protection systems and disaster prevention. Over the last decade, a paradigm shift in risk management has emphasized the need for incorporating a so-called social dimension of risk, whereby building sustainable disaster risk reduction (DRR) policy through adaptation strategies is deemed equally important.

Risk assessments are a key practice in building effective DRR strategies, since they have the potential to identify places of high risk, and to anticipate places that would benefit most from FRM policy implementations. As such, risk assessments require to incorporate this social dimension of risk to create holistic assessments.

This thesis addresses the need for such an integrated framework to assess river flood risk, incorporating both its technical and social dimensions. The assessment framework is then applied to a region susceptible to river floodings from the Maas river in the Dutch province of Limburg. The goal of this thesis is to enhance understanding of risk, and to support decision-making processes for planners and experts in the field of FRM.

The study creates a novel risk assessment framework, whereby the main risk components of vulnerability, exposure, and hazard are quantified and combined into a single risk index. Socio-economic, and physical community characteristics are assessed to identify the main drivers of vulnerability among flood affected populations. Assets at risk are analysed to determine flood exposure levels. Hydrological models simulating flood events are used to quantify flood hazard levels.

Results show considerable heterogeneity of risk areas within the study area. Risk is progressively concentrated within urban areas, particularly in the south of Limburg, near Maastricht, and areas around the Geul and Geleenbeek tributary, due to the combination of steep terrain, and vulnerable socio-economic population characteristics.

The findings of the study provide valuable insights into the spatial distribution and drivers of flood risk along the Maas river and its tributaries. By identifying high-risk areas and vulnerable populations, the integrated risk assessment framework facilitates the development of targeted mitigation and adaptation strategies to enhance resilience to river flood disasters, guiding stakeholders and decision-makers towards effective and sustainable DRR strategies while considering strengths and weaknesses of local populations.

1 Introduction

1.1 Context and background

The Netherlands is a low-lying delta country with a complex network of rivers mouthing into the North Sea. As such, parts of the country are exposed to river floodings from the Maas, Rijn, and Scheldt river. Climate change developments, such as global temperature rise, will continue to put pressure on these river basins by altering the frequency and intensity of rainfall patterns throughout river basins. This has the potential to significantly increase future discharge levels for major rainfed rivers such as the Maas (van den Hurk et al., 2006; Te Linde, 2007; Klijn et al., 2012; PBL, 2013; Detrembleur et al., 2015; Haasnoot et al., 2015; Arnell & Gosling, 2016). Despite a long history of government efforts aimed at mitigation and adaptation, communities living in the vicinity of the Maas river are under an ever increasing threat of flooding. (Robinson & Botzen, 2020).

Since the late nineties, the Dutch government has initiated the national 'Deltaplan Grote Rivieren' campaign (i.e. the Delta plan for major rivers). As part of this campaign, a multitude of programmes were initiated along the Maas river, which is considered to be one of such major rivers. These programmes, named 'Maaswerken', were mainly aimed at increasing river flood safety by creating room for the river and increasing its discharge capacity. This was realised through spatial interventions such as dike relocations, deepening of river beds, or floodplain extensions. The delta plan brought about a new planning paradigm in flood management. This paradigm shift prioritised creating room for rivers to flood rather than reinforcing the existing dikes (Rijke et al., 2012).

The delta plan was largely influenced by various large scale high water events across the European Union, such as the extreme highwater events that occurred in the Maas river in 1993, 1995, and 2021 (Slomp, 2012). In 1993, extreme rainfall has led to unprecedented discharge levels for the Maas river (3.039 m3/s & 45,90m +NAP at Borgharen) (van der Kleij, 1994; KNMI, 2020). This has caused considerable flooding of the Maas, mainly in the unembanked areas of Southern Limburg. The Maas reached similar discharge- and high water levels in 1995 and 2021 due to large amounts of precipitation and snowmelt in their catchment areas. Predominantly the events in 1993 and 1995, but also 2021, have led to large scale economic damages, evacuations, and feelings of unsafety, anxiety and worry among local communities (Robinson & Botzen, 2020; ENW, 2021).

Traditional disaster risk reduction (DRR) strategies in the Netherlands mainly emphasize technically-oriented mitigation solutions. These solutions are comprised of technological or engineered systems, such as dikes and levees, used to minimise risk through preventing damage (Ward et al., 2013). Such man-made interventions have proven to be effective in preventing flooding disasters (PBL, 2024).

However, engineered solutions cannot solely be relied upon in DRR due to their inherent limitations, including dike failure or expansion capacity. Dike failures could cause floods as a result of dike breaches at one or more breach locations, or high water waves could rise over, or in some cases, seep through the dike (Ministry of Infrastructure and Water Management, 2018). Additionally, physical barriers can only be expanded or elevated to a certain extent before interfering with adjacent land uses.

To further reduce the risk of a flood disaster, beyond just the technical dimension, risk can be reduced through the exploration and effective management of the social and economic dimensions of risk (Imperiale & Vanclay, 2021). These dimensions shape the vulnerability and exposure of people and communities. It considers their social characteristics, environment, and amenities at their disposal that influence their capability of dealing with the negative impact during, and after, a flood event. The socio-economic dimension of risk are more oriented toward adaptation as opposed to mitigation (Marin et al., 2021). Local dynamics play an important role in this dimension, as understanding vulnerability on a local scale (e.g. people's health, community, culture, livelihoods) can support community resilience and strengthen coping strategies for floods (Imperiale & Vanclay, 2021).

In risk management, an increasing focus has been placed on this socio-economic dimension over the past decade (Kreibich et al., 2017; Vojtek, 2023). Dutch central and local water governing policies are increasingly aimed at multi-layered safety, where flood resilience practices such as citizen participation and raising people's flood preparedness, are considered equally important. (Terpstra & Gutteling, 2008; de Jong & van den Brink, 2013). The introduction of the Dutch National Water Plan in 2009 served as a starting point for these developments (Van Buuren et al., 2016).

Reducing disaster risk through exposure aims to ensure that important societal structures or activities (e.g., buildings or economic activity) are not located in high risk zones. Exposure is therefore highly interrelated with spatial planning practices. Due to the improvement of technological prevention systems over the past decades, spatial planners and communities feel a growing sense of safety behind dikes (Botzen et al., 2009). As a result, they often tend to overlook the danger of building and living in or near floodplains (Roth & Warner, 2007). This can be explained by the 'levee-effect', whereby the absence of frequent flood- or high water events tends to lead to an increased vulnerability due to lower sense of urgency among planners and communities (Di Baldassarre et al., 2015).

The technical dimensions of flood risk management (FRM) have made significant advancements in the Netherlands through the implementations in the Delta plan. Risk areas along the Maas are largely embanked, and hydrological models can quite accurately predict possible hazards (Ward et al., 2013). However, to further enhance DRR, it is necessary to build sustainable and effective strategies and systems, which can cope with more extreme hydrological events, and which are better prepared to deal with a flood event. A better understanding of vulnerability and exposure to river flooding becomes crucial to realise such strategies and systems (Riddell et al., 2019). There is a growing need for FRM to comprehensively assess vulnerability and exposure of different populations, incorporating both its social and economic dimensions (Cutter et al., 2008).

1.2 Research needs

Traditional Dutch FRM practices tend to focus predominantly on the technical dimension of DRR. Risk assessments are an important tool in DRR to develop and explore possible flood scenarios to better understand drivers of risk (Riddell et al., 2019). In Dutch risk assessments, either the hazard itself is considered (e.g. maximum possible inundation depth at different scenario's), or the performance of protection systems is quantified by analysing the possibilities of a dike failure or a dike breach (Jongejan & Maaskant, 2015). Such measurements are given more attention in policy than social adaptation strategies intended to assess vulnerability factors (de Jong & van den Brink, 2013; van Buuren et al., 2016; Koks et al., 2015).

Existing risk assessments, developed by governmental bodies in the Netherlands, define risk as the potential consequence a flood, expressed in either material damages or potential loss of life (Rijksoverheid, 2024). Both, however, assume that the total population at risk is equally able to adapt and recover from flood events (Koks et al., 2015; Kirby et al., 2019). Vulnerability drivers such as age, ethnicity, or income are hardly factored in such risk assessments, on the national and local government level.

Different community characteristics can affect people's ability to adapt to, cope with, and recover from floods (Bulti et al., 2019). As such, in the event of a disaster, not every inhabitant at risk is equally likely to suffer from the same negative consequences. For example, timely evacuation of flooded areas might become more problematic due to the lessened mobility of older populations living in those areas (Cutter et al., 2003; Tascón-González et al., 2020; Tate et al. 2021). To better represent the possible impact of flooding on people, a more comprehensive and interpretable approach to risk assessment, beyond uniform measurements such as monetary damage or loss of life is needed. This approach should also factor local place and population dynamics that influence drivers of vulnerability and exposure.

Vulnerability and exposure are inherently spatio-temporal and multi-dimensional concepts (Cardona et al., 2012). They are a result of people and communities and their constantly evolving interaction with their surroundings (Cutter & Finch, 2008; Karagiorgos et al., 2016). They should thus be analysed in a local context rather than a one-size fits all approach (Cutter et al., 2003; Wood et al., 2015). This could shine light on the extent to which vulnerability and exposure relate to exogenous factors like urbanization, climate variability, policy interventions or land use changes (Ran et al., 2020; Tate et al., 2021; Vojtek, 2023). It is needed to adopt a holistic approach that integrates local place dynamics to create a comprehensive assessment framework for vulnerability and hazard exposure.

1.3 Research gap

In recent years, various studies have attempted to create a holistic risk assessment framework (Olson et al., 2020). Within the Dutch context, Koks et al., (2015) provide a simplified risk assessment framework whereby elements of hazard, exposure, and vulnerability are combined, and used to advise FRM policy making in the Netherlands. This thesis aims to build upon the holistic framework developed by Koks et al., (2015), by elaborating on the quantification of each separate risk element. Approaches to quantify hazard (Maranzoni et al., 2022), exposure (Ziegelaar & Kuleshov, 2022), and vulnerability (Cutter et al., 2003; Kirby et al., 2019) will be combined to construct a novel framework to assess river flood risk.

1.4 Objectives and research questions

This research will design a holistic flood risk assessment framework by employing a combination of existing risk assessments (Koks et al., 2015; Kirby et al., 2019; Ziegelaar & Kuleshov, 2022; Maranzoni et al., 2022). This framework will be applied to the Maas river, including tributaries, in the Dutch province of Limburg. The approach is based on a combination of three quantifiable indices: (1) a flood vulnerability index, (2) a flood exposure index, and (3) a flood hazard index. The goal of this research is thus to map the patterns of vulnerability, hazard, and exposure related to river floodings from the Maas river in Limburg, and analyse what the main drivers of risk are. The aim is to provide planners and experts in the field of FRM insights into the potential drivers of risk, and how these can vary over the study area. The central research question addressed in this thesis will be as follows:

> **"What combination of risk indicators can help identify primary drivers of high flood risk regions along the Maas river in Limburg?"**

The thesis will be structured by answering the sub-research questions:

1. What is the spatial distribution of vulnerability and what are the primary drivers of vulnerability on a district level along the Maas river?

2. What is the spatial distribution of exposure and what are the primary drivers of exposure on a neighbourhood level along the Maas river?

3. What are the drivers of hazard intensity and how are these drivers distributed along the Maas river?

4. Which areas exhibit the highest overall risk according to the combination of vulnerability, exposure, and hazard intensity indicators?

5. What specific recommendations can be made for FRM policies to effectively incorporate DRR using this framework?

The societal value of the research outcome is to contribute to DRR discourse by identifying local drivers of risk along the Maas river in Limburg. An improved understanding of risk could be used to guide policymakers or other experts in the field of FRM to prioritise project funding to areas most in need of disaster adaptation or mitigation policies. Moreover, understanding of the socio-economic drivers of risk can help uncover patterns and make predictions of areas that might become more vulnerable in the future.

2 Theoretical Background

Although there is no general consensus in literature on the exact definitions, an important distinction should be made between the key disaster risk concepts used in this research. Disaster risk is most frequently adopted in literature by the definition of the united nations: "The potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society or a community in a specific period of time, determined probabilistically as a function of hazard, exposure, vulnerability and capacity." (UNDRR, 2023). Risk can be seen as the interplay between hazard frequency and intensity, people's and communities' vulnerability, and their exposure (Klijn et al., 2015; Chen, 2021; Ziegelaar & Kuleshov, 2022). It is commonly conceptualised similarly to Olson et al. (2020) (eq. 1):

$$Risk = Vulnerability * Exposure * Hazard \tag{1}$$

Section 2.1 will further elaborate on the three main components of risk, and their conceptualisation within this thesis.

2.1 Vulnerability

Vulnerability is a multi-dimensional concept. It describes the extent to which a communities' characteristics and conditions make them more susceptible to the negative impacts of a hazard (Cardona et al., 2012). It associates with potential social, economic, and physical impacts (e.g., harm, damage, or loss) that a community faces when exposed to a hazard (UNDRR, 2023). Factors influencing vulnerability include age, employment, access to resources or key infrastructure, and housing quality.

This research quantifies the social, economic, and physical dimensions of vulnerability using a vulnerability index. This index follows a similar approach to previously computed (socio-economic) vulnerability indices for, among others, floods in the USA (Cutter et al., 2003), and Germany (Fekete, 2009). The proposed multi-dimensional vulnerability index measures the extent to which individuals, households, and populations are able to cope, adapt, and respond to hazards, in this case river floods. Increased socio-economic vulnerability implies a lower capacity to do so due to unfavourable socio-economic circumstances (Koks et al., 2015), making them more vulnerable to deal with, and recover from, flooding hazards (Tate et al., 2021).

Differences in vulnerability lead to unequal capacities of groups to anticipate, cope and recover from hazard impacts (Kuhlicke et al., 2011). Common socio-economic vulnerability indicators include age, gender, ethnicity or literacy (Cutter et al., 2003; Cutter et al., 2008; Tascón-González et al., 2020). In this research, variables relating to vulnerability in the physical environment, such as access to key infrastructure, housing quality, and vehicle ownership will also be taken into account for vulnerability calculations (Huang et al., 2015; Kirby et al, 2019).

2.2 Exposure

Exposure, as opposed to vulnerability, aims to assess to what degree communities or the environment are in physical contact with the hazard (Tate et al., 2021). The definition of exposure by the intergovernmental panel on climate change (IPCC) has been adopted: "The presence of people; livelihoods; services and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected by a flood event" (IPCC, 2022). Flood exposure relates to the valuable societal components - such as people, buildings, agricultural land, or nature areas - located in flood prone areas, and thus are at risk to be impacted, damaged, or destroyed (Koks et al., 2015; Tate et al., 2021).

Exposure indicators aim to describe flood severity by estimating the quantity of physical elements are exposed, whereas vulnerability aims to provide insights on characteristics of those who are exposed (Tate et al., 2021).

This research follows an approach similar to Ziegelaar & Kuleshov (2022), who constructed a flood exposure index for the Hawkesbury-Nepean catchment area in Australia. Their research described land use type, locations of critical infrastructure, and population density as taken as proxies for exposure (Girgin et al., 2017; Ziegelaar & Kuleshov, 2022). Modifications to this methodology will be made in order to fit the specific characteristics of the study area in Limburg. As such, additional exposure indicators such as the density of the built environment, and business density will be added to the index calculation.

2.3 Hazard

Hazard refers to the frequency and intensity of an event taking place. River flood hazards, in this thesis, refer to the above average river discharges measured at Eijsden water measurement station (Rijkswaterstaat, 2024). Such high water events have the potential to cause flooding, and may result in loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation (UNDRR, 2023). The extent of such negative impacts is dependent on the levels of vulnerability and exposure within a hazardous area, and on the characteristics of the physical environment.

Assessing flood hazards is an increasingly important practice in various fields, including spatial planning, emergency management, and insurance management (De Bruijn et al., 2015). Detailed and timely information on the degree of a flood hazard at different locations, could enable such decision makers to anticipate and weigh their considerations. For example, spatial planners could avoid developing residential areas in hazardous areas based on flood hazard assessments. Governments could also make use of such hazard maps to effectively communicate hazard information and create disaster awareness among flood affected populations (De Moel et al., 2009; De Bruijn et al., 2015).

Maps delineating different hazard zones (hazard maps) can be interpreted in multiple ways, depending on the user's background, expertise, and perspective (De Bruijn et al., 2015). How a hazard is assessed by a FRM expert depends on the definition of the hazard. There is no objective answer to which of the following flood events is more hazardous: a small, shallow flood that is recurring often, or a large flood with high inundation depths, but with a small chance of happening. Whereas for example spatial planners might view the small flood as more hazardous, emergency planners might consider the rare flood event to be more hazardous. This thesis classifies high probability hazards as more hazardous, even though the resulting flood is likely to be less intense.

3 Materials

3.1 Area selection

The integrated risk assessment framework can be used to assess risk from river related flooding. Therefore, the framework will be applied to the Maas river basin in Limburg, since this area is known for its history with river flooding and high water events in general. Past flood events in 1993, 1995, and 2021 have caused widespread damage across communities, in particular in the south of Limburg (e.g., Borgharen, Itteren, Valkenburg) (ENW, 2021).

Applying an integrated risk assessment to this area would thus be useful for Dutch FRM. Especially when there are concerns among spatial planners about a decreasing sense of urgency towards flood adaptation measures among communities at risk due to an increased presence of protection and mitigation measures such as dikes (Di Baldassarre et al., 2015).

3.2 Study area

The Maas river originates in France and enters the Netherlands at Borgharen, in the south of the province of Limburg (figure 1). It's catchment area encompasses parts of Belgium, France, Germany, Luxembourg and the Netherlands (Ward et al., 2013). The Maas basin in Limburg is densely populated with about 1 million inhabitants (Provincie Limburg, 2024) and the river system passes through large urban areas including Maastricht, Roermond, and Venlo.

Limburg is bordered by Belgium to the south and Germany to the east. The topography is mostly flat, with elevations gain of up to around 300 metres above sea level in the South. As a result of this relatively steep terrain, south Limburg has numerous small river and creek catchments that discharge in the main Maas river, such as the Geul or Geleenbeek tributaries. Further upstream, the terrain is flatter, causing the river to branch out less.

The river system is largely rainfed, so discharge levels are fluctuating throughout the year and are dependent on levels of rainfall and snowmelt in the catchments (Rijkswaterstaat, 2024). The river is characterised by frequent and rapid high water peaks resulting from excessive rainfall in the Belgian Ardennes. Here, the steep topology and impermeable soil cause the precipitation to create a snowball effect, and reach the Maas through its tributary systems (Deltares, 2018). Usually, these discharge levels peak in winter and spring season (Rijkswaterstaat, 2024).

The study region is known for its historic flood events, such as the Maas floodings in 1993 and 1995 which have caused over an estimated 100 million of property damages (ENW, 2021). While the main river system is mostly embanked, smaller tributaries are often not, which causes them to overflow regularly. Although smaller in size, these floods can also have disastrous outcomes, such as the flooding of the Geul river in the city centre of Valkenburg in the summer of 2021 (ENW, 2021).

3.3 Assessment framework

Limburg is subdivided on the municipal, district, and neighbourhood level. This thesis analyses vulnerability through socio-economic and physical dimensions that will be assessed on the district level. Exposure is assessed on the neighbourhood level, due to better data availability (CBS, 2024)

A distinction is made between districts (figure 2) and neighbourhoods (figure 3) considered flood prone and non-flood prone. based on the spatial intersection of inundation depths within hydrological models developed by the Risk Map of the Netherlands (Klimaateffectatlas, 2024) with districts and neighbourhoods in Limburg. In total, this intersection analysis was able to distinguish 142 flood prone districts, and 399 flood prone neighbourhoods throughout the study area.

Figure 1: Study area for this thesis. The map shows the Maas river and its branches that will be considered in this thesis as potential flood hazard sources. Data obtained from ESRI (2024)

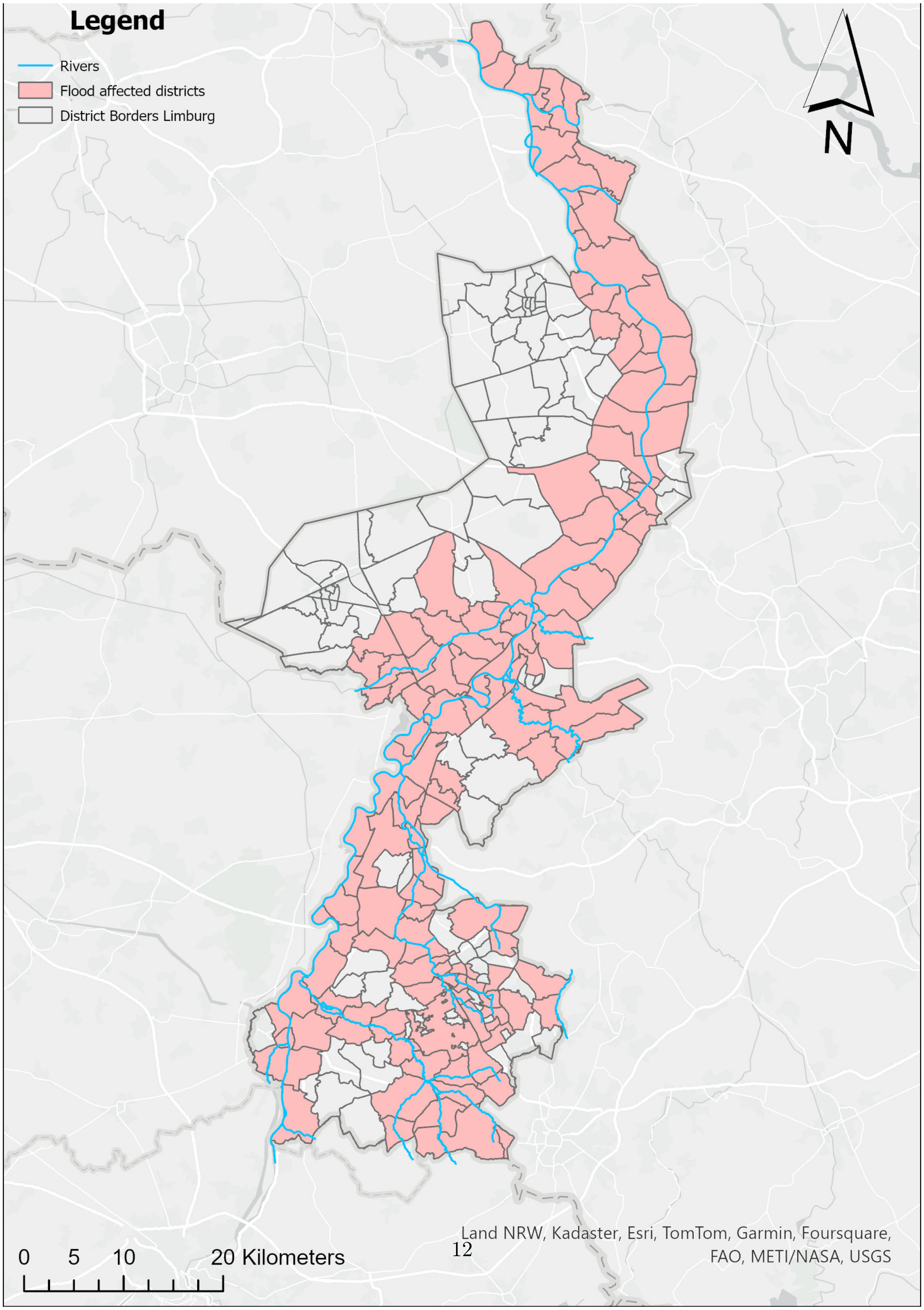


Figure 2: Flood affected districts within the study area (n = 142). Data obtained through intersection analysis with modelled flood inundation depths (Klimaateffectatlas, 2024)

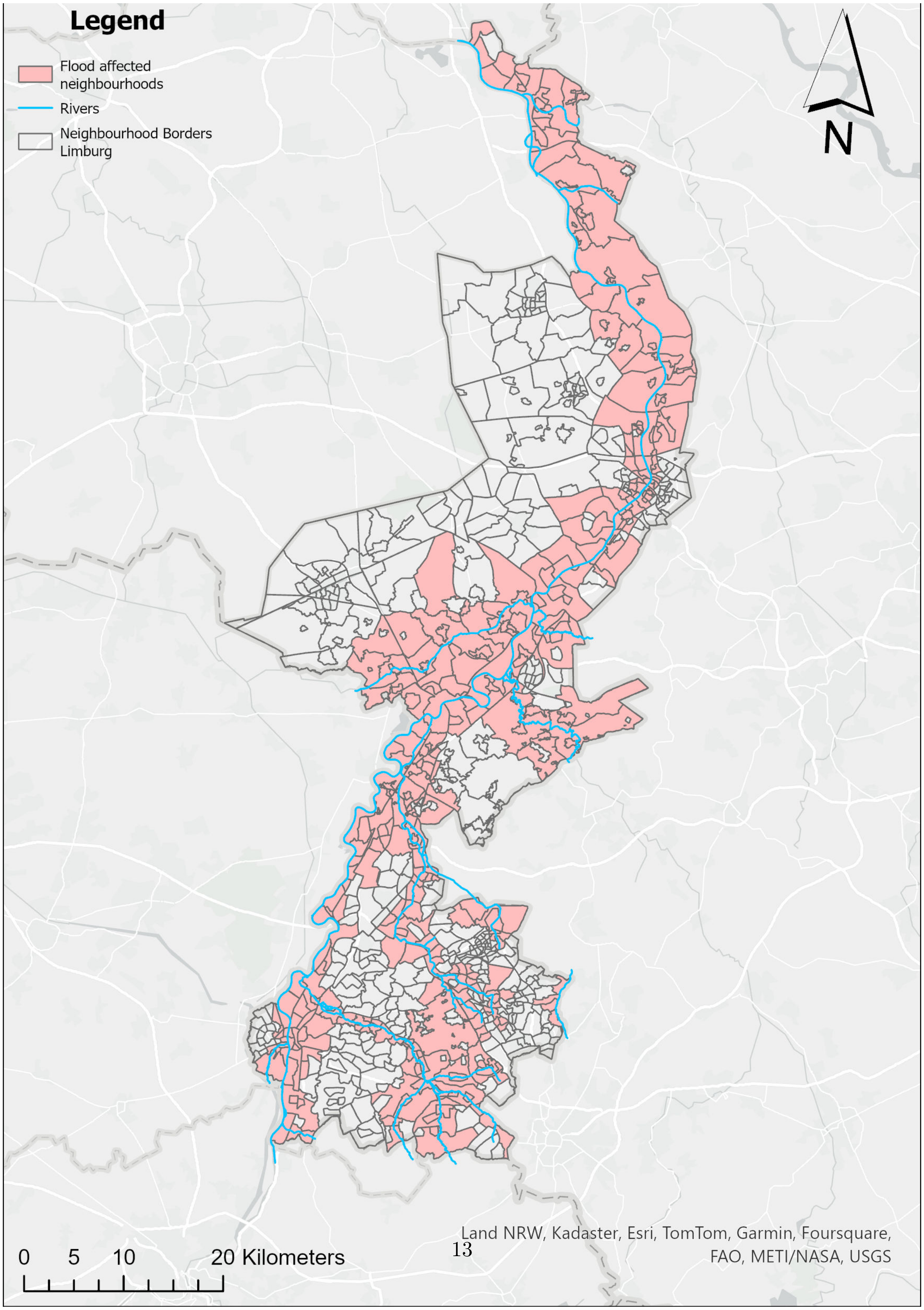


Figure 3: Flood affected neighbourhoods within the study area (n = 399). Data obtained through intersection analysis with modelled flood inundation depths (Klimaateffectatlas, 2024)

4 Methodology

4.1 Methodological framework

This thesis will combine three separate indices for vulnerability, hazard, and exposure in order to create an integrated flood risk assessment framework. Each index is composed of multiple quantifiable indicators retrieved from various data sources. A validation analysis will then be performed once the risk index is developed and applied to the study area in order to test the robustness and reliability of the model. Next, a sensitivity analysis will enable us to understand the influence of individual parameters on the model's results and assess its response to variations in input values. These processes are essential for identifying key drivers of risk and evaluating the model's stability. A flowchart of the proposed methodology is presented in figure 4.

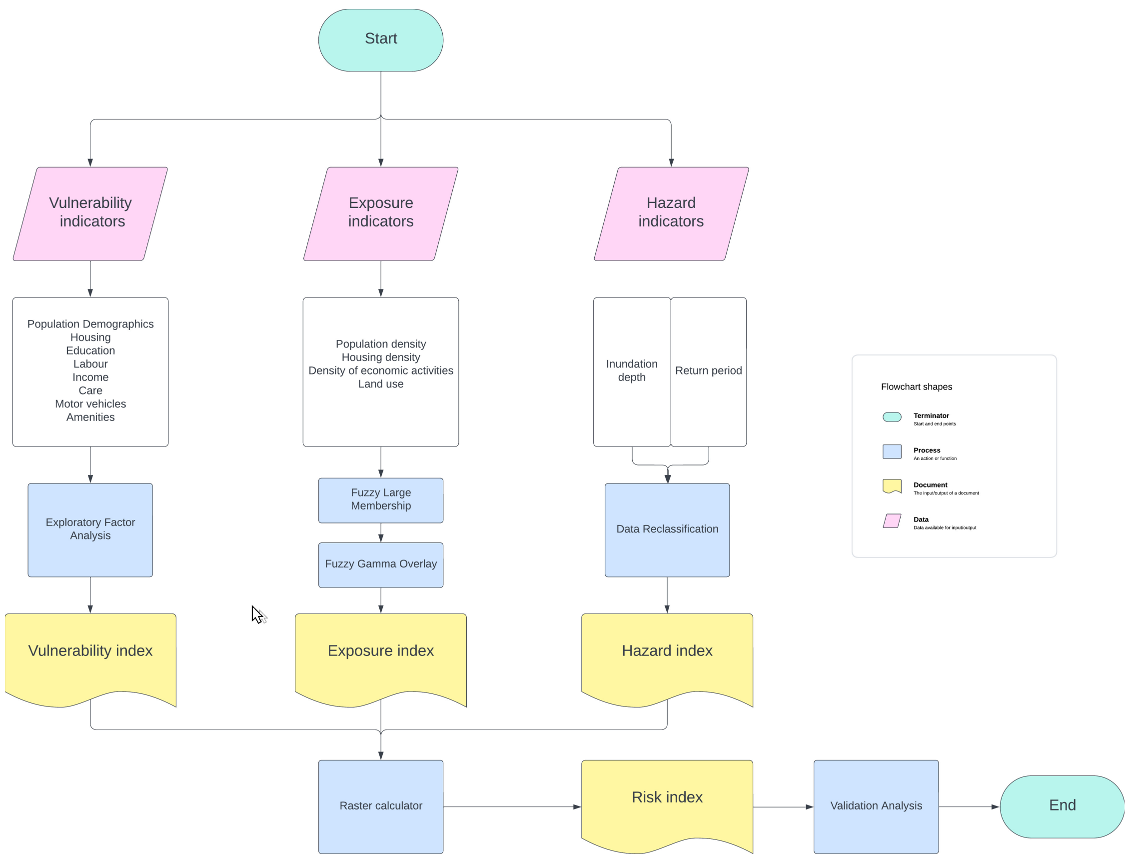


Figure 4: flowchart of the proposed methodology used within this thesis. Created by author.

4.2 Vulnerability

4.2.1 Data

The input data used to calculate a social vulnerability index is derived from the 'wijk- en buurtkaart' dataset created by the Dutch Central Bureau of Statistics (CBS), in collaboration with the Dutch cadastre. The 'wijk- en buurtkaart' is an annually updated dataset that contains demographic and socioeconomic data for the Netherlands on the municipal, district, and neighbourhood scale. The data is released over three versions, where each higher version is updated with more detailed data. Older datasets are released in higher versions, thus contain more complete data. This study combines data from 'wijk- en buurtkaart' for the year 2020 (version 3), 2021 (version 2) and 2022 (version 1). In essence, the most recently published dataset of 2022 is used, where it is supplemented with additional variables that are not yet updated in version 1, but are updated in versions 2 and 3.

The administrative border geometries were also taken from the most recent dataset of 2022. Over the period of 2020 – 2022, some administrative units have changed borders, due to for example the merger of municipalities or a changed intra municipal district- or neighbourhood administration. This has resulted in a few cases of missing data when transferring the data for municipals, districts and neighbourhoods across different timescales.

Higher administrative units in the dataset contain fewest missing data cases. Data on the municipal level is complete, but rather coarse. Data on the neighbourhood level is incomplete at times, but is fine scaled. Therefore, the social vulnerability index is constructed at the district level, where there is an acceptable trade-off between scale and data completeness. Any missing data on the district level is supplemented with municipal level data in which that district is located.

The combined CBS/Kadaster dataset contains variables distributed over 12 themes: population demographics, companies, housing, energy consumption, education, labour, income, care, social security, motor vehicles, geographic area, and amenities (CBS, 2022). From this dataset, a total of 19 variables related to vulnerability were selected (table 1)

The following paragraphs will justify in more detail the selection of each variable as a proxy for vulnerability, and explain the nature of its relationship with vulnerability. The arguments made throughout this section aim to build on existing literature as much as possible, but contain some assumptions when inadequate previous research has been conducted. It is also important to note that the arguments are based on general observed patterns within population groups, and do not necessarily represent every individual within those groups.

Theme	Variable	Explanation	Unit	Relationship with vulnerability	Year	Data source
Population demographics	P_Female	Female population	%	(+)	2022	CBS, Kadaster
	P_14_years_and_younger	Inhabitants 14 years and younger	%	(+)	2022	CBS, Kadaster
	P_65_years_and_older	Inhabitants 65 years and older	%	(+)	2022	CBS, Kadaster
	P_Divorced	Divorced population	%	(+)	2022	CBS, Kadaster
	P_Widowed	Widowed population	%	(+)	2022	CBS, Kadaster
	P_N_W_Immigrants	Non-western immigrant population	%	(+)	2022	CBS, Kadaster
Housing	P_One_person_households	One person households	%	(+)	2021	CBS, Kadaster
	P_Rented_housing	Rented houses	%	(+)	2021	CBS, Kadaster
	P_Housing_2000	Houses built until 2000	%	(+)	2021	CBS, Kadaster
Education	High_education	Inhabitants with higher education*	No. of inhabitants	(-)	2020	CBS, Kadaster
	Low_education	Inhabitants with lower education*	No. of inhabitants	(+)	2020	CBS, Kadaster
Labour	P_Net_labour_pp	Net labour participation	%	(-)	2020	CBS, Kadaster
Income	Income	Average income per inhabitant	1.000€	(-)	2020	CBS, Kadaster
	P_High_income_hh	High income households**	%	(-)	2020	CBS, Kadaster
	P_Low_income_hh	Low income households**	%	(+)	2020	CBS, Kadaster
Care	In_need_of_care	inhabitants in need of care***	No. of inhabitants	(+)	2020	CBS, Kadaster
Motor vehicles	Car_hh	Cars per household	No. of cars	(-)	2020	CBS, Kadaster
Amenities	Distance_firestation	Average distance to fire station	km	(+)	2021	CBS, Kadaster
	Distance_hospital	Average distance to hospital	km	(+)	2021	CBS, Kadaster

Table 1: Overview of selection of vulnerability indicators used for further analysis. Data obtained from CBS (2022). * = High education includes having achieved at minimum a bachelor's degree (in Dutch; HBO). Low education includes having achieved at maximum: primary school, pre-vocational secondary education (in Dutch; VMBO), lower-secondary education (first 3 years), or vocational education level 1 (in Dutch; MBO1). ** = High income includes those persons in households that belong to the national 20% highest income household. Low income includes households with purchasing power less than 9249 euro per year compared to prices in 2000. *** = recipients of financial support under 'wet maatschappelijke ondersteuning' (i.e. societal support law). These include people with disabilities, or chronic psychological- or psychosocial issues.

Population demographics Effects of a flood can be long lasting and have the potential to disrupt society, even when not life threatening. These effects, however, do not impact the population equally. A multitude of studies have indicated that demographic characteristics play a key role in shaping vulnerability with respect to floods (Morrow, 1999; Cutter, 2003; Flanagan et al., 2011). Particularly the marginalized groups within society, that have a disadvantageous socio-economic status, are adversely affected by a flood event in both the short- and long term. This implies direct flood impact, as well as the recovery phase after a flood event. Special attention for these groups is often overlooked in emergency planning.

About 50.2% of the population in Limburg is female (Provincie Limburg, 2024). On average, females in the Netherlands work less full-time hours than males (Kirby et al., 2019). This is likely the result of observed societal gender patterns and culturally embedded role behaviours, such as raising children. Women therefore tend to suffer more negative consequences from floods (Cutter, 1996; Neumayer & Plümper, 2007; Lowe et al., 2013). Lower incomes, family care responsibilities, and sector-specific employment were also found to be among the main reasons (Morrow, 1999; Neumayer & Plümper, 2007).

Mobility constraints of old age groups (65+ years) cause challenges for evacuating from dangerous areas (Cutter, 2003). These same constraints prevent taking adequate preparedness measures (e.g. moving assets out of harm's way, or blocking water from coming into a house). Young age groups (0-14 years), on the other hand, face difficulties protecting themselves, as they do not possess adequate resources, knowledge, or experience to cope with the danger (Flanagan et al., 2011). Children and the elderly generally lack self-reliance, and are dependent on (care of) others (Hewitt, 1997), making them more vulnerable to flooding. This demographic is thus highly correlated with negative disaster impact (Morrow, 1999). Young people made up around 12.8 per cent of the population in 2019 in Limburg, whereas old age groups accounted for about 25.5 per cent of the population (Provincie Limburg, 2024)

Apart from material damage, floods can greatly impact psychological well-being (Robinson & Botzen, 2020). Vulnerable populations include women, elderly, and divorced or widowed, who are more likely to suffer from stress, anxiety, and depression in the aftermath a flood event (Flanagan et al., 2011). Moreover, divorced and widowed populations often reside in single-headed households, where the absence of a partner can limit their access to financial and social resources (Morrow, 1999; Gu et al., 2018).

Such a lack of resources is also commonly found among immigrant populations, especially those with a non-western background (Morrow, 1999; Flanagan et al., 2011). Lower literacy rates, poorer housing conditions, and lower incomes cause this group to be more susceptible to the effects of flooding. Effective communication can be difficult due to cultural differences and language barriers. As such, this group often struggles to access key information that might have relieved flood impact and enhanced recovery in the long term. Non-western immigrants receive less post-flood funding due to inadequate insurance, discrimination, or knowledge on how to apply for funding (Munoz & Tate, 2016).

Housing Housing quality and housing ownership type can function as proxies for vulnerability (Morrow, 1999; Cutter, 2003; Lim & Skidmore, 2019). Poorly constructed homes are less resilient to water damage. Newly constructed homes ought to comply with stricter building regulations and zoning laws, and are more likely to withstand damage. Houses constructed before 2000 were taken as an indicator for vulnerability in this thesis, since these types of residences are more likely to be damaged in the case of a flood event. Moreover, older homes are generally populated by lower income groups (Lim & Skidmore, 2019), thus they are automatically associated with higher vulnerability.

Renters and one-person households are considered more vulnerable, as they generally lack financial resources for home ownership, or do not have the benefit of multiple income sources. Renters are less likely to take flood prevention measures in their homes (Gu et al., 2018). Because they have no ownership, they lack control over the protection, structure and insurance of their properties (Morrow, 1999). Dwellers in one-person households are dependent on themselves when it comes to preventing damage to inventory and building structure in the case of a flood event.

Education Higher educated communities are more likely to possess the knowledge and skills necessary to comprehend and respond to flood-related information, enabling them to make more informed decisions in times of crisis (Wang et al., 2018). Education contributes to an increased awareness of the potential risks associated with living in flood-prone regions, fostering a proactive attitude towards preparedness and mitigation measures (Mishra & Suar, 2007).

Higher education levels are also associated with improved economic opportunities, whereas lower educated groups generally earn less (Cutter et al., 2003). Differences in socio-economic status may thus result in unequal access to resources and social networks, leaving less-educated groups more isolated and vulnerable to the impacts of floods (Morrow, 1999).

Labour Employment indicates a stable source of income and increased access to financial resources. These can greatly benefit the long-term recovery phase as a buffer to cover potential damage. Being employed also provides stability, which was found to reduce the risk of suffering psychological effects (Markhvida et al., 2020). Net labour participation was selected to quantify employment as an indicator for vulnerability within this thesis.

Income The level of income reflects the financial resources at a households disposal to cope with the impacts of floods. More financial resources leads to less vulnerability in the impact phase, as well as the recovery phase (Kirby et al., 2019). Higher income groups have more buffers to deal with damages and continue life after a flood event. These groups are usually more resilient because they are also higher educated, employed, and live in well-constructed homes (Morrow et al., 1999; Cutter et al., 2003).

Care Population groups that are in special need of care require the assistance of others to take preparedness measures or to mobilize themselves in the event of a flood. Physically or mentally disabled groups are often marginalized in society, and have limited social and financial resources at their disposal (Cutter et al., 2003). This group is often unemployed and dependent on financial government support. Emergency planning often overlooks people in need of special care and are often left out of plans (Baan & Klijn, 2010).

Motor vehicles Access to motorized vehicles increases self-sufficiency of people and households in relation to floods (Cutter et al., 2003). Vehicle ownership creates possibilities for households to escape when an area is evacuated due to imminent flood risk. Furthermore, higher vehicle ownership is often an indicator for increased wealth, which tends to decrease vulnerability. Cars per households was therefore considered as a proxy for vulnerability in this research.

Amenities Firemen play a key role in the event of a flood disaster due to their training, responsibilities, and resources. Also in the preparedness phase, proximity of fire departments is beneficial because it increases chances of timely and adequate aid and results in faster response time for emergencies.

Hospitals can also serve as a temporary shelter to house flood affected communities. Proximity of shelters allow for more accessibility and will result in less negative impacts. Therefore, distance to critical infrastructure such as fire stations and hospitals are considered to be indicative of vulnerability in this thesis (Ziegelaar & Kuleshov, 2022).

4.2.2 Data indexing

Exploratory Factor Analysis (FA) was used in this thesis in order to combine these variables into a single index. FA is a statistical method used for identifying underlying relationships – or latent factors – that explain observed patterns in the original dataset (Murphy, 2021). It is a variable reduction technique, meaning that FA aims to summarise correlated variables, while accounting for as much variance in the original dataset as possible, in order to derive a set of factors that summarise vulnerability characteristics (Fekete, 2009). FA therefore does not generate new variables, but rather linear combinations of existing variables (Murphy, 2021).

The resulting factors consist of a set of loadings, that determine how significant each variable influences that factor. Factors that capture high amounts of variance are more likely to explain differences in vulnerability patterns over the study area than factors that account for relatively low percentages of variance. Moreover, within a dataset of 19 interdependent variables, FA can untangle shared variance by grouping correlated variables in factors. Thereby, it can help reducing the risk of multicollinearity (Kyriazos & Poga, 2023).

For meaningful FA, the dataset must contain at least some degree of variable correlation. These correlations will be tested using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequcy and the Bartlett's test of Sphericity (Gu et al., 2018). KMO tests the partial correlation strength between variables (Kaiser, 1974). The KMO test result ranges between 0 and 1, where values closer to 1 indicate higher correlation among variables. Results below 0.5 would suggest FA is not applicable due to weak variable correlations (Kaiser, 1974). The Bartlett's test of Sphericity tests the null hypothesis that the correlation matrix is similar to an identity matrix (e.g., no correlation between variables) (Bartlett, 1951). Both tests will be applied to the vulnerability variables in order to test the degree of suitability of FA.

Some variables, such as the proportion of inhabitants with higher education, hold a negative relationship with vulnerability, meaning that higher values lead to a decrease in vulnerability. These variables were inverted so that a higher value of that variable also represents higher vulnerability. Absolute variables were adjusted to percent, per capita, or density (Kirby et al., 2019).

The FA is performed with RStudio software using the 'psych' package. The exploratory factor analysis model uses varimax rotation with Kaiser normalisation. Varimax rotation is a orthogonal rotation technique that simplifies the structure of the factors, and ensures higher factor independency (Fekete, 2009; Kirby et al., 2019; Murphy, 2021). Varimax rotation minimizes the number of variables that have high loadings on each factor, thereby reducing the cross loadings (Murphy, 2021).

Kaiser normalisation was applied to extract only the factors with eigenvalues greater than one. An eigenvalue represents the amount of variance contained by a factor in a data matrix (Piedmont, 2014). Extracting eigenvalues greater than 1 indicates that a factor is worth retaining, since it accounts for more variance than any single item in the matrix would on its own (Piedmont, 2014). Variables with factor loadings less than 0.3 are not considered to be part of a factor.

4.2.3 Vulnerability index

From the resulting set of latent factors, a vulnerability index will be constructed using a weighted model. The weights are determined by the proportion of variance explained by each factor, rescaled to 100% (Kirby et al., 2019). Factors that are able to account for more variance in the data will thus be more influential to the index (Gu et al., 2018).

The highest loading variable for each factor will be normalised using min-max normalisation (eq. 2), so that index values range between 0 and 1.

$$V_n = \frac{X_n - \min(X_n)}{\max(X_n) - \min(X_n)} \tag{2}$$

Where V is the normalised value of the highest loading variable X in the n-th factor.

These values are then multiplied by the corresponding rescaled factor variance to weight index scores. In short, the vulnerability index will be calculated using the following formula (eq. 3) (Kirby et al., 2019):

$$\sum_{n=1}^{k} V_n \cdot w_n \tag{3}$$

Where the Vulnerability Index is calculated by the summation of the normalised value of the highest loading variable V of the n-th factor multiplied by the rescaled variance – or weight w -of the factor. The total number of factors is represented by k.

4.3 Exposure

4.3.1 Data

This thesis uses a combination of sources for data gathering to create a flood exposure index (table 2). Firstly, the database developed by CBS and the cadastre, as discussed in the section 4.1, also contains data on population- and housing density, and the number of companies registered per neighbourhood, district, and municipality. This data was retrieved for the year 2022 at the neighbourhood level. Neighbourhoods in figure 3 are considered for exposure analysis.

Additionally, a 'Landgebruik Nederland' (LGN) (i.e. land use map of the Netherlands) dataset created by Wageningen Environmental Research was extracted (WENR, 2024). LGN land use is an open satellite derived land use dataset with a 5x5 metre resolution that identifies a total of 39 distinct land uses over the year 2022.

As such, four indicators were selected to create an exposure index (table 2). The following paragraphs discuss the selection and quantification methods of each indicator more in-depth:

Theme	Variable	Explanation	Unit	Relationship with Exposure	Year	Data source
Population density	Pop_Dens	Density of the population	Population / km^2	(+)	2022	CBS, Kadaster
Housing density	OAD	Density of addresses	Addresses / km^2	(+)	2022	CBS, Kadaster
Density of economic activity	COMP	Density of businesses	Businesses / km^2	(+)	2022	CBS, Kadaster
Land use	-	Land use	Community value (0-1)	(+)	2024	WENR

Table 2: Overview of selection of exposure indicators used for further analysis. Data obtained from CBS (2022) and WENR (2024)

Population density A higher population density implies a greater concentration of individuals in a given area. In the context of flood risk, highly populated areas (e.g. urbanized areas) are likely to face more significant challenges in evacuation, emergency response, and recovery (Cremen et al., 2022). Additionally, a more dense population is likely to have a higher concentration of assets at risk (De Brito et al., 2017; Cremen et al., 2022).

Housing density Housing density reflects the exposure of the built environment to flooding. A densely built area is indicative of more residences in an area. High density in hazardous areas increases a communities' potential losses to housing stock during a flood.

Density of economic activities The concentration of businesses in area serves as a proxy for the economic exposure to flooding. Increased company density implies a greater concentration of economic assets at risk, including tangible (e.g. inventory), and intangible (e.g. employment opportunities) assets. Concentrated economic activity makes an area more valuable, thus has a positive relationship with exposure (De Brito et al., 2017).

Land use Land use is commonly used as an indicator for flood exposure (Ziegelaar & Kuleshov, 2022; Cremen et al., 2022). Each type of land use contributes differently to flood exposure, since each type is associated with a certain community value. Community value of a land use is determined by the potential community costs associated in case this type of land use gets destroyed or damaged during a flood event (Ziegelaar & Kuleshov, 2022). As such, agricultural cropland has a higher community value than floodplains, because losing this type of land use would result in more costs than losing floodplain.

In order to quantify the effect of land use on flood exposure, a land use reclassification will be applied using ArcGIS Pro (appendix A), where each land use will be assigned a numerical value of 0 to 1 based on this community value (table 3). Higher numeric values correspond to a higher community value, thus greater levels of exposure. Community values corresponding to land use reclassifications are retrieved from Ziegelaar & Kuleshov (2022), who assigned community values based on findings from literature. Community values used in this thesis can be found in table 3.

Reclassified land use	Community value	Rating
Water bodies	0.1	Very low
Grazing	0.3	Low
Small infrastructure	0.3	Low
Forestry	0.5	Moderate
Natural areas	0.5	Moderate
Cropping	0.7	High
Large infrastructure	0.9	Very high
Built environment	0.9	Very high

Table 3: Reclassified land use and their corresponding community value. Community values and ratings are based on Ziegelaar & Kuleshov (2022).

4.3.2 Data standardisation

Each of the population density, housing density, and density of economic activity indicators will be standardised using the fuzzy membership tool in ArcGIS Pro. Data standardisation ensures that each indicator contributes proportionally to the exposure index, regardless of their original scale or magnitude. Fuzzy membership is a widely accepted tool for index-based flood risk assessments (Ziegelaar & Kuleshov, 2022). Because higher indicator values indicate higher levels of exposure, a fuzzy large spread was applied. Fuzzy large standardises all values to a value between 0 and 1, based on the degree of membership to a specified class for a given spread and midpoint (Ziegelaar & Kuleshov, 2022). The land use indicator layer will not be fuzzified, as the reclassified community values already have a range between 0 and 1.

4.3.3 Exposure index

The final exposure index was calculated using fuzzy gamma overlay. This tool overlays the standardised fuzzy layers in an equal weighted technique using fuzzy sum-, and product, taken to the power of gamma (Ziegelaar & Kuleshov, 2022). A standard value of 0.9 was chosen for gamma, as this is considered to be the generic value in overlay analysis (Aitkenhead et al., 2021; Ziegelaar & Kuleshov, 2022).

Additionally, a pearson correlation analysis will be conducted for each separate indicator, to see how heavily the indicator correlates with the exposure index. This will gain insights in which indicator(s) are most influential in determining overall exposure, and whether linear relationships between the indicators and the index are statistically significant.

4.4 Hazard

4.4.1 Data

In order to quantify hazard intensity, flood characteristics such as inundation depths are commonly adopted in literature (De Bruijn et al., 2015; Koks et al., 2015; Maranzoni et al., 2022). In compliance with the floods directive, countries across the European Union are required to deliver flood hazard maps, delineating areas of potential flood extent- and severity. As such, the Dutch ministry of infrastructure and water management have produced and published these hazard maps for the Netherlands on the platform 'risicokaart' (i.e. risk map of the Netherlands) (Klimaateffectatlas, 2024). Areas with potentially significant flood risk, or so-called 'GPSOR' areas, were designated, along with the type of flood expected to occur in these areas. Flood types include floods in embanked and unembanked areas along main or regional waterways (Rijkswaterstaat, 2024). Dutch flood hazard maps display flood severity, indicated by maximum possible inundation depths over a series of simulated flood scenario's in these GPSOR areas throughout the Netherlands (figure 3). A total of four maps are produced, representing various return periods (T=10, 100, 1000, and 10 000) of hydrological events. Each map has a spatial resolution of 25 x 25 metres.

Flood simulations are run by the ministry of infrastructure and water management in the Netherlands. Floods in embanked areas of the Maas river in Limburg are simulated from a set of dike breaches at different locations using 1D-2D hydraulic models. For each embanked segment of the Maas, dike failure probabilities are calculated in VNK2 reports (Rijksoverheid, 2024). As a result, the hazard maps indicate the simulated maximum inundation depths that could occur in a grid at four different discharge levels (Slager, 2019).

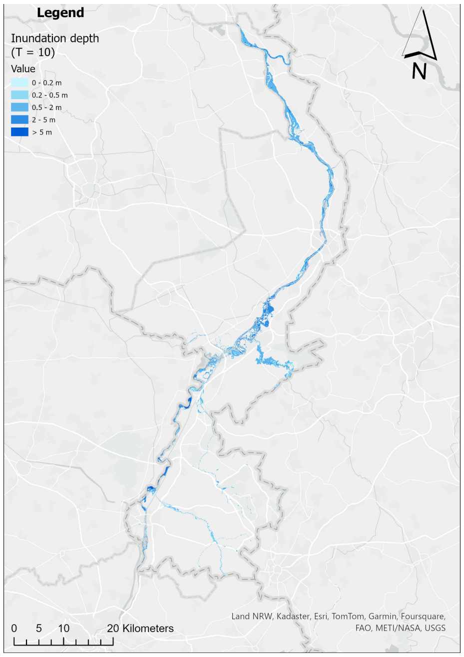
Unembanked areas of the Maas river in Limburg are mostly the outer-dike areas along the main river, or areas along tributaries. Floods in unembanked regions are the possible result of high water levels due to rainfall in the river catchments, rather than a dike failure or levee breach. Maximum inundation depths are simulated at similar discharge levels as in the embanked areas (table 4) For reference, the peak discharge level of the Maas river during the 2021 flood was 3260 m^3/s, measured at Borgharen (Van der Veen, 2021).

Map	**Probability per year**	**Discharge Maas (Borgharen) in $\mathbf{m^3/s}$**
1	1/10	2300
2	1/100	3220
3	1/1000	3860
4	1/10000	4400

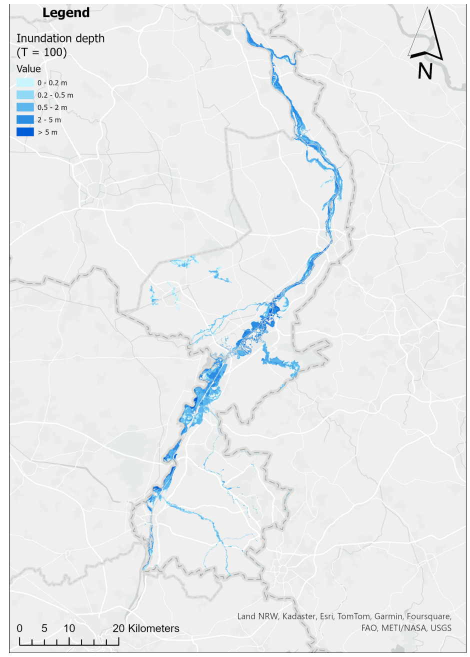
Table 4: Discharge levels used as inputs for flood simulations ran by the risk map of the Netherlands, with their occurrence probabilities (Slager, 2019)

It is worth noting that inundation depths in these hazard maps are not expected to take place simultaneously after a single flood event, but rather show the aggregated result of multiple flood simulations, thus the potential place based severity (Koks et al., 2015).

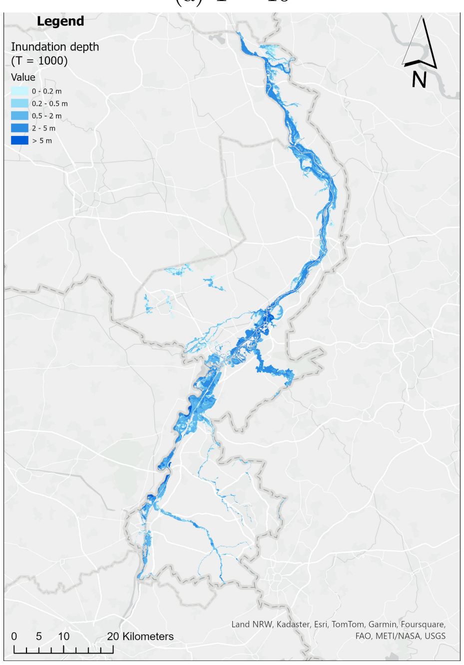
For the construction of the hazard index, the flood risk maps of the Netherlands are used. These are updated in cycles of six years, where the most recent update took place in 2022. The data was accessed and downloaded through the portal klimaateffectlas.nl (klimaateffectatlas, 2024), and imported into ArcGIS Pro software.



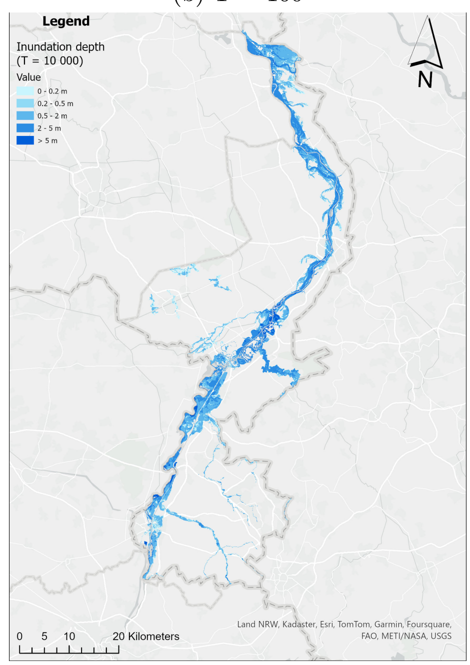
(a) T = 10



(b) T = 100



(c) T = 1000



(d) T = 10 000

Figure 5: Maximum possible inundation depths at four different return periods (T), as modelled by the Ministry of Infrastructure and Water Management (2022). Data obtained through: www.risicokaart.nl.

4.4.2 Hazard index

The final hazard index will be derived from the potential inundation depth maps simulated by the risk map of the Netherlands. Both flood likelihood and flood intensity will be considered for the construction of the hazard index. Because hydrological events with lower return periods are more likely to occur, inundation depths at more probable scenario's are considered more hazardous than similar inundation depths at higher return periods (Maranzoni et al., 2022). As such, this thesis considers hazard from a spatial planner's perspective, rather than an emergency planner's perspective, where mapping low frequency hazards would be more beneficial (De Bruijn et al., 2015).

The classification scheme used to combine the maximum possible inundation depths (h) into a single hazard index map is presented in table 5. The thresholds in this table are based on a paper by Maranzoni et al. (2022), who have developed a method to combine return periods (T) and flood intensity characteristics. Rather than creating flood hazard maps for a fixed return period (Chakrabory,et al., 2021), this method captures both flood likelihood and severity. A distinct flood hazard zone is assigned to a grid cell if the condition in table 5 is met, given no higher hazard condition is met (Maranzoni et al., 2022)

As a result, five distinct hazard zones were differentiated within the study area. Each hazard zone was given a corresponding hazard index score (table 5) so that the final hazard index is scaled between 0 and 1.

Hazard zone	**Flood hazard level**	**Condition**	**Hazard index score**
0	None	$\mathrm{h}_{T=10\,000}$ & $h_{T=1000} = 0\,m$	0
1	Low	$\mathrm{h}_{T=10\,000}$ *or* $h_{T=1000} > 0\,m$	0.25
2	Moderate	$\mathrm{h}_{T=100} > 0\,m$	0.5
3	High	0.5 m $< \mathrm{h}_{T=10} < 1\,m$, *or* $h_{T=100} > 1\ m$	0.75
4	Very high	$\mathrm{h}_{T=10} > 1\,m$	1

Table 5: Flood hazard classification based on specific conditions for inundation depth (h) in metres (m) per return period (T). Data obtained from Maranzoni et al. (2022)

4.5 Risk

4.5.1 Risk index

After the construction of all three indices, a risk index will be constructed following the definition of risk in section 2, as the interplay between vulnerability, exposure, and hazard (eq. 1). First, all layers are rasterised to a resolution of 25 x 25. Next, these layers will be multiplied using the raster calculator tool in ArcGIS Pro with an equal weighting approach, as none of the risk components is assumed to be more influential than another.

Zero values in either one of the vulnerability, exposure, or hazard index indicate that an area is not considered at risk of flooding, and therefore will not be considered for risk analysis. Consequently, these areas will also be given a risk value of zero. Therefore, the final risk index will only contain a value when the values in all three indices are non-zero, or considered at risk of flooding.

4.5.2 Validation

The main goal of integrated flood risk assessments is to gather information about areas at risk of future flooding (Jongman et al., 2012). Evaluating accuracy and reliability of the assessment methodology is a key practice in risk assessments, especially since uncertainties regarding these future flood events play a major role (Efraimidou & Spiliotis, 2024). Validating risk assessments can be challenging, mainly because risk is not a measureable parameter in the field, and since post flood data with high spatial resolution is often insufficient (Molinari et al., 2017; Efraimidou & Spiliotis, 2024). Some studies, such as Fekete (2009), have included such validation techniques. However, accurate flood outcome data for the study area of this thesis is lacking.

Therefore, within the scope of this thesis, the risk assessment framework will be validated by using a similar dataset for vulnerability and exposure from 2015 (CBS, 2015). The results of the two risk indices, including its components, will then be compared in order to check the robustness of the assessment framework.

5 Results

5.1 Vulnerability index

Exploratory FA was conducted on the original dataset of 19 variables related to social vulnerability in the 142 flood affected districts in Limburg. A correlation matrix (figure 6) was computed in R in order to obtain the eigenvalues that determine the amount of factors to retain using kaiser's criterion. The scree plot (figure 7) was derived from this correlation matrix, and shows the eigenvalues per factor. The eigenvalue threshold of one is presented as the red dotted line in the scree plot. Following kaiser's criterion, four factors can be extracted with an eigenvalue greater than one (figure 7). This implies that each of these factors are able to explain more variance than a single observed variable would do on its own (Piedmont, 2014).

KMO test results suggested that FA was highly likely to be suitable for the dataset with an overall MSA of 0.82. This indicates sufficient correlation among variables, and suggests that the extracted factors are likely to be reliable representations of underlying data structures (Kaiser, 1974).

Additionally, the Bartlett's test for sphericity proved to be statistically significant ($\chi^2 = 2435.94$, $p < 0.0001$) at $\alpha = 0.05$. This result rejects the null hypotheses that the variables are not interrelated and thus unsuitable for extracting latent factors (Bartlett, 1951). These results further strengthen the evidence that FA is appropriate.

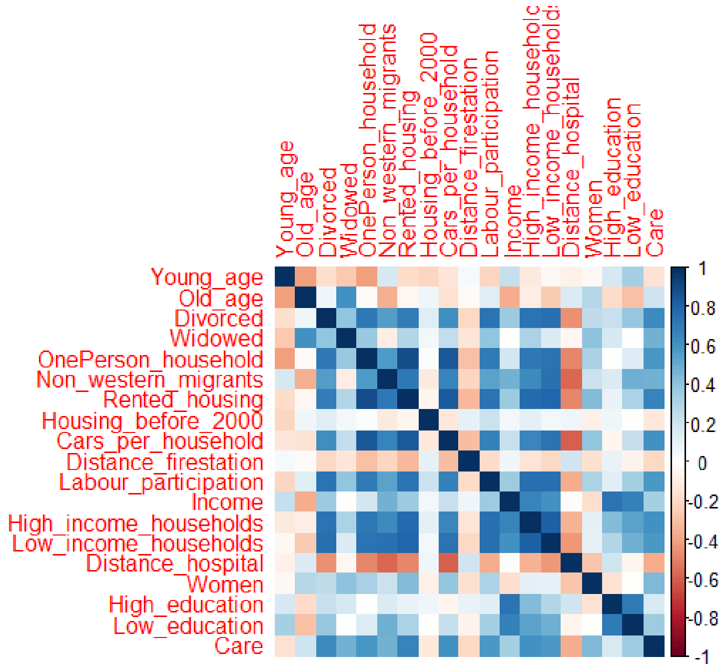


Figure 6: Correlation matrix between all 19 variables used in Vulnerability analysis. Data obtained from CBS (2024).

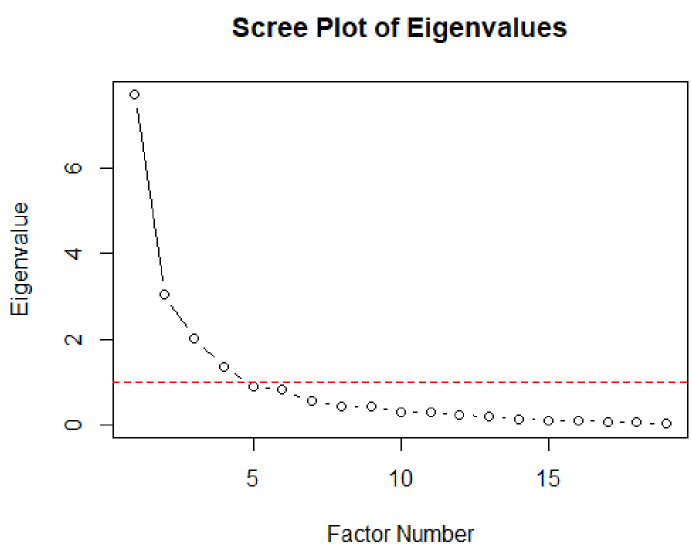


Figure 7: Scree plot showing eigenvalues used to extract the desired amount of facors based on Kaiser's criterion. Data obtained through CBS (2024).

The four factors extracted from FA were able to account for two-thirds (66.69%) of the total variance. All factor loadings are presented in table 6. Each factor is given a label based on the high loading variables in that factor; these represent the underlying – latent – structure of the dataset.

The first factor pertains to household compositions with variables such as percentage of foreign population, percentage one person households, cars per household, and rented housing playing all loading highly onto the factor. The higher a variable's factor loading, the more influential it becomes for that factor. Percentage of one person households was taken as a measure for the latent factor household composition, as this is the highest loading variable for that factor.

Factor 2 is influenced most by income and education variables. Note that percentage of population with lower education was inverted; meaning that a higher values indicate less people with only having achieved lower education. High and low education therefore have the same directional effect on the factor. Highest loading variable income was standardised as a measure for the factor socio-economic status.

The population percentage above 64 years old and percentage of widowed population were among the highest loading variables on the third factor. This factor is associated with characteristics of older population groups, where widow rates are also more common. Therefore, the latent factor was nicknamed 'old age'.

Factor 4 is distinguished by percentage of population under 14 years of age. The negative loading would suggest a decrease in factor value with higher proportions of young people. This is likely due to the negative correlations of this variable with other variables (figure 6). To illustrate, variables such as average income or one-person households are generally lower as young populations increase, because these young groups are not yet a life stage where they generate an income, nor form a household.

The third and fourth factor contain fairly weak loadings compared to the other factors. As the amount of factors in the FA model increase, each additional factor needs to explain a smaller proportion of the total variance. This often results in lower loadings, since the variance is shared among more factors.

Once the highest loading variable for each was extracted and standardised, index scores could be computed using rescaled factor variance (figure 7) as weights. Factors that are capable of capturing more variance are also more likely to account for differences in vulnerability patterns across flood affected districts in Limburg. As table 7 shows, the factor household composition is most important in differentiating values in the vulnerability index.

Values in the final vulnerability index are calculated using eq.3, and range between 0.244 in the district 'Hout-Blerick' in the municipality of Venlo, and 0.733 in the district 'De Hei' in the municipality of Heerlen (figure 8). The mean vulnerability score among all 142 districts is 0.429. This value represents that, on average, flood affected districts show moderate levels of vulnerability. Also, districts showing higher scores than the mean value, are considered to be more vulnerable based on the combination of the highest loading variables in each of the four factors.

Districts that are not flooded in the inundation model developed by the risk map of the Netherlands are also not considered for vulnerability analysis. Including these districts in vulnerability analysis could possibly skew the index values of flood affected districts, by altering the loading values or by potential data outliers

The index rates dense commercial and residential areas higher in terms of vulnerability, likely because of the abundance of single family households represented by the first latent factor. Especially (urban) districts in the south of Limburg generally score higher on the vulnerability index. The five highest scoring index values can be found in this part of Limburg, of which four districts

Input variables	Factor 1	Factor 2	Factor 3	Factor 4
Divorced (%)	0.709	0.320		
One person households (%)	0.933			0.352
Non-western immigrants (%)	0.740	0.315		-0.342
Rented housing (%)	0.921			
Cars per household	0.914			
Net labour participation (%)	0.718	0.302		
High income households (%)	0.700	0.585		
Low income households (%)	0.789	0.466		
Distance to hospital	-0.629			
In need of care (%)	0.623		0.416	
Income		0.899		
High education (%)		0.826		
Low education (%)		0.736		
65 years and older (%)			0.866	
Widowed (%)			0.674	0.359
14 years and younger (%)				-0.646
Houses built untill 2000 (%)				
Distance to firestation	-0.336			
Females (%)	0.406		0.424	
interpretation				
High positive loadings	Divorced, household status, non-western immigrants, housing type	Income, education	65 years and older, widowed	-
High negative loadings	-	-	-	14 years and younger
Latent factor name	Household composition	Socio-economic status	Old age	Young age
Percent explained variance	34.28%	16.83%	9.71%	5.87%

Table 6: Factor analysis results as computed in Rstudio. Table shows variable loadings per extracted factor, includes labeling of each latent factor, and the amount of explained variance per latent factor. Data obtained through CBS (2024).

Factor number	Explained variance	Rescaled variance (weight)
Factor 1	34.28 %	51.40 %
Factor 2	16.83 %	25.24 %
Factor 3	9.71 %	14.56 %
Factor 4	5.87 %	8.80 %
Total	66.69 %	100 %

Table 7: Percentages of explained variance for all four extracted factors from FA, rescaled to 100%. These percentages will be used as factor weight contribution to the vulnerability index. Data obtained from CBS (2024).

are located within the municipality of Heerlen.

Southern Limburg contains large urban cores such as Maastricht, Heerlen, or Sittard. A lot of retail and industry is concentrated in these cities, along with institutions such as Maastricht university and other universities of applied science. This might partly explain the high proportion of single person households. Southern Limburg is also known as one of the highest aging regions of the Netherlands (CBS, 2024), contributing even more to high vulnerability scores.

Index values are lowest in the north of the study area (excluding city centres), where rural economies and agriculture play a more prominent role. As such, the proportion of single person households is considerably lower in the north. Aging is not as prominent here as it is in the south. Possibly due to increased connectivity with the rest of the Netherlands, which could attract commuters. There are little to no differences in socio-economic variables between high and low scoring regions. This suggests that income is distributed more proportionally across the whole study area than single person households, old age groups, and young age groups.

The FA analysis method does have its inherent limitations. FA is a statistical dimension reduction technique, where underlying data structures are uncovered based on correlations. It cannot prove to what extent outcomes correspond to actual vulnerability in the real world. Rather, the outcome can be interpreted as to how the selected variables within the specific study area may contribute to different social vulnerability patterns based on findings from literature on this topic (Kirby et al., 2019). Index validation using household survey data (Fekete, 2009), or data from past flood outcomes (Tellman et al., 2020) could provide more meaningful insights into how well a modelled vulnerability index corresponds to reality. Household surveys or empirical flood data in Limburg (e.g. in 1993, 1995, or 2021) was not obtained in order to verify the index, as this is considered to beyond the scope of this thesis.

The vulnerability index constructed here offers a simplified method to provide spatial planners, emergency managers, and other experts in the field of FRM with insights into drivers and attributes of vulnerability. This method is meant to be reproduceable and easily applicable to other regions and other inputs. Further modifications can be made by including more variables into factor scores rather than only the highest loading variable, or by applying one of the aforementioned validation methods to the index.

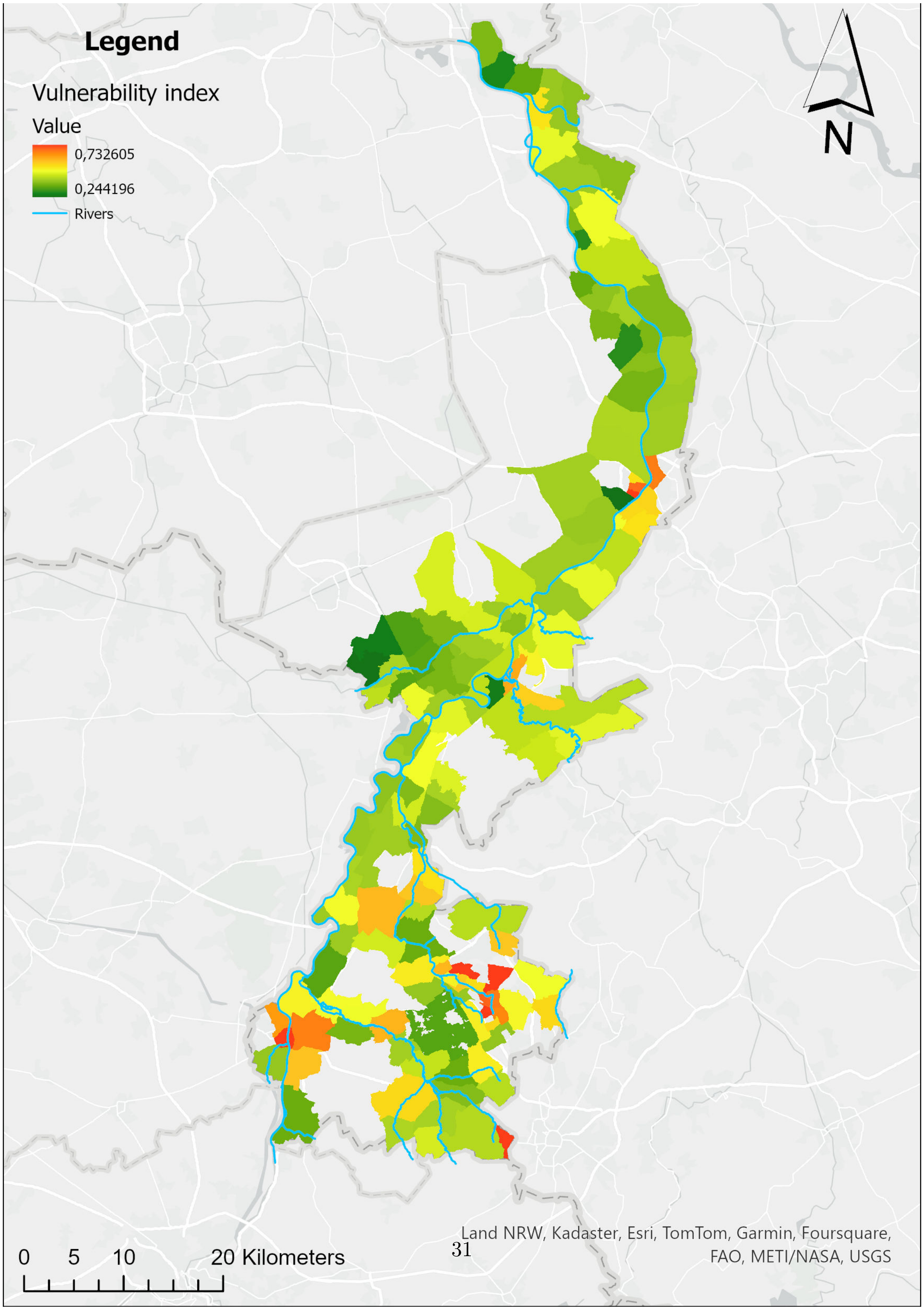


Figure 8: Vulnerability index values as calculated using equation 3. Index values are displayed per district and range between 0.244 (dark green) and 0.733 (red). Data obtained from CBS (2024).

5.2 Exposure index

In order to assess and map the exposure indicators and final exposure index in flood exposed neighbourhoods in Limburg, five distinct exposure risk classes are assigned to fuzzified indicators and land use (Ziegelaar & Kuleshov, 2022). These classes are subdivided in: very low, low, moderate, high, and very high. The classification values were based on natural breaks and can be found in table 8 for each exposure indicator. The fuzzy large spreads and midpoints used for each indicator can be found in appendix B.

These risk values and classes do not have meaning on itself, but are given meaning in comparison to each other. Values closer to one indicate higher levels of exposure, whereas values closer to zero indicate lower exposure levels.

Population density after fuzzy standardisation is displayed in figure 9. Highest densities can be found in urban areas in the south of Limburg, such as Maastricht, Heerlen, Geleen and Sittard. Some smaller urban cores have high population density, such as Valkenburg or Vaals. Further up north population density gradually declines, with the exceptions of cities such as Roermond or Venlo. From figure 9 it can be seen that there are considerable differences in population density in flood affected neighbourhoods in Limburg. Population exposure is on both sides of the extremes, and not much in between. This proves the urban-rural divide that is present in the province. It should be noted that places with very low population densities, might still be significantly exposed, or considered dense in other contexts. The figure shows that these areas are, in relation to other flood affected neighbourhoods in Limburg, less inhabited.

Figure 10 shows a map of the housing density throughout flood affected neighbourhoods in Limburg. It is imperative that this map is somewhat similar to the population density map, as it contains a similar bias towards urban areas. However, some differences can be observed between the two maps. Some neighbourhoods display very low population density, and a low to moderate housing density. This implies low occupancy rates per dwelling, and might suggest the presence of companies (a registered premise without resident). Vice versa, urban areas that show very high population density, but lower housing densities, would imply higher occupancy rates. This might be due to stacked housing in large urban cores in cities like Maastricht or Venlo.

Figure 11 displays a map of density of economic activities measured by the number of businesses registered per neighbourhood. A clear bias towards urban areas can clearly be observed here. Economic activities are largely concentrated in urban areas, where labour supply is highest. Additionally, rural businesses (e.g. farms) take up more space, where their urban counterparts are more concentrated.

The reclassified land use map is shown in figure 12. Very high land use exposure can be found mainly in urban areas. The reclassified land use map, however, does not make distinctions between the degree of urbanity, like the other indicators do. High exposure represents the cropland, which is found throughout the whole province in between urban areas. Moderate exposure is largely observed around forest and nature areas along the Maas in the northern part of Limburg, and in national parks such as 'de Meinweg', east of Roermond. Low levels of exposure consist of areas used for grazing. These areas largely surround the main river, as they often serve also serve as floodplain. However, grazing pratices are also common further inland, such as in the southeastern part of Limburg.

Figure 13 shows the final flood exposure map in flood affected neighbourhoods in Limburg based on the combination of four indicators (i.e. population density, housing density, density of economic activities, and land use) at a 25x25 metre resolution. The map demonstrates that the relatively more exposed regions are predominantly urban. Also, the map shows that, in general, regions in the

Exposure class	Population density values	Housing density values	Density of economic activity values	Land use values	Exposure index values
Very low	0 – 0.102	0 – 0.124	0 – 0.066	0.1	0 – 0.124
Low	> 0.102 – 0.384	> 0.124 – 0.337	> 0.066 – 0.205	0.3	> 0.124 – 0.290
Moderate	> 0.384 – 0.701	> 0.337 – 0.597	> 0.205 – 0.387	0.5	> 0.290 – 0.549
High	> 0.701 – 0.892	> 0.597 – 0.826	> 0.387 – 0.647	0.7	> 0.549 – 0.774
Very high	> 0.892 – 1	> 0.826 – 1	> 0.647 - 1	0.9	> 0.774 - 1

Table 8: Exposure classes and their corresponding values that are used for classification of each exposure indicator and the exposure index. Created by author.

south of Limburg are more exposed than in the north. Areas of high exposure are predominantly along the main Maas river channel, along with the Geul and Geleenbeek.

Finally, the pearson correlation tests points out that the indicator population density spatially correlates most to the final exposure index ($R = 0.956$, $p < 0.0001$). Housing density and density of economic activities also correlated highly to the index with R = 0,844, $p < 0.0001$ and $R = 0.820$, $p < 0.0001$ respectively. This suggests that there are strong, positive linear correlations between population density, housing density, and density of economic activities on the one hand, and the exposure index on the other hand (Turney, 2024). The land use indicator correlated moderately ($R = 0.493$, $p < 0.0001$) to the exposure index. It was found that all indicators correlated positively to exposure. This implies that higher values in each of the indicators correspond to higher values in the final exposure index (Turney, 2024).

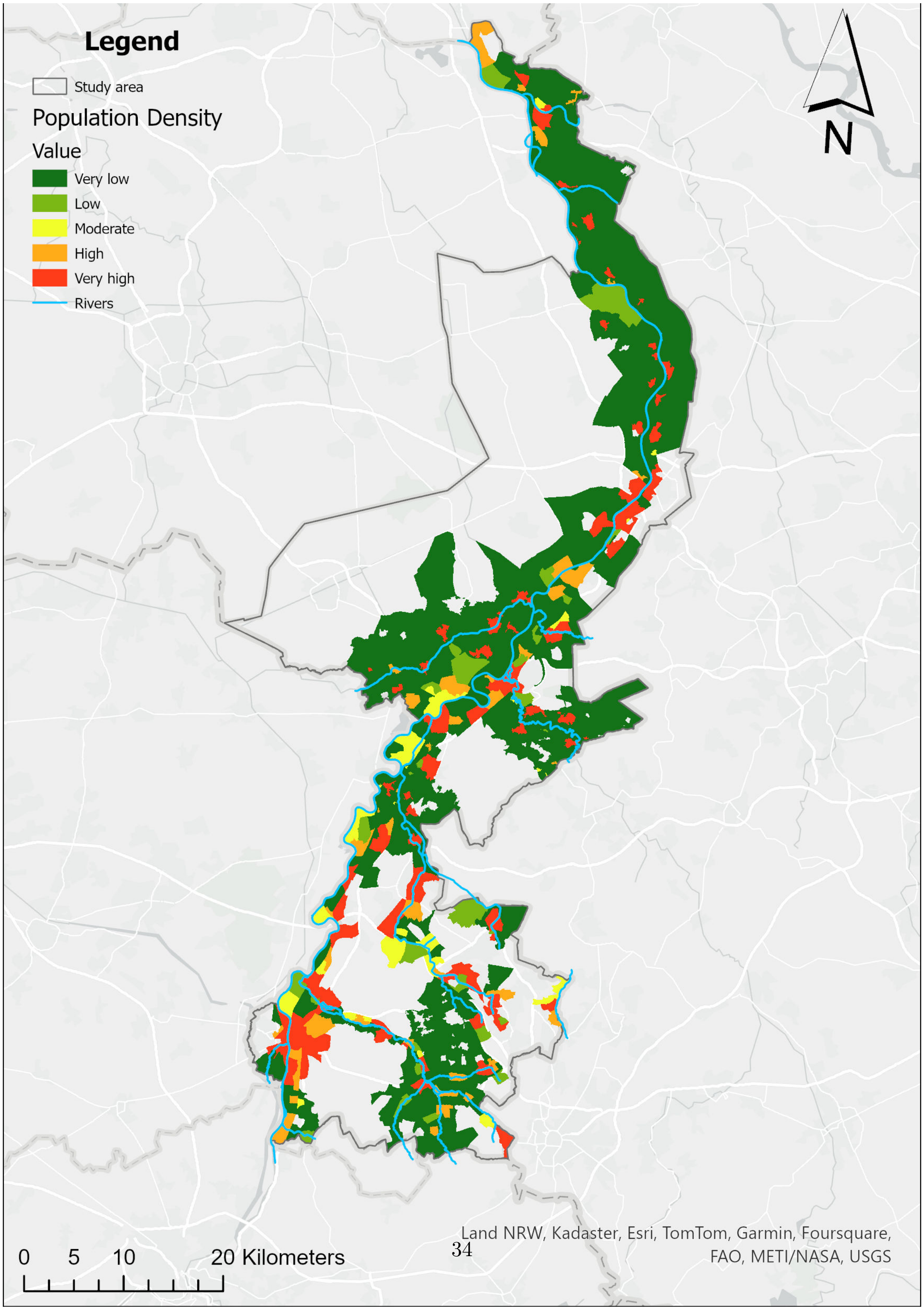


Figure 9: Population density after Fuzzy large standardisation was applied. Classes range from very low to very high based on classifications in table 8. Data obtained from CBS (2022).

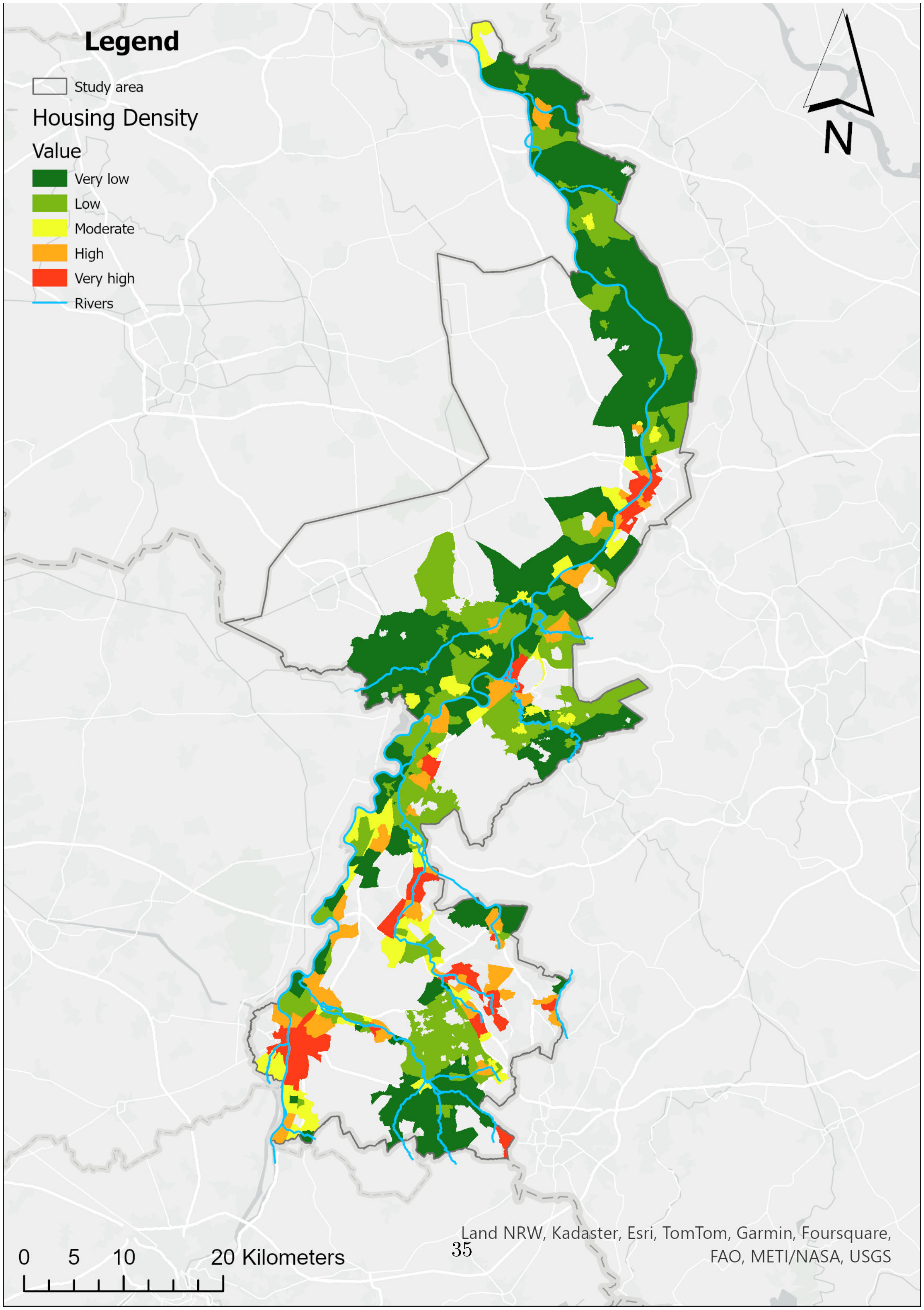


Figure 10: Housing density after Fuzzy large standardisation was applied. Classes range from very low to very high based on classifications in table 8. Data obtained from CBS (2022).

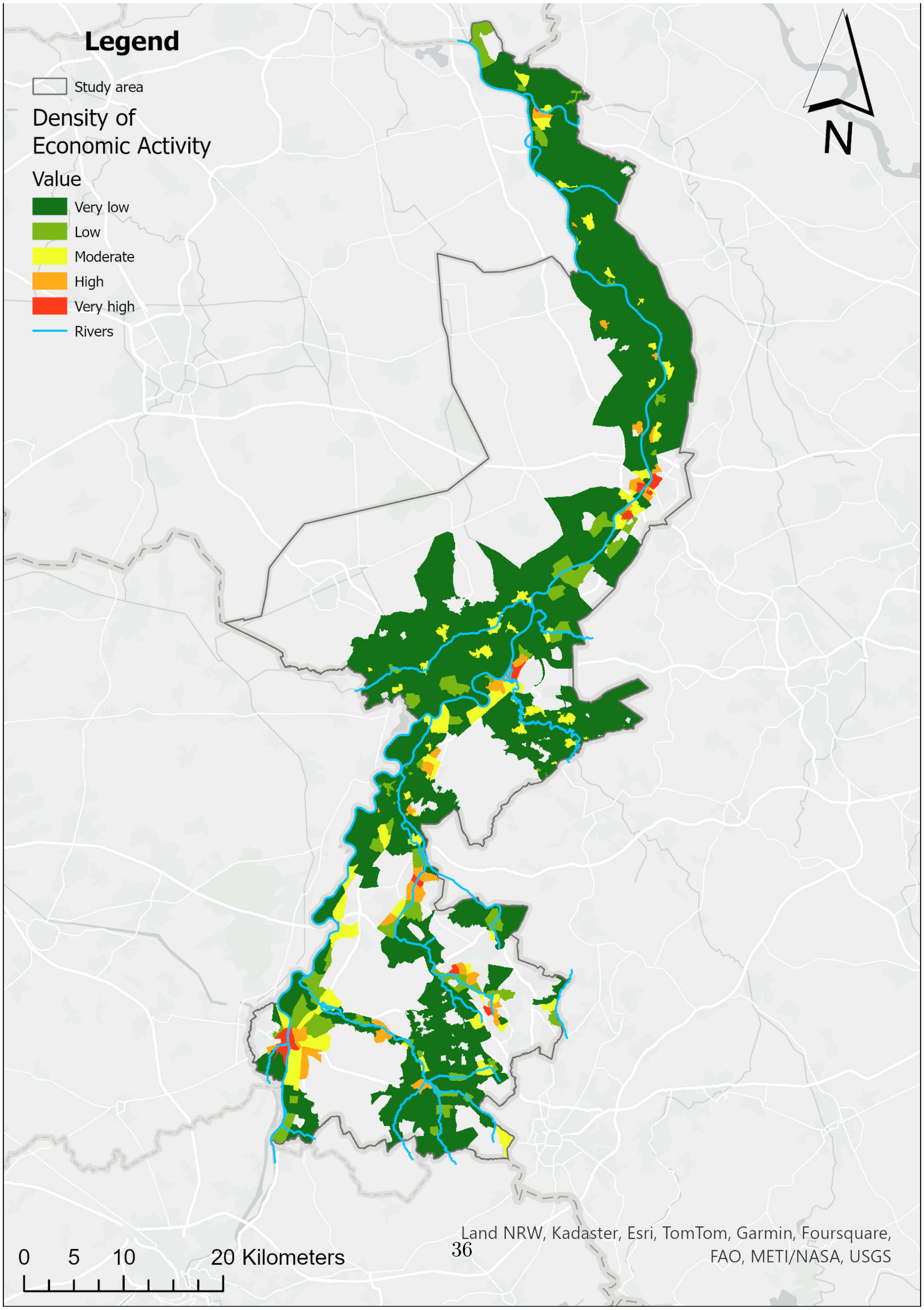


Figure 11: Density of economic activity after Fuzzy large standardisation was applied. Classes range from very low to very high based on classifications in table 8. Data obtained from CBS (2022).

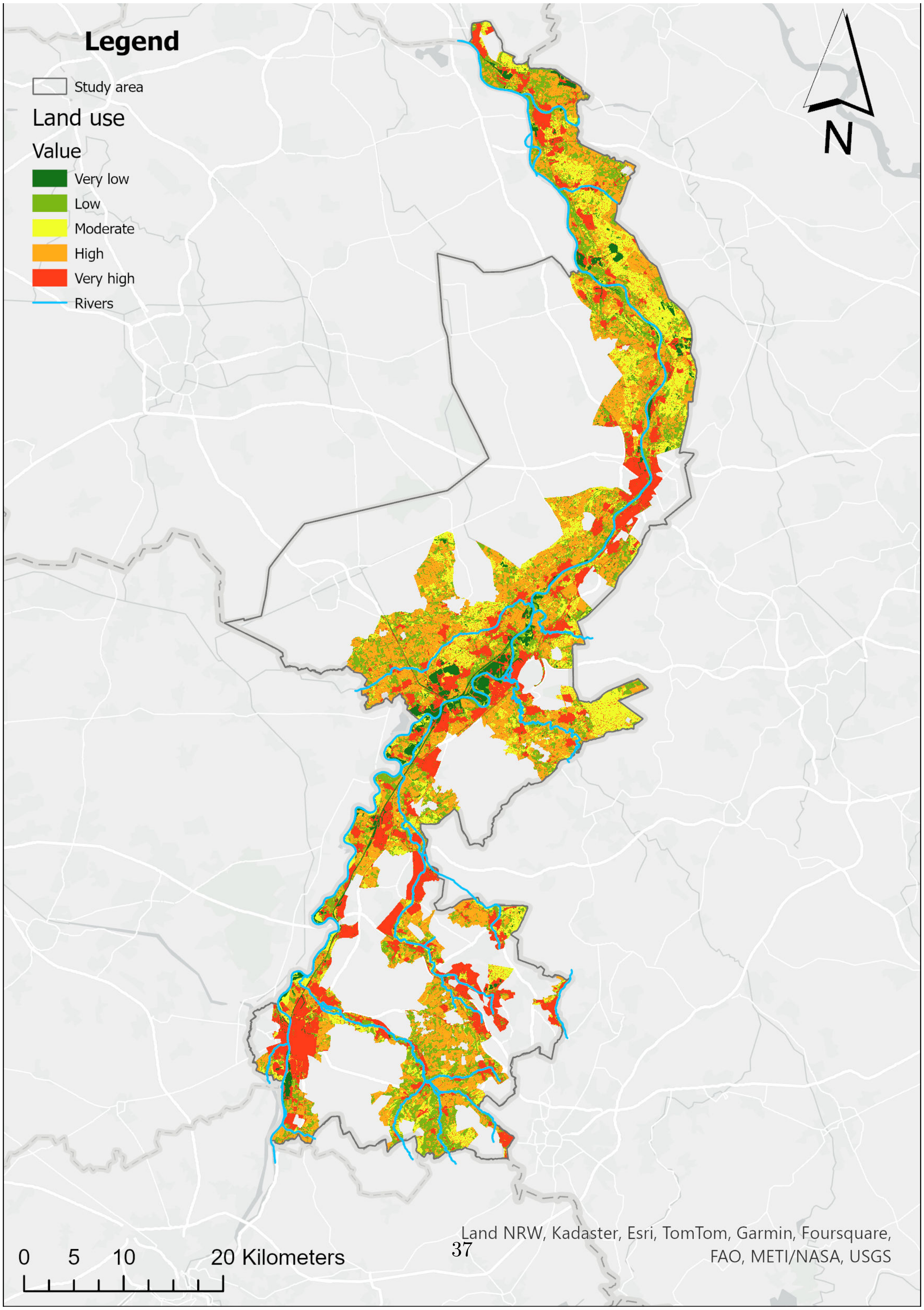


Figure 12: Land uses after community value was assigned land use reclassifications. Classes (community values) are: 0.1 (Very low), 0.3 (Low), 0.5 (Moderate), 0.7 (High), and 0.9 (Very high) based on classifications in Ziegelaar & Kuleshov (2022), which can be found in table 8. Data obtained from WENR (2024).

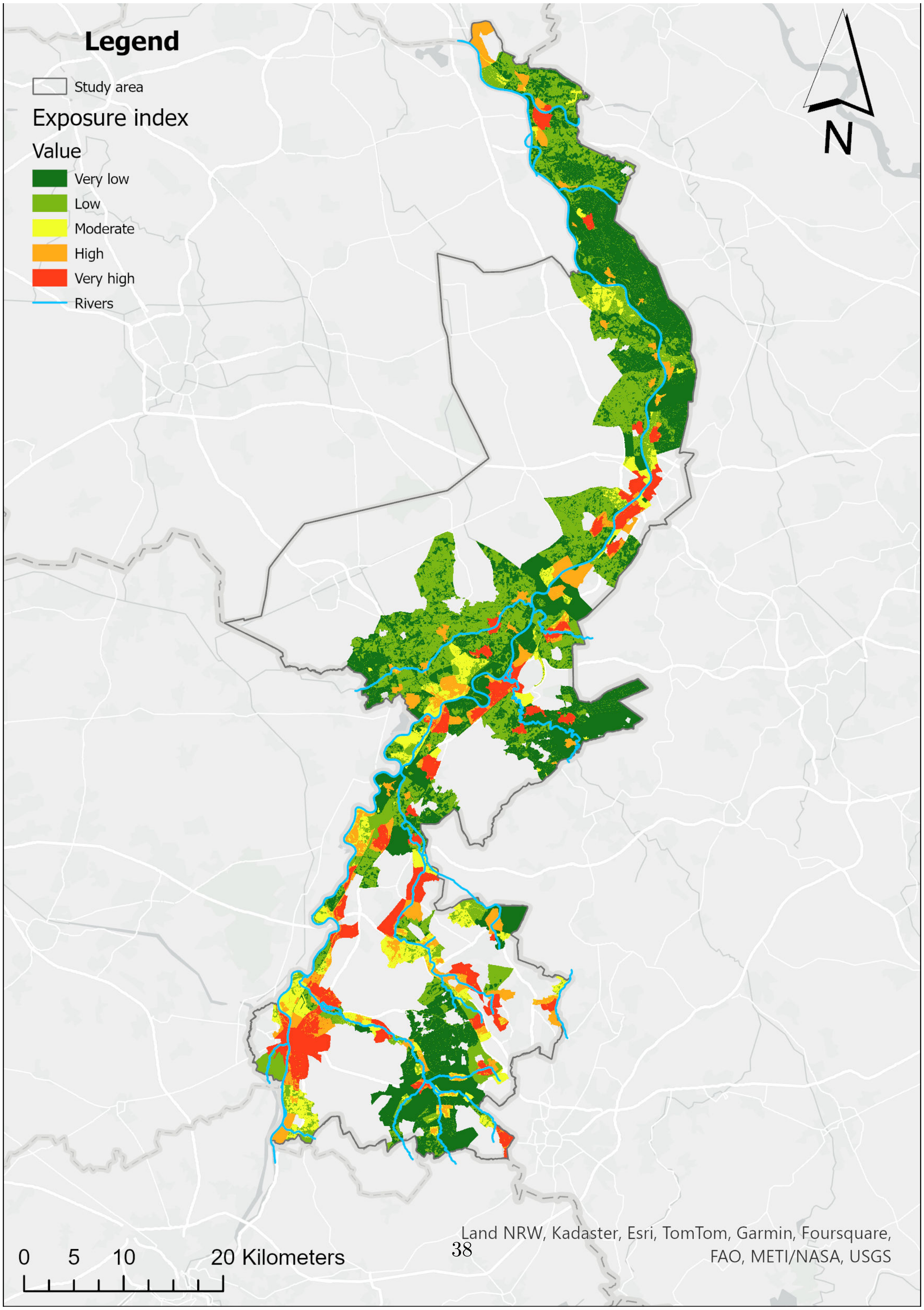


Figure 13: Exposure index after Fuzzy overlay was applied to combine exposure indicators (table 2). Classes range from very low to very high based on classifications in table 8. Data obtained from CBS (2022), and WENR (2024).

5.3 Hazard index

Flood hazard severity was calculated using modelled inundation depths developed by the risk map of the Netherlands. The depths were reclassified based on thresholds presented in table 4.8. The study area was subdivided into five different flood hazard zones based on Maranzoni et al. (2022). (figure 14). In general, highest flood hazard zones can be observed directly along river channels. In hazard index calculation, inundation depths occurring at lower return periods – thus covering a lesser extent - are prioritised over higher flood return periods.

Smaller river branches have lower average discharge levels, thus also a smaller potentially flooded area. Such small rivers or streams, however, often pass through city centres where creating room for the river, or building dikes is challenging. This is illustrated by the 2021 floods along the Geul river, that destroyed and damaged numerous properties within the city centre of Valkenburg (ENW, 2021).

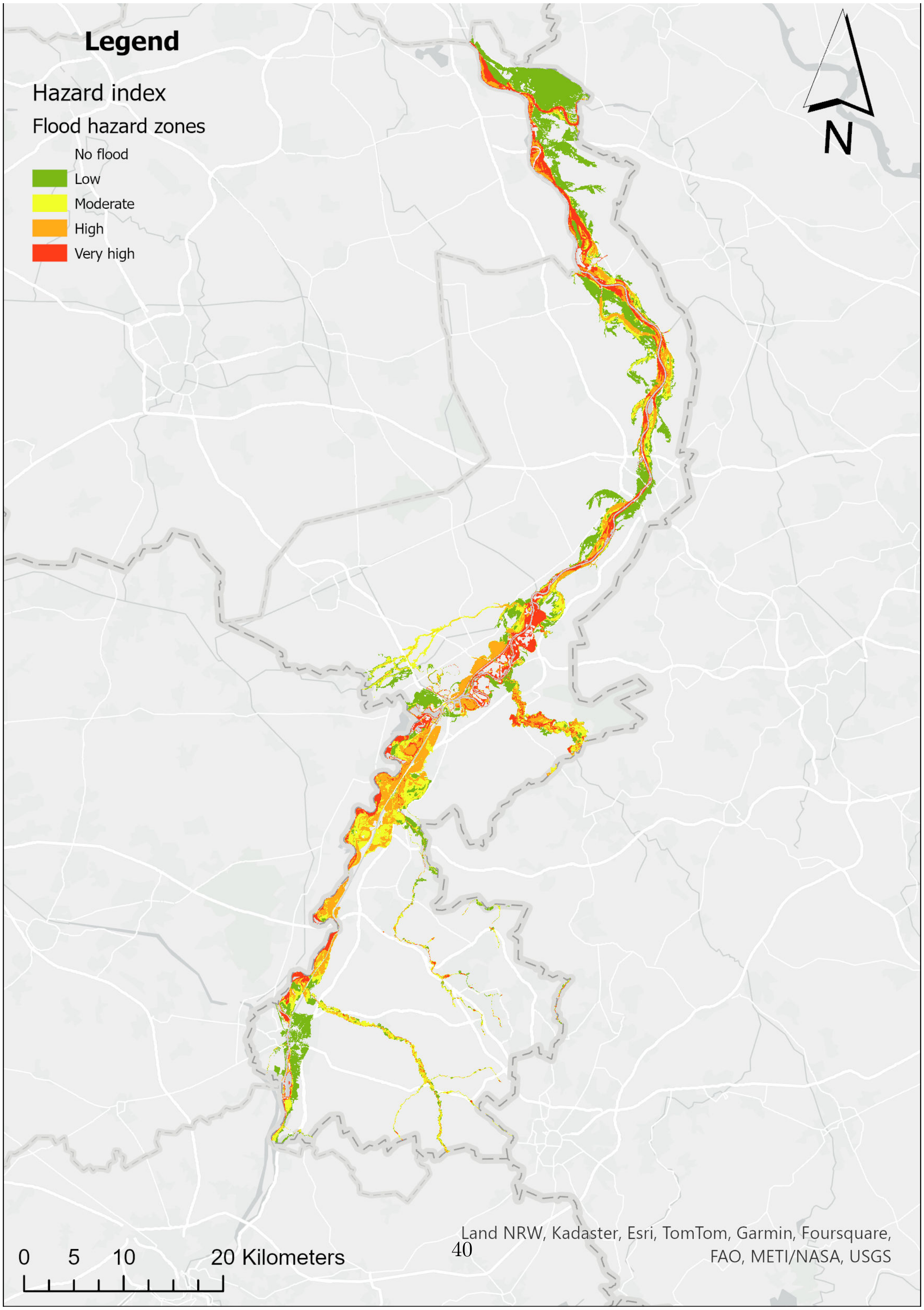


Figure 14: Distinct flood hazard zones based on classifications retrieved from Maranzoni et al. (2022) in table 5. FLood hazard zones range from low (light green) to very high (red). Data obtained from Ministry of Infrastructure and Water Management (2024).

5.4 Risk index

Figure 15 presents a map of the risk index applied to the study area. The output was calculated using eq. 1 by following the steps proposed in the methodology section. The risk index depicts a 25x25 resolution raster denoting areas of high and low risk through the multiplication of hazard, vulnerability, and exposure indices. Numerical values in all of the indices are designed to range between 0 and 1, enabling direct and meaningful comparisons with the other indices.

Risk index values could theoretically range between 0 and 1 as well, but are inherently lower, because of its threefold multiplication with decimal values. The values in the risk index range between 0 and around 0.7. This range serves as a normalised scale, where it can facilitate the interpretation of risk when compared to the similar study area over time, or to a different study area.

It should be acknowledged that these values in isolation are meaningless to the interpretation of risk. Rather, the index has the potential to make comparisons between regions in terms of the magnitude of risk. Only trough comparative analysis meaningful conclusions regarding relative risk levels can be drawn.

Differences between high and low risk are highlighted per district (figure 16a) and neighbourhood (figure 16b). These values are obtained by calculating the mean risk value through zonal statistics. The corresponding risk classes are classified using natural breaks.

Highest risk areas are predominantly clustered around the main river channels from southern Limburg up to Roermond. Especially the 'Grensmaas' – the part of the Maas river that forms the border with Belgium – depicts high values of risk. Risk values around the Maastricht area are very high, since this is the most dense urban core within the study area.

Generally, flood affected neighbourhoods and districts in the north of Limburg display considerably lower average risk values than the south. High to very high risk zones downstream of Roermond can only be found in urban areas near Reuver, Venlo, or Arcen.

Risk is also considerably concentrated around tributaries in south Limburg. Along the Geul river very high to high risk values are found on the neighbourhood scale mainly within cities and town limits (Valkenburg, Meerssen, Gulpen), but also in areas between. Areas in vicinity of the Geleenbeek river also display very high to high risk values throughout nearly all neighbourhoods. Similar values are observed along the Worm and Roer tributaries.

In contrast, smaller tributaries in the north (e.g. Swalm or Eckeltsche beek) show moderate to very low risk values, even when passing through urban or residential areas.

Calculated risk values largely coincide with results of the other indices, which also displayed more extreme values for the southern part of Limburg. In vulnerability and exposure analysis especially, higher values were observed along urban areas, where the potential damages of a flood were found to be highest.

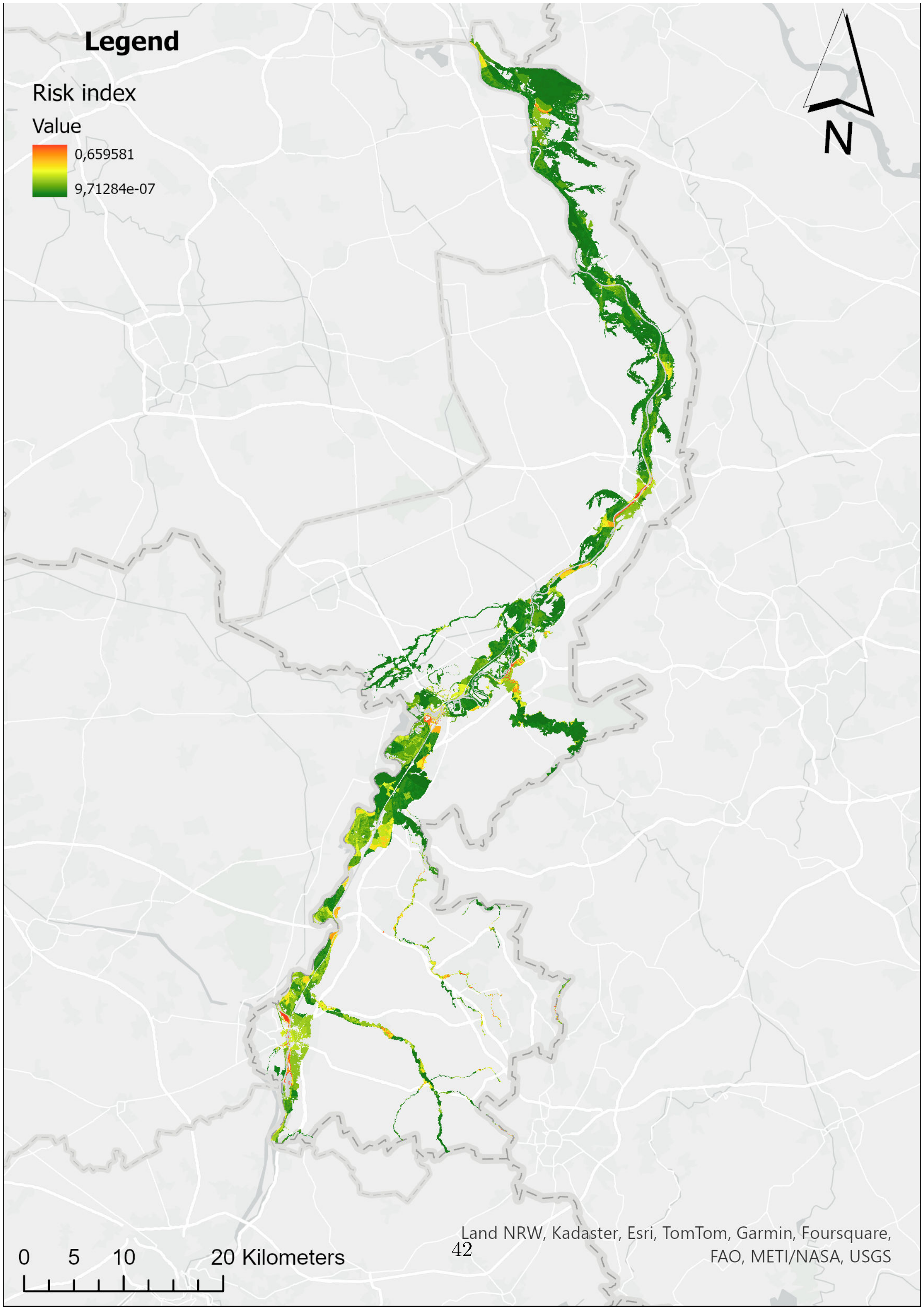
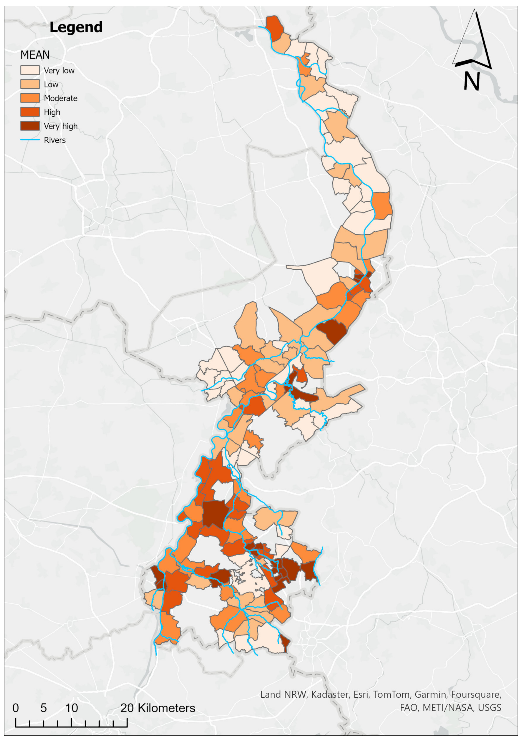
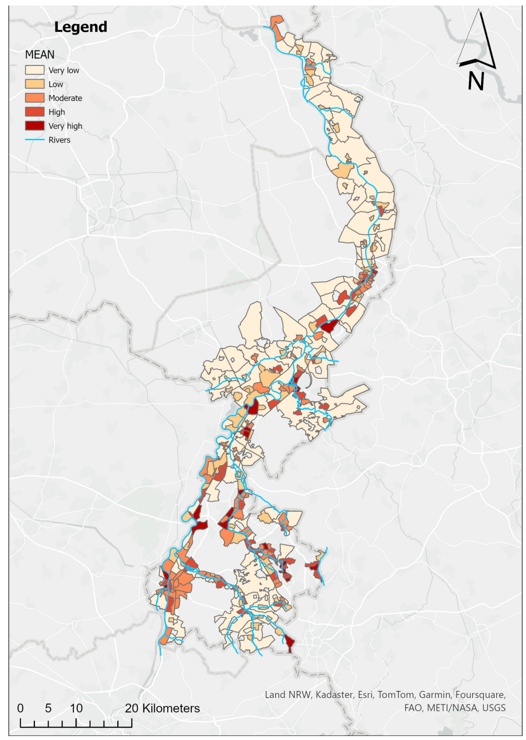


Figure 15: Risk index values calculated according to equation 1, Risk index values range between 0 (green) and 0.660 (red). Data obtained from CBS (2022), Ministry of Infrastructure and Water Management (2024), and WENR (2022).

The way in which mean risk value is presented in figure 16, does generalise the data. While figure 16 gives a good overview of the average risk level per neighbourhood and district, the mean value does not show exact flood extent. As such, a neighbourhood might exhibit very high flood risk, while only one pixel in that unit is flooded. Vice versa, fully flooded neighbourhoods with smaller risk values would receive a lower mean risk value. This presentation, however, facilitates comparison of risk values between regions more than a presentation of the actual risk values, which would give a more accurate presentation of the result.



(a) Mean risk value per district



(b) Mean risk value per neighbourhood

Figure 16: Mean risk values per district (a), and per neighbourhood (b) based on zonal statistics of risk values in each administrative unit. Risk classes range from very low to very high.

It should be acknowledged that the risk index, as presented here, offers a framework that decision makers and FRM experts could benefit from as a starting point for understanding the different drivers of risk on social and technical level. The inputs to the applied methodology are subjective in nature and are designed so that these can be easily modified to fit characteristics of another study area. It is meant to be easy to interpret and replicate, and possible to tweak inputs based on data availability.

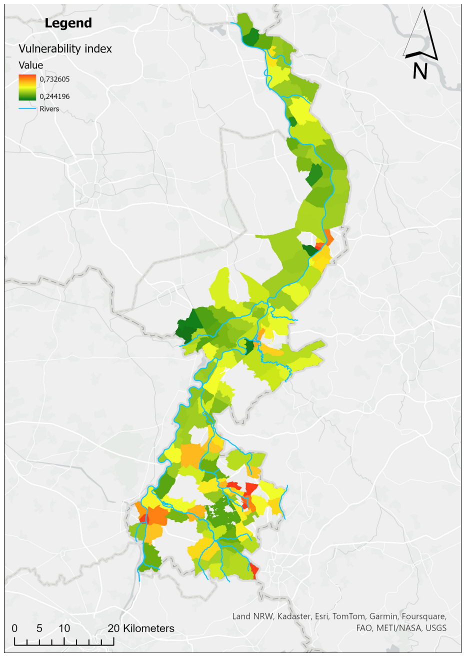
5.4.1 Validation

The methodology was applied to calculate vulnerability and exposure indices for a similar dataset for the year 2015 (CBS, 2015). Data on hazard parameters for the study area for 2015 were not available, and therefore remain unaltered. The results of vulnerability analysis for 2015 are shown in figure 17b. In addition, a difference raster was obtained by subtracting values from the 2022 dataset with values from the 2015 dataset in order to assess differences in vulnerability over time (figure 17c). Similar model results for exposure analysis using the 2015 data are shown in figure 18b, along with the difference raster (figure 18c).

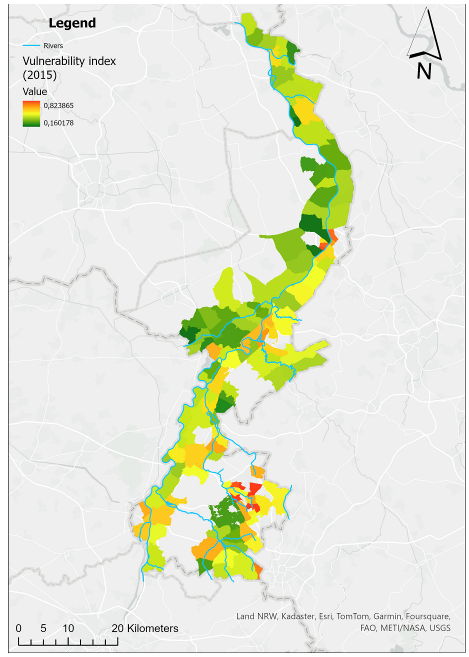
Spatial coverage of the difference raster does not fully overlap with original dataset due to the temporal difference between the two datasets. A total of 22 missing geometries were found for exposure analysis on the neighbourhood scale, and 11 missing geometries were found for vulnerability analysis on the district scale.

The conclusions that can be drawn from figure 17 and 18 are twofold. First, the observed vulnerability and exposure index values stay relatively similar, with a slight increase in mean vulnerability values (0.031) and exposure values (0.032) over the study area between the period 2015 - 2022. Second, small variations in index outcomes highlight urban-rural divides within the study area. Figure 17c and 18c show slight increases for vulnerability and exposure in cities, whereas rural areas show slight decreases. These trends can be explained by the ongoing urbanisation within the region, and the persisting growth of urban economies.

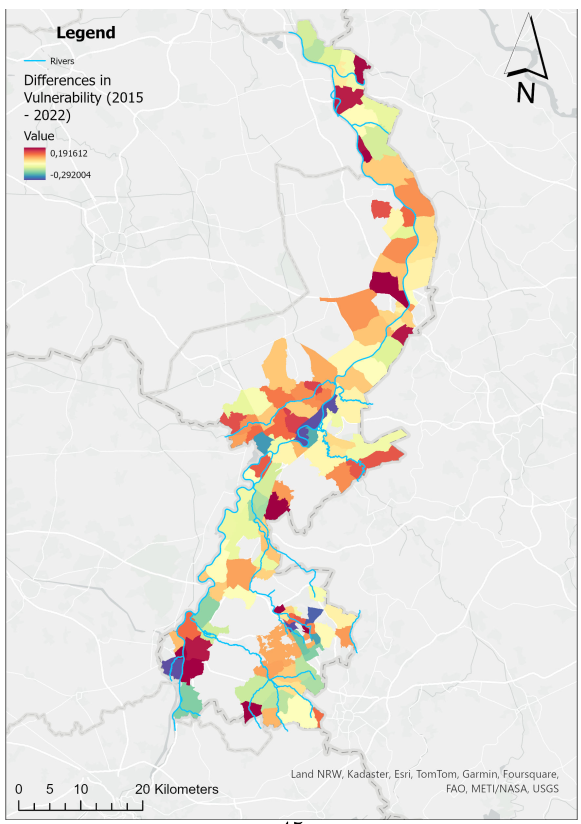
Differences in mean risk index value can be observed in figure 19c. Overall, outcomes of the risk assessment using the dataset from 2015 overlap with the result obtained from the latest dataset, with an average increase in risk values of only 0.009 over the study region. The validation results suggest that while there are slight changes in mean risk index value over time, the overall patterns or trends identified by the risk assessment framework remain consistent or similar between the older and latest datasets. These findings contribute to the robustness of the risk assessment framework, and prove that the framework is able to capture fundamental risk drivers effectively and is not overly sensitive to minor disruptions in input data.



(a) Vulnerability index values for 2022

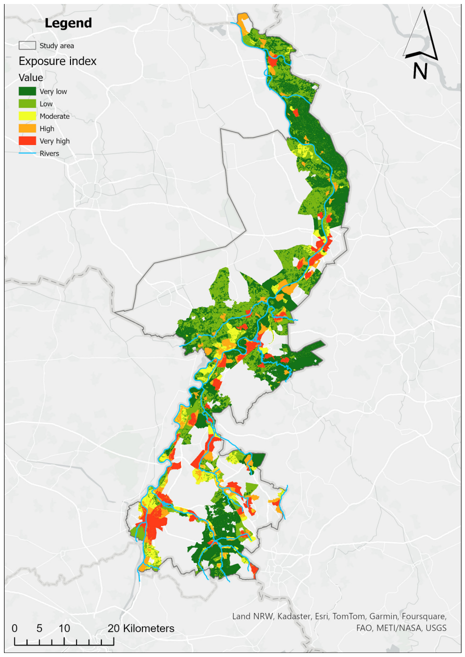


(b) Vulnerability index values for 2015

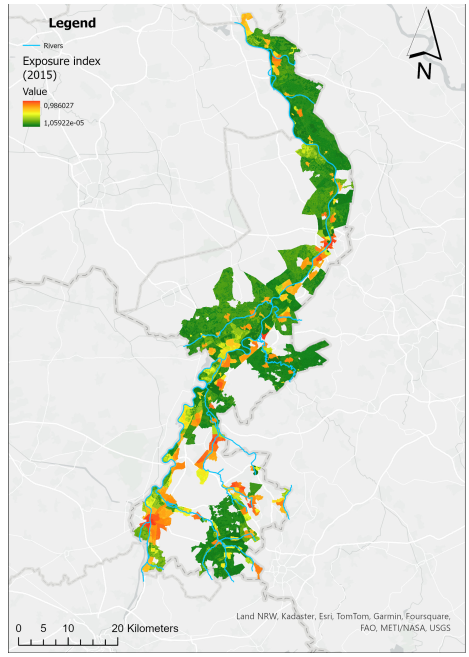


(c) Differences in vulnerability values between 2015 and 2022

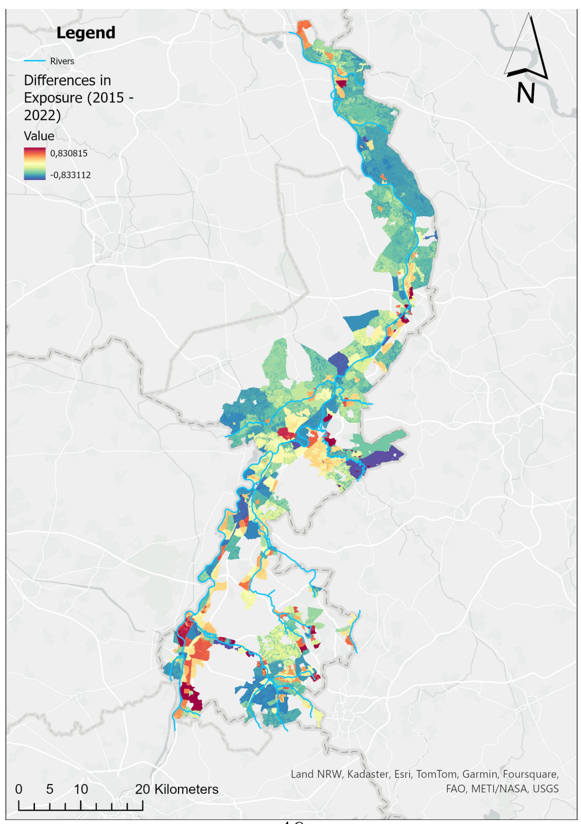
Figure 17: Vulnerability index values within the study area, along with their differences. Areas in red indicate increased vulnerability, blue areas indicate decreased vulnerability. Data obtained from CBS (2015;2022)



(a) Exposure index values for 2022

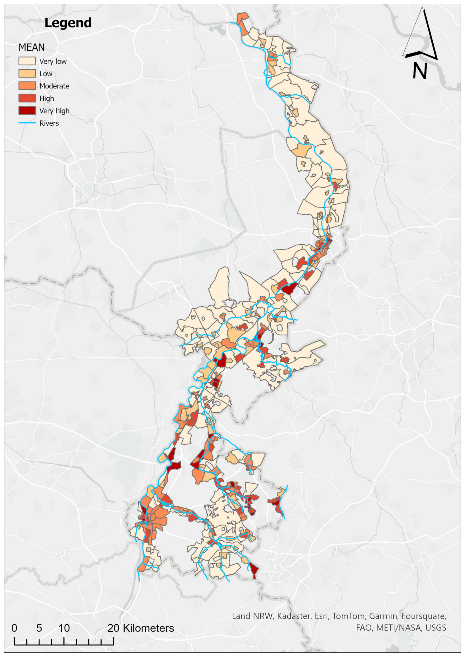


(b) Exposure index values for 2015

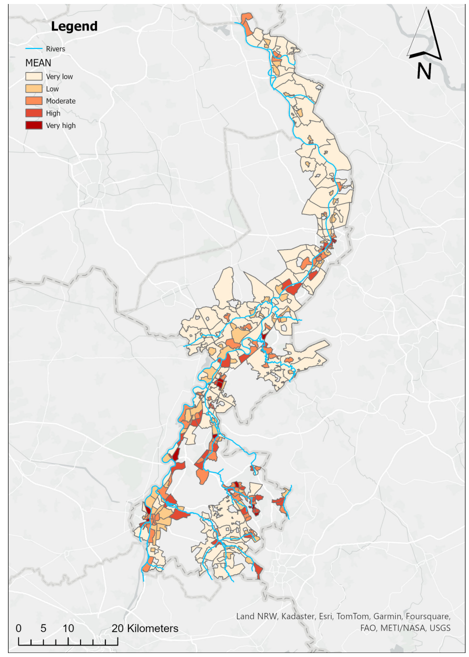


(c) Differences in exposure values between 2015 and 2022

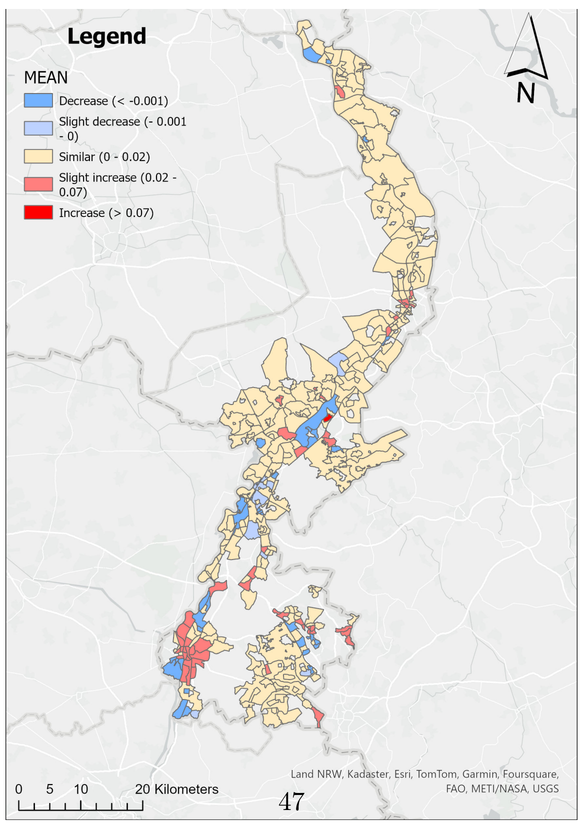
Figure 18: Exposure index values within the study area, along with their differences. Areas in red indicate increased exposure, blue areas indicate decreased exposure. Data obtained from CBS (2015;2022)



(a) Mean risk index value per neighbourhood for 2022



(b) Mean risk index value per neighbourhood for for 2015



(c) Differences in mean risk index value per neighbourhood between 2015 and 2022

Figure 19: Mean risk index value per neighbourhood within the study area, along with their differences. Areas in red indicate increased exposure, blue areas indicate decreased mean risk values. Data obtained from CBS (2015;2022).

6 Discussion

The results indicate that there are considerable differences in vulnerability, exposure, and hazard patterns throughout the whole study region. This highlights the importance of recognising the local dynamics into each of the risk dimensions.

Within current Dutch DRR policies, responsibilities are shared between the national government, whose main responsibility include establishing and maintaining safety of primary flood defenses, and local governments (e.g., province, municipality, and water boards) whose responsibilities are oriented towards maintaining the regional flood defenses, and who are in charge of spatial planning practices with respect to flood management (Ministry of Infrastructure and Water Management, 2018). Failing to recognise the spatial heterogeneity of risk through applying 'command-and-control' measures lead to less effective DRR methods (Koks et al., 2015). For example, zoning laws and building codes are often applied to areas as a whole without considering local community characteristics (Filatova, 2014; Koks et al., 2015).

In crisis management, safety regions are responsible for coordination and effective disaster communication. These institutions regularly update and initiate step-by-step preparedness protocols during high water events. As such, they are also responsible for issuing a possible evacuation (VRZL, 2024). Within this field, recognising spatial variety within the population might also be beneficial in integrating risk reduction measures. For example, evacuations could first be issued to areas with higher proportions of elderly, who, due to impaired mobility, might require different and adapted evacuation protocols.

In order to implement DRR and flood resilience measures optimally, they should not be implemented through top-down, uniform decision making processes (Filatova, 2014), but rather should be adapted to the needs and abilities of local communities and individuals. Flood preparedness measures taken on the individual or household scale include flood-proofing your home (e.g., tile flooring, or elevating power outlets), or using water barriers. Such efforts have been proven to reduce the negative impacts of a flood event (ENW, 2021). Areas with vulnerable groups due to higher proportions of elderly, single person households, or low income households require a different approach to risk reduction than less vulnerable groups. The vulnerable groups are to a lesser extent able to incorporate such individual efforts due to financial and mobility constraints (Koks et al., 2015), and might benefit more from flood mitigation measures.

In contrast, the less vulnerable or less exposed groups are more likely to feel a sense of safety toward flooding, and therefore tend to ignore individual flood preparedness measure (Husby et al., 2014). In such areas, creating risk awareness - for example through information meetings - among these groups might yield more effective DRR outcomes.

The proposed framework, along with the indicators selected within this thesis provide a comprehensive overview to assess risk, and to identify and understand the drivers behind each of the risk components. This information could provide insights for local authorities such as municipalities, water boards, or safety regions to discover what the local area characteristics of vulnerable or exposed populations are, and, consequently, which tailor made solutions are feasible and necessary to implement for effective flood resilience measures in each of those areas. Identifying areas of higher risk could then be addressed through effective budget allocations.

The framework proposed in this thesis provides a simplified method to quantify risk and identify spatial variations in risk patterns. In order to fully grasp the multi faceted concept of risk, a more thorough and detailed approach would be more suitable. Such an approach, however, would require more costly resources such as time, expertise, and financing. The proposed approach provides an insightful method to spatially differentiate between the degree of risk. This method is meant to be easily reproducible, and can be applied to a variety of study areas and spatial scales at which risk is desired to be assessed.

As such, the added societal value of this thesis research outcome (the developed risk index) is not to predict damage or fatality outcomes after a flood event as precise as possible, but rather to facilitate decision making processes, and to enable stakeholders to prioritize resources, or implement adaptation measures to enhance overall flood resilience throughout all flood affected communities.

7 Conclusion

Traditional risk assessments in the Netherlands tend to approach risk from a technical perspective, where hazard characteristics are predicted, or the performance of protection systems are calculated by estimating their failure chances (Jongejan & Maaskant, 2015). These risk assessments, performed by Rijkswaterstaat (i.e. Department of Waterways and Public Works), often ignore the social risk dimension and assume that the total population at risk is equally capable to adapt and recover from flood events, whereas this is not the case in reality (Koks et al., 2015; Kirby et al., 2019). This thesis aimed to incorporate local place and population dynamics of vulnerability and exposure, in order to create an integrated risk assessment approach that combines technical, as well as social aspects of risk.

This thesis used an index-based approach to obtain risk values in a 25x25m resolution raster. In order to calculate these risk index values, indices were calculated for three main risk components: vulnerability, exposure, and hazard. These indices each consisted of different methods for indicator selection, and were then combined into a single risk index using an equal weighted approach.

This thesis aimed to provide an answer to the research question posed in section 1.4: *"What combination of risk indicators can help identify primary drivers of high flood risk regions along the Maas river in Limburg?"* . This central research question was answered through five main subquestions:

RQ 1: Through factor analysis it was found that main drivers of vulnerability include (1) household composition, measured by the proportion of single person households, (2) socio-economic status, measured by income per inhabitant, (3) Old age, measured by by the proportion of inhabitants of 65 and older, and (4) young age, measured by the proportion of inhabitants under 15 years of age.

RQ 2: Fuzzy overlay analysis has pointed out that population density, housing density, density of economic activities, and land use all contribute positively to exposure. Of these indicators, the former was found to correlate most to exposure patterns within the study area. Regions showing high exposure levels were predominantly urban.

RQ 3: By combining return periods of flood events with hazard intensity characteristics, measured as the maximum possible inundation depth occurring after a series of flood simulations, this thesis identified flood likelihood and severity over the Limburg province. Highest hazard levels were observed closely along river channels, most notably around the Maas, Roer, Geul, and Geleenbeek rivers.

RQ 4: Overall calculated risk index values uncovered two important trends developing within the study area: flood prone regions in the Dutch province of Limburg. Firstly, the risk index shows that highest flood risk can be found in urban areas, where the concentration of people, assets, and employment opportunities are greatest. Urban areas are protected by primary dikes, which, if they have a failure or a breach, result in higher water depths. Local socio-economic characteristics do vary within those cities, as shown in the vulnerability index. However, in general, urban areas show highest risk regardless of socio-economic characteristics.

Second, the southern part of the study area, upstream from Roermond shows considerably higher risk values than the north of the study area. This is not only the result of terrain differences between the two parts of the study area, but can also be attributed to exposure, and socio-economic vulnerability patterns. Within southern Limburg, risk areas along the main maas river, and the Geul and Geleenbeek tributaries, show exceptionally high values.

RQ 5: Research outcomes can be used by FRM experts and planners to identify local drivers of risk. Considering the heterogeneity of risk values within potentially flooded areas enables planners to apply tailor-made solutions to effectively mitigate and adapt to flood risk. For example by prioritising evacuation plans for communities with lower levels of mobility.

Although the created risk index reveals a general overview of risk patterns throughout the study region in Limburg, it is always subject to potential errors. The assessment framework is not able to fully capture all facets of flood risk accurately, which might lead to certain misinterpretations. In order to improve the robustness of the framework, future improvements can be made by validating the risk index using real world flood outcomes (e.g., damage reports), similarly to Fekete (2009), or by applying this framework as a stepping stone to elaborate on each of the indicators. For example, by including multiple variables per factor in vulnerability calculation.

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9 Appendices

9.1 Appendix A: Reclassified land uses

The LGN dataset retrieved from WENR (2024) contains a total of 39 land use classes. These land use classes have been reclassified into 8 different classes before assigning community values to each reclassified land use. The section below highlights which original land use classes have been subdivided into new classes.

Built environment:

- Urban built-up areas
- Semi urban built-up areas
- Forest in built-up areas
- Forest in semi built-up areas
- Grass in built-up areas
- Grass in semi built-up areas
- Solar parks
- Built-up areas outside urban areas

Cropping:

- Maize
- Potatoes
- Sugar beet
- Cereals
- Other agricultural crops
- Greenhouses
- Orchards
- Flower bulbs
- Tree nurseries
- Fruit cultivation
- Other land use outside urban areas

Forestry:

- Coniferous forest
- Deciduous forest

Grazing:

- Pasture
- Other grasslands

Large infrastructure:

- Main roads & railways
- Semi-paved roads and other infrastructure

Natural areas:

- River sandbanks
- Heathland
- Grassy heathland
- Very grassy heathland
- Raised bogs
- Forest in raised bogs
- Other swamp vegetation
- Reeds
- Forest in swamp areas
- Natural grasslands
- Peat bogs with low vegetation
- Swamp with low vegetation
- Other low vegetation
- Peat bogs with high vegetation
- Swamp with high vegetation
- Other high vegetation

Small infrastructure:

- Narrow roads

Water bodies:

- Fresh water

9.2 Appendix B: Fuzzy spread and midpoint

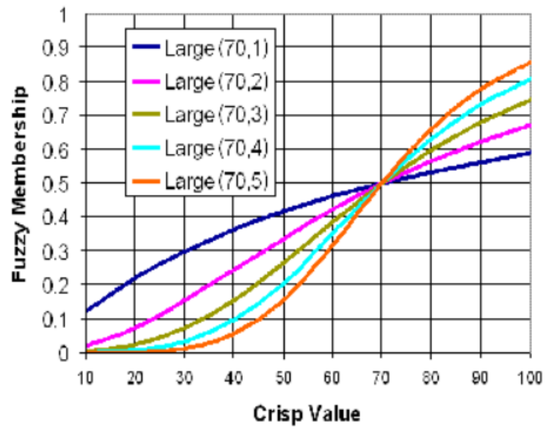

Figure 20: Overview of different Fuzzy Large midpoints (x) and Fuzzy Large spreads (y).Retrieved from ESRI (2024).

Indicator	**Fuzzy Large Midpoint**	**Fuzzy Large spread**
Population density	500	2
Housing density	500	2
Density of economic activity	300	2

Table 9: Fuzzy Large midpoint and Fuzzy Large spread used for fuzzy standardisation

9.3 Appendix C: R script

```r

# Download data on neighbourhood, district and municipal level for 2020
Municipality2020 <- as.data.frame(st_drop_geometry(st_read("WijkBuurtKaart_2020/gemeente_2020_v3.shp")))
District2020 <- as.data.frame(st_drop_geometry(st_read("WijkBuurtKaart_2020/wijk_2020_v3.shp")))
Neighbourhood2020 <- as.data.frame(st_drop_geometry(st_read("WijkBuurtKaart_2020/buurt_2020_v3.shp")))

# Download data on neighbourhood, district and municipal level for 2021
Municipality2021 <- as.data.frame(st_drop_geometry(st_read("WijkBuurtKaart_2021/gemeente_2021_v2.shp")))
District2021 <- as.data.frame(st_drop_geometry(st_read("WijkBuurtKaart_2021/wijk_2021_v2.shp")))
Neighbourhood2021 <- as.data.frame(st_drop_geometry(st_read("WijkBuurtKaart_2021/buurt_2021_v2.shp")))

# Download data on neighbourhood, district and municipal level for 2022 (all data before 2022 should not be spatial)
Municipality2022 <- st_read("WijkBuurtKaart_2022/gemeente_2022_v1.shp")
District2022 <- st_read("WijkBuurtKaart_2022/wijk_2022_v1.shp")
Neighbourhood2022 <- st_read("WijkBuurtKaart_2022/buurt_2022_v1.shp")

# Merge data in one for Municipality
Municipality2021 <- left_join(
  Municipality2021,
  Municipality2020 %>% select(all_of(c('GM_CODE', setdiff(names(Municipality2020), names(Municipality2021))))),
  by = "GM_CODE")
Municipality <- left_join(
  Municipality2022,
  Municipality2021 %>% select(all_of(c('GM_CODE', setdiff(names(Municipality2021), names(Municipality2022))))),
  by = "GM_CODE"
)
rm(Municipality2020, Municipality2021, Municipality2022)

# Merge data in one for District
District2021 <- left_join(
  District2021,
  District2020 %>% select(all_of(c('WK_CODE', setdiff(names(District2020), names(District2021))))),
  by = "WK_CODE")
District <- left_join(
  District2022,
  District2021 %>% select(all_of(c('WK_CODE', setdiff(names(District2021), names(District2022))))),
  by = "WK_CODE"
)
rm(District2020, District2021, District2022)

# Merge data in one for Neighbourhood
Neighbourhood2021 <- left_join(
  Neighbourhood2021,
  Neighbourhood2020 %>% select(all_of(c('BU_CODE', setdiff(names(Neighbourhood2020), names(Neighbourhood2021))))),
  by = "BU_CODE")
Neighbourhood <- left_join(
  Neighbourhood2022,
  Neighbourhood2021 %>% select(all_of(c('BU_CODE', setdiff(names(Neighbourhood2021), names(Neighbourhood2022))))),
  by = "BU_CODE"
)
rm(Neighbourhood2020, Neighbourhood2021, Neighbourhood2022)

```

Figure 21: R code snippet that combines CBS 'Wijk- en buurtkaart' dataset for version 1,2, and 3. Created by author using RStudio software

```
# Perform factor analysis with varimax rotation and Kaiser's criterion
fit <- factanal(mydata, sum(ev$values > 1), rotation="varimax")
print(fit, digits=10, cutoff=0.3, sort=TRUE)
```

Figure 22: R code snippet used to run factor analysis model. Created by author using RStudio software