Master's Thesis – master Sustainable Development

Applying Intersectionality Theory to Pluvial Flood Risk

An empirical analysis of social vulnerability to urban pluvial flooding in Europe

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Utrecht University Faculty of Geosciences

Master's degree Sustainable Development

Track Environmental Change and Ecosystems

Master Thesis 30 ECTS

Date 29.07.2022

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Word count 24749 (incl. tables and figures)

Summary

Climate change projections indicate that extreme precipitation events will increase in the future, leading to increased pluvial flooding and flood hazards. While there is increasing attention toward flood risk analysis and adaptation, pluvial flood risk is still only marginally addressed in research. Additionally, urbanization intensifies the frequency of flooding in cities because of a reduction in permeable surfaces. In the face of climate hazards, multiple forms of climate injustices in today's cities are well-documented and are usually faced by marginalized and low-income communities. Despite this knowledge, research indicates that traditional urban (flood) adaptation policies are most often founded on exclusionary and technocratic approaches that tend to neglect the structural causes of social vulnerabilities. Intersectionality theory can help to uncover and address these multidimensional levels of vulnerability and can be utilized to inform such adaptation measures. Hence, this research will focus on pluvial flooding impacts in European urban areas with an additional focus on intersectional social vulnerabilities relating to climate justice issues within pluvial flood protection planning. Informed by intersectionality theory, this research presents an intersectional vulnerability index (IVI) to pluvial flooding in a European urban context. The IVI is built around 10 dimensions of social vulnerabilities (education, housing, special needs populations, economic status, gender, nationality, family structure, age, people without social networks, and infrastructure dependence). The IVI is then computed into a readily transferable composite index (CI).

The index is applied to two case studies and helps to unveil the most socially vulnerable districts and compounding social vulnerabilities of people through statistical analysis. Paired with an urban flood exposure dataset, districts are being identified that experience relatively high social vulnerabilities combined with relatively high pluvial flood exposure levels. The paper further discusses pluvial flooding and social vulnerabilities in a climate justice context, identifying structures of intersecting discriminations and resulting vulnerabilities and disproportionality in flood impacts. The thesis concludes with recommendations to enhance social justice within FRM.

Keywords: pluvial flooding, intersectionality, climate justice, urban, Europe

Acknowledgements

This thesis was written as part of the Master's programme Sustainable Development, which I followed in the track Environmental Change and Ecosystems at the University of Utrecht. I first and foremost want to thank my Supervisor, Murray Scown, for his detailed and motivating feedback and for strongly supporting me in learning and working with GIS and improving my knowledge in conducting statistical analyses using R. Without him, I do not believe I could have learned so much during these months of writing the thesis. I also want to thank Victor who spent many hours after already long days of work reading this thesis, helping me to make my writing more concise and also for listening to all my complaints and ideas during the past months. Lastly, I also want to thank Paulina whose emotional support and humour made the thesis process much more enjoyable.

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1. Introduction

1.1. Background

Flood is one of the major climate-related disasters and the most prevalent natural hazard in Europe threatening lives, properties, and infrastructure (Hosseinzadehtalaei et al., 2020; Prokić et al., 2019a). Over the past 150 years, the total urban area exposed to flooding in Europe has increased by 1000% (Jongman, 2018). Additionally, Hosseinzadehtalaei and colleagues' (2020) study on floods over Europe shows that pluvial flood risk will further increase by up to 87% under future climatic and socioeconomic changes. While there is increasing attention toward flood risk analysis and adaptation, pluvial flood risk is still only marginally addressed in research (Nicklin et al., 2019; Prokić et al., 2019b). Pluvial flooding is usually caused by intense rainfalls and can be defined as an overland flow or ponding before the water runoff can enter any watercourse, drainage system, or sewer. During a pluvial flood event, water is usually hindered from entering the aforementioned systems because of exhausted drainage capacities (Prokić et al., 2019a). Climate change projections indicate that extreme precipitation events will increase in the future, leading to increased pluvial flooding and flood hazards (Dodman et al., 2022).

In the EU, about 75% of the population lives in urban areas, and it is expected that the number will grow up to 82% by 2050 (UN-Habitat, 2011). Urbanization intensifies the frequency of flooding in cities because of a reduction in green (e.g., city parks, green roofs) and blue spaces (e.g., ponds, rivers) and an overall reduction in permeable surfaces (Cutter et al., 2018). The hydrological cycle in cities is largely affected by this lack of permeable surfaces, leading to a decrease in infiltration and an increase in runoff peak (Pallathadka et al., 2021). Thus, urban areas are especially prone to both compounding and cascading risks stemming from the interactions between severe weather events and urbanization (Dodman et al., 2022).

While pluvial flood risk to urban populations is generally assumed to increase in the future, risks and their impacts are experienced differently by different people. Flood risk is the potential for harmful impacts of flooding on human or ecological systems and is determined by flood hazards and the vulnerability and exposure of the people and systems affected (IPCC, 2022). Hence, the interactions of hazards, exposure, and vulnerability make up risk, but while flood hazard and exposure can be rather easily quantified and determined in many cases, this is not the case for vulnerability. Vulnerability can generally be defined as the susceptibility to be adversely affected in the face of a hazard. This means that some people or groups have less capacity to anticipate, resist, cope with, and/or recover from disasters such as floods and are, therefore, more vulnerable (Field, 2012). Cutter et al. (2003), describe social vulnerability in the context of climate hazards as twofold: first, relating to social inequalities and the deficiency in people's abilities to respond and, second, relating to place inequalities that contribute to the vulnerability of places because of increased exposure to hazards.

Social inequalities and place inequalities are regularly perpetuated in socio-political structures. In the face of climate hazards, multiple forms of climate injustices in today's cities are well-documented and are usually faced by people of colour, migrants, and low-income communities (Anguelovski et al., 2019). Despite this knowledge, research indicates that traditional urban (flood) adaptation policies are most often founded on exclusionary, inequitable, and technocratic approaches that tend to neglect the structural causes of social vulnerabilities (Amorim-Maia et al., 2022; Robin & Broto, 2021). Such adaptation approaches tend to result in policies that are blind to structural discrimination leaving historically embedded injustices (e.g., sexism or racism) untouched (Amorim-Maia et al., 2022).

Thus, it is important to account that some groups within society are more vulnerable to experiencing adverse impacts from urban pluvial flooding than others because of persistent inequalities that are not addressed through adaptation. Moreover, vulnerable groups are not always distinct, susceptibilities can be compounded, and many factors increasing people's vulnerabilities overlap (Versey, 2021). Prioritizing adaptation measures that account for inequities and associated compounding and overlapping vulnerabilities is needed to inform practices that aim to minimize (unjust) climate vulnerabilities in cities. Intersectionality theory can help to uncover and address these multidimensional levels of vulnerability and can be utilized to inform such adaptation measures.

1.2. Problem definition and knowledge gap

Social vulnerability is increasingly considered in European flood risk assessment research (see, for example, Aroca-Jimenez et al., 2017 (Spain); Fekete, 2009 (Germany); Kirby et al., 2019 (Netherlands); Koks et al., 2015 (Netherlands); Sayers et al., 2018 (UK); Twigger-Ross et al., 2014 (England)). However, compared to river and coastal floods, pluvial flooding is generally underrepresented in research (Nicklin et al., 2019; Prokić et al., 2019b) and in the above-mentioned examples either not considered (Aroca-Jimenez et al., 2017; Fekete, 2009; Kirby et al., 2019; Koks et al., 2015) or only touched upon (Sayers et al., 2018; Twigger-Ross et al., 2014). Yet, due to the frequency of pluvial floods, cumulative direct damages from pluvial floods equal, if not exceed, the impacts of river and coastal floods (Nicklin et al., 2019). Moreover, there seems to be little to no focus on intersectionality regarding the impacts of flood risks (or even climate risk) in Europe in the scientific literature. Cohen (2017, p. 4) states that within high-income countries "there is neither a well-developed body of information about the effects of climate change by gender, nor how public policy that is intended to cope with or mitigate climate change affects people differently, whether by gender or any other form of difference". Amorim-Maia et al. (2022, p.1) note that “there is comparatively little simultaneous scholarly engagement with intersectionality, climate change adaptation, and urban justice”. This thesis argues that to address issues such as pluvial flooding in a just way, intersectionality theory should be applied to understand and examine the interdependent and overlapping systems of disadvantage and oppression that limit people’s adaptive capacity and create new or exacerbate existing vulnerabilities (Amorim-Maia et al., 2022).

To summarise, social vulnerability to pluvial flooding and intersectionality relating to climate risks (in Europe) are already separately underrepresented in research. The combination of the two poses a clear knowledge gap with no scientific articles published in English that link intersectionality and pluvial flood risk. The combination of intersectionality and pluvial flood risk will contribute to the understanding of social justice implications in the context of flood risk management (FRM) planning in Europe.

1.3. Research aims and questions

To address the identified research gap, this research’s aim is to use intersectionality theory to determine vulnerability to pluvial flooding in European cities, and to compare the exposure of vulnerable communities in two cities using state-of-the-art pluvial flooding maps. This enables the identification of those most vulnerable, where they are located, and whether they are disproportionately exposed to pluvial flooding compared to other less vulnerable segments of the community. This knowledge can inform the development of more equitable pluvial Flood Risk Management (FRM) policies and potentially transformative approaches to deal with persisting disadvantages and power structures (Amorim-Maia et al., 2022a; Kaijser & Kronsell, 2014). The framework will be tested and applied by conducting a comparative case study analysis of two German cities; Frankfurt and Cologne.

The thesis aim will be achieved through four objectives:

1. Develop an Intersectional Vulnerability Index (IVI) in the context of pluvial flooding in Europe
2. Map the IVI for the two cities (case studies)
3. Map flood exposure over the index for the two case studies
4. Make recommendations on how to address intersectional vulnerabilities in policy

To achieve the research aim and objectives, the following main research question has been formulated: *How is intersectional social vulnerability to pluvial flood risk spatially distributed in*

Cologne and Frankfurt and does increased vulnerability overlap with pluvial flood exposure? To answer the main research question, five sub-questions have been formulated:

1. Where do high social vulnerabilities lie in the two cities' districts?
2. Which factors determine the high social vulnerability in the two cities?
3. To what extent do determinants of high social vulnerability correlate/compound?
4. To what extent are communities with high social vulnerability exposed to urban pluvial flooding?
5. To what extent do intersectional social vulnerabilities and pluvial flood exposure differ between the two cities (and their districts)?

By answering research sub-question 1, it will be investigated how districts in the two cities vary in their social vulnerability which could inform policies for FRM on which districts need the greatest attention. Research sub-question 2 will look into the districts with high vulnerability scores (identified by answering sub-question 1) and distinguish the specific dimensions driving high social vulnerability to better inform adaptation measures. For example, if a large number of elderly people in a specific district is identified as a determinant of social vulnerability, this requires different adaptation measures (e.g., increased assistance in the case of an evacuation) than when a relatively high number of migrants live in a district (e.g., they might rather need more information about risks in their native language). Research sub-question 3 explores to what extent dimensions of vulnerability (e.g., limited education and low income) correlate to reveal if vulnerabilities are potentially compounding in people which would indicate structural disadvantages faced by certain demographics over others. Research sub-question 4 investigates if there is a disproportionate exposure to pluvial flooding of identified vulnerable districts. Hence, it is investigated if vulnerable communities live in more flood-prone areas compared to the average population which would indicate a further enhancement of risk and inequalities. Research sub-question 5 is conducted to compare the cities relative to each other (which is relevant from a scientific perspective to investigate patterns, differences, and similarities), and not only relative to themselves (which is more relevant for city planners). It is hoped that results from this research will lead to valuable insights into the distribution of intersecting social vulnerabilities in an urban pluvial flood context in Europe.

1.4. Research Framework

The overall structure of the thesis is shown in Figure 1. To achieve the research aim and objectives, the research is divided into three phases with Phase 1 being divided into two parts (Phase 1a and 1b). Hence, the research is planned as follows: In Phase 1a, a literature review on intersectionality theory, combined with a review on pluvial flooding impacts in Europe, and Cutter et al.'s (2003) foundational

Social Vulnerability Index (SoVI) will inform the development of an index (Phase 1b) of intersectional social vulnerability (IVI) to pluvial flooding in European cities. In Phase 2, the IVI will be applied to an empirical case study analysis using socio-demographic statistical inputs from Cologne and Frankfurt to answer the research sub-questions. By applying the IVI to the two case studies, it can, first, be evaluated which city districts are especially susceptible to pluvial flood risk (sub-question 1); second, what socio-demographics drive vulnerabilities in the cities (sub-question 2); third, to what extent socio-demographic determinants of vulnerability correlate (sub-question 3); fourth, if socially vulnerable groups are disproportionately exposed to pluvial flooding (sub-question 4); and fifth, to what extent vulnerabilities differ in the two cities (sub-question 5). The results can inform socially just and district-specific flood adaptation recommendations (Phase 3).

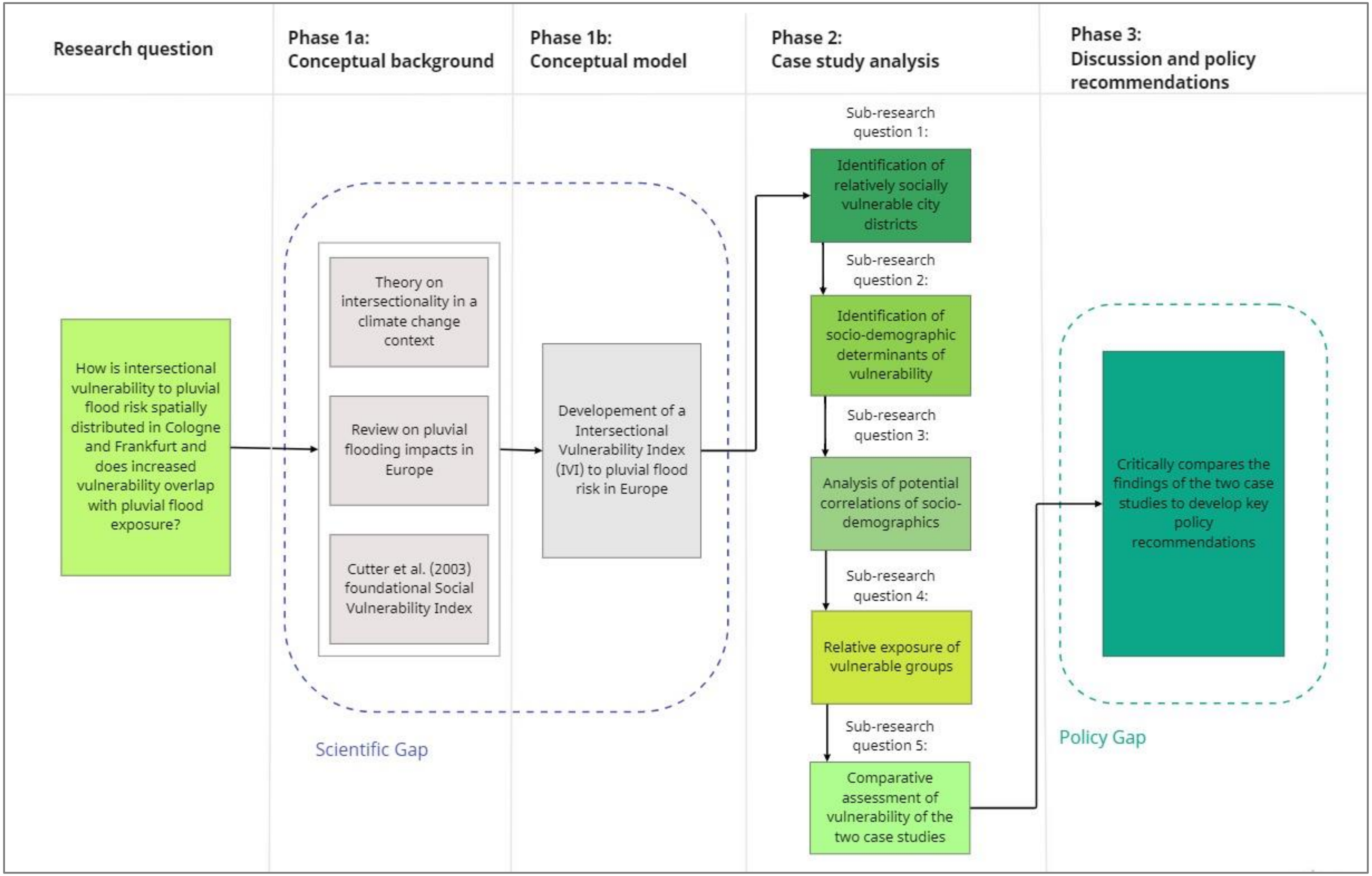

Figure 1: Schematic overview of the different research phases.

1.5. Scientific and societal relevance

This research contributes to the scientific debate on intersectional climate justice and challenges the traditional flood risk assessment and management approaches. Conceptually integrating the impacts of pluvial flooding and intersectional social vulnerabilities is contributing to the scientific debate around climate justice. These aspects appear to get little attention in the academic literature and tend to be generally considered separately (Amorim-Maia et al., 2022). The intersectionality perspective at the heart of this research allows one to challenge the traditional flood risk assessment approaches that tend to solely focus on reducing damage based on economic losses and fatalities (Koks et al., 2015; Rentschler et al., 2022). Such an approach assumes a homogeneous social vulnerability of all people by focusing on technocentric and structural flood adaptations to reduce exposure and neglects the social dimensions of risk (Koks et al., 2015). Hence, this research contributes to the scientific literature connecting climate hazards (pluvial flooding) with social dimensions of risk (intersectional vulnerabilities) which continues to be a connection barely represented in a European context (Cohen, 2017). Lastly, this research aims to provide an intersectional social vulnerability index (IVI) that can be used and scaled to investigate vulnerabilities in various European cities by researchers and practitioners alike.

Integrating intersectionality and social vulnerability considerations in pluvial flooding adaptation is societally relevant for the following reasons: Since socially vulnerable groups have a decreased capacity to prepare, anticipate, and/ or recover from climate-related events (Field, 2012), it is important to identify those vulnerabilities to be able to assist the most vulnerable in society in coping and overcoming flooding events. If the focus is continuously put on aggregate monetary losses, we will continue to treat people as a homogenous group, disregarding social dimensions and justice principles (Walker et al., 2021). Moreover, this technocentric and economic approach risks to exacerbate existing social inequalities by potentially increasingly protecting the richer populations and their assets because of higher potential economic losses (Boda et al., 2022). The failure to consider how impacts and non-material losses are felt across different intersections of identity “can lead to adaptation policy and practice that reinforce existing social inequalities” (Walker et al., 2021, p. 171) since planners risk overlooking districts with high social vulnerability, where flood risk measures are most urgently needed to protect lives and livelihoods (Rentschler et al., 2022). Hence, this research can inform more socially just FRM approaches that are addressing objective deprivations and existing inequalities and provides practical implications for society.

2. Conceptual framework

The following chapter first briefly introduces climate justice theory and then focuses on the concept of intersectionality. The section on intersectionality is followed by examples of (intersectional) social inequalities in Europe. A non-exhaustive literature review (sensu Table 1 in Grant & Booth's (2009) typology of review methods) is then presented on pluvial flooding impacts in Europe to contextualize the phenomenon in relation to vulnerabilities. Literature was collected through keyword searching of the multidisciplinary database Scopus. From the database, only peer-reviewed academic articles were selected to secure the high quality of the research. To review pluvial flood impacts, key terms, and abbreviations "(pluvial AND flood*) AND (europe OR eu)" were used to search article titles, abstracts, and keywords. For the review on intersectionality in a climate hazard context, the key terms "intersectional* AND ("climate change" OR flood*)" were used with a specific focus on European contexts. Next, Cutter and colleagues' (2003) Social Vulnerability Index (SoVI) will be introduced explaining the major social categories used in the index. Lastly, intersectionality theory, social inequality in Europe, the review of pluvial flooding impacts, and Cutter et al.'s SoVI will be combined to inform the development of the IVI which will be applied in the empirical analysis of the two case studies.

2.1. Intersectionality and climate justice

Climate justice as a theory views climate change and efforts of mitigation and adaptation as ethical considerations and wider justice concerns (Robinson & Shine, 2018). Climate justice is focused on the equitable sharing of burdens and benefits of climate change while safeguarding the rights of the most vulnerable (Robinson & Shine, 2018). According to Sultana (2022), at its core, climate justice is about paying attention to how climate change impacts people differently and disproportionately, aiming to reduce oppression and marginalization and enhance justice and equity. Understanding which communities or groups of people suffer disproportionately from climate hazards necessitates thoroughly examining who is excluded or marginalized as a result of climate change processes, as well as from any adaptation or mitigation measures (Sultana, 2022). Intersectionality strongly relates to climate justice theory by aiming to expose the most marginalized within society and the overlapping and intertwined systems of discrimination and oppression that some people face (Amorim-Maia et al., 2022).

Intersectionality as a theory has progressed within black feminist theory and is founded on a feminist understanding of power and knowledge production, aiming to recognize intersecting discriminations based on categories such as gender, ethnicity, religion, wealth, level of education, sexual orientation, and other social identities or positions (Atewologun, 2018; Bauer et al., 2021; Kaijser & Kronsell, 2014). Intersectionality was first termed by legal scholar Kimberley Crenshaw (1989) who sought to understand and draw attention to the dual discriminations African American women were facing within the law. Termed 'synergistic' discrimination by Crenshaw (1989), she outlined a new theoretical approach towards understanding discrimination based on various social categories that are intrinsically intertwined (e.g., race and gender), demonstrating that the disadvantage experienced by, for example, black women is unique and cannot be described by solely adding racist experiences of black men and sexist experiences of white women (Crenshaw, 1989). With this, intersectionality exposes that people are often members of multiple social categories (e.g., gender, ethnicity, sexual orientation, religion, etc.) and that these categories are interconnected so that the personal experience of people is linked to their membership in those various categories (Atewologun, 2018). As a critical framework, intersectionality provides the language and tools to investigate and display interconnections and interdependencies of such socially constructed categorizations and social systems (Atewologun, 2018) by asking: Who is disadvantaged? Why are those people underprivileged? What social categorizations leading to structural disadvantages intersect in one person? What societal structures constitute disadvantages and privileges faced by people associated with different social categories? Atewologun (2018) offers examples of such categorizations and systems which include: "social identities (e.g., woman, Pakistani), sociodemographic categories (e.g., gender, ethnocultural), social processes (e.g., gendering and racializing), and social systems (patriarchy and racism)" (p. 2). Experiences deriving from those intersecting identity streams are influenced by and negotiated through structural systems of oppression such as sexism and racism (Bauer et al., 2021). Thus, embedded within intersectionality is the idea that social categories and systems are always related to power, making it a crucial component of intersectional analysis (Atewologun, 2018). Discriminatory structures are maintained by a certain group that tends to benefit from the existence of oppressive and discriminatory power structures because those serve their interests by confining and immobilizing groups of people (Hampton, 2021). Concerning climate hazards, there is mounting evidence that women, Black, Indigenous, and low income-communities will experience disproportionately adverse impacts (Amorim-Maia et al., 2022a). Research has shown that this relates to various intersecting structural disadvantages of these groups founded in a reduced likelihood to own land and resources, having less education and training, fewer opportunities to participate in decision-making processes, and less access to health services, information, and institutional support (Amorim-Maia et al., 2022a).

Concluding, intersectionality describes discriminatory structures and disadvantages attributed to certain groups within society and acknowledges that categories of discrimination often overlap. Vulnerabilities of those groups are constituted based on various (intersecting) structural disadvantages.

Regarding climate change, and pluvial flood risk in particular, intersectionality theory can be seen as contributing to climate justice by identifying structural discriminations which lead to unequal disadvantages for certain groups over others.

2.2. (Intersecting) Social inequalities in Europe

Income and wealth are the strongest driving factors of socio-economic inequality in Europe (OECD, 2017). The range of inequality levels varies between EU countries, yet, the average income of the richest 10% has been rising since the 1980s from 7 to 9.5 times the earnings of the poorest 10% of the population (OECD, 2017). The disparity in wealth is even larger. The 10% of wealthiest households hold 50% of the total wealth whereas the poorest 40% hold only about 3% (OECD, 2017). The socio-demographic status of a population determines their ability to absorb losses from hazards. Losses of the poor are far more devastating in relative terms because of the reduced ability to protect themselves or recover from a disaster (Cutter et al., 2009).

When looking for intersections, the most vulnerable to poverty have long been senior citizens who have now been surpassed by the demographic of young people and families with children (OECD, 2017). Poverty levels of people with employment have especially intensified for single parents and one-income couples with children (OECD, 2017).

Concerning gender, while the gender gap in employment and earnings has generally declined in most EU countries, the employment gap now persists at 9.8% and the earnings gap at 12.8% (OECD, 2017). Women are more vulnerable because they are also more likely to live in poverty. Women are also more likely to have low-status jobs which potentially disappear after a disaster in the face of an economic recession (Cutter et al., 2009). On top of that, women more often take on roles as mothers or caregivers making them responsible for the very young and old which increases their overall vulnerability (Cutter et al., 2009). Immigrant women, especially when arriving as adults, are generally more likely than any other demographics to end up without education, work, and training (OECD, 2017).

Foreigners or people with parents that have not been born in the residing country perceive to be more often the target of discrimination compared to their peers (OECD, 2017). Racial and ethnic minorities are on average more vulnerable because they are more likely to live in poverty and more often face discrimination regarding access to real estate or insurance needs (Cutter et al., 2009). In most areas, immigrants tend to have lower rates of employment and incomes than the native-born and they are twice as likely as their native-born colleagues to live below the poverty line while in employment (OECD, 2017). Generally, groups most exposed to ethnic discrimination vary between EU countries. Yet, young people, the unemployed, and the elderly are more often the recipients of ethnic discrimination (OECD, 2017). Moreover, children whose parents are immigrants that have been raised and educated in the host country are still facing continuing disadvantages compared to children with native-born parents. Within the EU, the unemployment rate of young nationals with foreign parents is around 50% higher than among their peers with native-born parents (OECD, 2017).

The age of a person determines their level of needed assistance, children or very old people are generally dependent on help. This is also the case for the mentally and physically challenged. Moreover, old people are also on average poorer and have poorer health than the average population (Cutter et al., 2009). Regarding health and disabilities, there are clear intersections relating to age but also to the economic status and the educational level of people. Across the EU, 17% more people report being in good health in the highest income quintile, compared to people in the lowest income quintile and diseases that are major causes of disability and reduced life qualities show strong disparities between different socioeconomic groups (OECD, 2017). People with a minimum level of formal education are more than twice as likely as those with the highest level of education to have chronic obstructive pulmonary disease and diabetes (OECD, 2017).

Since education and economic status are generally lower for immigrants or their children and economic status is lower for women than men and lowest for one-income families or single parents, this is another example of the intertwined vulnerabilities compounding in individuals based on societal structures and norms that make access to wealth and education more difficult for some than others.

2.3. Pluvial flooding impacts in European cities

To establish an overview of the direct impacts of pluvial flooding in an urban and European context, six categories were identified relating to adverse impacts of pluvial flooding: damage to residential assets (1) and critical infrastructure (2); infectious diseases (3); mental health problems (4); death and physical harm (5); and displacement (6). The following section will describe the impacts and vulnerabilities relating to those categories in more detail. The categories have been established based on a literature review on pluvial flooding impacts in Europe which was further expanded by the insights from the IPCC's Working Group (WG) II (2022) observed impacts of climate change on human systems.

Residential Assets

Residential assets are usually (in economic terms) the most valuable national asset (Paprotny et al., 2020) with dwellings accounting for 46% of Europe's gross value of tangible fixed assets (Paprotny et al., 2020). Yet, when exposed to flooding, not only dwellings are potentially damaged but also their contents. Damages to both constitute the largest share of economic damages from natural hazards (Paprotny et al., 2020). Damages to residential buildings are usually calculated by quantifying the monetary value of the exposed dwellings and their contents (Paprotny et al., 2020). Hence, the type of house affects the related damage to the building and the total damage (van Ootegem et al., 2018). According to van Ootegem and colleagues (2018), income correlates negatively with the damage to the building, so poorer people experience higher damage to dwellings. However, the authors note that damage to the content is higher for rich people (van Ootegem et al., 2018). Unfortunately, the authors do not investigate why this is the case. The statement indicates, however, that rich people are generally less exposed, or their houses are built better but when they are exposed, they have more valuable goods to be damaged. Yet, while damages might be higher in economic terms for richer neighbourhoods, wealthier people are more likely to afford the recovery and tend to be better insured. For example, a study by Gropper and Kuhnen (2021) on US households found a strong wealth-insurance correlation, revealing that wealthier people have on average better life and property insurance coverage. So, even though absolute economic damage may be lower for poorer people, the impact in qualitative terms tends to be much greater (Boda et al., 2022; Cutter et al., 2009), revealing a greater vulnerability of low-income households.

Furthermore, damages to households and residential assets are often calculated based on insurance claims (see e.g., Paprotny et al., 2020; Thieken et al., 2005, and examples listed in Prokić et al., 2019c). This approach omits damages experienced by people without insurance and reveals that the current system for estimating financial damages is already biased to some extent because people who do not have or cannot afford insurance are not accounted for. This generally shows that people without insurance (e.g., lack of financial means to afford insurance or knowledge of insurance or flood risks) or the knowledge on how to claim damages (e.g., people with lower education who have difficulties understanding the bureaucratic workings or people that do not speak the native language fluently) are disadvantaged and, therefore, more vulnerable.

Critical Infrastructure

Gibson et al. (2020) identify critical infrastructure services that have become critical to modern society, which include clean water supply, sewer treatment system, public transport, road and rail networks, energy generation and transmission networks, ambulance stations and health care services, and telecommunication/ICT networks. The authors stress that those infrastructural systems are increasingly interconnected and disruptions of one will have a cascading effect on others. Electrical substations, telecommunication, or other critical infrastructures that are not directly affected by a flooding event may still lose power due to the failure of other substations (Gibson et al., 2020). This is important to account for because it shows that areas that are not directly affected by flooding can be impacted when critical infrastructure in other areas is flooded.

Examples of damages to critical infrastructure in European cities are presented in the following. In the summer of 2007, a pluvial flood in the UK impacted essential services leading to half a million people being without water or electricity supply. Transport networks also failed, and emergency facilities and telecommunications were put out of action (Prokić et al., 2019b). In July 2011, Copenhagen experienced its biggest single rainfall ever recorded which led to the flooding of the city's roads and transport networks and €65 million in municipal infrastructural damages. The same happened in southern Italy after a heavy rain event in October 2018 (Prokić et al., 2019b). During an urban flooding event in September 2009 in Istanbul, highways turned into rivers and transportation and communication infrastructures were also damaged (Prokić et al., 2019b).

Those impacts seem to hit people without social networks (e.g., lack of ability to move temporarily to family/friend with access to drinking water, sewage pumping, etc.), a lack of financial stability (e.g., needing extra money for bottled water, or electricity generators), physically or health restricted people (e.g., in need of daily assistance or medical supervision), or people with greater dependencies (e.g., on public transport) especially hard.

Infectious Diseases

Exposure of humans to urban water sources poses health risks when pathogenic micro-organisms are present (Sales-Ortells & Medema, 2014). An increasing number of storms and increasing intensities in rainfall increase the concentration of pathogens (Sales-Ortells & Medema, 2014). Sales-Ortells and Medema's (2014) study on waterborne diseases in the Netherlands, found that the highest mean event probabilities of developing gastrointestinal illness were found for playing or residing in pluvial flooding from a combined sewer overflow (34%) (and 4.7% when playing or residing in the pluvial flood from stormwater sewers). Both values exceed the EU Bathing Water Directive threshold for excellent water quality which is set at 3%. Another study showed that exposure to most diseases was enhanced after being exposed to stormwater (Sales-Ortells & Medema, 2015). Similarly, Boudou et al. (2021) found atypical peaks in infections in water-borne diseases in Ireland during April 2016 and June/July 2016 leading to the hypothesis that the Winter 2015/16 flooding event was likely the source.

Overall, Sales-Ortells and Medema's (2014, 2015) and Boudou et al.'s (2021) research illustrate the risks of waterborne diseases that will continue to increase with climate change pressures and more frequent pluvial flooding events. Especially vulnerable to water-borne diseases are people that are not able to evacuate before the flooding or who cannot evacuate safely during or after a flooding event. People who do not have the knowledge of the dangers of being exposed to floodwater have also a higher vulnerability (e.g., children playing in flood waters).

Mental Health

Mental health problems such as psychological distress and anxiety can affect people exposed to a flooding event. Moreover, even after the physical (infrastructural) recovery from a flooding event, mental illnesses (such as distress) pose long-term health problems for some (Fewtrell & Kay, 2008). Mental health problems can arise for everyone, yet, it seems to be especially important to consider for low-income households that do not have the means to quickly find new housing or pay for repairs. People without insurance might also suffer more from anxiety and distress. Moreover, there is still a stigma attached to mental disorders and people seeking psychological help (Hantzi et al., 2018). Hence, people lacking knowledge or information about how to get psychological help or other socio-cultural barriers preventing people from seeking help are potentially enhancing vulnerability by hindering or slowing down recovery.

It is important to note that aggregated data on actual physical and mental illness is hardly available since not everyone will seek help and not every reported (mental) illness will be related to the flooding event (Fewtrell & Kay, 2008). As a result, there is generally very weak data available except for immediate deaths or severe injuries that can be attributed to a particular flood event (Fewtrell & Kay, 2008). The lack of data makes it even more important to consider health effects in flood risk management and establish support for people at higher risk for anxiety, stress, and other mental illnesses.

Death and Physical Injury

Death and physical injury can be easily attributed to a flooding event. Yet, while it is usually stated how many casualties a specific flooding event has caused, more details of the people deceased are generally not stated. For example, EM-DAT records the number of people affected during an event but only in absolute terms (see EM-DAT, n.d.). Yet, it can be assumed that people with limited mobility are at the highest risk because of their inability to (quickly) escape (e.g., older people, physically disabled people, children). The German flood in July 2021 highlighted the risk for people with disabilities when 12 people living in a group home for the disabled drowned because they did not manage and were not assisted to evacuate in time (Cerimovic & Rall, 2021). Hence, people with disabilities, general dependencies on others' help, and older people need special attention in the case of a necessary evacuation.

Displacement

The IPCC's WG II (2022), predicts that displacement will increase in the mid-and long-term due to the intensification of heavy precipitation and associated floodings. The report also confirms that weather extremes are already and increasingly driving displacement in all regions of the world leading to perpetuated vulnerability (IPCC, 2022). While none of the articles examined in this thesis discussed displacement in an urban European context, it is important to note that displacement affects people differently because of differential vulnerabilities. Hurricane Katrina, which unfolded in New Orleans in 2005, permanently displaced more African-Americans than any other group (Versey, 2021). Moreover, African-Americans, non-citizens, and renters were the least likely to return to New Orleans in the year after the hurricane (Versey, 2021). In the EU, across all countries, workers with a lower level of education are at the highest risk of displacement (OECD, 2017). Desai et al., (2021) also note that displacement in the face of a natural hazard mainly affects those already most vulnerable. An urban dweller with a regular income, savings, financial securities, and insurance will be less likely to have to relocate after a disaster than someone who lacks those securities. Hence, this points to greater vulnerabilities of people who are generally marginalized and discriminated against within society and people of lower-income communities without insurance.

2.4. Cutter and colleagues' SoVI (2003)

Cutter and colleagues (2003) pioneered the development of a methodological framework to assess social vulnerability relating to climate hazards (see Appendix 1) (Kirby et al., 2019). The authors developed the Social Vulnerability Index (SoVI) for a US-American context, selecting 42 indicators (see Appendix 2) encompassing economic resources, socio-demographic categories of residents, and type and density of infrastructure which they then aggregated into a single index. The index is calculated by conducting a Principal Component Analysis (PCA), determining 11 factors that explain 76.4 % of the variance among all counties. Based on the 11 factors a composite index score was calculated in an additive model for each US county.

Cutter et al. (2003) identified that characteristics that are generally accepted in literature to have an influence on social vulnerability are socioeconomic status, race, gender, and age. Additionally, social vulnerability is generally higher for populations with special needs or those who lack the support systems necessary after the recovery from a disaster. Such being the physically or mentally challenged, the homeless, transients, seasonal tourists, and non-native speaking immigrants (Cutter et al., 2003). Some of those categorizations can be explained by underlying structural disadvantages that are often intersecting or constituting each other and will be explained in more detail in the following.

When accounting for social vulnerabilities, it is important to investigate the proportions of residents characterized by these broad categories, but also how social categories intersect and can influence people's experiences and potentially enhance a community's vulnerability (Cutter et al., 2009). This will be done by encompassing various broad categories of social vulnerabilities in the IVI and by investigating compounding vulnerabilities in the analysis.

2.5. Indicators of intersectional vulnerabilities to pluvial flooding

Based on the insights gained from pluvial flooding impacts in a European context and informed by intersectionality theory and Susan Cutter and colleagues' SoVI, Table 1 presents the Intersectional Vulnerability Index (IVI) to be used in this thesis, with operationalizable indicators along ten dimensions affecting vulnerability: economic status, gender, nationality, age, education, family structure, special needs populations (SNP), infrastructural dependence, housing, and lack of social networks.

Table 1: Dimensions of vulnerability and operationalizable indicators used to calculate the Intersectional social Vulnerability Index (IVI) to pluvial flooding in European cities

Dimensions*	**Description**	**Potential intersections**[1]	**Indicators**[2] **(directionality)**[3]
Economic Status	Having financial resources has been found to work as a buffer against severe impacts of a flooding events because it enhances the possibility to recover more quickly (Cutter et al., 2009; Twigger-Ross et al., 2014). Moreover, low-income households tend to be less likely to have insurance and stress and anxiety after a flood has been shown to be higher for low-income households (Gropper & Kuhnen, 2021; Twigger-Ross et al., 2014). Wealth generally enables communities and individuals to recover more quickly due to insurance, social safety nets, and entitlement programs (Cutter et al., 2003). Personal Wealth might be a better indicator of socioeconomic status than income alone but is usually not provided in demographic databases on a district scale.	- Gender - Nationality - Education - Age	- Recipients of social benefits (+) - Unemployed (+) - Median per capita income (-) // Wealth (-)
Gender	Research suggests that women experience physical and psychological flood-related health problems more severe and they tend to have greater care responsibilities carrying an additional physical and emotional burden for dependent household members (Walker & Burningham, 2011).	- Nationality - Socio-economic status - Religion	- Females participating in the labour force (-) - Females (+) - Non-binary (+)

[1] This list might not be all encompassing and potential intersections might have been overlooked. Intersections can occur among all socially vulnerable groups which tend to be the socioeconomically disadvantaged, women, gender nonconform people, racial and ethnic minorities, religious minorities, the uninsured, lower-income children and families, the elderly, the homeless, immigrants, refugees, the urban and rural poor, the disabled, those living with existing chronic conditions, and more (Kosanic et al., 2022; Osborne, 2015; Versey, 2021).

[2] For data availability and indicators for Cologne and Frankfurt see Table 3 in the Method chapter.

[3] Increase (+), decrease (-) social vulnerability.

	Moreover, women also have a more difficult time during recovery due to sector-specific employment and lower wages (Cutter et al., 2003). Moreover, 2% of the world's population identifies as transgender, gender fluid, non-binary or other ways (Varrella, 2022). Urban areas are usually more progressive and the percentage of people identifying as non-binary or genderqueer (NBGQ) may be even higher in larger cities such as Frankfurt and Cologne. Moreover, the percentage of people identifying as non-binary might also continue to increase when stigma decreases and acceptance increases. The NBGQ are marginalized and, as such, are at risk of stigmatization and developing negative health outcomes (Brandelli Costa et al., 2019). Yet, data collection on NBGQ is scarce. Collecting data on this demographic would provide a more nuanced image of the composition of a city's gender distribution and could also help identify vulnerabilities or discriminations specifically faced by people identifying as non-binary.		
Nationality	Language and cultural barriers affect access to post-disaster funding (Cutter et al., 2003) and hinder pre-disaster warnings. Moreover, racist structures lead to heightened vulnerability of this group because of higher social exclusion (Samers, 1998). Minority groups have generally lower incomes, lower education, poorer health, and lower general life satisfaction than the average population (Verkuyten, 2008).	- Gender - Socio-economic status - Religion - Education (language)	- Foreigners (+) - Nationals with a migration background (+)
Age	Very old as well as young people are generally less mobile and dependent on others' help in case of an evacuation. Moreover, if daycare services are affected by flooding, parents must need to stay at home which increases the burden of care (Cutter et al., 2003). The elderly are also	- Poorer health (Elderly) - Socio-economic status (elderly)	- Inhabitants 65 and older (+) - Inhabitants 0-14 (+)

	more vulnerable because of poorer health and less financial means compared to the average population (Cutter et al., 2009).		
Education	Education is positively linked with higher income which in turn is linked with lower vulnerability (Cutter et al., 2003). Lower education also reduces the ability of people to understand warning information or access to financial support post-disaster (ibid.).	- Nationality - Socio-economic status	- Students attending a Gymnasium (-) - Academic workforce (-)
Family Structure	Single-parent households or families with many dependents tend to have limited financial resources to outsource caring responsibilities and thus, must balance those responsibilities with the work that generates income (Cutter et al., 2003; OECD, 2017). Regarding people in need of care in private households; Not only is the person itself highly vulnerable in the case of flood exposure due to restricted mobility and potential prior health issues, but the person doing the care work is usually also in a more precarious situation due to enhanced responsibilities, stress, and the (unpaid) additional workload (OECD, 2017).	- Socio-economic status - Caregiver role (Gender)	- Families with children (+) - Single-parent household (+) - Households with additional caring responsibilities (elderly, disabled) (+)
Special needs populations	Special needs populations tend to be difficult to measure and identify but are especially vulnerable during a flooding event because of their invisibility (Cutter et al., 2003). Moreover, prior poor health worsens the psychological and physical impacts of flooding (Twigger-Ross et al., 2014). Disabled people are also more dependent on help in case of a necessary evacuation. Seasonal workers and transient are often not familiar with their geographical surroundings and tend to lack support networks in the area and potentially face language barriers (Cutter et al., 2003).	- Nationality - Gender - Socio-economic status - Age	- Retirement facilities and long-term care places (+) - People with physical and mental disabilities (+) - Homeless[4] (+) - Seasonal workers / Transient (+)

[4] Very difficult for municipalites to accurately account for in statistical data collection. Yet, this group must not be ignored in flood risk management and adaptation planning.

Infrastructure Dependence	Loss of sewers, waterways, bridges, communications and transportation infrastructure compounds potential disaster losses (Cutter et al., 2003). In the face of pluvial flooding, evacuation depends on means to leave the threatened area. Car ownership (and potentially well-functioning public transportation networks) increases mobility, and flexibility, and can speed up evacuations. Moreover, after a flooding event, when road networks or train tracks are damaged, diversified means of transportation can enhance mobility and reduces the impact of a flooding event (e.g., being able to reach family or friends or get to work).	- Socio-economic status - Gender - Nationality - Lack of social networks	- Dependence on public transportation (+) // Availability of public transport infrastructure (-) - Cars registered per inhabitant above 18 years (-)
Housing	Renters usually (but not always) rent because they are either transient or do not have the financial means to buy housing. Renters, hence, are on average less wealthy and are more likely to lack access to information on financial support after a flooding event and potentially lose their ability to return or afford to house elsewhere when their rentals become uninhabitable (Cutter et al., 2003; Versey, 2021). While insurance holders are generally financially better protected against a flood, they also tend to be wealthier than the average population, which overall decreases their vulnerability (Gropper & Kuhnen, 2021).	- Socio-economic status - Education - Nationality	- Renter-occupied housing units (+) - People with property insurance (-)
Lack of Social Networks	People lacking a social network are more likely to not receive (warning) information or support during and after a flood (Twigger-Ross et al., 2014). Social networks also reduce vulnerability in the sense that they can provide provisional housing in case of an evacuation or can provide means of transportation and help evacuate.	- Nationality - Age - Infrastructure dependence	- count of contact with friends and family per week (-) - count of contact with neighbours or other loose acquaintances per week (-)

3. Methodological framework

3.1. Research strategy and case study selection

This thesis employs a mixed-method design, combining a critical theoretical approach with quantitative empirical case studies. The research strategy of a comparative case study analysis has been chosen to apply and test the IVI in two separate locations and because a case study analysis is fit to explore the empirical context of a relatively unexplored field. Moreover, by applying the IVI to two European cities, it is aimed to investigate if vulnerabilities are similar in both cities. If vulnerabilities appear similar, this might indicate a pattern that could be further studied by applying the IVI to more cities in Europe and might indicate that broadly-applicable adaptation strategies and risk management plans could be developed and deployed across multiple cities. If not, this would indicate a need to develop socially-just adaptation strategies that are specifically tailored to a city (or even district). To assess this, a hierarchical method for the case study analysis was chosen because it permits the investigation of patterns in two places separately and allows for the identification of potential similarities or differences (Verschuren & Doorewaard, 2010).

To investigate exposure to pluvial flooding (sub-question 3), it was opted to use the Copernicus Climate Change Service's novel and high-resolution dataset on pluvial flood risk assessment in European cities (Mercogliano et al., 2021). The dataset restricted the selection of case cities because it has so far only been established for 20 European cities (Antwerp, Brussels, Frankfurt am Main, Köln (Cologne), Paris, Amersfoort, Birmingham, London, Vienna, Prague, Budapest, Riga, Stockholm, Milan, Rimini, Bilbao, Pamplona, Amadora, Athens, and Bucharest) (Mercogliano et al., 2021). Since this thesis is the initial step in this line of research, it is, therefore, wanted to minimize the number of variables (i.e., country, climate, capital/non-capital). By this, it is aimed to investigate if already in a very similar context, differences in determinants of vulnerabilities persist. Hence, out of those 20 cities, Cologne and Frankfurt have been selected for a comparative case study analysis based on the criteria outlined in Table 2.

Table 2: criteria for case study selection

Inclusion criteria and explanation	Possible city combinations
Two cities in the same country because of more closely comparable climate, infrastructure, and political setting:	Bilbao and Pamplona Birmingham and London Antwerp and Brussels Cologne and Frankfurt
Language restrictions exclude Spanish documents:	~~Bilbao and Pamplona~~ Birmingham and London Antwerp and Brussels

	Cologne and Frankfurt
Both non-capitals to ensure better comparison:	~~Birmingham and London~~ ~~Antwerp and Brussels~~ Cologne and Frankfurt

Yet, it is being acknowledged that a comparison across different political settings could also reveal interesting insights. In the future, exploring the effects of these variables in differing contexts is desirable, but is beyond the scope of this research.

3.2. Background to case cities

Frankfurt and Cologne are both situated in northwestern Europe, they are non-capital cities, and lay in the same climate zone with a maritime north climate. Cologne is located along the Rhein River and Frankfurt is located along the Main which is a tributary of the Rhein (see Figure 2).

Figure 2: Location of Cologne and Frankfurt and their respective federal states (North Rheine-Westphalia and Hesse). Source: Created by author.

Frankfurt is one of the most affluent cities in Germany with an average GDP of €96,670 per capita (Wollny, 2022b). By contrast, Cologne has an average GDP per capita of €61,027 (Wollny, 2022a). The two cities also differ in population size with Cologne having a population of 1.09 million (Stadt Köln, 2020) while Frankfurt has 759 thousand inhabitants (Stadt Frankfurt am Main, 2020).

Regarding flood protection in Germany, the 16 federal states are mainly responsible for the concrete design of strategies and measures against flooding (BMVU, n.d.). Yet, responsibility for individual flood risk management projects can also lie with the municipalities or water boards, depending on the distribution of competencies within the respective federal states (BMVU, n.d.). There are also state overarching flood risk management plans often relating to rivers crossing state lines. For example, the federal states along the Rhein River in Germany (Figure 3) have published the 'Flood Risk and Management plan Rhein 2021' which is a flood risk management plan for Germany's Rhein region (Federal State Ministries, 2021). The Main River (Frankfurt), as a tributary of the Rhein and one of a total of nine areas that are part of the Rhein catchment area, is also considered in the plan.

Figure 3: Flood risk management: States participating in Germany's Rhein region protection plan. Source: Adapted from Federal State Ministries, 2021

The Rhein flood plan provides information on the area's climate, hydrology, and the consequences of climate change. Moreover, the plan sets out the responsibilities of flood management, the flood management coordination of the Rhein catchment in Germany and beyond and presents methods to estimate risks and create risk maps. Moreover, the plan provides overarching goals; to avoid and reduce risks before a flood and to reduce flood consequences during and after a flood. Pluvial flooding is only mentioned as a general risk but not as a flood risk per se and the plan does not consider social justice or equity aspects (Federal State Ministries, 2021).

North Rhine-Westphalia (the state in which Cologne is located) and Hesse (the state in which Frankfurt is located) have, however, also separate flood risk management plans while Cologne also has a flood protection concept specifically for the city. Besides the overarching Rhein region plan covering both, the Cologne and Frankfurt area, in the following, the two other current flood risk plans for Cologne (state, city) and the one for Frankfurt (state) are briefly described.

Flooding and Flood Risk Management in Cologne

With the city's proximity to the Rhine River, Cologne had to adjust and deal with river floodings for centuries, but also heavy precipitation events with associated sewage flooding have affected Cologne in the past (Netzel et al., 2021). The last severe flooding event occurred in June 2021 with the river level rising to more than eight meters due to heavy rainfalls. Areas not in proximity of the river were also affected by flooding because the drainage capacity of the city's sewage was exhausted due to extreme precipitation (Steeger, 2021). Some areas were hit with 145mm of precipitation within 12 hours, which equals twice the average amount of precipitation for the whole month of June (74mm) leading to pluvial flooding in some areas of the city (Bröder, 2021). The city now pledges to work on becoming more resilient in the face of extreme precipitation events (Bröder, 2021).

For Cologne, a summary of actions has been published by the state based on the 'Flood Risk and Management plan Rhein 2021' (District government, 2021). The state's plan for Cologne lists actions taken or planned in the area to prepare for flooding and reduce risks. The proposed actions generally focus on projects related to river flooding, land use planning, physical flood protection, retention plans, communication and information strategies, and the management and training of emergency services (District government, 2021). Regarding extreme precipitation, Cologne established a task force for municipal heavy rain risk management [Arbeitshilfe kommunales Starkregenrisikomanagement] in 2018 (Ministry NRW, 2018). The task force focuses on risk analysis and published a hazard map for pluvial flooding which can be freely accessed. The task force also published a plan which focuses, similar to the other flood risk management plans, on informing citizens and businesses about risks, protection measures, and planning infrastructural measures to reduce damages (Ministry NRW, 2018). The policies do not consider social aspects or demographic vulnerabilities.

While the state is generally responsible for flood risk management planning in Germany, in Cologne, the City Drainage Companies Cologne [Stadtentwässerungsbetriebe Köln] (StEB Köln) are locally responsible for flood management and protection since 2004 (Stadt Köln, n.d.). Cologne's current flood protection concept [Hochwasserschutzkonzept] was finalized in February 1996 and still serves as the city's concept today (Stadt Köln, 1996). The concept does not consider any social justice issues relating to flood exposure of different demographics and follows the traditional approach of overall precautionary flood protection communication combined with technical protection systems (Stadt Köln, 1996). It also needs to be noted, that the concept states that anthropogenic climate change is considered a "controversial debate" (Stadt Köln, 1996, p. 16), despite the fact that climate change has, since 1996, been proven to be unequivocally human-induced (Cook et al., 2016). In the flood protection concept, pluvial flooding is not mentioned specifically as a threat to be combatted. However, extreme precipitation is named as leading to sewage overflow which is named a cause of flooding.

In summary, Cologne has three action plans focusing on flood protection: (1)The Rhein region's flood risk plan, (2)The state plan (for Cologne) derived from the Rhein region's flood risk plan, including the formation of a task force on extreme precipitation, and (3) the city's flood protection concept. The Rhein region plan and the city concept only briefly address pluvial flooding as a general risk to contribute to other forms of flooding whereas North-Rhein Westphalia's plan for Cologne considers pluvial flooding to a greater extent. None of the plans considers social or intersectional vulnerabilities of the population or measures to protect the most vulnerable within society.

Flooding and Flood Risk Management in Frankfurt

In August 2014, the latest extreme precipitation event hit Frankfurt which led to an overflow of the drainage systems and basement floodings. Frankfurt does not have its own flood protection concept like Cologne but falls under the jurisdiction of the state of Hesse. The latest flood risk management plan for Frankfurt is part of a larger plan covering the Main area (orange in Figure 4) and was published in December 2021 (Regional Council of Darmstadt, 2021).

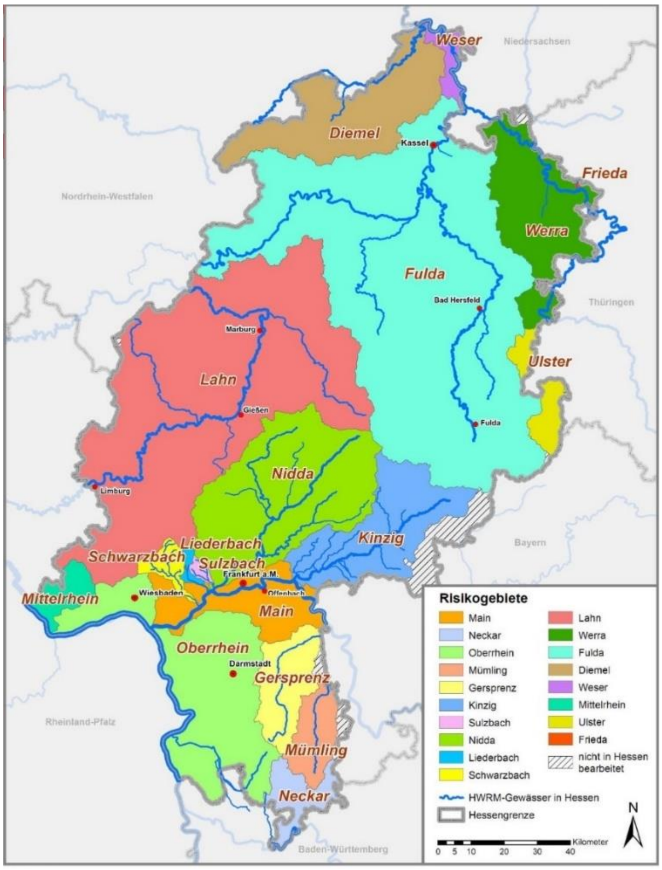

Figure 4: Flood risk management: different areas of responsibility in Hesse. Frankfurt lies within the orange 'Main' area. Source: Regional Council of Darmstadt, 2021

Hesse's Main-area protection plan provides a rather technical assessment of risk areas with the broad aim to protect human health, the environment, cultural heritages, and the economic sector (Regional Council of Darmstadt, 2021). Like Cologne, Frankfurt focuses mainly on prevention measures, relying on communication, risk assessment and planning, and technical solutions to protect the city from flooding. There is also a strong focus on shifting responsibilities to the citizens by relying heavily on information campaigns. The city's website contains general and district-specific information on floods, leaflets for download, current reports and flood warnings as well as links to gauge and flood news for citizens to inform themselves. The plan does not consider pluvial flooding beyond stating that "heavy rain events can occur throughout the country but […] are spatially limited and difficult to predict" (Regional Council of Darmstadt, 2021, p. 29) which is similarly stated in the Rhein region plan. For this reason, extreme precipitation events are classified as a general risk but not as a flood risk by the Regional Council which is similar to Cologne's classification of pluvial flooding. The Council also pledges to better inform municipalities and citizens about the risks of heavy precipitation and potential protection measures. After the severe flooding events in Rhineland Palatinate and North Rhine-Westphalia in June 2021, Frankfurt also published an [extreme-precipitation map] for the city to point out high-risk areas of pluvial flooding (Hettfleisch, 2021). Hence, pluvial flooding might be increasingly considered in the near future.

Summing up, Frankfurt has two action plans focusing on flood protection; The Rhein region's flood risk plan and Hesse's state plan. The Rhein region plan and the State plan for the Main River region only briefly address pluvial flooding as a general risk but do not consider it a flood risk. Like Cologne, Frankfurt does not consider social or intersectional vulnerabilities in its plan or efforts to account for such and protect the most vulnerable within society.

3.3. Vulnerability indicator selection and data collection

The IVI developed in this thesis is based on: (1) literature on intersectionality theory in a climate hazard context, (2) academic literature on pluvial flooding impacts in a European context, and (3) Cutter et al.'s (2003) foundational work on social vulnerability to environmental hazards. Cutter and her colleagues' work is well-established in the scientific field around social vulnerability and climate hazards and has been cited and discussed by more than 2,800 peer-reviewed journal articles or books.

Cutter et al's (2003) Social Vulnerability Index (SoVI) could not be directly applied in this thesis because the index was developed for a US-American and climate hazard context (Roncancio et al., 2020). Since social vulnerability encompasses many factors that influence a communities' capacity to prepare for, cope with, and recover from climate impacts also relating to preexisting conditions, contextual differences need to be accounted for when measuring social vulnerability beyond cultural borders (Holand & Lujala, 2013). Hence, it was decided to use Cutter and her colleagues' SoVI to enhance and improve the IVI along with academic literature sources for a European and pluvial flooding context (previously presented in chapter 2).

For the quantitative part of the research, statistical data on the socio-demographic composition of the two cities' districts needed to be acquired to apply the IVI to the two cases. Cologne has 86 city districs and Frankfurt 46. However, statistical data is not available for Frankfurt's airport district (Flughafen) even though approximately 200 people live in this district (Stadt Frankfurt am Main, n.d.). Therefore, the district will be excluded from the analysis and 45 districts will be considered for Frankfurt. The necessary statistical data was attained from the two municipalities' statistical databases (Cologne: https://www.stadt-koeln.de/politik-und-verwaltung/statistik/ and Frankfurt: https://frankfurt.de/de-de/service-und-rathaus/zahlen-daten-fakten/publikationen/fsa and https://statistik.stadt-frankfurt.de/strukturdatenatlas/stadtteile/html/atlas.html). However, data of the districts could not be acquired for all indicators listed in the IVI (see Table 3).

Table 3: Dimensions and indicators of the IVI with available indicators for both cities.

Dimension*	Overall Indicators	Availability Cologne	Availability Frankfurt
Economic Status	Social benefits	Needs-based social benefits in % of all inhabitants	Needs-based social benefits in % of all inhabitants
	Unemployment	Unemployment in %	Unemployment density in %
	Median purchasing power (or income or wealth)	/	Median gross income (full-time employed)
Age	65 and older	Seniors in % of the total population (65 and older)	Seniors in % of the total population (65 and older)
	Inhabitants 0-14	Children (0-14) in % of total population	Children (0-14) in % of total population
Gender	% females participating in the labour force	/	Females working in % (including female children and senior citizens)
	% females	Females in % of total population	Females in % of total population
	% non-binary	/	/
Nationality	People with migration background	Germans with a migration background in %	Germans with a migration background in %
	Foreigners	Foreigners in % of the total population	Foreigners in % of the total population
Family Structure	Households with child(ren)	Families with children in % of all households	Families with children in % of all households
	Single-parent household	Single parents in % of all households	Single parents in % of all households
	Number of people in care per household	/	/
Education	% of the population with a high school diploma	Students attending Gymnasiums in % (Quota)	Students attending Gymnasiums in % of all students transferring after elementary school
	People with a university degree	Employed with an academic degree in % (of all socially insured employees)	Employed with an academic degree in %
Special needs populations	Per capita residents in nursing homes	Full inpatient care places (without short-term and daycare) in % of all inhabitants	/
	Per capita residents in housing collectives/ group homes for disabled	/	/
	Homeless	/	/
	Seasonal workers / Transient	/	/
Housing	% renter-occupied housing units	/	People living to rent in %
	People with property insurance	/	/
Infrastructure Dependence	% usage of public transportation	/	train/tram traffic area used in % of the total area
	Cars owned per capita	Cars per 1,000 adult residents	Cars per 1,000 adult residents
Lack of Social Networks	/	/	/

Overall, data were obtained for 13 out of 24 indicators for Cologne and 16 out of 24 indicators for Frankfurt. Those indicators for which data could not be obtained, or for which caveats apply, are briefly described here.

Both Cologne and Frankfurt provide no data on citizens' social networks (dimension: Lack of Social Networks). Hence, this dimension has been excluded from this paper's further analyses. The dimension of Special Needs Populations (SNP) has only been included in Colone based on only one indicator which is 'full inpatient care places' (without short-term and daycare). Furthermore, the data is only available for 9 larger city areas. Hence, equal distribution was assumed over districts falling within the specified areas. Data on residents in housing collectives, group homes for the disabled, or short-term and daycare residents are not publicly available. Moreover, data on seasonal workers or transient people are also not available, nor is data on homeless people.

The dimension Housing has only been included in Frankfurt and only includes the indicator of people living to rent. The data is only available for 13 larger city areas and equal distribution was assumed over districts falling within the specified areas. Data on property insurance was not publicly available for either city. Moreover, Cologne does not provide data on public infrastructure or usage of public transportation (Infrastructure). Generally, the dimension Infrastructure only accounts for means of transportation to indicate the mobility of the residents and other critical infrastructural impacts are not considered in this IVI. This is because it is hard to predict critical infrastructural damages due to pluvial flooding and the potential cascading effects of such without very high-resolution exposure analyses informing the input data of the IVI. Both cities have no data on people in care per household (Family Structure), and Cologne does not provide data on percentages of females participating in the workforce, nor on the median income per household. A more detailed list of all indicators that have been included and their measurements can be found in Appendix 3.

Under the dimension 'Economic status', median gross income is used as an indicator. When comparing cities in varying socio-economic contexts, this should be adjusted for purchasing power to conduct a more accurate comparison.

3.4. Composite index construction

To answer the main research question, an index to measure intersectional vulnerability to pluvial flooding (IVI) was built using a top-down assessment approach. The IVI (Table 1) was built because even though other vulnerability indices in a climate hazard or even flooding context exist (e.g.,(Aroca-Jimenez et al., 2017; Cutter et al., 2003, 2013; Koks et al., 2015; Sayers et al., 2018; Tapia et al., 2017), they do not specifically focus on pluvial flooding impacts in a European urban context. Moreover, most indices are not immediately transferable to other cases because the weightings of the different vulnerabilities have been established by conducting Principal Component Analysis (PCA) in specific geographical contexts (e.g, Aroca-Jimenez et al., 2017). Principal Component indices cannot be readily calculated across new settings in a comparable way because every PCA creates latent variables of an entirely statistical nature that are unique to the dataset plugged into it. Furthermore, in the light of intersectionality, when conducting a PCA, correlations of vulnerabilities are usually discarded, so that vulnerabilities are not accounted for twice (e.g., a foreign, low-income, single mom is considered as being only vulnerable 'once'). While this seems like a logical approach to not account for individual people several times in one study, it neglects that compounding vulnerabilities exist and that this single-parent and foreign female might be overall more vulnerable and in need of different assistance than a foreign businessman with high economic status. Hence, this research possibly accounts for people several times when calculating the IVI score per district based on the different dimensions included (see Table 1). Yet, this is done not only to account for districts with on average more vulnerable demographics but to also include compounding vulnerabilities and hence, intersectionality in pluvial flood risk.

To overcome the problem of non-transferability and the removal of compounding vulnerabilities that arises when conducting PCA, this research developed a more simplified but readily transferable composite index (CI). Composite indices aggregate individual indicators into a single number and measure multi-dimensional, relational constructs (Parsons et al., 2021). The CI was computed by, first, normalizing the available statistical data (indicators) to a common range of 0–1 per district (86 in Cologne and 45 in Frankfurt) and indicator. Second, the directionality of indicators was reversed for the indicators where high values are assumed to lead to a reduction in vulnerability (i.e., that for all indicators the higher values would indicate greater vulnerability). In the third step, the normalized indicators were combined to calculate a sub-index for each dimension (e.g., children and seniors were grouped under the dimension 'Age') and again normalized to a range of 0-1. The combination of indicators under the different dimensions was conducted to ensure that the vulnerability weighting was the same despite different numbers of indicators informing the dimensions. Based on the vulnerability score per dimension level and district, the overall vulnerability score per district could be calculated. The IVI score can then be defined as follows:

$$IVI = (D_1\,(I_{1..i}) + D_2\,(I_{1..i}) + \ldots + D_n\,(I_{1..i}))\;/\;n$$

Where IVI represents the overall intersectional vulnerability to pluvial flooding per district, calculated as the unweighted average of all *n* Dimensions (D), derived as the unweighted average of all *i* indicators (I) within each dimension, scaled between 0 and 1. In other words, the indicators within a dimension are averaged to give a score for that dimension, and then the dimension scores are averaged to give the overall IVI score for each district.

By computing the IVI for each city district, it was revealed which districts have a relatively high score and are hence, the most socially vulnerable communities within the respective city (research sub-question 1). The indicators' normalization and computation of the CI were conducted using the 'vegan' package of the programming software R (all codes can be found in Appendix 4). The IVI scores and associated districts were then plotted in QGIS for visualization.

To identify areas of 'high' and 'low' vulnerability within each city, districts were grouped as 'high vulnerability'-districts if their overall vulnerability score was above one standard deviation (Std Dev) of the respective city's average IVI. Districts below one Std Dev of the mean IVI were grouped as 'low vulnerability' districts. Before calculating the Std Dev of the city districts IVI, the datasets were first tested for normal distribution. Cologne's IVI is covering 75,6% of the districts within one Std Dev and Frankfurt's 62,2%. These values were considered close to a normal distribution (68,27%) and therefore not transformed. The shape of the frequency distribution of each city's IVI scores was also visually examined and found to be approximately normal. Using the Std Dev as a measure for data extremes was chosen because it is a well-established parameter describing dispersion or spread of data around a mean in statistical analysis and provides the ability to investigate scores outside the approximate two-thirds data distribution around the mean (Denis, 2020).

To answer research sub-question 2, the 'high' and 'low vulnerability' districts were used to investigate which of the dimension(s) used for computing the IVI is driving vulnerabilities up or down in these districts. By not conducting a PCA, it allows for investigating which specific socio-demographic dimension(s) are determining vulnerability in a specific district, which can help to inform appropriate adaptation policies. By contrast, PCA reduces the data to latent variables, which may or may not bear resemblance to the individual indicators used. The analysis was conducted by plotting the eight dimensions (Table 3) for the two groups ('high vulnerability' and 'low vulnerability') as boxplots displaying the vulnerability (CI) scores. This was done in R using the 'ggplot2' package. To explore if dimensions that seemed to drive vulnerabilities correlate (and potentially compound; sub-question 3), a correlation matrix was created on the vulnerability dimensions of the IVI for the 'high' and 'low' vulnerability districts (1 Std Dev beyond the mean). Another correlation matrix was created for all city districts to see whether correlations are observable throughout the cities. The correlation matrixes were created using the package 'corrplot' in R.

3.5. Spatial analysis of vulnerability and flood exposure

To answer research sub-question 4, the socio-demographic data needed to be related to pluvial flooding exposure. To do this, two additional datasets were necessary:

(1) the 'Flood risk indicators for European cities from 1989 to 2018'-dataset, developed on behalf of the Copernicus Climate Change Service (Mercogliano et al., 2021), was used to identify the extent of pluvial flooding in the cities' districts. It is generally recognized that attaining reliable spatial and temporal data at a proper spatial and temporal scale about extreme weather events represents a great challenge for disaster risk reduction policy and in practice (CMCC, 2022). Yet, Mercoliano et al. (2021) present a new hourly high-resolution (i.e., at ≃2.2 km) precipitation dataset (ERA5@2km) obtained by dynamically downscaling ERA5 reanalysis over 20 European cities, providing a state-of-the-art basis for impact analysis of extreme precipitation at the city scale (CMCC, 2022; Reder et al., 2022). The authors provide two different digital elevation models (LIDAR and EU-DEM). In this research, the EU-DEM model was used despite a less precise resolution because LIDAR was not available for Frankfurt and only covered parts of Cologne. The dataset can be downloaded here: https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-european-risk-flood-indicators?tab=overview.

(2) To compare the flood exposure with the IVI, spatial maps of the city districts were needed to correlate exposure with the data retrieved. Shapefiles that can be attached with the data were retrieved here: (Cologne: https://www.offenedaten-koeln.de/dataset/stadtgebiet-koeln and Frankfurt: https://www.offenedaten.frankfurt.de/dataset/frankfurter-stadtteilgrenzen-fur-gis-systeme/resource/842dd252-ad7f-46f2-a064-17f44399dad2).

To investigate the extent and severity of pluvial flood exposure in relation to social vulnerability (sub-question 4), the districts' IVI scores were compared to pluvial flooding levels using the spatially explicit dataset from the Copernicus Climate Change Service (C3S) (Mercogliano et al., 2021). The dataset provides water depth (m) after extreme precipitation events for five return periods (5, 10, 25, 50, and 100-years). Because of time restrictions, the analysis was conducted for both cities but only three return periods (5, 10, and 50 years). For the two cities and three return periods, the IVI score was plotted in relation to '% of area flooded' to show the extent of flooding relative to the district size. Additionally, 'highest water levels (m)', and 'average water depth (m)' were also plotted relative to the IVI to display the *severity* of exposure levels. The spatial overlay of the exposure maps and districts and the calculation of the max, mean, and count (area flooded) values were done in QGIS (Figure 5) using the zonal statistics tool.

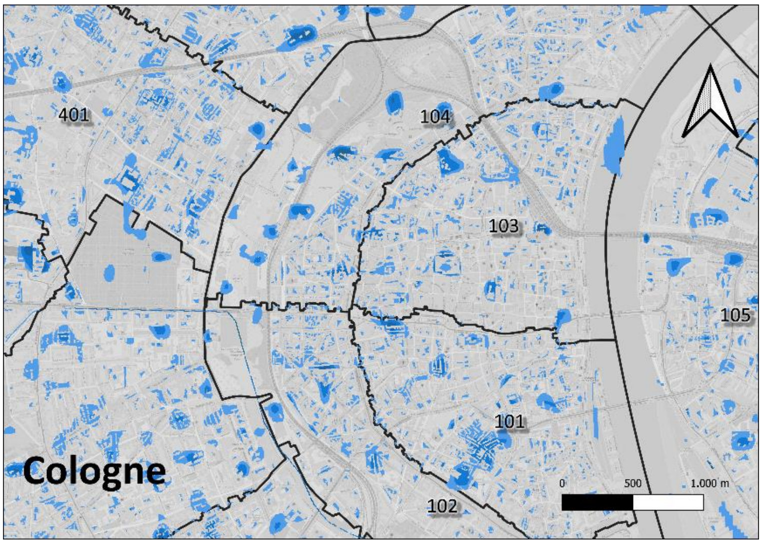

Figure 5: An excerpt of a flood exposure map (return-period 50 yrs) of Cologne. Numbers represent the district IDs and associated names can be found in Appendix 5. Source: Created by author.

Correlation analyses were performed to explore any patterns between flood extent and severity and intersectional vulnerability, to investigate if the districts show a significant relationship between the IVI and flood exposure. The correlation analysis of pluvial flood area, maximum and mean depths, and the IVI was conducted in R using the Spearman correlation method. This method was used because Spearman's Rho can capture the non-linear but monotonic relationship between variables because it is based on the ranked values for each variable (Denis, 2020).

3.6. Case studies comparison

From a policy perspective, it is most important to analyse social vulnerabilities and flood exposure on a city level and relative to the city's districts to identify city-specific hotspots of vulnerability that can be addressed. However, from this paper's scientific perspective, it is also relevant to compare the cities relative to each other (in a comparative case study) to investigate patterns, differences, and similarities. To compare intersectional social vulnerability and pluvial flood exposure risk between the two cities (sub-question 5), the composite vulnerability indices needed to be calculated anew so that they were relative to the highest and lowest overall scores of both cities, combined. The dimensions SNP and housing were taken out of the index because of missing data in one of the two cities. The cities were analysed separately and then together because, for the actual implementation of flood risk management plans, an analysis on the individual city level is needed to identify the most vulnerable districts and determinants of vulnerabilities within the specific city to create the most suitable and socially-inclusive plan. Yet, when calculating the different CIs and the IVI for the cities individually, it is not possible to compare them because the original indicator scores of the districts were normalized relative to the districts within each city, and not relative to all districts from both cities simultaneously.

After recalculating the two cities' ICs and IVIs, the frequency distribution statistics of both cities' IVI scores were then calculated and compared. The 'high -' and 'low vulnerability' districts were calculated again. This was done by calculating the Std Dev for each city separately but based on the cities' combined IVI scores. Again, city districts that had IVI values beyond one Std Dev of their respective mean were considered high and low vulnerability districts. Boxplots were again created to compare the scores of the dimensions of the IVI of the cities' high and low vulnerability districts. Lastly, flood exposure (the % of the areas flooded, and max and mean water depths) for the three return periods (5, 10, and 50yrs) were plotted and correlated with social vulnerability (the IVI score), this time combing both cities in one plot and with the adjusted IVI score (relative to both cities). This was done to specifically highlight the cities' districts where high vulnerability and exposure coincide and to display vulnerability levels and exposure relative to both cities.

3.7. Reliability and validity

The reliability and validity of the methods will be briefly discussed here. Validity relates to the accuracy of measure. There are some limitations to the methods that may reduce accuracy. The IVI developed in this research is a simplified social vulnerability index established by conducting a non-exhaustive literature review of pluvial flood impacts and intersectionality, however, informed by foundational work (Cutter et al., 2003) on the matter. This type of literature review lacks the intent to maximize the scope of the data collected and hence, conclusions reached are possibly open to bias because of the potential that sections of the literature might be omitted (Grant & Booth, 2009). Yet, while acknowledging this weakness, this type of non-exhaustive literature review has been chosen because it is assumed that an array of most topical articles will be sufficient in establishing a topical index that can be enhanced by informing it with Cutter et al.'s (2003) well-established index. Moreover, intersectionality theory, despite its broad applicability and far-encompassing scope, will never be all-encompassing when identifying vulnerabilities and intersections thereof. However, according to Kaijser and Kronsell (2014), this is not avoidable and as part of the research strategy, the individual researcher may need to prioritize the most interesting or relevant intersections in the particular case, keeping the bigger picture in mind. This will be done by combing the review of pluvial flood impacts and intersectionality theory. Lastly, while this research aims to inform socially-inclusive adaptation policies, it is outside of the scope of this research to analyse city-level policy plans in detail. Instead, the city policy plans regarding flood management are screened for social justice components and briefly discussed. The discussion section will provide recommendations on how to improve or integrate social justice components in future adaptation policies.

Concerning reliability, both, the IVI and the quantitative empirical case studies are built on secondary data from reliable sources. Yet, it needs to be acknowledged that the IVI can only portray intersectional social vulnerability in a simplified manner and will never attain to cover intersectional social vulnerability in its full complexity. By using Cutter et al.'s (2003) peer-reviewed and widely applied SoVI as a guide to inform this research, it is assumed that this will increase the reliability of the IVI. The data sources and datasets used in this research are reliable being the statistical data provided by the cities' public authorities and the pluvial flood risk dataset developed on the behalf of the Copernicus Climate Change Services.

Regarding the reliability of the methods applied, the computation of composite indicators (CIs) is a recognized tool in policy analysis with CI providing a simple comparison of countries or in this case cities and city districts (OECD, 2008). However, when poorly constructed, CI's can send misleading policy messages which need to be accounted for in the interpretation of the results (OECD, 2008). Yet, the IVI and the associated dimension scores should generally not be interpreted as definite but should be used to identify trends and to draw attention to the issue of social vulnerability in a pluvial flood risk context. The GIS and statistical methods conducted in R that were applied to conduct the empirical case studies are well-established.

Regarding ethical issues, since this thesis uses aggregated data, which is not personally identifiable, the research process should not pose any ethical implications. However, the findings of this research may have ethical and normative implications which will be considered and handled carefully.

4. Results

The following chapter presents the main findings of this research's quantitative analysis. The sections of this chapter address the five research sub-questions of this thesis, presenting the distribution of social vulnerabilities in the different city districts according to the IVI (4.1), identifying the determinants of vulnerabilities (4.2) and determinant correlations among them (4.3), investigating flood exposure relative to vulnerabilities (4.4), and comparing vulnerabilities and exposure in the two case cities (4.5).

4.1. Spatial distribution of Vulnerabilities

This section displays vulnerability maps for Cologne and Frankfurt, ranking vulnerability scores according to the IVI. Moreover, maps with high and low vulnerability districts (the districts with the IVI scores diverging +/- one Std Dev of the mean) will be displayed. Throughout the section, district IDs are used to identify the districts.

Cologne

Intersectional vulnerabilities in Cologne have scores ranging from 0.25 to 0.77, with a mean of 0.48, as measured by the IVI (Figure 6). Cologne shows a pattern of having less vulnerable districts in the city's centre (see Figure 6A) (101-105, 302, 303) and vulnerability tends to be higher in districts further away from the centre. Yet, this cannot be generalized, and still, several districts on the periphery of the city have relatively low vulnerability scores (e.g., 306, 713, 808, 905). The most vulnerable district according to the IVI is Chorweiler (609) in the northwest of Cologne, followed by Finkenberg (716) in the southeast. Hahnwald (207) is the district with the lowest IVI score in Cologne, shortly followed by the centre districts (103, 104, 102).

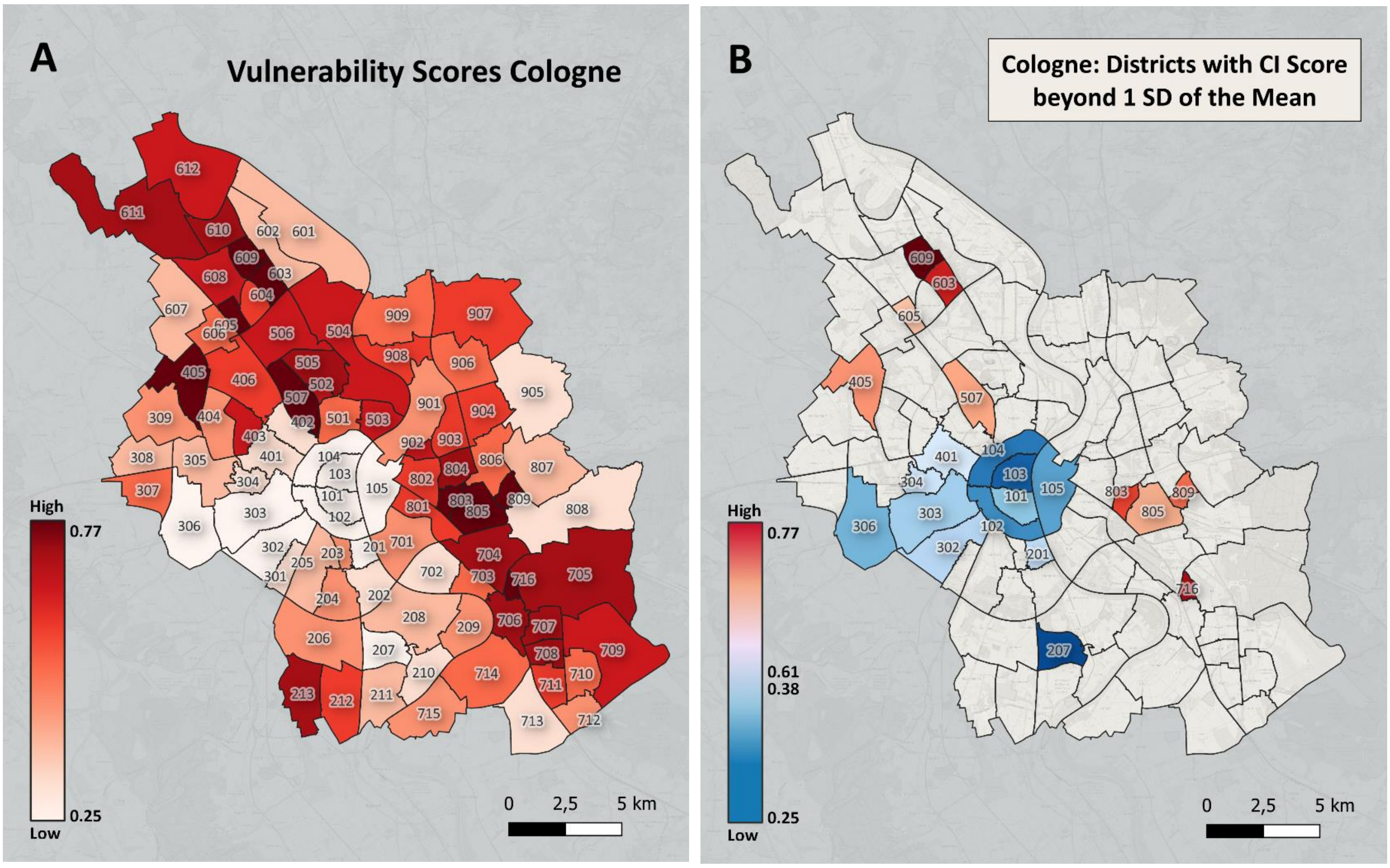

Figure 6: (A) Vulnerable districts in Cologne according to the IVI from low (light red) to high (dark red). (B) High vulnerability (red) and low vulnerability districts (blue) in Cologne. High and low vulnerability districts are minimum one Std Dev away from the mean of the city's overall IVI score. On the panel B legend, the values 0.63 and 0.38 at the center indicate the cutoff at +/- one Std Dev from the mean of 0.48.

In Cologne, 12 districts out of 86 fell below one Std Dev of the mean value of overall vulnerability and nine districts have values more than one Std Dev above the mean (Figure 6B). Hence, in total, 21 districts were considered high and low vulnerability districts in Cologne. Figure 6B displays districts with scores below one Std Dev of the overall IVI mean of Cologne in blue and districts with scores above one Std Dev of the mean IVI score in red. The least and most vulnerable districts are listed in Table 4. A list of all districts can be found in the Appendix 5.

Table 4: Cologne's high and low (social) vulnerability districts (1 Std Dev beyond the mean)

Group	ID	Name	IVI Score
high vul	609	Chorweiler	0,769
high vul	716	Finkenberg	0,764
high vul	603	Seeberg	0,6766
high vul	803	Vingst	0,6598
high vul	809	Neubrück	0,6404
high vul	405	Bocklemünd/Mengenich	0,6366
high vul	507	Bilderstöckchen	0,6346
high vul	805	Ostheim	0,6171
high vul	605	Lindweiler	0,6134
low vul	401	Ehrenfeld	0,38

low vul	304	Braunsfeld	0,3727
low vul	201	Bayenthal	0,3678
low vul	302	Sülz	0,3669
low vul	303	Lindenthal	0,3612
low vul	101	Altstadt-Süd	0,3568
low vul	306	Junkersdorf	0,3432
low vul	105	Deutz	0,3425
low vul	102	Neustadt-Süd	0,3216
low vul	104	Neustadt-Nord	0,3058
low vul	103	Altstadt-Nord	0,2967
low vul	207	Hahnwald	0,2503

Frankfurt

Vulnerabilities in Frankfurt range from an IVI score of 0.42 to 0.76 (Figure 7A), with a mean of 0.60. Similar to Cologne, Frankfurt also shows a pattern of districts with lower IVI scores in the centre and increasing scores towards the city's peripheries. Yet, Nieder-Erlenbach (42) and Harheim (44) are two districts with two of the lowest IVI scores and are both located in the very north of Frankfurt's city borders. Overall, the highest IVI scores (highest vulnerabilities) are generally located in the west and east of Frankfurt whereas the least vulnerable districts are located in Frankfurt's centre and along one line south and north of the city's centre.

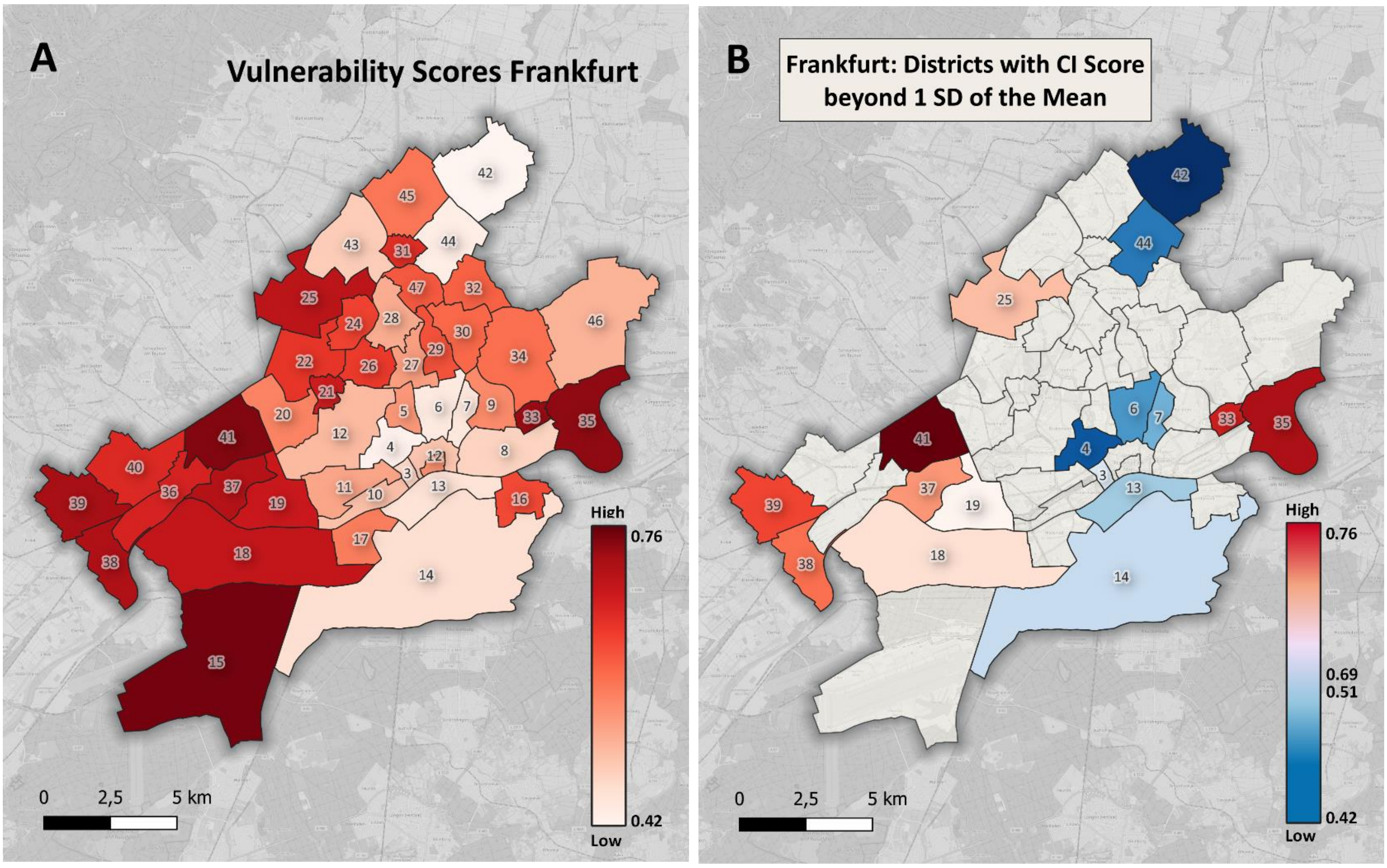

Figure 7: (A) Vulnerable districts in Frankfurt according to the IVI from low (light red) to high (dark red). (B) High vulnerability (red) and low vulnerability districts (blue) in Frankfurt. High and low vulnerability districts are minimum one Std Dev away from the mean of the city's overall IVI score. On the panel B legend, the values 0.69 and 0.51 at the center indicate the cutoff at +/- one Std Dev from the mean of 0.60.

For Frankfurt, out of 45 districts, nine districts had scores more than one St Dev above the mean IVI and eight districts fell below one St Dev; hence, 17 districts are considered high and low vulnerability districts for Frankfurt. Figure 7B displays the districts with scores below one Std Dev of the overall IVI score in blue and districts with scores above one Std Dev of the overall score are shown in red. Frankfurt's least and most vulnerable districts are listed in Table 5.

Table 5: Frankfurt's high and low (social) vulnerability districts (1 Std Dev beyond the mean)

Group	ID	Name	IVI Score
high vul	41	Sossenheim	0,758819
high vul	35	Fechenheim	0,739674
high vul	33	Riederwald	0,73527
high vul	39	Zeilsheim	0,732121
high vul	38	Sindlingen	0,701986
high vul	37	Nied	0,697157
high vul	25	Niederursel	0,693746
high vul	18	Schwanheim	0,692223
high vul	19	Griesheim	0,691495
low vul	3	Bahnhofsviertel	0,507688
low vul	14	Sachsenhausen-Süd	0,499664
low vul	13	Sachsenhausen-Nord	0,47726
low vul	7	Nordend-Ost	0,471745
low vul	6	Nordend-West	0,458348
low vul	44	Harheim	0,453441
low vul	4	Westend-Süd	0,435464
low vul	42	Nieder-Erlenbach	0,422677

4.2. Determinants of high intersectional vulnerability

Cologne

In Cologne, when comparing the median values of the eight dimensions between the high and low vulnerability districts (districts one Std Dev above/below the mean), it becomes visible that the education scores have by far the greatest difference (Table 6 and Figure 8). Thereafter follow family structure, nationality, and economic status. Age lies further behind and even more so gender. Infrastructure has a similar median score for high and low vulnerability districts, while social needs populations (SNP) have a higher dimension score in the low vulnerability districts than in the high vulnerability areas. For the dimensions age, gender, infrastructure, and snp some of the high and low vulnerability districts overlap in their scores.

Figure 8: IVI Concepts plotted as boxplots comparing low and high vulnerability districts for Cologne. Higher values (closer to 1) indicating greater vulnerability whereas values close to zero indicate the lowest vulnerability. I.e., a high education score means high overall vulnerability in this dimension and overall lower numbers of high education absolvents.

Table 6 Differences in medians of low and high vulnerability districts in Cologne per dimension.

Dimension	Difference Medians	Rank
Education	0,74	1
Family structure	0,50	2
Nationality	0,46	3
Economic status	0,45	4
Age	0,37	5
Gender	0,16	6
Infrastructure	0,07	7
Special Needs Populations (SNP)	-0,08	8

Frankfurt

In Frankfurt, the greatest differences in medians between high and low vulnerability areas are found in the dimension of economic status, followed by education, nationality, and then family structure (see Table 7 and Figure 9). Hence, the four dimensions with greatest difference in the median score between high and low vulnerability districts are the same for Frankfurt and Cologne, however, with a changed order. Thereafter follows the difference in the median scores for gender, followed by age. In Frankfurt, as for Cologne, infrastructure is very small in difference, and housing (like snp in Cologne) contributes negatively to vulnerability of the high vulnerability districts compared to the low vulnerability districts. For the dimensions age, family structure, housing, and infrastructure, some of the high and low vulnerability districts values are overlapping. Economic status and education have each one outlier in the low vulnerability districts that falls within the dimension score range of the high vulnerability districts.

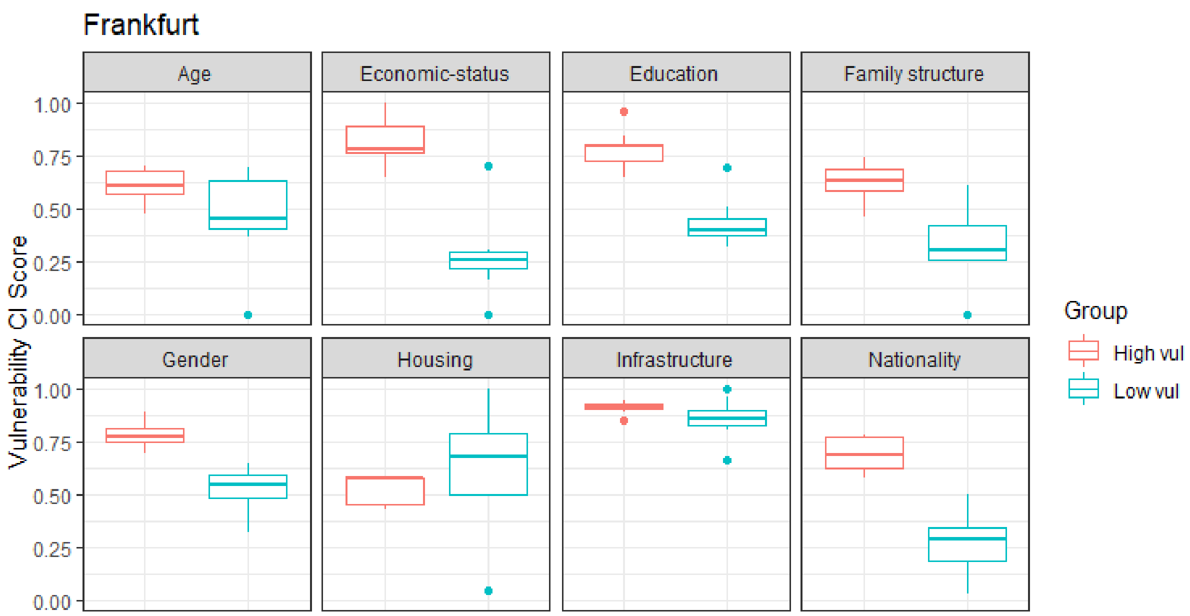

Figure 9: IVI Dimensions plotted as boxplots comparing low and high vulnerability districts for Frankfurt. Higher values (closer to 1) indicating greater vulnerability whereas values close to zero indicate the lowest vulnerability.

Table 7 Differences in medians of low and high vulnerability districts in Frankfurt per dimension.

Dimension	Difference Medians	Rank
Economic status	0,52	1
Education	0,40	2
Nationality	0,40	3
Family structure	0,33	4
Gender	0,23	5
Age	0,16	6
Infrastructure	0,06	7
Housing	-0,11	8

Considering both cities, the differences in medians are larger in Cologne than in Frankfurt (see Table 6 & 7). In particular, education in Cologne has a much greater difference in median than any other dimension in either city. Moreover, economic status ranks first in Frankfurt and only fourth in Cologne, but the difference between the medians of the high and low vulnerability districts is almost as large for Cologne as it is for Frankfurt. Hence, while being the first ranking determinant in the respective cities, education is more strongly driving differences in vulnerability in Cologne than economic status in Frankfurt. Economic status is similarly driving differences in both cities.

4.3. Compounding vulnerabilities

Cologne

There are generally stronger correlations among dimensions for the high and low vulnerability districts than for all districts (Figure 10). Moreover, when correlating the eight dimensions, most correlations in Cologne are positive, while there are no strong negative correlations.

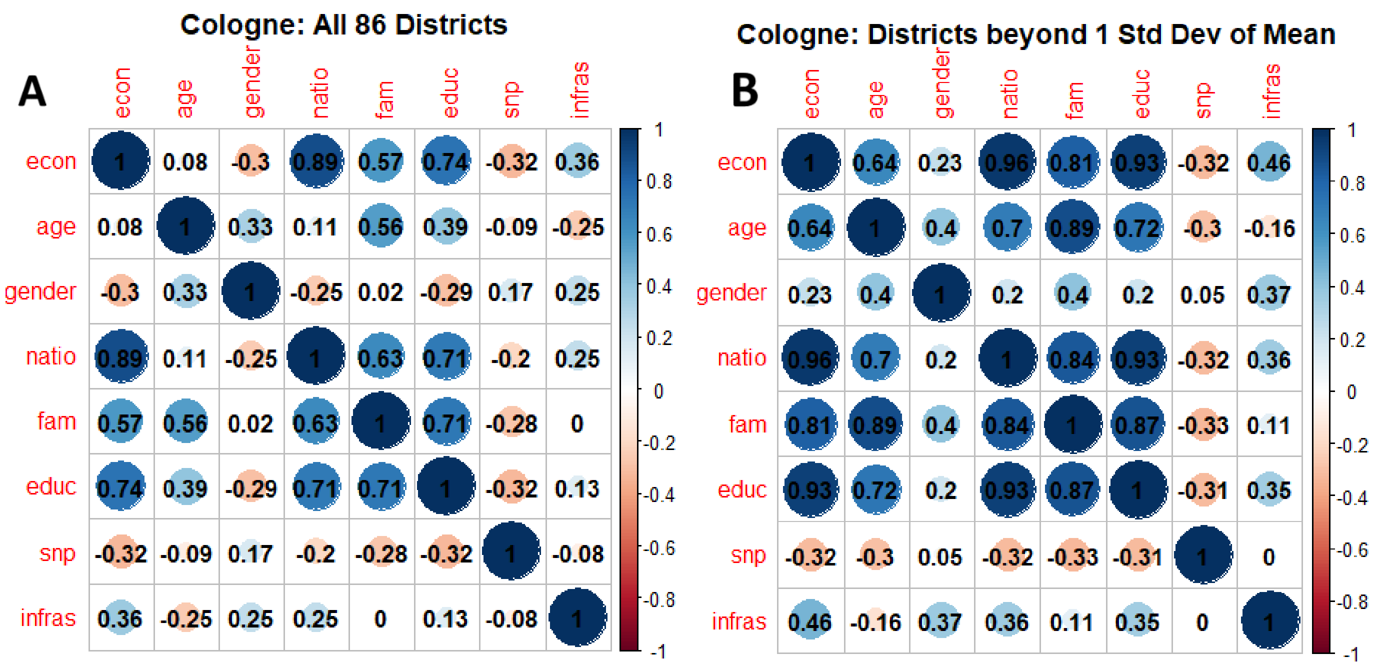

Figure 10: Plot of 8 concepts' correlation in Cologne with associated correlation coefficient. All districts (A) and high and low vulnerability districts (B). Dimension abbreviations: econ= economic status, natio=nationality, fam=family structure, educ=education, infras=infrastructure.

In the city's high and low vulnerability districts (Figure 10B), there are generally five dimensions (economic status, nationality, education, family structure, and age) that all positively correlate with each other (rho > 0.6). High correlations (rho > 0.8) can be found between family structure with age, education, nationality, and economic status. Moreover, the strongest correlations are found between education and nationality (rho = 0.93), education and economic status (rho = 0.93), and nationality and economic status (rho = 0.96). When considering all districts (Figure 10A), only nationality and economic status are highly correlated (rho > 0.8). Moreover, when comparing the correlation results of all districts with the high and low vulnerability districts, one key difference is that gender has some negative correlations, however, very weak (rho ≤ -0.3) for all districts whereas correlations with high and low vulnerability districts are all positive.

Frankfurt

The strength of correlations of the eight dimensions in Frankfurt seems to be more similar for all districts and the high/low vulnerability districts (Figure 11) than was the case for Cologne.

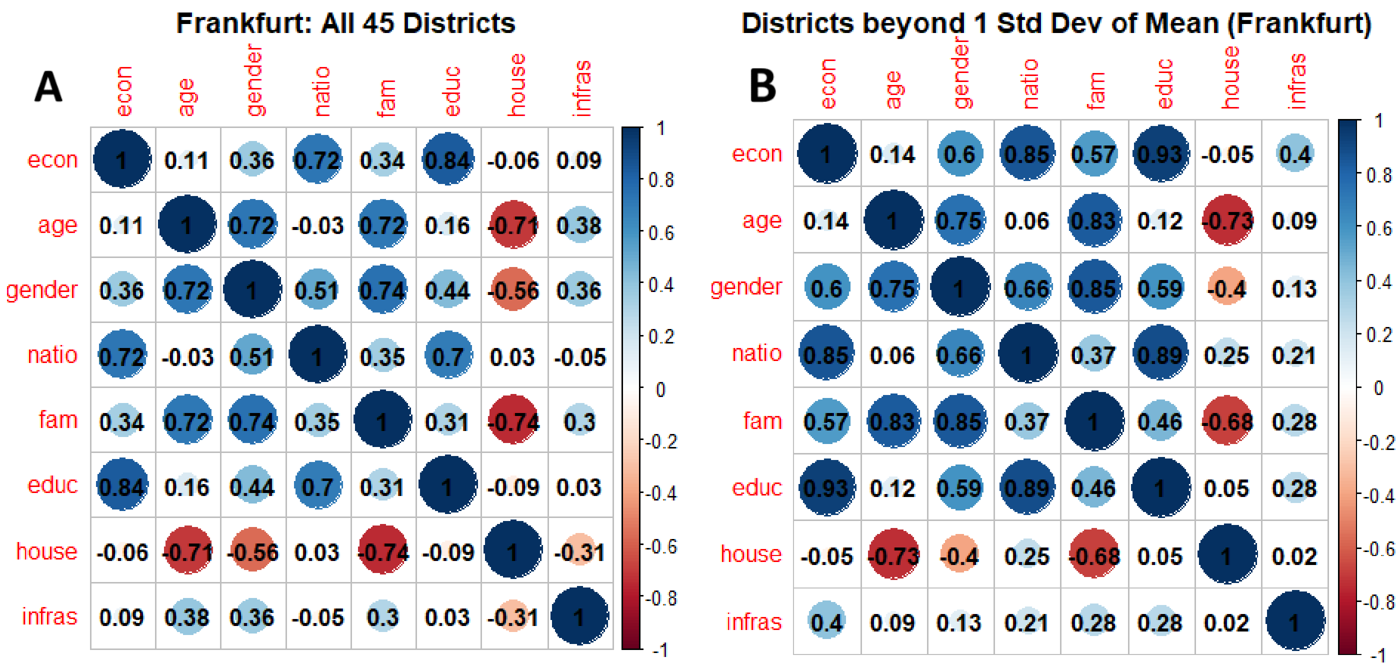

Figure 11: Plot of 8 dimensions' correlation in Frankfurt with associated correlation coefficient. All districts (A) and high and low vulnerability districts (B). Dimension abbreviations:econ= economic status, natio=nationality, fam=family structure, educ=education, infras=infrastructure.

When only considering the high and low vulnerability districts (Figure 11B), as for Cologne, Frankfurt has five dimensions (economic status, gender, nationality, family structure, education) with strong positive correlations. Yet, different from Cologne, not all five dimensions correlate strongly with one another and gender is part of the five correlating dimensions and age is not. There are strong correlations between nationality and education, nationality and economic status, family structure and gender, and family structure and age (rho> 0.8). The strongest correlation has education with economic status (rho = 0.93). Moreover, negatively correlated is housing with family structure (r = -0.68 (-0.74 considering all districts)) and housing with age (r = -0.73). Correlations are on average slightly higher for the high and low vulnerability distrcts than for all districts but the overall patterns are similar. The only greater difference is that the correlation between infrastructure and housing is weakly negative (rho = -0.31) for all districts (Figure 11A) but positive when only considering the high and low vulnerability districts.

4.4. Relative flood exposure

This section correlates flood exposure with vulnerability (IVI scores) among all districts. Illustratively, the 50yrs return periods for Cologne and Frankfurt are presented in Figure 12 and 13. Plots for the 5- and 10yrs return periods can be found in the Appendix 6. Table 8 lists the Spearman's rho for all three return periods of the districts IVI scores correlated with their corresponding flood exposure.

No significant correlations could be found between the IVI and flood depth (mean and max) nor between the IVI and the size of the area flooded for any of the three return periods (5y, 10y, 50y). Hence, districts with high vulnerability scores according to the IVI are generally not more exposed to flooding than districts with lower vulnerability scores. Yet, there are still certain districts (especially in Frankfurt) for which high social vulnerability and increased exposure levels coincide.

Table 8: Spearman's Rho correlation of vulnerability with flood exposure for three return periods

RHO	**Percentage of area flooded**		**Max water depth**		**Average water depth**	
IVI per district	**Cologne**	**Frankfurt**	**Cologne**	**Frankfurt**	**Cologne**	**Frankfurt**
5yrs return period	-0.02	-0.066	-0.16	0.25	0.19	0.021
10yrs return period	0.013	-0.066	-0.12	0.13	0.17	-0.034
50yrs return period	0.055	0.07	0.063	0.18	0.16	0.065

In Cologne, high mean water depth coincides with relatively high vulnerability scores in Ostheim, Bilderstöckchen, and Vingst (Figure 12C). Generally more exposed to flooding (regardless of lower vulnerability scores) are the districts Fühlingen, Immendorf, and Gremberghoven (% of area flooded) (Figure 12A), Eil and Merheim (max depth) (Figure 12B), and Klettenber and Rath/Heumar (mean depth) (Figure 12C). In Frankfurt, districts where relatively high exposure coincides with a relatively high IVI score are Hausen and Fechenheim (% of area flooded) (Figure 13A), Höchst, Nied, and Sossenheim (max depth) (Figure 13B), and Nied (mean depth) (Figure 13C). Generally more exposed to flooding (regardless of lower vulnerability scores) are the districts Sachsenhausen-Nord, Westend-Nord, and Innenstadt (% of area flooded) (Figure 13A), and Berkersheim and Seckbach (mean depth) (Figure 13C).

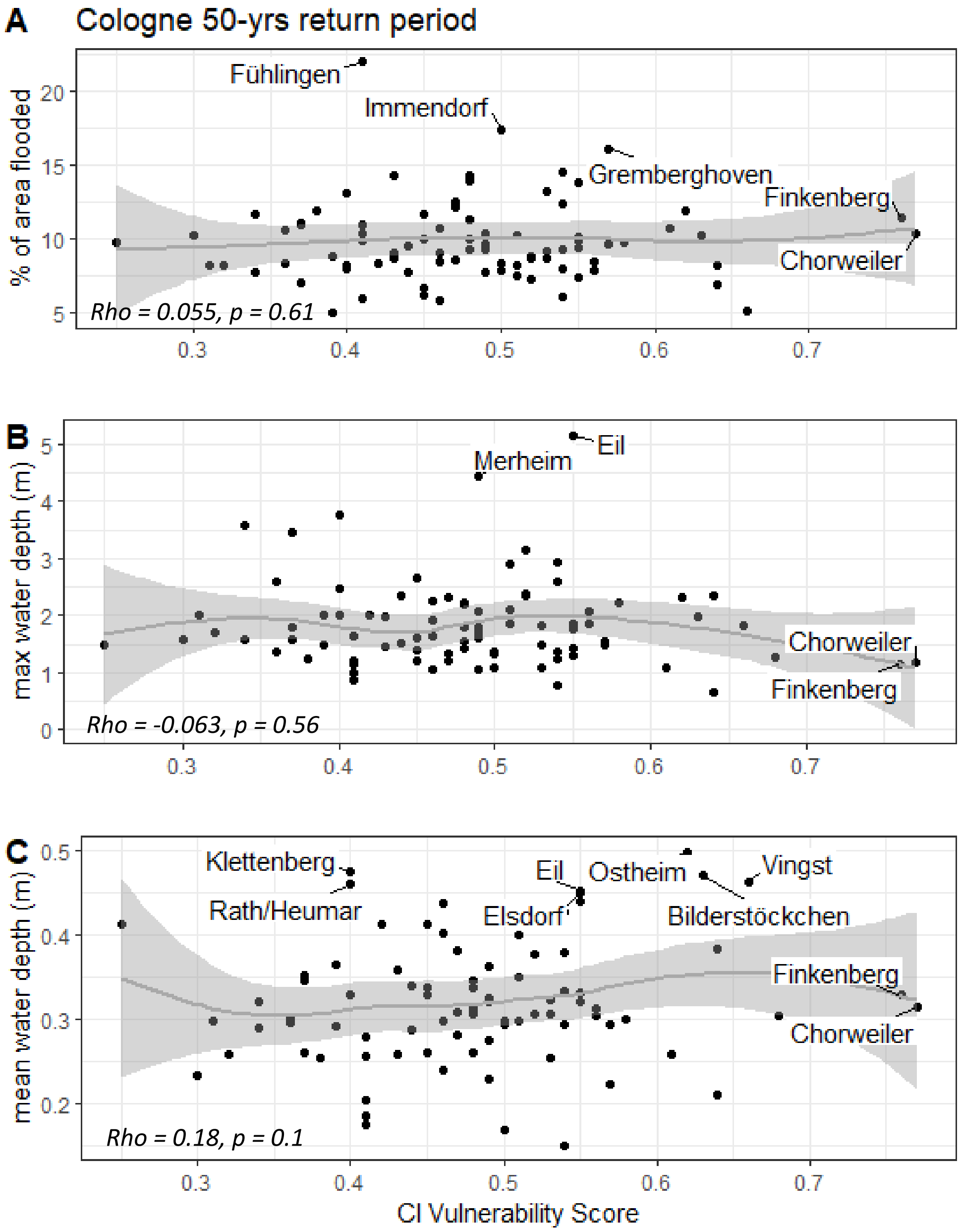

Figure 12: Flood exposure in Cologne in relation to the IVI for a 50yrs return period. The grey line is a lowess curve to visualize any trends. The correlation coefficient calculated with the Spearman rank correlation method is indicated by Rho and the corresponding p-value. The outliers (districts with relatively high exposure levels or IVI scores) are labelled with the district name. Plots for 5- and 10yrs return periods can be found in Appendix 7.

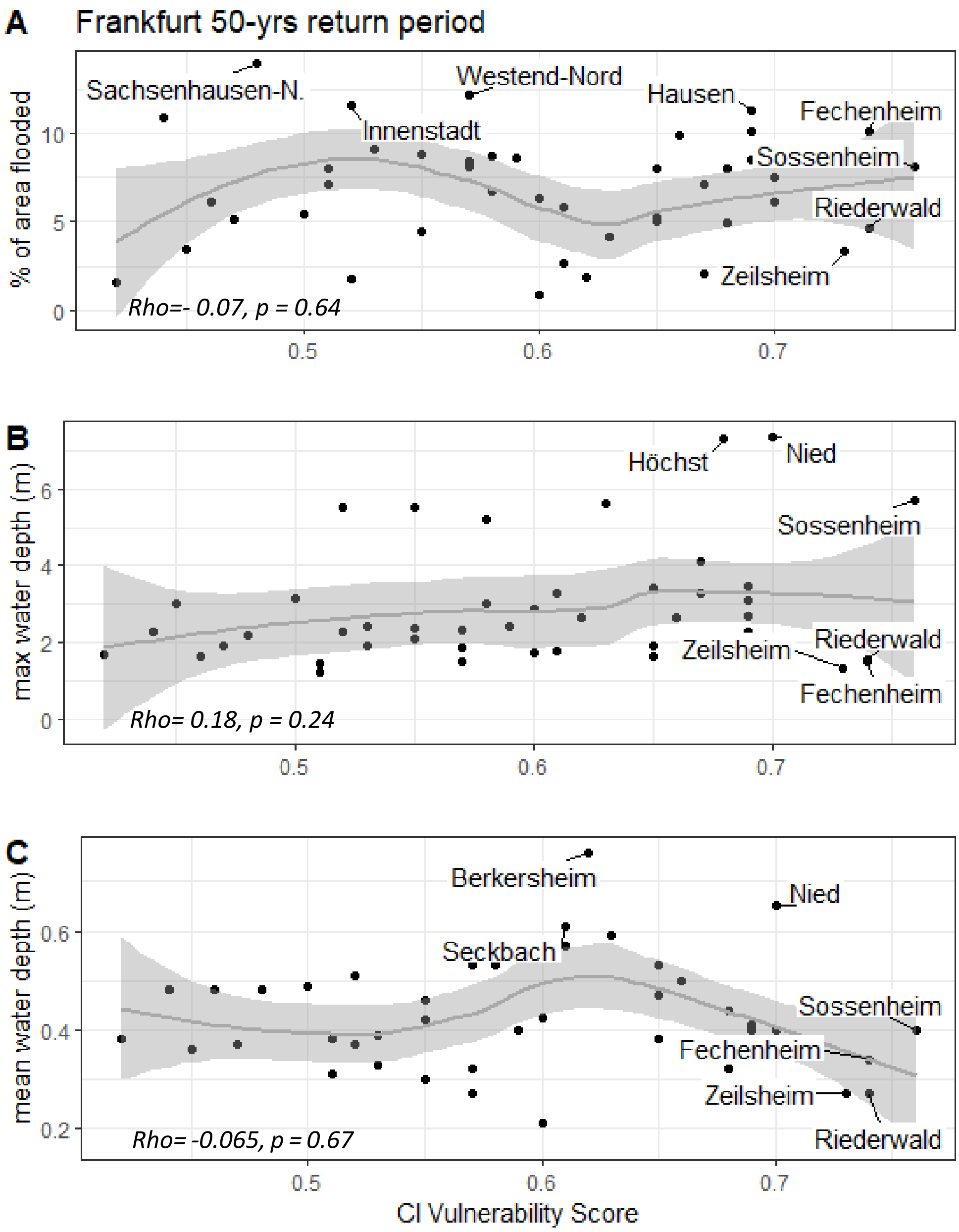

Figure 13: Flood exposure in Frankfurt in relation to the IVI for a 50yrs return period. The grey line is a lowess curve to visualize any trends. The correlation coefficient calculated with the Spearman rank correlation method is indicated by Rho and the corresponding p-value. The outliers (districts with relatively high exposure levels or IVI scores) are labelled with the district name. Plots for 5- and 10yrs return periods can be found in Appendix 7.

4.5. Comparison of cities

Vulnerabilities and the IVI

Vulnerability scores are much more widely distributed in Cologne than in Frankfurt when comparing the distributions of IVI scores calculated for the two cities combined (Figure 14). Both IVI scores are normally distributed, and Frankfurt's mean (0.55) is similar to but slightly higher than Cologne's (0.53). In contrast to the similar means, the ranges of IVI scores differ considerably between the two cities. IVI scores in Cologne have a range of 0.56, which is almost twice the range of 0.29 for Frankfurt (see also Table 9).

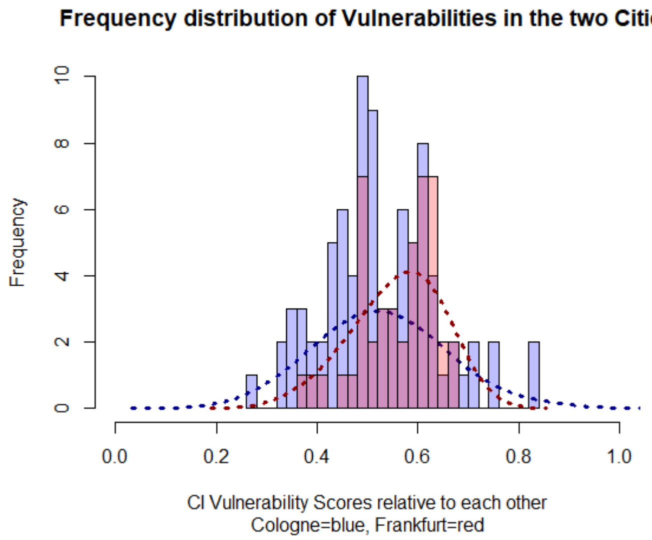

Figure 14: Frequency distribution of the IVI scores of the two cities (Frankfurt and Cologne) relative to one another. Included are 86 districts of Cologne and 45 districts of Frankfurt.

Table 9: Cologne and Frankfurt frequency distribution statistics

City	mean	min	max	std. dev.	range
Cologne	0,53	0,28	0,84	0,11	0,56
Frankfurt	0,56	0,38	0,67	0,08	0,29

A total of 34 districts make up the high and low vulnerability districts (districts above/below one Std Dev of the mean IVI score) of the two cities calculated based on the new combined IVI score but with the city-specific standard deviations. Because of Cologne's wider range, most districts are located in Cologne. A list of the included districts with recalculated IVI scores can be found in Appendix 8.

In Cologne compared to Frankfurt, all high vulnerability districts have higher median dimension scores except for education which has a higher score in Frankfurt (Figure 15). Four dimensions (age, family structure, gender, and infrastructure) have higher median scores in Cologne for both the high vulnerability and the low vulnerability districts compared to Frankfurt. For family structure, the median scores of the low vulnerability districts are, however, very similar between the two cities. Moreover, all of the dimension scores of gender and infrastructure are rather equally distributed between the cities and vulnerability groups, however, the range within Frankfurt's low vulnerability districts is relatively large. In Frankfurt's low vulnerability districts, the range of economic status is also relatively large. For two of the dimensions (economic status and nationality), Cologne has higher (in the high vul districts) and lower (in the low vul districts) scores than Frankfurt which relates to Cologne's overall wider IVI score range. The biggest differences in the median scores of the two cities are found in the low vulnerability districts regarding education and nationality. Educational vulnerability is very high in Frankfurt's low vulnerability districts and the score of nationality is especially low in Cologne's low vulnerability areas. Overall vulnerability is highest in Cologne's high vulnerability and lowest in its low vulnerability districts. This is not surprising due to the city's wider distributional range of vulnerabilities compared to Frankfurt (Figure 15). SNP and housing have not been compared because data on the indicators was only availble for one of the cities.

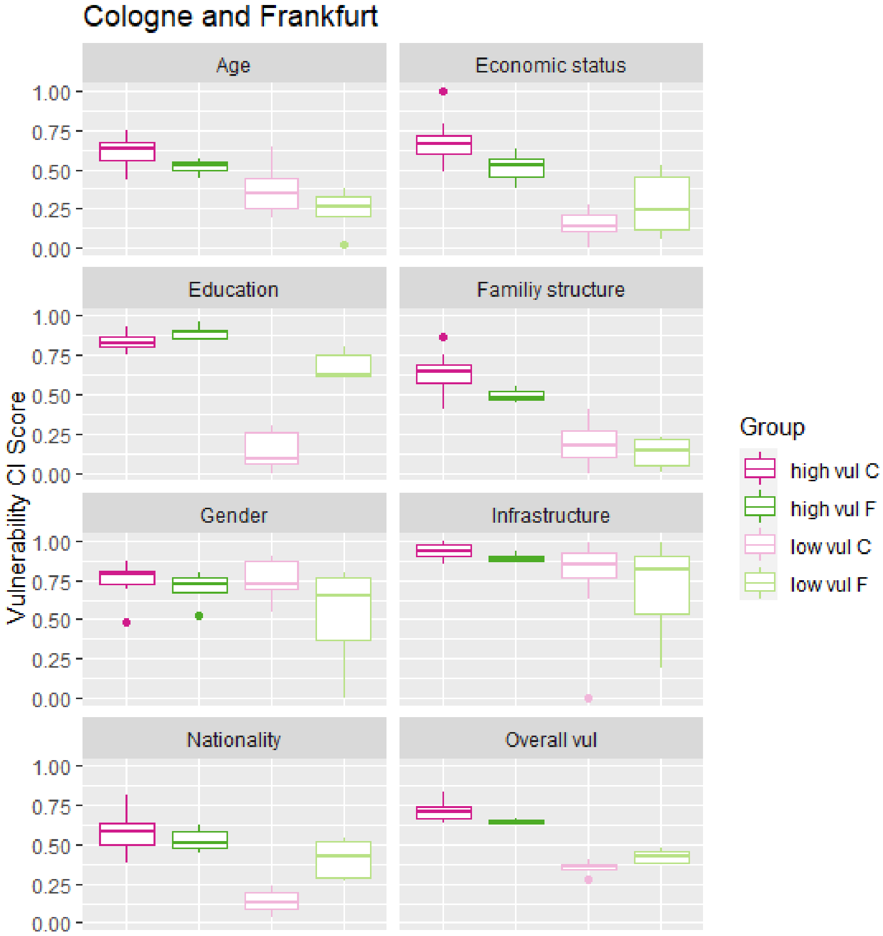

Figure 15: IVI dimensions plotted as boxplots comparing low and high vulnerability districts for Frankfurt and Cologne relative to one another. The group of high vulnerability districts in Cologne entails 11 districts whereas Frankfurt's group comprises five. The low vulnerability districts group encompasses 12 districts for Cologne and six for Frankfurt. SNP and housing have not been compared due to a lack of data.

Exposure to flooding

Across the two cities, overall exposure to flooding (% of the area flooded) is greater in Cologne than in Frankfurt. The severity of flooding (average water depth and max water depth), however, is generally greater in Frankfurt than in Cologne (Table 10). The same pattern is visible when considering the city districts individually. Cologne's districts; Fühlingen, Immendorf, and Gremberghoven lead with the amount of area flooded (in %) and the highest flooding depths can be found in Frankfurt's districts; Höchst and Nied. The highest mean water depths also occur in Frankfurt, in the districts Berkersheim, Nied, and Seckbach (Figure 16).

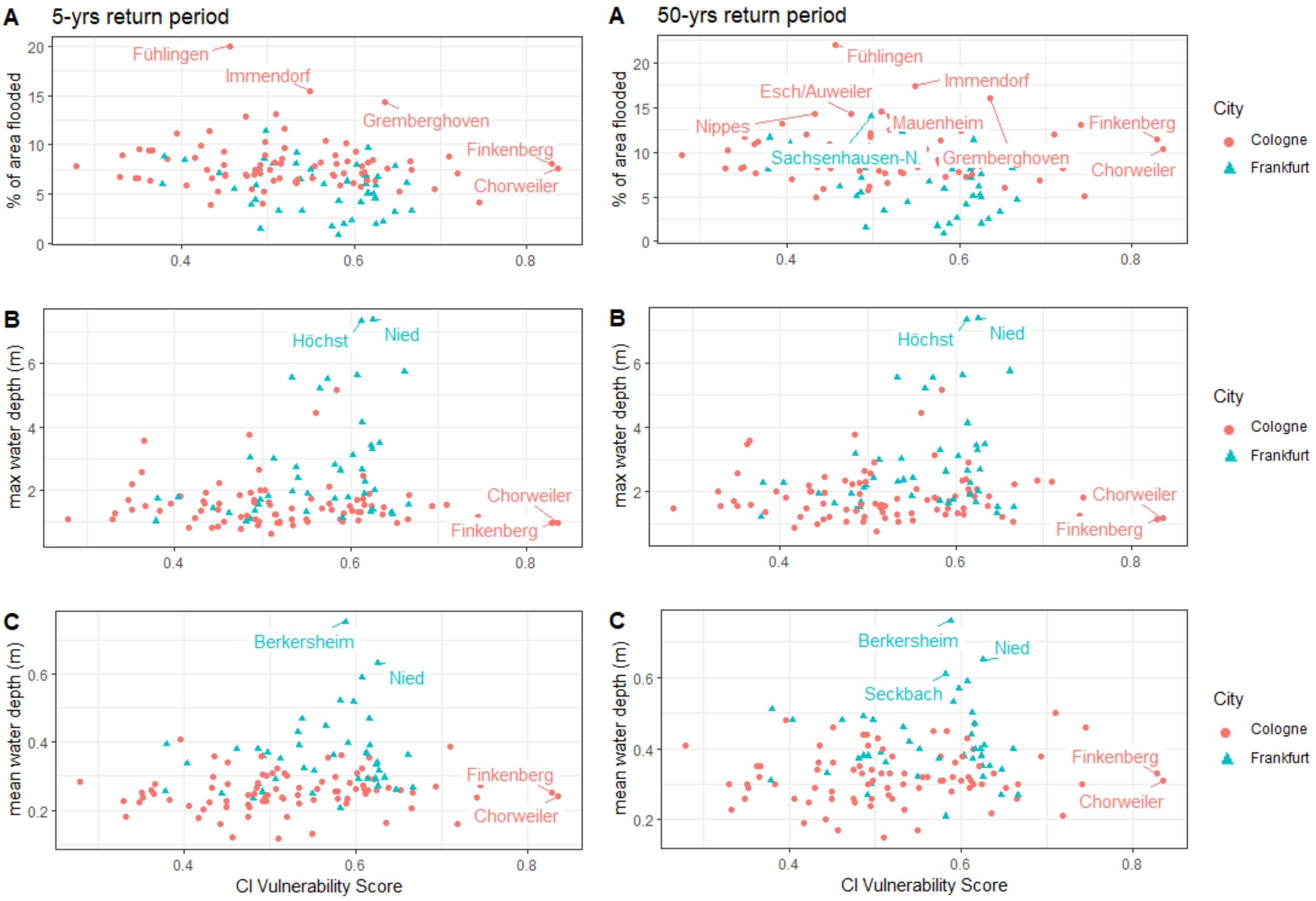

Figure 16: Flood exposure in Cologne (red) and Frankfurt (blue) in relation to the IVI for a 5 and 50yrs return period. Plots for 10yrs return periods can be found in the appendix.

Table 10: Flood exposure comparison of Cologne and Frankfurt for three return-periods

Return Period	Flooding in % of the city area		Average of max water depth per district (m)		Average water depth (m)	
	Frankfurt	Cologne	Frankfurt	Cologne	Frankfurt	Cologne
5-yrs	5,16%	7,78%	2,65	1,53	0,36	0,26
10-yrs	5,57%	8,35%	2,43	1,63	0,38	0,28
50-yrs	6,39%	9,53%	2,87	1,85	0,43	0,32

5. Discussion

This chapter will discuss three overall themes: First, the case city results. Second, the methods used and their limitations, justifications, and recommendations for improvement are discussed. Third, the concepts of climate justice, intersectionality, and disproportionality will be discussed in a flood and, more broadly, a climate hazard context. Throughout the discussion chapter, recommendations will be given on potential improvements of FRM concerning the inclusion of intersectional and social justice components. The main recommendations are summarized in a table at the end of the chapter.

5.1. Case cities

This section of the discussion focuses on the case city results. The first sub-section discusses the different dimensions and determinants of vulnerabilities in the case studies and the potential explanations for the ranking of the determinants. In the second sub-section, the compounding vulnerabilities in the case cities will be discussed and the last sub-section discusses the exposure of the case city districts in relation to the IVI.

High and low vulnerability districts – the case cities and vulnerability determinants

Of the overall 8 dimensions considered in the IVI, the major determinants of vulnerability were education, nationality, family structure, and economic status, with the largest determinants being education (in Cologne) and economic status (in Frankfurt).

Compared to Frankfurt, Cologne's high and low vulnerability districts are more segregated in regard to the dimensions of education, family structure, and nationality. Education in Cologne has by far the largest difference between the low and high vulnerability districts in all dimensions in either city and is hence, the greatest driver of vulnerabilities in the high vulnerability districts of the city. The low vulnerability districts in Cologne have especially low values, indicating that many people in these districts have academic degrees (adults) or are attending a gymnasium (children and teenagers). Education scores also high in Frankfurt's high vulnerability districts but scores are especially diveregent in the low vulnerability districts of the two cities, where Frankfurt has still a relatively high score compared to Cologne. A similar pattern is shown in the dimension of nationality which differs largely within both cities' high and low vulnerability districts, but even more so in Cologne. Family structure also has a large difference in median scores between the high and low vulnerability districts in both cities. Generally, the overall vulnerability score (of nationality, family structure, and education) of Cologne's low vulnerability districts is much lower than Frankfurt's whereas the high vulnerability districts have similar scores but are slightly higher (except for education) in Cologne. This indicates a general pattern of greater segregation in Cologne than in Frankfurt, thus, education, family structure, and nationality may be combining to exacerbate unequal vulnerabilities, especially in Cologne. For policy, this might imply little overlap between those demographics residing in the city's high and low vulnerability districts and an increased need to make sure that warnings, preparation, and recovery measures reach demographics of both the low and high vulnerability districts and especially support the socially vulnerable districts. Including stakeholders and residents from high vulnerability districts in decision-making processes regarding FRM could help to make FRM planning more just and inclusive (Amorim-Maia et al., 2022).

Economic status is the first ranking determinant of vulnerabilities in Frankfurt which can be explaind by gentrification and Frankfurt's industries. Economic status determines what neighbourhoods and housing people can afford, which can often spur gentrification so that low-income people are generally outcompeted for housing in certain areas (Arundel & Hochstenbach, 2020). Moreover, Frankfurt's city context and industries potentially explain why this factor is especially divergent in Frankfurt's low and high vulnerability districts. Frankfurt has the highest job density in Germany and generates the highest gross domestic product (GDP) per person employed (Stadt Frankfurt am Main, 2016). Hence, this increases the financial gap between wealthy people and the unemployed or people in low-income sectors. Regarding Frankfurt's main industries, the city is one of the most important financial centres in the world (alongside London and New York) with the European Central Bank (ECB) having its headquarters in the city. Together with the consulting and insurance industry, the financial sector forms a cluster in the city's central financial district (Stadt Frankfurt am Main, 2016) which provide jobs that are very high paying. Consequently, this might explain why economic status is a driving factor of vulnerability patterns in Frankfurt where incomes (especially in certain industries and areas) are disproportionately high compared to many others.

Age and gender were to a lesser extent determining vulnerabilities in both cities indicating that both dimensions were fairly evenly distributed amongst the high and low vulnerability districts of both cities. Yet, while not being large determinants of vulnerabilities, gender and age are important attributes increasing vulnerabilities and should always be accounted for in FRM planning. Especially children and the old need enhanced attention and assistance in case of a flooding event. Women are also more likely to be the caretaker for such groups and might require more financial support in the aftermath of a flooding event when care facilities are not available.

In both cities, infrastructure scores were barely different between the high and low vulnerability districts, potentially indicating that infrastructure is not a key determinant of patterns in vulnerability.

The SNP (Cologne) and housing (Frankfurt) scores in the IVI were on average higher in the low vulnerability districts than in the high vulnerability districts of the cities, hence, leading on average to a reduction of the overall IVI score in the most vulnerable districts. The rather surprising results of infrastructure, SNP, and housing – considering that vulnerabilities often overlap and were, hence, assumed to be at least directionally similar – can potentially be explained by the indicator choices but also by the specific demographic composition of the two case cities and will be discussed in the following.

Regarding the dimension of infrastructure (comprising the mobility of residents) used in the IVI, car ownership and public transport infrastructure are potentially weak indicators in a German urban context because of widespread car ownership and well-establish public infrastructure networks. Cologne's IVI only considers the number of cars owned by residents. Frankfurt's IVI considers two indicators under the dimension of infrastructure; cars owned per resident and, additionally, public transport infrastructure. Both indicators are assumed to increase mobility due to increasing choices of means of transportation. Yet, as in most high-income countries, the car is the primary mean of transportation for individuals in Germany (Canzler, 2021). Only one in five German households does not have a car and those are mostly comprised of single-person households of older people or younger people in training. In Germany, a country with 83 million inhabitants (including children), more than 46 million cars are registered (Canzler, 2021). Hence, owning a car is not a very strong indicator considering the widespread use and ownership of individual passenger vehicles. However, people residing in an urban area with a high density of public transport networks are generally less in need of a car (Canzler, 2021). Nevertheless, car ownership is still a valid indication of wealth and hence reduced vulnerabilities because the ownership of car(s) correlates strongly with household size and, above all, household income (Canzler, 2021). Additionally, the public transport system is generally well established in German cities. In Frankfurt, the system consists of the U-Bahn (subways), S-Bahn (commuter trains), trams, and buses and Frankfurt has one of Germany's largest public transport networks (Frankfurt am Main, n.d.). Hence, the indicator of public transport infrastructure might not reveal much information in an urban context such as Frankfurt but would still be relevant to consider in more rural areas with little to no availability of public transportation. Moreover, if data on the dependence on public transportation would be available, this could be used to potentially indicate heightened vulnerabilities. This is because flood disruptions lead to transit cancellation, rerouting and increased travel times, which results in travel delays and loss of job accessibility often impacting low-income households disproportionately (He et al., 2021).

The data input used to determine SNP vulnerabilities is potentially misleading. SNP as a dimension of the IVI is only considered in Cologne because of the lack of data in Frankfurt. In Cologne, only one indicator (Full inpatient care places (without short-term and daycare)) is considered because there is no publicly available data on other indicators (e.g., retirement facilities, people with physical and mental disabilities, homeless, and seasonal workers or transient people). While SNP is an important indicator of vulnerable groups in the face of pluvial flooding (e.g., people that are dependent on physical assistance), it was not found to be a major determinant of vulnerabilities in the most vulnerable districts of Cologne. It is assumed that the indicator should correlate with other indicators of social vulnerabilities because SNP are very likely to face compounding vulnerabilities due to higher unemployment levels, lower-income levels, discrimination, and poverty in general (Hirschberg & Welti, 2021). Thus, the negative effect of Cologne's SNP indicator on the overall vulnerability of the high vulnerability districts compared to the low vulnerability districts could be misleading because of the indicator choice (availability). Without comparison to overall SNP, the indicator 'full inpatient care places' might not provide adequate information because more care services could potentially contribute to reduced vulnerabilities – if they are prepared for flood response – since people are cared for and accounted for. When conducting vulnerability analysis, the SNP in care should be compared to the overall number of SNP not getting care places or extensive support. However, due to the unavailbility of data, comparing people in care places with overall estimates of SNP was not possible and the choice of conducting the analysis with a limited indicator has been taken to still investigate potential effects. In the face of a lack of data on overall SNP, care facilities should, nevertheless, be accounted for in evacuation planning and the needs of people with disabilities, transient people, or the homeless should be accounted for even when community data is missing or only available at the city scale.

To understand the results regarding the dimension of housing, it is important to consider Frankfurt's city context. The dimension of housing is only being considered in Frankfurt and only includes people living to rent due to a lack of data in Cologne and on insurance holders. People living to rent as an indicator of vulnerability was chosen because it can be assumed that people usually rent because they are either transient or do not have the financial means to buy housing (Cutter et al., 2003). People that rent because of their lower economic status are more likely to lose their ability to return or afford to house elsewhere when their rentals become uninhabitable after a flooding event (Cutter et al., 2003; Versey, 2021). Yet, Frankfurt's transient group of renters might explain the high rates of renters in Frankfurt's least vulnerable and wealthy centre districts. Besides Frankfurt's high average GDP and major financial and consulting industries, the proportion of foreigners among employees lies above the German average at 18%; in addition, 15.6% of the companies have a foreign background (Stadt

Frankfurt am Main, 2016). Furthermore, 24.7% of all employees in Frankfurt have an academic degree, which in Germany is only exceeded by two other cities (Stadt Frankfurt am Main, 2016). Moreover, according to Arundel and Hochstenbach (2020), higher-educated young adults typically prefer to live in centrally-located gentrifying neighbourhoods within cities. Thus, Frankfurt's international industries with many foreign and highly educated employees that are not necessarily bound to Frankfurt as a long-term location could explain that most renters are located in some of Frankfurt's wealthiest districts.

Nevertheless, the indicators of infrastructure, SNP, and housing are overall valuable in a pluvial flood risk context and should be included in future research in this field. Yet, data sources and indicators should be expanded and the specific context of an area should be understood to interpret potentially surprising results that do not align with assumptions made based on the scientific literature.

Compounding vulnerabilities

The findings of this thesis indicate that multiple dimensions likely compound in highly vulnerable districts. While Cologne and Frankfurt show different patterns of compounding vulnerabilities, however, economic status, (limited) education, and nationality showed high correlations across both cities and when including all districts and only the high and low vulnerability districts.

These three strongly correlating dimensions indicate the strong effect of compounding disadvantages. In the EU, immigrants or children of immigrants are structurally disadvantaged in education with lower percentages attending gymnasiums and higher education (OECD, 2017). Furthermore, foreigners or nationals with foreign parents are more likely to live in poverty even when employed and the chances of unemployment for young nationals with foreign parents are around 50% higher than among their peers with native-born parents (OECD, 2017). Regarding education and socioeconomic status, there is a gap in Europe between children from wealthier and less wealthy parental backgrounds which is reflected in Cologne by the strong correlation between the two dimensions. According to the OECD's report (2017), a child from an advantaged socio-economic background will score on average 20% higher in mathematics than a child from a disadvantaged background. Structural disadvantages are likely to be exacerbated by stereotypes and discrimination. According to the ENAR's shadow report 2012-2013, the most vulnerable groups in Europe facing discrimination in employment are migrants from non-EU countries including undocumented migrants, refugees, and asylum seekers., Muslims and especially Muslim women, Roma and travellers, people of African descent and Black Europeans, and all women with a minority or migrant background (Miet et al., 2013). Yet, it also needs to be noted that the dimension of economic status in Cologne is comprised of two indicators: unemployment and people who receive social benefits (In Frankfurt, the median income is additionally included). While this covers the group of people with the lowest economic status, it would also be valuable to include the average income of the districts' inhabitants to distinguish districts with a low unemployment rate and little need for social benefits but low income from relatively high-income districts. Yet, data on the median income was only available on a city scale in Cologne and not per city district as was needed for this analysis.

In the high and low vulnerability districts of both cities, family structure corelates strongly with age. The correlation between these two dimensions can be explained by the indicators determining the two dimensions. The dimension family structure comprises families with children and single parents whereas the dimension age comprises inhabitants under 15 years and above 65 years. Hence, there is an obvious correlation between children and families with children.

Cologne's high and low vulnerability districts, unlike Frankfurt's, also show evidence of strong compounding effects of family structure with economic status, nationality, and education. The correlations between family structure (families with children and single parents) and low economic status can potentially be explained because poverty levels are highest among the demographic of single parents and one-income couples with children in the EU (OECD, 2017). Hence, the findings for Cologne reflect this trend. Correlations between family structure and nationality are likely due to higher birth rates in first- and second-generation migrant families. In 2019, the birthrate among immigrants in Germany was over two children per woman which is well above the German average of 1.54 children per woman (Goldenberg, 2020). Yet, the number of childbirths per woman also strongly correlates with education in Germany, where migrants with higher education have as few children as the German average (Goldenberg, 2020). This also relates to the correlation between family structure and education which indicates that the more children live in a district, the lower the education of the population; The dimension of education consists of two indicators: the percentage of employees with an academic degree and the percentage of students attending a gymnasium. Considering that poverty levels coincide with lower education and that single-parents and one-income families with children are among the poorest in Europe (OECD, 2017), this could explain the correlation effects of the two dimensions (family structure and education).

Gender appears to be a compounding factor for vulnerabilities in Frankfurt but not in Cologne. In Frankfurt, gender correlates to some extent with age, nationality, family structure, and economic status. The dimension of gender in Frankfurt comprises the number of women per district (increasing vulnerabilities) and the number of women in employment per district (decreasing vulnerabilities). The correlation with age indicates that when more women reside/ work in one district, there are also more children or elderly. This correlation could be explained by increased caring responsibilities of females and hence increased proximity or co-living with children and people of age. The correlating effects of gender and family structure might be due to higher levels of female caretakers and single mothers compared to single fathers. Economic status and gender are most likely correlating due to the gender pay gap which is around 12.8% in Europe (OECD, 2017). In Germany, the gender pay gap lies even higher at around 20% and almost 50% of women work part-time because of a lack of care infrastructure (Rühlemann et al., 2019). The described possible explanations for these correlations are all factors that should be taken into account and should generally be addressed to reduce overall higher vulnerabilities of women.

Housing appears to be negatively correlated with family structure and age in Frankfurt, indicating that the more people are owning a home in one district, the more children and/or old people live in the districts. This could be due to Frankfurt's economic industry and demographic setup as discussed in the first subsection but could also have different reasons. Yet, renters in Frankfurt's wealthy districts are on average less vulnerable and might to the largest extent rent because of their cosmopolitan lifestyles.

Overall, the (mainly) positive correlations in the two case cities reveal compounding vulnerabilities which validates the need for intersectionality theory and that FRM planners account for intersecting vulnerabilities. In Cologne, compounding vulnerabilities get amplified when only considering high and low vulnerability districts. Hence, compounding effects increase in the most vulnerable areas which indicates disproportionate vulnerabilities in the high vulnerability districts compared to the overall city and suggests stronger socio-demographic gentrification of Cologne's high and low vulnerability districts compared to the city's general socio-demographic distribution. By contrast, in Frankfurt, the strength of correlations is more similar for all districts and the high and low vulnerability districts, which indicates less disproportionate compounding factors in Frankfurt's high vulnerability districts compared to the rest of the city and in comparison to Cologne because of the smaller range of vulnerability scores. Thus, Cologne and Frankfurt's districts show some general patterns of compounding vulnerabilities which get worse with increasing vulnerabilities in Cologne but not in Frankfurt.

The IVI and flood risk exposure in the case cities

There is no city-wide disproportionate exposure risk in socio-demographically vulnerable districts. In the two case cities, correlations between high vulnerability and exposure could not be found for any of the three return periods. This shows that districts with a high IVI score are, on average, not more exposed to pluvial flood risk than districts with lower IVI scores. This is not necessarily to be expected since, in many parts of the world, the most vulnerable and poor populations live in areas that are least protected from or prone to exposure to flooding (Rentschler et al., 2022). Yet, Germany is a high-income country with a better-functioning welfare system than most comparable affluent societies (Wagener, 2017), providing housing and financial assistance to people with low incomes, parents, and SNP. While there are also increasing income gaps and poverty in Germany, people do not live in inadequate slum and squatter settlements because the most basic lodgings have running water, electricity, sewage systems, and garbage collection (Wagener, 2017). However, while there is not yet a correlation between exposure and districts with high social vulnerabilities, this could become an increasing issue in European urban centres if extreme events become more frequent and severe and wealthy people who can afford it, move to safer areas. Hence, disproportionate exposure of the most vulnerable should be continuously part of FRM considerations and also brought to the attention of the city government that decides on housing developments in flood-prone areas.

Although no city-wide trends were observed, several neighbourhoods are at heightened risk because of high exposure coinciding with high vulnerabilities. The severity of impacts from any extreme and non-extreme weather and climate event – in this case, that of pluvial flooding – strongly relates to the level of vulnerability and exposure to the said event (Cardona et al., 2012). This means that the higher the level of exposure and/or the higher the level of vulnerability, the more severe the resulting impacts from a pluvial flooding event and the more likely the occurrence of a disaster (Cardona et al., 2012). The lack of correlations between vulnerability and exposure in the two cities indicates, at first, that vulnerable populations are not disproportionately exposed to flooding on a city-wide scale. Yet, only because there is no visible pattern or statistically significant correlation, the need to account for the intersections of high exposure and high vulnerability districts is not lessened. Disaster risk will always be highest in districts with combined high exposure and vulnerability levels and FRM policies need to account for such areas and the specific needs of their populations. In Cologne, the districts Ostheim, Bilderstöckchen, and Vingst have high mean water depth levels coinciding with relatively high social vulnerability. In Frankfurt, districts with relatively high exposure levels coinciding with relatively high IVI scores are Hausen, Fechenheim, Höchst, Nied, and Sossenheim. These districts would require special attention in FRM plans because they are hotspots of disaster risk.

5.2. Methods

The discussion section on the methods first discusses the data availability and suggestions for improvement of the IVI based on increased data collection. Second, the IVI is compared to Cutter's and colleagues' SoVI to identify the strengths and weaknesses of the IVI and discuss why certain dimensions that are included by Cutter et al. (2003) are not included in the IVI. Third, the aggregation of socio-demographic data and the trade-offs when "flattening" multiple dimensions of vulnerability into one index will be discussed. Forth and last, this section discusses the implications of this research's district-level resolution regarding flood risk exposure and vulnerability.

Data availability and recommendations for future data collection

When constructing the IVI of the two case cities, it became visible that there is a lack of (publicly available) data, required to fully inform about intersectional vulnerability to pluvial flooding. The data available still allowed for the successful calculation of the IVI but more available data would have improved the index. This is especially the case for the dimensions that were based on only one indicator, potentially decreasing some of the dimensions' significance and strength in determining social vulnerabilities. As was seen for Cologne's indicator of SNP which by itself gave limited insights into the actual composition of SNP across the city and hence, could not actually account for this broad group and its enhanced vulnerabilities.

To account more accurately for compounding vulnerabilities, data collection could generally focus more on accounting for intersections. The way by which data is currently collected, the intersecting characteristics of individuals within a neighbourhood stay unknown. So if a district, for example, is comprised of 50% elderly and 50% immigrants, these might be the same 50% of people or the exact opposite. Cologne did not provide any intersectional statistical data on the city's socio-demographics. This is different in Frankfurt, where data collected on education, employment, and welfare recipients is often disaggregated by gender (binary) and migration background. Yet, in both cities, this could be advanced to account for more specific disadvantages and/or discriminated groups by collecting data across the nine dimensions included in the IVI and more specific groups of enhanced vulnerabilities named in this thesis. Identifying more socio-demographic intersections by collecting more interconnected data could help to improve the understanding of compounding and intersecting vulnerabilities even before extensive statistical analyses. The IVI developed and calculated in this thesis could be used to inform correlations of demographics and potential intersections that could in the future be collected (e.g., the educational status of single-parent households or income by age, etc.).

The data availability of indicators was not studied beyond the two case cities and hence might be different in other European cities. Yet, to improve the understanding of social and intersectional vulnerabilities in the case cities (and beyond), data collection should be expanded regarding intersectional statistics, non-binary genders, insurance owners, renters, SNP, and people with a lack of social networks. Moreover, Cologne (and places beyond) should also collect data on median gross income, female participation in the workforce, and usage of public transportation on a district level. Table 11 lists the data that has been missing in both case cities and should be collected and expanded on. For more detail on why information on those demographics is considered relevant in a flood risk context see the IVI (Table 1).

Table 11: Socio-demographic data to improve the understanding of social and intersectional vulnerabilities in the context of pluvial flooding

Indictors for which data should be collected
- Non-binary and genderqueer (NBGQ)
- Intersectional statistics
- Insurance owners
- Number of people in care per household
- Homeless
- Seasonal workers and transients
- Residents in need of assistance
- Residents with a lack of social networks

Cutter's SoVI and the IVI

Compared to Cutter et al.'s (2003) SoVI, the IVI is much more simplified being built on rather broad categories of social vulnerability with limited indicators determining the individual categories. The indicators and dimensions of the IVI were chosen based on literature specifically concerning pluvial flood risk. The IVI has overall 24 indicators split under nine broader vulnerability dimensions. By contrast, the SoVI used 42 independent variables that were then computed into 11 factors using PCA. The 11 factors in turn were used to calculate a composite index (CI) score.

For the computation of the IVI, the step to conduct a PCA was not taken. This was done to overcome the problem of non-transferability. PCA can not be transferred to any other region because every PCA is unique to the dataset plugged into it, and factors (principal components) may bear absolutely no resemblance among different PCAs. By contrast, the dimensions of this thesis' IVI are retained, regardless of the city in which it is applied. However, the IVI also lacks some transferability since the range normalisation depends on the dataset. This could, however, be overcome by, for example, setting a set range with minimum and maximum benchmarks across all German (or European) cities.
Moreover, PCA was also not conducted because it removes compounding vulnerabilities. When conducting PCA compounding vulnerabilities are removed because PCAs are latent variables of an entirely statistical nature. By contrast, this research's dimensions are clear and consistent and can be correlated with one another to identify which tangible factors (as opposed to latent variables) are

compounding. Moreover, Cutter et al. (2003) calculated their SoVI on a spatial scale of US counties. This means that socio-demographic data is spatially more aggregated but also yields potentially higher data availability.

Some of the factors used in the SoVI have not been considered in this study whose aim was to focus on social vulnerabilities based on structural disadvantages or discriminations leading to higher vulnerability in the face of pluvial flooding events. The indicators of population (specifically the density of the built environment), infrastructure, and single-sector economic dependence used in Cutter et al.'s (2003) SoVI will briefly be discussed and contrasted with the indicators used in the IVI.

The SoVI index of Cutter et al. (2003) considers the density of the built environment which is measured in the density of manufacturing and commercial establishments, housing units, and new housing permits because areas with high densities might expect the greatest structural losses from a hazard event (Cutter et al., 2003). Yet, while this measure reduces biases by not focusing on the economic value of housing and instead measures as heightened vulnerability (and hence the need for greater protection) areas with high numbers of people affected, it is also rather a structural and economic focus on vulnerability than one that is actually based on social and intersectional vulnerabilities. Yet, structural and economic vulnerabilities can also intersect with social/ individual vulnerabilities but that would require a detailed spatial analysis of intersections of social and structural vulnerabilities which was outside the scope of this thesis. Hence while this dimension might also yield interesting insights into the numbers of people affected, it is not accounted for in this research because it does not per se indicate intersectional social vulnerability. Moreover, this would also open up an ethical discussion on if people's lives and safety can be measured against each other (I.e., is it morally right to consider the life of many people more important than the life of one person?). Moreover, due to the city-level spatial scale and urban focus of this research, this indicator has generally a reduced relevance because the density is much more uniform in a city than when comparing urban and rural areas (which opposed to this research, Cutter et al. 2003 have done).

The dimension of infrastructure has also been considered differently by Cutter et al. (2003). The IVI constructed in this thesis considers within the dimension of infrastructure, car ownership and public transport availability, two indicators of the mobility of the population. Yet, the conceptual framework of this paper as well as Cutter et al. (2003) emphasize the potentially serious effect on the population in case of damage to critical infrastructure. Cutter et al. (2003) state that the loss of sewers, bridges, water, communications, and transportation infrastructure compounds potential disaster losses which poses an increasing financial burden on poorer communities. To account for this, Cutter et al. (2003)

use two individual indicators: the debt to revenue ratio of a county and the percentage of people employed in public utilities. The authors assume that this helps to indicate the wealth of a county and the potential to rebuild quickly after a disaster. This is irrelevant when comparing districts within the same city, but might be an interesting indicator to account for when conducting a comparison between cities or larger areas in different economic settings. The indicator also does not have an individual focus but more generally indicates how well a local government can support its residents in the recovery process (and/or adaptation process). For example, after Hurricane Katrina, poor neighbourhoods were likely to be excluded from governmental grant programs as they are less likely to have property and flood insurance and more often lack official papers on mortgage and land ownership (Crowley, 2006). In such a case, the wealth of a governmental entity (county, municipality, etc.) might not be a good indicator of reducing vulnerabilities if despite living in wealthy regions, low-income people and people without insurance are nevertheless excluded from financial aid. In general, like this study, Cutter et al. (2003) do not account for specific damage to critical infrastructure but instead, use the indicator of the financial means of the county for recovery. Damage to critical infrastructure is difficult to account for because damage could occur in one district, but the effects could be felt across several districts (e.g., when the generator fails in one area, major parts of the city could be impacted) or even impact people from other districts disproportionally (e.g., because damage to a bridge would not allow them to get to work). It has, therefore, also not been included in this paper's IVI. Yet, future research could shed light on how certain damages to critical infrastructure might affect individuals or city districts differently because of their enhanced dependency on certain structures or specific locations. Yet, it should be noted and accounted for that monetary, population, and infrastructure metrics often dominate existing evaluations of damage after a disaster which tends to skew the focus to highly populated places and areas of concentrated capital, overlooking other vulnerable areas (Boyd et al., 2021).

Related to infrastructure, Aroca-Jimenez et al. (2017) include indicators on the accessibility of health facilities, shelters, and schools in their social vulnerability index which can help to estimate the resilience of an area but, again, does not specifically address social vulnerabilities of people based on their identities and social categorizations. Cutter et al. (2003) also account for the quality of human settlements (housing type and construction, infrastructure, and lifelines) which is also less interesting in an urban setting in Germany where people generally live in relatively stable houses (Wagener, 2017).

Single-sector economic dependence is another indicator used by Cutter et al. (2003) which has been excluded from the IVI constructed in this thesis. Cutter and colleagues’ indicator predicts that the singular reliance on one economic sector for income generation creates economic vulnerability in the area considered because of a greater likelihood of many people losing their job in the face of a disaster. Cutter et al. (2003) list extraction of natural resources, fishing, agriculture, or tourism as industries where the recovery may take longer in the face of a disaster. Paavola and Adger (2006) support this, arguing that people's dependency on sources of income such as agriculture or fishing determines to some extent their vulnerability. Yet, in an urban setting, farming and extraction industries are little prevalent but tourism could potentially be included in a vulnerability analysis in an urban setting. Yet, this indicator has been excluded from this analysis because it also does not focus on social vulnerabilities of people based on their identities and social categorizations and because a detailed analysis of the case studies industries is outside the scope of this thesis.

Resolution: The IVI and Flood Exposure

The flood exposure and vulnerability analysis of this research was conducted at the city district level. Yet, calculating social and intersectional vulnerabilities on a city district scale reduces more nuanced understandings of vulnerabilities. Grouping data on such a scale can obscure heightened vulnerabilities in one area of a district due to relatively low levels of vulnerability in another area of the same district. Hence, the community data resolution on a district scale, while relevant for policy, might not precisely account for vulnerabilities and discriminations individual people or groups of people face in their everyday lives. Because the specific vulnerabilities prevalent (or absent) in their district of residence might not align with their personal vulnerabilities and needs. Moreover, by range normalizing vulnerabilities of dimensions (e.g., between 1-0), one might skew actual vulnerabilities because relative high numbers of, for example, children, are categorized as '1' whereas the overall number of children is generally relatively low compared to, for example, SNPs with potentially much higher relative numbers. This indicates the relativity of statistical analysis and the importance for FRM to look at the overall count of high-ranking vulnerability determinants because determinants could be high ranking due to their strong divergence or generally low numbers and not always because of overall high numbers of an indicator. This could lead to the prioritization of certain hotspots over others despite not being the largest sociodemographic distributer to risk. Yet, even low numbers of vulnerable people should be accounted for since they would still potentially need special attention in case of a flooding event. Nevertheless, the city district level is a relevant scale for policy implementation because smaller scales are difficult to govern. Moreover, community data is not available in a higher resolution (smaller classifications) in Germany.

Due to this research's chosen district-level resolution, no concrete analysis was conducted on where the water accumulates within the districts which could skew the actual level of risk. Like the IVI, the exposure levels were calculated on the district level to display the overall pattern of exposure throughout the two case cities and relative to the cities' districts and district sizes. Yet, exposure analysis on the district level loses information on concrete exposure of residents and infrastructure. For instance, high water levels in one district could accumulate mainly in green or blue spaces where a larger accumulation of water poses potentially little risk. Moreover, the analysis of this research gives no insight into what type of infrastructure or buildings are affected. The high-resolution 'Flood risk indicators for European cities from 1989 to 2018'-dataset (Mercogliano et al., 2021) used to calculate exposure in the city districts would allow for a more detailed analysis of affected infrastructure. Yet, due to time limitations, this was outside the scope of this master thesis since it would have meant collecting and determining the specific (critical) infrastructural compositions of the two case cities' districts and establishing a harmonized spatial dataset to represent the cities' (critical) infrastructure.

Future research, also when retaining the social vulnerability analysis at the district level, could investigate pluvial flood exposure on a higher resolution to investigate which critical infrastructure (such as hospitals, schools, but also power plants or telecommunication networks) is affected, and where. Thus, before aggregating the flood water depth to the district level, an impact analysis could be conducted on which specific areas and (critical) infrastructure might be impacted. This could be done by incorporating more information about the infrastructural setup through e.g., remote sensing and by subtracting green spaces and natural catch basins from the impact analysis. Novel spatial datasets may also aid in such analyses; for example, Nirandjan et al. (2022) recently published the first publicly available harmonized spatial dataset representing Critical Infrastructure systems globally. While their dataset is currently available at a spatial resolution of 0.10 x 0.10 degrees, and thus, not to be applied at the city scale, the authors suggest that their code can be used to further develop the dataset (in case of data availability) for any location and any resolution (Nirandjan et al., 2022).

Increasing resolution and data availability and generally linking socio-demographic community data to more detailed flood exposure analysis will increase the utility of scientific research that combines hazard predictions and equity (Moss et al., 2021). This would help to balance some detail and generalization regarding the district-level resolution that will support policy planning with more concrete knowledge on potential infrastructural damage and could improve preparedness. Moreover, the exposure analysis could also in turn inform the IVI giving better insights into which (critical) infrastructure would be impacted and what that could mean for the population residing in the area.

Aggregating community data – strengths and weaknesses

The aggregation of social vulnerabilities in an index score risks flattening the understanding of root causes of discrimination and vulnerability. Indicators and dimensions of the IVI are grounded in the scientific literature on pluvial flood risk and environmental hazard impacts on populations and are intended to reflect (intersecting) social vulnerabilities. Yet, ‘social vulnerability’ to environmental hazards has been produced over time through laws, markets, prejudices, and behaviours and hence is deeply connected to historically-rooted inequalities (Fussell, 2015). Thus, Fussell (2015) criticizes that the aggregation of social vulnerabilities in an index score (or several scores of different vulnerability dimensions) flattens the understanding, history, and social mechanisms that produce unequal outcomes after a disaster. This is an important criticism to consider especially since this research seeks to incorporate intersectionality theory that intends to not only unveil compounding vulnerabilities but also to critique and reveal social structures of power, inequality, and discrimination (Bauer et al., 2021; Kaijser & Kronsell, 2014). Undeniably, addressing the root causes of inequality by deconstructing systems of oppression and marginalization should be the priority of any local or national government which is, however, not addressed by this research or the application of the IVI in general.

While acknowledging that it should be prioritized that deeper roots of inequality should be addressed, the manifestation of inequalities can still not be ignored and needs to be accounted for in any FRM planning. Moreover, some groups, such as children, the elderly, or the disabled will continue to require more assistance and care in the face of a flooding event and hence need to be continuously prioritized in evacuation planning. In the end, truly sustainable adaptation needs to identify and tackle the root causes of both environmental change and poverty (Brown, 2011), while also preparing for and responding to emergencies that might occur in the current situation.

5.3. Climate justice

To address injustices concerning climate change impacts and responsibilities, it is necessary to establish the most vulnerable actors who most likely will carry the greatest burden in the face of any climate disaster (Sultana, 2022). To address social inequality in pluvial flood risk management, intersectionality theory was used in this thesis to identify socio-demographic determinants of vulnerabilities. Additionally, flooding datasets were used to investigate (disproportionate) exposure. The following two sections will discuss intersectionality and disproportionality in pluvial flood risk in a European urban context. Both sections can be understood as contributing to the climate justice debate.

Intersectionality

An intersectional analysis of climate change is concerned with intersections of identity and social categorizations that lead to marginalization and inequalities resulting in vulnerabilities (Kaijser & Kronsell, 2014; Osborne, 2015). Moreover, intersectionality goes beyond those categorizations and criticizes structural inequalities and power relations of capitalist patriarchy (Kaijser & Kronsell, 2014;

Sultana, 2022). While structures of power have not been analyzed in this research, this thesis intended to embrace the complexities that are essential to the understanding of embedded social, political, and structural inequalities by touching upon such structures. This is done by, for example, emphasizing that women are not more vulnerable because they are women but because of their different standing in society's patriarchal structures that create different expectations and responsibilities resulting in a greater emotional workload, unpaid caring jobs, and lower incomes of women compared to their male counterparts. FRM planning on a local level, however, cannot influence or address such deep-rooted social structures but policy actors and planners should become increasingly aware of these societal processes to protect the most vulnerable. Moreover, the consideration of intersectional gender, class, and race aspects of climate justice can help ensure equitable and contextually appropriate interventions (Sultana, 2022).

The correlations of the different vulnerability dimensions in Cologne and Frankfurt can be related to intersectionality because they reveal that vulnerabilities are compounding and that people often not only belong to one marginalized or discriminated group, but several intersecting groups. This is because inequalities can perpetuate each other if not addressed as seen with first and second-generation migrant children being disadvantaged in school which results in fewer opportunities in the job market and lower incomes (OECD, 2017). Such educational disadvantages can be further exacerbated when fewer opportunities in job market and salary also depend on racist structures not just education (Nwabuzo, 2019). Despite that, within intersectional climate justice, it is important to not reproduce simplistic portrayals of e.g., the poor, Black, or women (Amorim-Maia et al., 2022). An intersectional lens must recognize and avoid reductionist narratives and thus, this research's simplifications also need to be recognized. In the end, people's experiences are always unique and broad categories such as 'migrant' or 'women' can help to indicate where groups of more vulnerable people gather but neglect to account for the broadly different experiences that people within these categories encounter. For example, a Dutch national in Cologne who speaks German well, resembles the majority population of the city, is highly educated, and has a wealthy background will have a very different experience and face very different hurdles than an older refugee from Syria who does not have a working permit, only speaks Arabic, and is additionally stigmatized because of their religion and ethnicity. Intersectionality aims to acknowledge that by recognizing that different social identities and categorizations interact to produce distinct forms of disadvantage and oppression.

This research aimed to portray intersecting social categorizations by correlating different dimensions of vulnerabilities in the face of pluvial flooding, but the analysis has stayed on a rather broad level due to the available socio-demographical data which does not provide information on intersecting social categories and identities (especially in Cologne) and hence, intersections are rather speculative and based on statistical analyses. However, for policy implementation in a European urban context, broader categories and scales of hotspots of vulnerabilities are necessary for operational purposes. Hence, it is important to find a balance between detail and practical applicability when accounting for social vulnerabilities. However, FRM should beware such simplifications and aim to enhance the understanding of intersecting demographical vulnerabilities of populations at the district level.

Single-focus lenses on social inequality leave little room to address complex environmental issues. Addressing vulnerabilities and forms of discrimination one at a time can divert attention away from broader efforts toward a more resilient and inclusive future (Amorim-Maia et al., 2022). As a result, there is an increasing need for planners and policymakers to adopt intersectional frames that address these inequalities holistically. FRM planning needs to focus on socially inclusive approaches that acknowledge and reduce root causes of systemic inequalities and not exclusionary rely on technocratic approaches.

Disproportionality

Disproportionality in terms of flooding impacts is understood in this thesis as district populations that face higher risk relative to others due to enhanced vulnerability or exposure. Heightened risk may manifest in district populations through high vulnerability or high exposure alone, or through a combination of (moderately) high exposure and vulnerabilities. Such districts could be considered disproportionately at risk of flooding impacts compared to districts with moderate or low vulnerabilities and exposure. Disproportionality, in this sense, could also be thought of as unequal risk—i.e., risk and its components are not evenly distributed among districts. Thus, highly exposed districts are disproportionately impacted because their population is likely to be more severely affected by flooding. Moreover, high social vulnerability populations, even under the same exposure levels as the least socially vulnerable, are disproportionately affected because of their reduced ability to cope with, adapt to, and recover from a disaster (Field, 2012). Hence, high vulnerability districts will be disproportionately impacted in the case of a flooding event due to the inhabitants' susceptibility to being adversely affected in the face of a disaster.

Generally, the burdens associated with risks and impacts from climate change are uneven and power-laden (Eriksen et al., 2015). Those with more power (social, economic, and political) can influence the structural drivers of unequal distribution of environmental burdens and benefits, often by marginalizing certain social groups (Dorkenoo et al., 2022). Disproportionality and vulnerability are socially constructed and manifest themselves through structures of power. Thus, disproportionality as a concept is closely linked to questions of justice and equity (Dorkenoo et al., 2022).

In general, discussions of disproportionality concerning environmental and climate hazards mostly revolve around the classic divide between low-income and high-income countries—contrasting the historical responsibility of climate change of high-income countries with the enhanced exposure and vulnerabilities in low-income countries (Dorkenoo et al., 2022). Disproportionality, however, can and does not only occur on a global scale but also within countries or even cities. Overall, there is evidence across sectors and regions that people who are already the most marginalized and vulnerable within society are also often disproportionately affected by environmental hazards (IPCC, 2022). Inequality and poverty constrain adaptation which also results in disproportionate exposure and impacts on the most vulnerable around the globe (IPCC, 2022).

In the two case cities, this thesis found no evidence of systemic, city-wide, disproportionate exposure to pluvial flooding in socio-demographically vulnerable districts compared to less vulnerable districts. Yet, despite no systemic evidence of intersecting high social vulnerabilities and exposure, there are in both case cities districts that are more exposed, more vulnerable, or both. Hence, there are still disproportionalities regarding flood risk impacts that need to be addressed in FRM planning.

Moreover, regarding the two case studies and European urban areas in general, in the face of climate change and increasingly extreme precipitation events, the systemic or structural disproportionality of exposure of the most vulnerable might still become reality. For example, when (after extreme flooding events) wealthier people decide to leave and move away from flood-prone areas, lower-income residents who cannot afford to live elsewhere might then increasingly occupy such areas. A study conducted in a US context suggests that this assumption has proven applicable in the face of large disasters which increasingly lead to the rich moving away from disaster-prone areas, while the poor are left behind (Boustan et al., 2020).

5.4. Policy recommendations

The case cities

In Germany, there are various actors across various scales involved with flood protection measures, such as state governments, regional governments, cities, and regions along river networks. In the two case studies, flood protection concepts often considered pluvial flooding only as a general risk but not as a flood risk and mainly focused on river flood protection strategies. The city of Cologne has, besides being considered in a state-wide and the Rhein-region-wide protection plan, its own FRM concept;

however, it has not been updated since its first initiation in 1996. Frankfurt does not have a flood protection concept for the city but is considered in a state-wide and Rhein-region-wide plan. None of the plans considers social or intersectional vulnerabilities of the population or measures to protect the most vulnerable within society. Yet, in the face of pluvial flooding and increasing risks of local extreme precipitation events, it will be important to incorporate more localized FRM concepts within wider flood risk protection strategies to prepare, adapt and cope with severe rain events and associated floodings and assist the most vulnerable. Moreover, city concepts would also need to be updated regularly according to new scientific knowledge in meteorology and climate science and in general incorporate climate justice considerations and vulnerabilities of the population.

The case cities and beyond

The policy recommendations regarding the inclusion of social justice components in FRM developed and presented in this thesis are summarized in Table 12. These recommendations are based on the results presented in this thesis and on socially-impactful measures mentioned in the literature. These recommendations are developed to complement current FRM planning at the city level and beyond. While these recommendations were built based on the analysis of Cologne and Frankfurt, they are assumed to be relevant for other cities if they are democratically adapted and contextualized.

Table 12: Policy recommendations to enhance social justice in FRM

Summary of policy recommendations
Extend the scope of flood impacts considered and acknowledge how impacts vary among social groups. It is important to make sure that warnings, preparation, and recovery measures reach and support the socially vulnerable (districts). While social vulnerability hotspots should be investigated and receive increased attention, low numbers of vulnerable people (in low vulnerability areas) also need to be accounted for in FRM.
Adopt intersectional frames that address social inequalities holistically. FRM planning needs to focus on socially-transformative approaches that acknowledge and address the root causes of both environmental change and social vulnerability. A first step to acknowledging and accounting for structural disadvantages could be identifying more socio-demographic intersections by collecting more intersectional data. Moreover, increasing resolution and data availability will increase the utility of scientific research and help to balance some detail and generalization for policy planning.
Prioritize districts where high social vulnerabilities and exposure levels coincide. Disaster risk will always be highest in districts with combined high exposure and vulnerability levels and FRM policies need to account for such areas and the specific needs of their populations. Therefore, FRM planning needs to account for the disproportionality of impacts and exposure.

Increase the participation of diverse community members in planning efforts. Including stakeholders and residents from high vulnerability districts in decision-making processes could help to make FRM planning more just and inclusive.

6. Conclusion

For this thesis, an intersectional vulnerability index (IVI) was established to calculate vulnerability scores based on demographical statistics per city district for the case studies Cologne and Frankfurt. The IVI was then overlayed with the Copernicus Climate Change Service's novel and high-resolution dataset on pluvial flood risk assessment in European cities to investigate highly exposed districts and relate vulnerability to flood exposure. The case city research has revealed certain districts in Cologne and Frankfurt that require increased attention in FRM planning because of high social vulnerabilities, high exposure levels, or relatively high social vulnerabilities intersecting with relatively high flood exposure levels. Intersectional social vulnerability was found to be driven by four main vulnerability dimensions in both cities; education, nationality, economic status, and family structure. Those vulnerabilities were the most divergent between the districts with high overall IVI scores (high vulnerabilities) and low overall IVI scores (low vulnerabilities) and, therefore, contributed the most to vulnerabilities in the most vulnerable districts.

Furthermore, intersectionality theory helped to inform the IVI but also enhanced the understanding of compounding and overlapping vulnerabilities that occur through intersections of identity streams and social categorizations. Ultimately, the more marginalized people are and the more intersecting discriminations they face, the greater their risks in the face of a flooding event due to reduced capacities to anticipate, cope with, and/or recover from a flood. Hence, FRM needs to account for the limitations and needs of the most vulnerable and ought to identify where they are located within a city, to what extent they risk being exposed to flooding or flooding impacts, and how to protect them. This research has aimed to contribute to an enhanced understanding of these issues by answering the central research question; *How is intersectional social vulnerability to pluvial flood risk spatially distributed in Cologne and Frankfurt and does increased vulnerability overlap with pluvial flood exposure?*

In Cologne, the districts with the highest social vulnerability (districts with values above one std dev of the mean IVI score) are Chorweiler, Finkenber, Seeberg, Vingst, Neubrück, Bocklemünd/Mengenich, Bilderstöckchen, Ostheim, and Lindweiler. In Frankfurt, the districts of high vulnerabilities are Sossenheim, Fechenheim, Riederwald, Zeilsheim, Sindlingen, Nied, Niederursel, and Schwanheim. These districts would require special attention in FRM planning with the specific considerations of what demographics live in these districts and the tailored support they would need (e.g., many elderly would need more evacuation assistance, more foreigners would need different language warnings, low-income people would need more financial support in the recovery process, and people who are foreign, old, and low-income would need a combination such measures).

The districts where high vulnerabilities and exposure overlap need the most attention in just FRM. Despite no evidence of systemic, city-wide, disproportionate exposure to pluvial flooding in socio-demographically vulnerable districts compared to less vulnerable districts, there are still various districts in both cities where (moderately) high vulnerabilities and exposure do intersect. In Cologne, the districts Ostheim, Bilderstöckchen, and Vingst have high percentages of the districts flooded coinciding with relatively high social vulnerability. In Frankfurt, districts with relatively high exposure levels coinciding with relatively high IVI scores are Hausen, Fechenheim, Höchst, Nied, and Sossenheim. These districts would require special attention in FRM plans because they are potential hotspots of disaster risk.

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8. Appendix

Appendix1: Cutter et al. (2003) social vulnerability concepts and metrices

TABLE 1

Social Vulnerability Concepts and Metrics

Concept	Description	Increases (+) or Decreases (−) Social Vulnerability
Socioeconomic status (income, political power, prestige)	The ability to absorb losses and enhance resilience to hazard impacts. Wealth enables communities to absorb and recover from losses more quickly due to insurance, social safety nets, and entitlement programs. *Sources*: Cutter, Mitchell, and Scott (2000), Burton, Kates, and White (1993), Blaikie et al. (1994), Peacock, Morrow, and Gladwin (1997, 2000), Hewitt (1997), Puente (1999), and Platt (1999).	High status (+/−) Low income or status (+)
Gender	Women can have a more difficult time during recovery than men, often due to sector-specific employment, lower wages, and family care responsibilities. *Sources*: Blaikie et al. (1994), Enarson and Morrow (1998), Enarson and Scanlon (1999), Morrow and Phillips (1999), Fothergill (1996), Peacock, Morrow, and Gladwin (1997, 2000), Hewitt (1997), and Cutter (1996).	Gender (+)
Race and ethnicity	Imposes language and cultural barriers that affect access to post-disaster funding and residential locations in high hazard areas. *Sources*: Pulido (2000), Peacock, Morrow, and Gladwin (1997, 2000), Bolin with Stanford (1998), and Bolin (1993).	Nonwhite (+) Non-Anglo (+)
Age	Extremes of the age spectrum affect the movement out of harm's way. Parents lose time and money caring for children when daycare facilities are affected; elderly may have mobility constraints or mobility concerns increasing the burden of care and lack of resilience. *Sources*: Cutter, Mitchell, and Scott (2000), O'Brien and Mileti (1992), Hewitt (1997), and Ngo (2001).	Elderly (+) Children (+)
Commercial and industrial development	The value, quality, and density of commercial and industrial buildings provides an indicator of the state of economic health of a community, and potential losses in the business community, and longer-term issues with recovery after an event.	High density (+) High value (+/−)

	Sources: Heinz Center for Science, Economics, and the Environment (2000) and Webb, Tierney, and Dahlhamer (2000).	
Employment loss	The potential loss of employment following a disaster exacerbates the number of unemployed workers in a community, contributing to a slower recovery from the disaster. *Source*: Mileti (1999).	Employment loss (+)
Rural/urban	Rural residents may be more vulnerable due to lower incomes and more dependent on locally based resource extraction economies (e.g., farming, fishing). High-density areas (urban) complicate evacuation out of harm's way. *Source*: Cutter, Mitchell, and Scott (2000), Cova and Church (1997), and Mitchell (1999).	Rural (+) Urban (+)
Residential property	The value, quality, and density of residential construction affects potential losses and recovery. Expensive homes on the coast are costly to replace; mobile homes are easily destroyed and less resilient to hazards. *Source*: Heinz Center for Science, Economics, and the Environment (2000), Cutter, Mitchell, and Scott (2000), and Bolin and Stanford (1991).	Mobile homes (+)
Infrastructure and lifelines	Loss of sewers, bridges, water, communications, and transportation infrastructure compounds potential disaster losses. The loss of infrastructure may place an insurmountable financial burden on smaller communities that lack the financial resources to rebuild. *Source*: Heinz Center for Science, Economics, and the Environment (2000) and Platt (1995).	Extensive infrastructure (+)
Renters	People that rent do so because they are either transient or do not have the financial resources for home ownership. They often lack access to information about financial aid during recovery. In the most extreme cases, renters lack sufficient shelter options when lodging becomes uninhabitable or too costly to afford. *Source*: Heinz Center for Science,	Renters (+)

Occupation	Some occupations, especially those involving resource extraction, may be severely impacted by a hazard event. Self-employed fisherman suffer when their means of production is lost and may not have the requisite capital to resume work in a timely fashion and thus will seek alternative employment. Those migrant workers engaged in agriculture and low-skilled service jobs (housekeeping, childcare, and gardening) may similarly suffer, as disposable income fades and the need for services declines. Immigration status also affects occupational recovery. *Source*: Heinz Center for Science, Economics, and the Environment (2000), Hewitt (1997), and Puente (1999).	Professional or managerial (−) Clerical or laborer (+) Service sector (+)
Family structure	Families with large numbers of dependents or single-parent households often have limited finances to outsource care for dependents, and thus must juggle work responsibilities and care for family members. All affect the resilience to and recovery from hazards. *Source*: Blaikie et al. (1994), Morrow (1999), Heinz Center for Science, Economics, and the Environment (2000), and Puente (1999).	High birth rates (+) Large families (+) Single-parent households (+)
Education	Education is linked to socioeconomic status, with higher educational attainment resulting in greater lifetime earnings. Lower education constrains the ability to understand warning information and access to recovery information. *Source*: Heinz Center for Science, Economics, and the Environment (2000).	Little education (+) Highly educated (−)
Population growth	Counties experiencing rapid growth lack available quality housing, and the social services network may not have had time to adjust to increased populations. New migrants may not speak the language and not be familiar with bureaucracies for obtaining relief or recovery information, all of which increase vulnerability. *Source*: Heinz Center for Science, Economics, and the Environment (2000), Cutter, Mitchell, and Scott (2000), Morrow (1999), and Puente (1999).	Rapid growth (+)
Medical services	Health care providers, including physicians, nursing homes, and hospitals, are important post-event	Higher density of medical (−)

	sources of relief. The lack of proximate medical services will lengthen immediate relief and longer-term recovery from disasters. *Source*: Heinz Center for Science, Economics, and the Environment (2000), Morrow (1999), and Hewitt (1997).	
Social dependence	Those people who are totally dependent on social services for survival are already economically and socially marginalized and require additional support in the post-disaster period. *Source*: Morrow (1999), Heinz Center for Science, Economics, and the Environment (2000), Drabek (1996), and Hewitt (2000).	High dependence (+) Low dependence (−)
Special needs populations	Special needs populations (infirm, institutionalized, transient, homeless), while difficult to identify and measure, are disproportionately affected during disasters and, because of their invisibility in communities, mostly ignored during recovery. *Source*: Morrow (1999) and Tobin and Ollenburger (1993).	Large special needs population (+)

SOURCE: Cutter, Boruff, and Shirley (2001); Heinz Center for Science, Economics, and the Environment (2002).

Appendix 2: Cutter et al. (2003) Indicators used in the SoVI:

TABLE 2

Variable Names and Descriptions

Name	Description
MED_AGE90	Median age, 1990
PERCAP89	Per capita income (in dollars), 1989
MVALOO90	Median dollar value of owner-occupied housing, 1990
MEDRENT90	Median rent (in dollars) for renter-occupied housing units, 1990
PHYSICN90	Number of physicians per 100,000 population, 1990
PCTVOTE92	Vote cast for president, 1992—percent voting for leading party (Democratic)
BRATE90	Birth rate (number of births per 1,000 population), 1990
MIGRA_97	Net international migration, 1990–1997
PCTFARMS92	Land in farms as a percent of total land, 1992
PCTBLACK90	Percent African American, 1990
PCTINDIAN90	Percent Native American, 1990
PCTASIAN 90	Percent Asian, 1990
PCTHISPANIC90	Percent Hispanic, 1990
PCTKIDS90	Percent of population under five years old, 1990
PCTOLD90	Percent of population over 65 years, 1990
PCTVLUN91	Percent of civilian labor force unemployed, 1991
AVGPERHH	Average number of people per household, 1990
PCTHH7589	Percent of households earning more than $75,000, 1989
PCTPOV90	Percent living in poverty, 1990
PCTRENTER90	Percent renter-occupied housing units, 1990
PCTRFRM90	Percent rural farm population, 1990
DEBREV92	General local government debt to revenue ratio, 1992
PCTMOBL90	Percent of housing units that are mobile homes, 1990
PCTNOHS90	Percent of population 25 years or older with no high school diploma, 1990
HODENUT90	Number of housing units per square mile, 1990
HUPTDEN90	Number of housing permits per new residential construction per square mile, 1990
MAESDEN92	Number of manufacturing establishments per square mile, 1992
EARNDEN90	Earnings (in $1,000) in all industries per square mile, 1990
COMDEVDN92	Number of commercial establishments per square mile, 1990
RPROPDEN92	Value of all property and farm products sold per square mile, 1990
CVBRPC91	Percent of the population participating in the labor force, 1990
FEMLBR90	Percent females participating in civilian labor force, 1990
AGRIPC90	Percent employed in primary extractive industries (farming, fishing, mining, and forestry), 1990
TRANPC90	Percent employed in transportation, communications, and other public utilities, 1990
SERVPC90	Percent employed in service occupations, 1990
NRRESPC91	Per capita residents in nursing homes, 1991
HOSPTPC91	Per capita number of community hospitals, 1991
PCCHGPOP90	Percent population change, 1980/1990
PCTURB90	Percent urban population, 1990
PCTFEM90	Percent females, 1990
PCTF_HH90	Percent female-headed households, no spouse present, 1990
SSBENPC90	Per capita Social Security recipients, 1990

Appendix 3: Data input Cologne and Frankfurt

	COLOGNE	Economic			Age		Gender		Nationality		Family structure		Education		snp	Housing	Infrastructure	
		People who recieve social benefits in % of all inhabitants (including retiree and children)	Unemployment in %	Median brutto income (full-time employed)	children (0-14) in % of total population	seniors in % of total population	females in % of total population	females working in % (including female children and senior citizens)	Germans with migration background in %	Foreigners in % of total population	Families with children % of all households	Single parents % of all households	students attending Gymnasiums in % (Quota)	Employed with academic degree in % (of all socially insured employees)	Full inpatient care places (without short-term and day care) in % of all inhabitants for 9 larger city areas (assumed equal distribution over districts falling within one area)	Renter occupied housing units	Cars per 1,000 adult residents	train/tram traffic area used in % of total area
	Vulnerability	+	+	-	+	+	+	-	+	+	+	+	-	-	+	+	-	-
ID	**Name**	**soc_ben**	**unemp**	**income**	**children**	**seniors**	**females**	**f_work**	**migr**	**foreign**	**fam_ch**	**single_p**	**gymn**	**academ**	**nurs**	**low_inc**	**car**	**train**
101	Altstadt-Süd	10,10	4,62	NA	7,15	15,87	50,01	NA	15,01	19,05	7,71	1,70	47,70	45,76	0,73	NA	381,00	NA
102	Neustadt-Süd	6,70	4,08	NA	9,19	11,28	50,25	NA	14,41	14,88	10,77	2,23	68,00	52,28	0,73	NA	365,00	NA
103	Altstadt-Nord	9,00	4,55	NA	6,22	15,46	47,49	NA	14,83	22,98	7,00	1,54	50,80	46,22	0,73	NA	600,00	NA
104	Neustadt-Nord	6,00	3,50	NA	9,32	14,16	50,01	NA	15,01	14,67	11,04	1,93	73,30	52,49	0,73	NA	508,00	NA
105	Deutz	8,80	3,82	NA	9,42	15,00	50,55	NA	16,34	17,56	11,95	2,92	52,70	43,09	0,73	NA	805,00	NA
1	**Innenstadt**	7,90	4,10	NA	8,38	13,97	49,79	NA	14,97	17,22	9,72	2,02	61,40		0,73	NA	487,00	NA
201	Bayenthal	5,90	3,06	NA	13,26	16,54	50,47	NA	16,70	19,21	17,66	3,31	54,40	46,36	0,69	NA	632,00	NA
202	Marienburg	9,00	2,93	NA	13,56	18,93	50,40	NA	21,70	16,80	19,98	3,34	40,40	45,26	0,69	NA	740,00	NA

203	Raderberg	12,90	4,94	NA	13,18	13,64	51,12	NA	19,55	19,06	18,55	4,20	35,80	33,14	0,69	NA	442,00	NA
204	Raderthal	10,20	3,74	NA	13,06	22,35	52,43	NA	16,10	11,62	18,66	4,05	41,10	31,91	0,69	NA	533,00	NA
205	Zollstock	9,20	4,04	NA	11,17	18,28	52,39	NA	18,06	15,24	14,72	3,50	40,30	33,14	0,69	NA	435,00	NA
206	Rondorf	7,60	3,05	NA	13,79	22,04	51,63	NA	17,52	14,69	20,76	4,32	38,50	24,26	0,69	NA	676,00	NA
207	Hahnwald	0,70	1,02	NA	15,92	22,75	49,27	NA	15,25	12,15	26,13	3,18	78,00	43,33	0,69	NA	1761,00	NA
208	Rodenkirchen	4,70	2,52	NA	13,18	25,96	53,67	NA	15,24	12,31	18,33	3,37	60,00	39,82	0,69	NA	620,00	NA
209	Weiß	6,50	2,81	NA	15,08	24,23	52,36	NA	13,75	9,19	23,23	4,81	49,40	33,16	0,69	NA	636,00	NA
210	Sürth	5,80	2,61	NA	15,35	18,39	52,03	NA	17,40	10,54	24,10	4,13	52,50	34,00	0,69	NA	809,00	NA
211	Godorf	16,30	5,94	NA	16,01	16,23	45,91	NA	18,61	29,90	21,45	4,02	11,10	10,50	0,69	NA	920,00	NA
212	Immendorf	11,00	4,70	NA	16,59	18,53	50,63	NA	22,16	16,20	25,18	4,70	27,50	13,78	0,69	NA	690,00	NA
213	Meschenich	30,10	9,51	NA	18,52	14,02	46,46	NA	20,56	45,25	27,54	5,34	13,40	8,95	0,69	NA	474,00	NA
2	**Rodenkirchen**	9,40	3,79	NA	13,72	19,63	51,42	NA	17,61	16,99	19,41	3,85	43,10		0,69	NA	616,00	NA
301	Klettenberg	3,30	2,21	NA	13,44	18,93	53,60	NA	12,90	7,26	17,83	3,07	76,50	49,86	0,78	NA	454,00	NA
302	Sülz	4,30	2,83	NA	11,30	14,58	53,13	NA	12,19	9,92	13,86	2,77	76,90	51,44	0,78	NA	456,00	NA
303	Lindenthal	2,80	2,11	NA	10,37	17,66	53,56	NA	13,19	10,04	13,57	2,17	80,70	54,50	0,78	NA	476,00	NA
304	Braunsfeld	4,50	2,71	NA	11,95	18,34	53,06	NA	14,38	10,67	15,62	2,76	80,70	51,42	0,78	NA	605,00	NA
305	Müngersdorf	8,40	3,51	NA	12,44	20,65	50,70	NA	16,81	17,41	20,64	3,70	57,70	39,43	0,78	NA	678,00	NA
306	Junkersdorf	4,70	2,77	NA	14,73	16,85	50,56	NA	15,66	10,83	21,52	3,12	80,10	48,52	0,78	NA	869,00	NA
307	Weiden	10,70	4,14	NA	12,42	24,04	52,12	NA	22,46	17,69	16,52	3,25	59,10	31,93	0,78	NA	542,00	NA
308	Lövenich	4,00	2,21	NA	15,62	21,80	52,35	NA	15,98	8,61	23,68	2,95	78,50	37,45	0,78	NA	699,00	NA
309	Widdersdorf	4,10	2,14	NA	22,82	14,48	50,92	NA	24,09	11,30	38,52	4,53	68,30	34,04	0,78	NA	661,00	NA
3	**Lindenthal**	4,90	2,73	NA	13,05	17,87	52,51	NA	15,59	11,26	17,54	2,91	73,80		0,78	NA	563,00	NA

401	Ehrenfeld	10,80	5,34	NA	10,71	11,54	50,40	NA	16,89	19,53	12,98	3,00	45,90	44,81	0,69	NA	399,00	NA
402	Neuehrenfeld	10,10	4,47	NA	12,52	16,12	51,11	NA	15,39	16,04	16,26	3,71	54,00	39,33	0,69	NA	405,00	NA
403	Bickendorf	18,50	6,74	NA	14,72	15,91	50,91	NA	24,31	22,45	20,93	5,81	27,90	20,38	0,69	NA	429,00	NA
404	Vogelsang	11,90	4,51	NA	14,89	19,78	50,99	NA	17,72	13,87	21,93	4,84	44,00	21,75	0,69	NA	647,00	NA
405	Bocklemünd/Mengenich	26,20	7,97	NA	17,14	20,69	52,05	NA	22,95	26,75	24,56	7,89	15,60	14,49	0,69	NA	461,00	NA
406	Ossendorf	15,80	5,40	NA	16,78	11,40	49,87	NA	28,90	20,01	27,87	6,40	33,30	20,31	0,69	NA	723,00	NA
4	**Ehrenfeld**	13,90	5,56	NA	13,31	14,70	50,78	NA	19,63	19,53	17,70	4,38	37,90		0,69	NA	462,00	NA
501	Nippes	7,40	3,44	NA	13,32	13,88	52,49	NA	16,08	15,22	17,47	3,37	63,00	44,45	0,95	NA	376,00	NA
502	Mauenheim	9,70	4,68	NA	13,32	18,81	51,24	NA	18,82	16,55	18,22	4,52	42,90	24,79	0,95	NA	447,00	NA
503	Riehl	7,40	2,72	NA	10,46	28,26	53,58	NA	17,85	14,33	15,41	3,41	59,60	36,90	0,95	NA	445,00	NA
504	Niehl	13,90	5,17	NA	13,90	18,55	51,51	NA	23,69	23,40	18,65	4,32	34,40	23,54	0,95	NA	899,00	NA
505	Weidenpesch	12,70	4,77	NA	11,90	19,40	51,42	NA	19,98	20,59	15,65	3,87	37,00	22,70	0,95	NA	458,00	NA
506	Longerich	9,80	3,53	NA	14,56	22,06	51,40	NA	19,08	14,96	20,15	3,89	38,10	21,74	0,95	NA	669,00	NA
507	Bilderstöckchen	19,30	6,93	NA	16,38	15,23	50,88	NA	27,33	28,57	23,67	5,59	29,20	17,00	0,95	NA	483,00	NA
5	**Nippes**	11,10	4,35	NA	13,52	18,15	51,90	NA	20,00	18,98	18,31	3,97	44,40		0,95	NA	533,00	NA
601	Merkenich	8,30	3,51	NA	13,83	17,97	49,51	NA	19,51	15,69	21,73	3,58	28,00	16,21	0,70	NA	802,00	NA
602	Fühlingen	8,40	3,20	NA	13,62	18,87	49,98	NA	18,20	10,61	20,47	4,18	40,00	23,85	0,70	NA	725,00	NA
603	Seeberg	28,20	7,81	NA	17,49	20,29	51,62	NA	37,51	35,10	27,19	7,23	19,70	10,19	0,70	NA	418,00	NA
604	Heimersdorf	7,80	3,19	NA	14,25	25,83	52,96	NA	23,27	11,37	20,88	3,53	40,60	16,83	0,70	NA	609,00	NA
605	Lindweiler	20,00	7,00	NA	15,76	24,17	52,04	NA	30,68	17,22	24,27	7,31	24,00	10,27	0,70	NA	560,00	NA
606	Pesch	6,00	3,10	NA	13,62	29,31	51,48	NA	22,94	12,41	20,27	3,86	41,00	14,97	0,70	NA	717,00	NA
607	Esch/Auweiler	7,00	3,26	NA	15,67	21,53	50,36	NA	22,03	10,36	24,45	3,55	54,50	20,86	0,70	NA	744,00	NA

608	Volkhoven/Weiler	15,50	5,65	NA	16,11	14,52	50,88	NA	42,49	19,46	27,35	5,93	33,20	12,25	0,70	NA	732,00	NA
609	Chorweiler	38,40	9,28	NA	18,80	19,84	53,02	NA	41,98	39,47	30,19	9,65	19,70	7,83	0,70	NA	344,00	NA
610	Blumenberg	10,40	4,80	NA	15,14	12,80	50,21	NA	49,57	20,09	29,32	5,50	29,90	12,36	0,70	NA	559,00	NA
611	Roggendorf/Thenhoven	19,10	6,39	NA	19,74	14,61	50,63	NA	26,77	19,26	29,14	6,52	16,70	19,09	0,70	NA	599,00	NA
612	Worringen	13,30	4,99	NA	15,58	19,78	50,80	NA	17,54	16,01	23,44	5,62	13,20	10,88	0,70	NA	612,00	NA
6	**Chorweiler**	17,70	5,63	NA	16,14	20,28	51,34	NA	30,46	21,67	25,18	5,82	27,50		0,70	NA	587,00	NA
701	Poll	11,70	4,61	NA	13,50	20,95	51,11	NA	19,77	14,55	18,29	3,99	49,80	25,01	0,73	NA	599,00	NA
702	Westhoven	8,60	3,61	NA	12,67	23,33	49,13	NA	22,85	12,95	16,95	2,52	62,00	24,70	0,73	NA	742,00	NA
703	Ensen	13,90	4,81	NA	14,37	20,11	50,38	NA	23,90	17,99	20,49	4,22	40,50	18,84	0,73	NA	554,00	NA
704	Gremberghoven	32,50	10,92	NA	18,74	14,08	47,65	NA	28,72	44,95	27,41	5,19	26,40	6,27	0,73	NA	1071,00	NA
705	Eil	15,30	5,51	NA	14,98	20,25	51,73	NA	28,36	20,10	21,31	5,21	27,50	11,99	0,73	NA	706,00	NA
706	Porz	17,30	6,41	NA	14,13	20,05	51,62	NA	32,10	23,66	20,35	4,59	37,50	16,11	0,73	NA	485,00	NA
707	Urbach	17,10	6,29	NA	14,98	21,32	51,18	NA	29,83	20,26	20,99	5,30	31,00	11,05	0,73	NA	531,00	NA
708	Elsdorf	7,50	3,15	NA	13,24	25,03	55,31	NA	28,35	11,84	25,20	5,31	59,00	14,50	0,73	NA	601,00	NA
709	Grengel	16,20	5,94	NA	15,35	20,15	49,31	NA	25,75	19,55	20,98	6,15	30,90	10,36	0,73	NA	647,00	NA
710	Wahnheide	13,80	5,71	NA	13,57	19,45	49,45	NA	19,70	19,81	18,61	4,52	30,60	11,08	0,73	NA	610,00	NA
711	Wahn	15,00	5,58	NA	17,10	15,67	49,73	NA	25,21	18,11	24,88	5,64	40,10	15,73	0,73	NA	668,00	NA
712	Lind	16,80	6,28	NA	13,73	22,14	47,85	NA	17,58	19,60	17,47	4,08	33,70	11,92	0,73	NA	656,00	NA
713	Libur	5,10	2,32	NA	16,44	15,19	49,42	NA	16,62	5,27	26,95	4,32	54,50	18,98	0,73	NA	630,00	NA
714	Zündorf	9,80	3,79	NA	12,83	26,27	52,36	NA	22,00	12,24	19,00	4,60	52,70	21,60	0,73	NA	610,00	NA
715	Langel	6,90	3,37	NA	15,37	22,11	50,13	NA	14,94	8,14	23,89	4,95	32,80	18,66	0,73	NA	708,00	NA
716	Finkenberg	47,20	11,68	NA	20,88	20,65	51,48	NA	38,01	47,10	29,91	6,10	11,10	8,40	0,73	NA	495,00	NA

7	**Porz**	16,30	5,76	NA	14,82	20,82	50,77	NA	25,74	20,20	20,92	4,75	37,10		0,73	NA	609,00	NA
801	Humboldt/Gremberg	23,60	8,67	NA	14,10	15,12	49,24	NA	27,37	32,87	17,46	4,81	27,00	18,42	0,63	NA	376,00	NA
802	Kalk	28,90	10,69	NA	13,97	12,53	48,04	NA	25,66	37,72	16,74	4,63	23,70	21,90	0,63	NA	349,00	NA
803	Vingst	28,10	9,52	NA	18,21	16,68	51,94	NA	33,40	32,61	26,80	8,58	23,70	10,28	0,63	NA	377,00	NA
804	Höhenberg	25,30	9,61	NA	13,79	16,03	50,11	NA	24,15	35,54	17,95	5,29	22,90	15,13	0,63	NA	366,00	NA
805	Ostheim	29,80	9,88	NA	19,99	14,46	50,37	NA	34,39	30,86	29,02	7,28	30,10	13,80	0,63	NA	472,00	NA
806	Merheim	12,50	4,58	NA	17,10	16,45	50,45	NA	31,03	19,23	26,69	4,59	42,10	19,47	0,63	NA	549,00	NA
807	Brück	7,80	3,33	NA	14,45	23,63	52,53	NA	16,50	10,14	21,08	4,16	44,00	26,91	0,63	NA	620,00	NA
808	Rath/Heumar	6,50	3,39	NA	13,79	22,65	51,11	NA	16,25	11,01	19,90	3,20	58,70	23,78	0,63	NA	687,00	NA
809	Neubrück	28,10	7,28	NA	18,68	21,98	51,98	NA	36,17	29,83	26,18	6,11	24,90	10,58	0,63	NA	441,00	NA
8	**Kalk**	22,30	7,95	NA	15,78	16,88	50,29	NA	27,14	28,31	21,32	5,29	30,90		0,63	NA	452,00	NA
901	Mülheim	25,10	8,82	NA	14,43	13,81	48,91	NA	22,61	32,27	18,50	4,78	24,20	25,32	0,54	NA	387,00	NA
902	Buchforst	24,70	8,48	NA	14,38	16,98	50,64	NA	28,65	29,59	20,06	6,26	23,80	14,21	0,54	NA	368,00	NA
903	Buchheim	23,00	7,91	NA	15,55	16,05	50,27	NA	28,85	28,33	21,80	5,60	33,90	17,98	0,54	NA	423,00	NA
904	Holweide	18,60	6,46	NA	15,34	17,00	51,63	NA	24,39	20,23	21,36	5,88	27,70	17,64	0,54	NA	538,00	NA
905	Dellbrück	9,50	3,78	NA	13,89	21,49	52,38	NA	14,73	10,22	19,44	4,06	45,40	26,73	0,54	NA	595,00	NA
906	Höhenhaus	16,40	5,53	NA	15,79	21,21	51,15	NA	20,34	16,33	23,45	5,71	30,50	18,25	0,54	NA	552,00	NA
907	Dünnwald	20,10	6,64	NA	16,54	18,89	51,12	NA	22,67	16,76	23,93	7,02	25,80	15,31	0,54	NA	542,00	NA
908	Stammheim	19,30	6,09	NA	15,66	20,91	51,50	NA	27,89	20,28	22,38	5,59	29,10	15,06	0,54	NA	526,00	NA
909	Flittard	17,20	6,04	NA	15,59	21,26	51,08	NA	19,66	16,10	21,97	5,13	31,90	11,85	0,54	NA	562,00	NA
9	**Mülheim**	19,60	6,84	NA	15,01	17,70	50,67	NA	22,44	22,46	20,64	5,28	29,80		0,54	NA	487,00	NA
	Cologne total	13,80	5,14	NA	13,64	17,66	51,07	NA	23,08	17,33	18,30	4,07	40,90	30,90	0,71	NA	532,89	NA

	FRANKFURT	Economic			Age		Gender		Nationality		Family structure		Education		snp	Housing	Infrastructure	
		Needs-based social benefits n % of all inhabitants	**Unemployment density in %**	**Median brutto income (full-time employed)**	**children (0-14) in % of total population**	**seniors in % of total population**	**females in % of total population**	**females working in % (including female children and senior citizens)**	**Germans with migration background in %**	**Foreigners in % of total population**	**Families with children % of all households**	**Single parents % of all households**	**students attending Gymnasiums in % of all students transferring after elementary school**	**Employed with academic degree in %**	**Senior residences and long-term nursing facilities**	**People living to rent in % per 13 districts - assumes equal distribution over the city ditricts that fall within the group of 13**	**Cars per 1,000 adult residents**	**train/tram traffic area used in % of total area**
ID	Name	soc_ben	unemp	income	children	seniors	females	f_work	migr	foreign	fam_ch	single_p	gymn	academ	nurs	renters	car	train
1,00	Altstadt	12,10	5,80	4708,83	9,54	15,61	49,28	58,30	23,45	36,45	12,30	3,71	NA	28,60	NA	87,00	496,00	0,00
2,00	Innenstadt	14,47	5,10	3903,28	7,22	14,26	47,47	59,10	19,27	45,54	8,08	1,94	4,25	24,40	NA	87,00	1493,00	0,00
3,00	Bahnhofsviertel	20,71	7,00	4653,00	6,86	6,89	38,05	54,30	14,47	49,99	7,11	1,66	3,32	26,50	NA	87,00	623,00	1,58
4,00	Westend-Süd	2,90	1,60	6374,89	13,33	14,53	51,06	57,80	19,85	27,29	16,71	2,63	9,65	39,30	NA	75,00	1119,00	0,29
5,00	Westend-Nord	7,85	2,50	5445,14	13,15	14,56	51,91	53,30	24,65	28,79	17,38	3,89	13,53	28,70	NA	75,00	388,00	0,00
6,00	Nordend-West	4,75	2,30	5329,18	12,12	14,15	51,27	63,40	18,67	21,35	15,61	2,81	13,17	36,50	NA	78,00	457,00	0,00
7,00	Nordend-Ost	7,29	2,80	4939,48	10,65	14,11	51,86	64,80	18,52	22,26	13,93	3,46	15,55	35,00	NA	78,00	356,00	0,00
8,00	Ostend	9,50	3,60	4615,44	10,65	15,54	51,20	62,30	21,54	28,53	13,70	2,82	9,88	30,40	NA	86,00	593,00	10,10
9,00	Bornheim	10,63	3,50	4346,80	11,40	17,86	52,86	63,30	22,23	23,78	14,98	3,96	16,63	27,00	NA	86,00	389,00	0,00
10,00	Gutleutviertel	18,80	8,10	4278,63	8,94	14,06	43,47	58,70	18,46	42,38	10,11	2,02	NA	25,50	NA	87,00	563,00	6,46
11,00	Gallus	15,01	4,30	4338,00	14,09	9,40	47,34	57,60	26,18	40,64	18,37	4,19	10,31	25,70	NA	87,00	838,00	23,41
12,00	Bockenheim	10,42	3,20	4812,76	13,10	11,65	50,11	59,70	22,29	33,15	16,99	3,33	10,03	31,70	NA	75,00	457,00	2,53

13,00	Sachsenhausen-Nord	8,33	2,80	5227,66	12,70	13,93	51,23	62,10	21,09	24,55	16,82	3,66	14,93	33,10	NA	72,00	435,00	4,97
14,00	Sachsenhausen-Süd	6,37	2,40	4905,26	12,00	20,21	51,56	60,90	20,92	24,27	16,20	3,05	12,58	28,80	NA	72,00	700,00	2,14
16,00	Oberrad	16,52	7,40	3567,00	11,86	18,13	49,43	56,20	24,27	33,73	16,86	4,19	12,43	15,30	NA	72,00	423,00	2,14
17,00	Niederrad	12,76	5,60	3882,82	12,36	14,74	50,15	59,40	23,59	36,24	16,57	3,81	10,50	20,30	NA	72,00	546,00	2,57
18,00	Schwanheim	15,12	7,10	3541,33	14,63	20,08	51,31	53,90	28,98	24,62	22,07	5,41	21,99	9,30	NA	69,00	527,00	0,11
19,00	Griesheim	16,74	7,50	2943,73	13,64	14,29	47,05	51,90	27,50	42,29	18,74	4,16	9,84	9,90	NA	69,00	415,00	2,94
20,00	Rödelheim	13,54	6,10	4003,05	13,63	15,85	50,01	58,80	22,04	33,73	18,65	3,92	11,61	22,00	NA	68,00	488,00	3,98
21,00	Hausen	12,27	5,80	3940,78	13,99	18,10	51,68	48,30	28,62	34,58	20,16	3,86	11,15	18,60	NA	68,00	382,00	0,00
22,00	Praunheim	12,92	6,00	3679,76	14,73	20,64	51,26	54,40	26,73	28,11	21,21	4,74	16,85	12,70	NA	68,00	508,00	0,44
24,00	Heddernheim	15,23	5,70	3673,33	14,42	18,51	52,35	54,50	28,39	25,06	21,07	6,02	24,02	13,20	NA	64,00	451,00	2,22
25,00	Niederursel	14,92	5,80	3623,58	15,09	19,01	51,75	50,70	30,25	29,85	22,53	4,79	16,05	13,20	NA	64,00	460,00	0,80
26,00	Ginnheim	13,92	5,80	3859,02	13,63	16,58	52,22	55,00	31,31	26,05	21,53	5,19	19,90	16,90	NA	71,00	430,00	1,92
27,00	Dornbusch	7,54	3,60	4317,92	12,25	20,99	53,03	58,50	23,96	22,25	17,28	3,57	16,02	24,40	NA	71,00	451,00	0,00
28,00	Eschersheim	8,35	4,40	4288,34	12,67	17,93	51,65	58,20	21,71	21,83	17,96	3,40	15,59	22,80	NA	71,00	469,00	2,01
29,00	Eckenheim	17,02	6,50	3597,72	13,47	18,34	51,70	53,60	29,17	29,88	18,24	5,18	17,34	14,50	NA	58,00	506,00	1,31
30,00	Preungesheim	11,88	5,00	3803,79	15,89	13,98	50,74	56,20	28,81	28,41	25,37	5,30	18,65	16,90	NA	58,00	490,00	0,69
31,00	Bonames	16,78	6,60	3328,63	13,86	19,46	50,78	52,20	30,45	28,73	19,46	4,96	17,26	11,10	NA	58,00	457,00	1,21
32,00	Berkersheim	13,91	5,30	3972,38	16,90	15,67	49,86	51,40	29,71	21,21	28,96	5,18	24,45	16,30	NA	58,00	584,00	2,16
33,00	Riederwald	21,16	8,30	3289,39	15,02	18,16	50,88	54,10	27,02	29,02	20,23	6,09	NA	8,20	NA	63,00	441,00	1,00
34,00	Seckbach	14,55	6,70	3529,50	13,37	20,84	50,06	57,00	20,42	29,24	18,85	4,38	14,99	14,30	NA	63,00	547,00	1,80
35,00	Fechenheim	22,26	9,60	2915,58	15,34	14,40	47,13	48,30	26,51	44,01	21,93	6,29	14,29	7,90	NA	63,00	535,00	3,29
36,00	Höchst	19,78	8,50	3377,20	14,97	10,89	48,51	53,90	26,65	41,53	21,64	5,05	12,17	12,10	NA	69,00	563,00	2,72

37,00	Nied	16,94	7,40	3469,15	14,00	16,75	49,13	52,30	27,40	37,84	20,75	4,58	12,09	10,20	NA	69,00	437,00	3,62
38,00	Sindlingen	16,68	7,30	3300,50	15,11	16,87	49,10	53,00	27,51	33,51	20,69	5,03	15,00	6,80	NA	69,00	497,00	1,54
39,00	Zeilsheim	17,04	7,60	3407,93	16,94	17,84	49,48	50,60	27,58	31,25	25,12	5,84	18,69	7,40	NA	69,00	518,00	1,28
40,00	Unterliederbach	14,66	6,70	3547,20	16,70	14,77	49,71	55,20	28,52	32,82	24,63	5,25	16,00	10,90	NA	69,00	498,00	3,04
41,00	Sossenheim	21,27	8,60	3284,74	15,36	16,39	50,15	49,90	30,27	37,13	22,45	5,21	14,03	7,80	NA	69,00	513,00	0,29
42,00	Nieder-Erlenbach	5,85	3,00	4485,12	14,53	20,08	50,94	59,80	15,58	13,76	23,96	4,49	32,59	18,40	NA	47,00	729,00	0,00
43,00	Kalbach-Riedberg	4,20	2,70	5364,89	21,80	9,05	50,56	55,60	29,80	23,64	38,34	4,82	20,39	26,00	NA	45,00	578,00	0,55
44,00	Harheim	5,86	2,80	4278,63	17,40	16,72	50,30	58,20	15,77	16,15	28,62	4,08	25,28	18,90	NA	47,00	646,00	0,00
45,00	Nieder-Eschbach	14,85	5,40	3644,25	13,93	19,79	51,51	52,50	30,80	23,96	20,81	4,65	19,43	13,20	NA	47,00	733,00	0,68
46,00	Bergen-Enkheim	7,51	4,40	4022,52	12,92	21,89	51,40	58,30	20,36	20,10	19,74	4,07	20,23	16,50	NA	63,00	595,00	0,03
47,00	Frankfurter Berg	13,85	5,50	3777,17	15,78	14,59	50,42	53,90	31,67	27,34	26,57	4,74	17,35	14,50	NA	58,00	503,00	3,18
#Frankfurt	Frankfurt am Main	12,30	5,60	4173,86	13,58	15,74	50,39	57,30	24,58	29,98	18,76	4,08	13,62	21,70	NA	68,91	543,00	2,19

Appendix 4: All codes written for conducting the results

1. Composite index calculation: Cologne and Frankfurt separately

```
#Data input
# setup
library(vegan)
library(rgdal)
library(sp)
library(raster)
library(xlsx2dfs)
library(xlsx)

setwd("F:/01_Data_analysis_Thesis_2022")

##Frankfurt
#rCalculation composite indices Frankfurt}
Frankfurt.raw <- read.csv2("01_Frankfurt_final_R.csv", head=T)
F.stdz <- Frankfurt.raw
names(F.stdz)
names(F.stdz)[1] <- "ID"

F.stdz[,3:19] <- decostand(Frankfurt.raw[,3:19], method="range", na.rm = T)
summary(F.stdz)


#r Reversing values that decrease vulnerability; 1= highest vulnerability; 0= lowest vulnerability}
F.stdz.2 <- F.stdz
F.stdz.2 [,c(5,9,14,15,18,19)] <- 1- F.stdz[,c(5,9,14,15,18,19)]


#r Combining indicators to overal vulnerability categories}

(Frankfurt <- data.frame(id=F.stdz$ID,
                         name=F.stdz$Name,
                         economic=NA,
                         age=NA,
                         gender=NA,
                         natio=NA,
                         fam=NA,
                         educ=NA,
                         snp=NA,
                         house=NA,
                         infras=NA,
                         overall_vul=NA))


Frankfurt$economic <- rowMeans(F.stdz.2[,3:5], na.rm = T)
Frankfurt$age <- rowMeans(F.stdz.2[,6:7], na.rm = T)
Frankfurt$gender <- rowMeans(F.stdz.2[,8:9], na.rm = T)
Frankfurt$natio <- rowMeans(F.stdz.2[,10:11], na.rm = T)
Frankfurt$fam <- rowMeans(F.stdz.2[,12:13], na.rm = T)
Frankfurt$educ <- rowMeans(F.stdz.2[,14:15], na.rm = T)
Frankfurt$snp <- (F.stdz.2[,16])
Frankfurt$house <- (F.stdz.2[,17])
Frankfurt$infras <- rowMeans(F.stdz.2[,18:19], na.rm = T)

#overall vulnerability per district
Frankfurt$overall_vul <- rowMeans(Frankfurt[,3:11], na.rm = T)
summary(Frankfurt)

#save file
#write.xlsx(Frankfurt, file="Frankfurt_CI.xlsx", sheetName = "CI_FFM",col.names = TRUE, row.names = TRUE, append = TRUE)

#r identify districts with highest/ lowest vulnerability (<>mean+std}
##### Log normal distrbution
Flog <- Frankfurt
log10(Flog$overall_vul)
```

```
Flog[12] <-log10(Flog$overall_vul)
Frankfurt <- Flog
#####

SD_F=sd(Frankfurt[1:45,12])
Mean_F=mean(Frankfurt[1:45,12])

#areas with highest vulnerability scores:
High <- Mean_F+SD_F
Low <- Mean_F-SD_F

vul_districts <- Frankfurt[1:45,c(1,2,12)]
highV_districts <- subset(vul_districts, overall_vul>High)

lowV_districts <- subset(vul_districts, overall_vul<Low)

##check for normal distribution; 68-95-99.7 rule
#~68% of the values should between the Low and High values
check= subset(vul_districts, overall_vul<High & overall_vul>Low) #28(45) = 62,2%
high2 <- Mean_F+(2*SD_F)
low2 <- Mean_F-(2*SD_F)
check2= subset(vul_districts, overall_vul<high2 & overall_vul>low2) #45(45) =100%
28/45

#r Zonal statistics Frankfurt}
library(raster)
flood5 <- raster("water-depth_05_FFM.tif")
dist.F <- raster("FFM_districts_raster.tif")

FFM.stats <- zonal(flood5, dist.F, fun= 'mean', na.rm=T

##Cologne
#r Calculation composite indices Cologne

Cologne.raw <- read.csv2("02_Cologne_final_R.csv", head=T)
 C.stdz <- Cologne.raw
 names(C.stdz)
 names(C.stdz)[1] <- "ID"

 C.stdz[,3:19] <- decostand(Cologne.raw[,3:19], method="range", na.rm = T)
 summary(C.stdz)


 #r Reversing values that decrease vulnerability; 1= highest vulnerability; 0= lowest vulnerability}
 C.stdz.2 <- C.stdz
 C.stdz.2 [,c(5,9,14,15,18,19)] <- 1- C.stdz[,c(5,9,14,15,18,19)]

 #r Combining indicators to overal vulnerability categories}

 (Cologne <- data.frame(id=C.stdz$ID,
                          name=C.stdz$Name,
                          economic=NA,
                          age=NA,
                          gender=NA,
                          natio=NA,
                          fam=NA,
                          educ=NA,
                          snp=NA,
                          house=NA,
                          infras=NA,
                          overall_vul=NA))


 Cologne$economic <- rowMeans(C.stdz.2[,3:5], na.rm = T)
 Cologne$age <- rowMeans(C.stdz.2[,6:7], na.rm = T)
 Cologne$gender <- rowMeans(C.stdz.2[,8:9], na.rm = T)
 Cologne$natio <- rowMeans(C.stdz.2[,10:11], na.rm = T)
 Cologne$fam <- rowMeans(C.stdz.2[,12:13], na.rm = T)
 Cologne$educ <- rowMeans(C.stdz.2[,14:15], na.rm = T)
 Cologne$snp <- (C.stdz.2[,16])
```

```
Cologne$house <- (C.stdz.2[,17])
Cologne$infras <- rowMeans(C.stdz.2[,18:19], na.rm = T)

#overall vulnerability per district
Cologne$overall_vul <- rowMeans(Cologne[,3:11], na.rm = T)
summary(Cologne)

#save file
#write.xlsx(Cologne, file="Cologne_CI.xlsx", sheetName = "CI_Koeln",col.names = TRUE, row.names = TRUE, append = TRUE)


#r identify districts with highest/ lowest vulnerability (<>mean+std}
SD_C=sd(Cologne[1:86,12])
Mean_C=mean(Cologne[1:86,12])

#areas with highest vulnerability scores:
High.C <- Mean_C+SD_C
Low.C <- Mean_C-SD_C

vul_C <- Cologne[1:86,c(1,2,12)]
highV_dist_C <- subset(vul_C, overall_vul>High.C)

lowV_dist_C <- subset(vul_C, overall_vul<Low.C)

##check for normal distribution; 68-95-99.7 rule
#~68% of the values should between the Low and High values
check= subset(vul_C, overall_vul<High.C & overall_vul>Low.C) #65(86) = 75,6%
high2 <- Mean_C+(2*SD_C)
low2 <- Mean_C-(2*SD_C)
check2= subset(vul_C, overall_vul<high2 & overall_vul>low2) #82(86) =95,4%
82/86*100

```

9. Boxplots: Calculation of determinants of vulnerabilities in the cities' high and low vulnerability districts (Cologne and Frankfurt separately):

```
 ## setup

install.packages("tidyverse")
library(tidyverse)
library("ggplot2")

setwd("F:/01_Data_analysis_Thesis_2022")

FFM.oneS <- read.csv2("Boxplots_R_FFM.csv", head=T)
FFM.new <- read.csv2("Boxplots_R_FFM_2.csv", head=T)
Col.oneS <- read.csv2("Boxplots_R_Col.csv", head=T)
Col.new <- read.csv2("Boxplots_R_Col_2.csv", head=T)

F.1 <- FFM.oneS
F.new <- FFM.new
C.1 <- Col.oneS
C.new <-Col.new

names(F.1)
names(F.1)[1] <- "Group"
names(F.new)[1] <- "Group"
names(C.1)[1] <- "Group"
names(C.new)[1] <- "Group"



##Main plots
plot1 <- ggplot(data= C.new) +  # ggplot function
  geom_boxplot(mapping= aes(x = Group, y = Value, color = Group))+
  facet_wrap(~Variable, nrow=2)
print(plot1 + ggtitle("Cologne")+labs(y= "Vulnerability CI Score", x=""))+
```

```
  theme_bw()+
  theme(axis.ticks.x=element_blank(),
             axis.text.x=element_blank())


plot2 <- ggplot(data= F.new) +  # ggplot function
  geom_boxplot(mapping= aes(x = Group, y = Value, color = Group))+
  facet_wrap(~Variable, nrow=2)
print(plot2 + ggtitle("Frankfurt")+labs(y= "Vulnerability CI Score", x=""))+
  theme_bw()+
  theme(axis.ticks.x=element_blank(),
        axis.text.x=element_blank())


## Test plots/ plots per concept
qplot(x=F.1[1:9,4], geom="boxplot") #rows with high vul, column economic status
qplot(y=F.1[1:9,4], x= "",geom="boxplot")

qplot(y=F.1[1:9,4], x= "",geom="boxplot", col=I("darkblue"))
qplot(y=F.1[1:9,4], x= "",geom="boxplot", col=I("darkblue"), fill=I("lightblue"))

qplot(y=F.1[1:9,4], x= "",geom="boxplot", col=I("darkblue"), fill=I("lightblue"), ylab= "Vulnerability Composite Index scores")

qplot(y=F.1[1:9,4], x= "",geom="boxplot", col=I("darkblue"), fill=I("lightblue"), ylab= "Vulnerability Composite Index scores", main="Frankfurt")

qplot(data=F.1, x=Group, y=Overall.vulnerability, geom = "boxplot")
qplot(data=F.1, x=Group, y=Economic.status, geom = "boxplot")
qplot(data=F.1, x=Group, y=Age, geom = "boxplot")
qplot(data=F.1, x=Group, y=Gender, geom = "boxplot")
qplot(data=F.1, x=Group, y=Nationality, geom = "boxplot")
qplot(data=F.1, x=Group, y=Family.structure, geom = "boxplot")
qplot(data=F.1, x=Group, y=Education, geom = "boxplot")
qplot(data=F.1, x=Group, y=Housing, geom = "boxplot")
qplot(data=F.1, x=Group, y=Infrastructure, geom = "boxplot")

ggplot(data=F.1, aes(x=Group, y=Housing))+geom_boxplot(color= "red")
boxplot(F.1[1:9,4:11]) #high vuln
boxplot(F.1[11:18,4:11]) #low

ggplot(data= F.new) +  # ggplot function
  geom_boxplot(mapping = aes(x = Variable, y = Value, color = Group, ylab= "Vulnerability Composite Index Scores"))

ggplot(C.new, aes(x = Variable, y = Value, color =Group)) +  # ggplot function geom_boxplot()

```

10. Correlation between dimensions: calculations and display:

```
 ##setup

install.packages("corrplot")
library(corrplot)

setwd("F:/01_Data_analysis_Thesis_2022")

Ccor <- read.csv2("CologneCI.csv", head=T)

names(Ccor)[1] <- "econ"

M = Ccor[,1:8]
M = cor(M)
Fcor <-read.csv2("FrankfCI.csv", head=T)
names(Fcor)[1] <- "econ"
MF = cor(Fcor)
```

```

##Plot Cologne
corrplot(M, method= 'circle',
         addCoef.col='black',
         title= "Cologne: All 86 Districts",
         mar=c(0,0,1,0))
corrplot(M, method= 'circle', order = 'hclust', addrect = 2)
corrplot(M, method= 'number', order = 'hclust')
corrplot(M, method= 'circle', order='AOE')



##Plot Frankfurt
corrplot(MF, method= 'circle',
         addCoef.col='black',
         title= "Frankfurt: All 45 Districts",
         mar=c(0,0,1,0))
corrplot(MF, method= 'circle', order = 'hclust', addrect = 3, addCoef.col='black')
corrplot(MF, method= 'number', order = 'hclust')
corrplot(MF, order = 'hclust', addCoef.col='black')
corrplot(MF, method= 'circle', order='AOE')

#boxplots only with low and high vul districts
Cc <- read.csv2("Boxplots_R_Col_2.csv", head=T)
names(Cc)[3] <- "econ"
L = Cc[,3:10]
L=cor(L)
corrplot(L, method= 'circle',
        addCoef.col='black',
         title= "Cologne: Districs beyond 1 Std Dev of Mean",
         mar=c(0,0,1,0))

Fc <- read.csv2("Boxplots_R_FFM_2.csv", head=T)
names(Fc)[3] <- "econ"
K = Fc[,3:10]
K=cor(K)
corrplot(K, method= 'circle',
        addCoef.col='black',
         title= "Districs beyond 1 Std Dev of Mean (Frankfurt)",
         mar=c(0,0,1,0))

## Rank magnitude of difference withing mean/ median of concepts
library(tidyverse)
library("ggplot2")

setwd("F:/01_Data_analysis_Thesis_2022")

FFM.new <- read.csv2("Boxplots_R_FFM.csv", head=T)
Col.new <- read.csv2("Boxplots_R_Col.csv", head=T)

F.new <- FFM.new
C.new <-Col.new

names(F.new)[1] <- "Group"
names(C.new)[1] <- "Group"


## calculate Median Cologne / make table

medianE <- aggregate(x = C.new$economic,
            by = list(C.new$Group),
            FUN = median)
medianA <- aggregate(x = C.new$age,
                     by = list(C.new$Group),
                     FUN = median)
medianG <- aggregate(x = C.new$gender,
                     by = list(C.new$Group),
                     FUN = median)
medianN <- aggregate(x = C.new$natio,
                     by = list(C.new$Group),
                     FUN = median)
```

```
medianF <- aggregate(x = C.new$fam,
                     by = list(C.new$Group),
                     FUN = median)
medianED <- aggregate(x = C.new$educ,
                     by = list(C.new$Group),
                     FUN = median)
medianSNP <- aggregate(x = C.new$snp,
                     by = list(C.new$Group),
                     FUN = median)
medianI <- aggregate(x = C.new$infras,
                     by = list(C.new$Group),
                     FUN = median)
medianO <- aggregate(x = C.new$overall_vul,
                     by = list(C.new$Group),
                     FUN = median)

(CologneMedian <- data.frame(group=medianE$Group.1,
                         economic=medianE$x,
                         age=medianA$x,
                         gender=medianG$x,
                         natio=medianN$x,
                         fam=medianF$x,
                         educ=medianED$x,
                         snp=medianSNP$x,
                         house=NA, #not cologne
                         infras=medianI$x,
                         overall_vul=medianO$x))

CMedian <-CologneMedian[2:3,]
CMedian

## calculate Median Frankfurt / make table

medianE <- aggregate(x = F.new$economic,
                     by = list(F.new$Group),
                     FUN = median)
medianA <- aggregate(x = F.new$age,
                     by = list(F.new$Group),
                     FUN = median)
medianG <- aggregate(x = F.new$gender,
                     by = list(F.new$Group),
                     FUN = median)
medianN <- aggregate(x = F.new$natio,
                     by = list(F.new$Group),
                     FUN = median)
medianF <- aggregate(x = F.new$fam,
                     by = list(F.new$Group),
                     FUN = median)
medianED <- aggregate(x = F.new$educ,
                      by = list(F.new$Group),
                      FUN = median)
medianH <- aggregate(x = F.new$house,
                       by = list(F.new$Group),
                       FUN = median)
medianI <- aggregate(x = F.new$infras,
                     by = list(F.new$Group),
                     FUN = median)
medianO <- aggregate(x = F.new$overall_vul,
                     by = list(F.new$Group),
                     FUN = median)

(FrankfurtMedian <- data.frame(group=medianE$Group.1,
                               economic=medianE$x,
                               age=medianA$x,
                               gender=medianG$x,
                               natio=medianN$x,
                               fam=medianF$x,
                               educ=medianED$x,
                               snp=NA,
                               house=medianH$x, #not cologne
                               infras=medianI$x,
```

```
                                  overall_vul=medianO$x))
FMedian <- FrankfurtMedian

```

11. Correlation between exposure and the IVI for all three return periods (Cologne and Frankfurt separately):

```
 #setup
install.packages("cowplot")
install.packages("ggpmisc")
install.packages("ggpubr")
library("ggpubr")
library("ggpmisc")
library(tidyverse)
library(ggplot2)
library(cowplot)
library(corrplot)
library(dplyr)
library(gridExtra)
library(ggrepel)

setwd("F:/01_Data_analysis_Thesis_2022/Exposure_stats")
F.5y <- read.csv2("FFM_5yrs.csv", head=T)
F.10y <- read.csv2("FFM_10yrs.csv", head=T)
F.50y <- read.csv2("FFM_50yrs.csv", head=T)

names(F.5y)[9] <- "percent_f"
names(F.5y)[3] <- "vul_s"
names(F.50y)[9] <- "percent_f"
names(F.50y)[3] <- "vul_s"
names(F.10y)[9] <- "percent_f"
names(F.10y)[3] <- "vul_s"

C.5y <- read.csv2("C_5yrs.csv", head=T)
C.10y <- read.csv2("C_10yrs.csv", head=T)
C.50y <- read.csv2("C_50yrs.csv", head=T)

names(C.5y)[9] <- "percent_f"
names(C.5y)[3] <- "vul_s"
names(C.50y)[9] <- "percent_f"
names(C.50y)[3] <- "vul_s"
names(C.10y)[9] <- "percent_f"
names(C.10y)[3] <- "vul_s"



tab <- as.data.frame(rbind(c(0.5526,0.6133), c(0.0634,0.1391), c(0.1608, 0.1391)))
dimnames(tab) <- list(Flooding = c("%", "max", "mean"),
                      Spearman_Corr = c("rho", "p.value"))
tab

# Plot C 50
##percent ploty = percent_f
C.50y$outliers <- NA

C.50y[c(which(C.50y$vul_s > 0.72), which(C.50y$vul_s < 0.2)),"outliers"] <-
as.character(C.50y[c(which(C.50y$vul_s > 0.72), which(C.50y$vul_s < 0.2)),"name"])

C.50y[c(which(C.50y$percent_f > 15), which(C.50y$percent_f < 0)),"outliers"] <-
as.character(C.50y[c(which(C.50y$percent_f > 15), which(C.50y$percent_f < 0)),"name"])

percent <- ggplot(data= C.50y, aes(x = vul_s,y =percent_f))+
  geom_point()+
  geom_smooth(col = "darkgrey")+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
```

```
                   label.size=NA,
                   label.padding = 0.1,
                   label.r=0)+
  theme_bw()


percent2<- print(percent + ggtitle("Cologne 50-yrs return period")+labs(x= "", y="% of area flooded"))

percent2 <- percent2+
  stat_cor(method = "spearman", label.x = 0.3, label.y = 0.1)



##Max plot
C.50y$outliers <- NA

C.50y[c(which(C.50y$vul_s > 0.72), which(C.50y$vul_s < 0.2)),"outliers"] <- as.character(C.50y[c(which(C.50y$vul_s > 0.72), which(C.50y$vul_s < 0.2)),"name"])

C.50y[c(which(C.50y$X_max > 4), which(C.50y$X_max < 0)),"outliers"] <- as.character(C.50y[c(which(C.50y$X_max > 4), which(C.50y$X_max < 0)),"name"])

max <-ggplot(data= C.50y, mapping= aes(x = vul_s, y = X_max)) +
  geom_point()+
  geom_smooth(col = "darkgrey")+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
                   label.size=NA,
                   label.padding = 0.1,
                   label.r=0)+
  theme_bw()

max2<- print(max +labs(x= "", y="max water depth (m)"))

max2<- max2+
  stat_cor(method = "spearman", label.x = 0.3, label.y = 0.1, r.label ="rho")

#Mean plot

C.50y$outliers <- NA

 C.50y[c(which(C.50y$vul_s > 0.72), which(C.50y$vul_s < 0.2)),"outliers"] <- as.character(C.50y[c(which(C.50y$vul_s > 0.72), which(C.50y$vul_s < 0.2)),"name"])

 C.50y[c(which(C.50y$X_mean > 0.45), which(C.50y$X_mean < 0)),"outliers"] <- as.character(C.50y[c(which(C.50y$X_mean > 0.45), which(C.50y$X_mean < 0)),"name"])
 mean <- ggplot(data= C.50y, mapping= aes(x = vul_s, y = X_mean)) +
   geom_point()+
   geom_smooth(col = "darkgrey")+
   geom_label_repel(aes(label = outliers),
                    na.rm = TRUE,
                    min.segment.length = 0,
                    max.overlaps = Inf,
                    label.size=NA,
                    label.padding = 0.1,
                    label.r=0)+
   theme_bw()

 mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))

 mean2 <- mean2+
   stat_cor(method = "spearman", label.x = 0.3, label.y = 0.1)


 C50y <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)


 C50y
```

```r



# Plot C 10
##percent plot
percent <- ggplot(data= C.10y, mapping=aes(y = percent_f,x = vul_s, ))+
  geom_point()+
  geom_smooth(col = "blue")

percent2<- print(percent + ggtitle("Cologne 10-yrs return period")+labs(x= "", y="% of area flooded"))

percent2 <- percent2+
  stat_cor(method = "spearman", label.x = 0.6, label.y = 19)

##Max plot
max <-ggplot(data= C.10y, mapping= aes(x = vul_s, y = X_max)) +
  geom_point()+
  geom_smooth(col = "blue")

max2<- print(max +labs(x= "", y="max water depth (m)"))

max2<- max2+
  stat_cor(method = "spearman", label.x = 0.6, label.y = 4.75)

#Mean plot
mean <- ggplot(data= C.10y, mapping= aes(x = vul_s, y = X_mean)) +
  geom_point()+
  geom_smooth(col = "blue")

mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))

mean2 <- mean2+
  stat_cor(method = "spearman", label.x = 0.6, label.y = 0.47)


C10y <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)


C10y

# Plot C 5
##percent plot
percent <- ggplot(data= C.5y, mapping=aes(y = percent_f,x = vul_s, ))+
  geom_point()+
  geom_smooth(col = "blue")

percent2<- print(percent + ggtitle("Cologne 5-yrs return period")+labs(x= "", y="% of area flooded"))

percent2 <- percent2+
  stat_cor(method = "spearman", label.x = 0.6, label.y = 19)

##Max plot
max <-ggplot(data= C.5y, mapping= aes(x = vul_s, y = X_max)) +
  geom_point()+
  geom_smooth(col = "blue")

max2<- print(max +labs(x= "", y="max water depth (m)"))

max2<- max2+
  stat_cor(method = "spearman", label.x = 0.6, label.y = 4.75)

#Mean plot
mean <- ggplot(data= C.5y, mapping= aes(x = vul_s, y = X_mean)) +
  geom_point()+
  geom_smooth(col = "blue")

mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))

mean2 <- mean2+
```

```
  stat_cor(method = "spearman", label.x = 0.6, label.y = 0.41)

C5y <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)

C5y

# Plot F 50
##percent plot
F.50y <- F.50y[,1:9]
F.50y$outliers <- NA

F.50y[c(which(F.50y$vul_s > 0.72), which(F.50y$vul_s < 0.2)),"outliers"] <- as.character(F.50y[c(which(F.50y$vul_s > 0.72), which(F.50y$vul_s < 0.2)),"STTLNAME"])

F.50y[c(which(F.50y$percent_f > 11), which(F.50y$percent_f < 0)),"outliers"] <- as.character(F.50y[c(which(F.50y$percent_f > 11), which(F.50y$percent_f < 0)),"STTLNAME"])

percent <- ggplot(data= F.50y, mapping=aes(y = percent_f,x = vul_s, ))+
  geom_point()+
  geom_smooth(col = "darkgrey")+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
                   label.size=NA,
                   label.padding = 0.1,
                   label.r=0)+
  theme_bw()

percent2<- print(percent + ggtitle("Frankfurt 50-yrs return period")+labs(x= "", y="% of area flooded"))

percent2 <- percent2+
  stat_cor(method = "spearman", label.x = 0.45, label.y = 0.1)

##Max plot
F.50y$outliers <- NA

F.50y[c(which(F.50y$vul_s > 0.72), which(F.50y$vul_s < 0.2)),"outliers"] <- as.character(F.50y[c(which(F.50y$vul_s > 0.72), which(F.50y$vul_s < 0.2)),"STTLNAME"])

F.50y[c(which(F.50y$X_max > 6), which(F.50y$X_max < 0)),"outliers"] <- as.character(F.50y[c(which(F.50y$X_max > 6), which(F.50y$X_max < 0)),"STTLNAME"])

max <-ggplot(data= F.50y, mapping= aes(x = vul_s, y = X_max)) +
  geom_point()+
  geom_smooth(col = "darkgrey")+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
                   label.size=NA,
                   label.padding = 0.1,
                   label.r=0)+
  theme_bw()

max2<- print(max +labs(x= "", y="max water depth (m)"))

max2<- max2+
  stat_cor(method = "spearman", label.x = 0.45, label.y = 0.1)
```

```
#Mean plot
F.50y$outliers <- NA

F.50y[c(which(F.50y$vul_s > 0.72), which(F.50y$vul_s < 0.2)),"outliers"] <- as.character(F.50y[c(which(F.50y$vul_s > 0.72), which(F.50y$vul_s < 0.2)),"STTLNAME"])

F.50y[c(which(F.50y$X_mean > 0.6), which(F.50y$X_mean < 0)),"outliers"] <- as.character(F.50y[c(which(F.50y$X_mean > 0.6), which(F.50y$X_mean < 0)),"STTLNAME"])

mean <- ggplot(data= F.50y, mapping= aes(x = vul_s, y = X_mean)) +
  geom_point()+
  geom_smooth(col = "darkgrey")+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
                   label.size=NA,
                   label.padding = 0.1,
                   label.r=0)+
  theme_bw()

mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))

mean2 <- mean2+
  stat_cor(method = "spearman", label.x = 0.45, label.y = 0.1)

FFM50y <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)


FFM50y

# Plot F 10
##percent plot
percent <- ggplot(data= F.10y, mapping=aes(y = percent_f,x = vul_s, ))+
  geom_point()+
  geom_smooth(col = "blue")

percent2<- print(percent + ggtitle("Frankfurt 10-yrs return period")+labs(x= "", y="% of area flooded"))

percent2 <- percent2+
  stat_cor(method = "spearman", label.x = 0.66, label.y = 11.5)

##Max plot
max <-ggplot(data= F.10y, mapping= aes(x = vul_s, y = X_max)) +
  geom_point()+
  geom_smooth(col = "blue")

max2<- print(max +labs(x= "", y="max water depth (m)"))

max2<- max2+
  stat_cor(method = "spearman", label.x = 0.66, label.y = 6.5)

#Mean plot
mean <- ggplot(data= F.10y, mapping= aes(x = vul_s, y = X_mean)) +
  geom_point()+
  geom_smooth(col = "blue")

mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))

mean2 <- mean2+
  stat_cor(method = "spearman", label.x = 0.66, label.y = 0.7)

FFM10y <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)


FFM10y

# Plot F 5
##percent plot
percent <- ggplot(data= F.5y, mapping=aes(y = percent_f,x = vul_s, ))+
```

```
 percent2<- print(percent + ggtitle("Frankfurt 5-yrs return period")+labs(x= "", y="% of area flooded"))

 percent2 <- percent2+
   stat_cor(method = "spearman", label.x = 0.66, label.y = 10.5)

 ##Max plot
 max <-ggplot(data= F.5y, mapping= aes(x = vul_s, y = X_max)) +
   geom_point()+
   geom_smooth(col = "blue")

 max2<- print(max +labs(x= "", y="max water depth (m)"))

 max2<- max2+
   stat_cor(method = "spearman", label.x = 0.66, label.y = 6.5)

 #Mean plot
 mean <- ggplot(data= F.5y, mapping= aes(x = vul_s, y = X_mean)) +
   geom_point()+
   geom_smooth(col = "blue")

 mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))

 mean2 <- mean2+
   stat_cor(method = "spearman", label.x = 0.66, label.y = 0.7)

 FFM5y <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)


 FFM5y
```

12. Composite index calculation: Cologne and Frankfurt combined:

```
 #Data input
library(vegan)
library(rgdal)
library(sp)
library(raster)
library(xlsx2dfs)
library(xlsx)

setwd("F:/01_Data_analysis_Thesis_2022")

##Frankfurt
#rCalculation composite indices Frankfurt}
FC.raw <- read.csv2("F_C_compare_R.csv", head=T)
FC.stdz <- FC.raw
names(FC.stdz)
names(FC.stdz)[1] <- "City"

FC.stdz[,4:15] <- decostand(FC.raw[,4:15], method="range", na.rm = T)
summary(FC.stdz)

#r Reversing values that decrease vulnerability; 1= highest vulnerability; 0= lowest vulnerability}
FC.stdz.2 <- FC.stdz
FC.stdz.2 [,c(13,14,15)] <- 1- FC.stdz[,c(13,14,15)]


#r Combining indicators to overal vulnerability categories}

(Cities <- data.frame(id=FC.stdz$ID,
                         name=FC.stdz$Name,
                      city=FC.stdz$City,
```

```r
                         economic=NA,
                         age=NA,
                         gender=NA,
                         natio=NA,
                         fam=NA,
                         educ=NA,
                         infras=NA,
                         overall_vul=NA))
Cities$economic <- rowMeans(FC.stdz.2[,4:5], na.rm = T)
Cities$age <- rowMeans(FC.stdz.2[,6:7], na.rm = T)
Cities$gender <- (FC.stdz.2[,8])
Cities$natio <- rowMeans(FC.stdz.2[,9:10], na.rm = T)
Cities$fam <- rowMeans(FC.stdz.2[,11:12], na.rm = T)
Cities$educ <- rowMeans(FC.stdz.2[,13:14], na.rm = T)
Cities$infras <- (FC.stdz.2[,15])
#overall vulnerability per district
Cities$overall_vul <- rowMeans(Cities[,4:10], na.rm = T)
summary(Cities)
#save file
#write.xlsx(Cities, file="Cities_CI.xlsx", sheetName = "CI_Cities",col.names = TRUE, row.names = TRUE, append = TRUE)
CrF <-Cities [1:86,]      #all districts Cologne with values relative to Frankfurt
FrC <- Cities[87:131,]   #all districts Frankfurt with values relative to Cologne
#r identify districts in Frankfurt with highest/ lowest vulnerability (<>mean+std}
SD_F=sd(FrC[,11])      #column 11 is column with overall IVI (vulnerability) score
Mean_F=mean(FrC[,11])
SD_C=sd(CrF[,11])      #column 11 is column with overall IVI (vulnerability) score
Mean_C=mean(CrF[,11])
#areas with highest vulnerability scores:
High <- Mean_F+SD_F
Low <- Mean_F-SD_F
High_C <- Mean_C+SD_C
Low_C <- Mean_C-SD_C
vul_districts <- FrC[1:45,c(1,2,3,11)]
highV_districts <- subset(vul_districts, overall_vul>High)
lowV_districts <- subset(vul_districts, overall_vul<Low)
vul_districtsC <- CrF[1:86,c(1,2,3,11)]
highV_districtsC <- subset(vul_districtsC, overall_vul>High_C)
lowV_districtsC <- subset(vul_districtsC, overall_vul<Low_C)
#write.xlsx(highV_districts, file="highV_districts.xlsx", sheetName = "highV_districts",col.names = TRUE, row.names = TRUE, append = TRUE)
#write.xlsx(lowV_districts, file="lowV_districts.xlsx", sheetName = "lowV_districts",col.names = TRUE, row.names = TRUE, append = TRUE)
#r Histogram}
p1 <- hist(CrF$overall_vul,30)                      # centered at 4
p2 <- hist(FrC$overall_vul,16)
plot( p1, col=rgb(0,0,1,1/4), xlim=c(0,1),main="Frequency distribution of Vulnerabilities in the two Cities",
        xlab="CI Vulnerability Scores relative to each other",
        ylab="Frequency", #86 districts to 45 districts
        sub="Cologne=blue, Frankfurt=red")  # first histogram
lines(density(CrF$overall_vul), col="blue", lwd=3) # add a density estimate with defaults
lines(density(CrF$overall_vul, adjust=2), lty="dotted", col="darkblue", lwd=3)
p4 <-plot( p2, col=rgb(1,0,0,1/4), xlim=c(0,1), add=T)  # second
lines(density(FrC$overall_vul), col="red", lwd=3) # add a density estimate with defaults
```

```r
lines(density(FrC$overall_vul, adjust=2), lty="dotted", col="darkred", lwd=3)

 rangeC <- range(CrF$overall_vul)
 rangeC

 library(psych)


 #r create summary tables descriptive statostic}

 (Cstats <- data.frame(City= 'Cologne',
                       mean=mean(CrF$overall_vul),
                       min=min(CrF$overall_vul),
                       max=max(CrF$overall_vul),
                       std.dev=sd(CrF$overall_vul),
                       range=range(CrF$overall_vul)))
 Cstats[2,2:5] <- NA
 Cstats

 (Fstats <- data.frame(City= 'Frankfurt',
                       mean=mean(FrC$overall_vul),
                       min=min(FrC$overall_vul),
                       max=max(FrC$overall_vul),
                       std.dev=sd(FrC$overall_vul),
                       range=range(FrC$overall_vul)))
 Fstats[2,2:5] <- NA
 Fstats

 StatsComp <-rbind(Cstats, Fstats)
 write.xlsx(StatsComp, file="StatsComp.xlsx", sheetName = "stats",col.names = TRUE, row.names = TRUE, append = TRUE)


```

13. Boxplots: Calculation of determinants of vulnerabilities in the cities' high and low vulnerability districts (Cologne and Frankfurt combined):

```r
 ## setup

install.packages("tidyverse")
library(tidyverse)
library("ggplot2")
library(xlsx2dfs)
library(xlsx)

setwd("F:/01_Data_analysis_Thesis_2022")

Cities2 <- read.csv2("Boxplots_cities_R.csv", head=T)
compC <-Cities2
names(compC)[1] <- "Group"

colors <- scale_colour_manual(values=c('#ca0020', '#0571b0', '#f4a582', '#92c5de'))

##Main plots
plot1 <- ggplot(data= compC) +  # ggplot function
  geom_boxplot(mapping= aes(x = Group, y = Value, color = Group))+
  facet_wrap(~Variable, nrow=4)

plot1 <- plot1 +
  scale_colour_manual(values=c('#ca0020', '#0571b0', '#f4a582', '#92c5de'))

plot1 <- plot1 +
  scale_colour_manual(values=c('#d01c8b', '#4dac26', '#f1b6da', '#b8e186'))

print(plot1 + ggtitle("Cologne and Frankfurt")+labs(y= "Vulnerability CI Score", x=""))+
       theme(axis.ticks.x=element_blank(),
             axis.text.x=element_blank())

```

```
write.xlsx(Cities2, file="Cities-comp_1STD-DEV.xlsx", sheetName = "1",col.names = TRUE,
row.names = TRUE, append = TRUE)

```

14. Correlation between exposure and the IVI for all three return periods (Cologne and Frankfurt combined):

```
 #setup
install.packages("cowplot")
library(tidyverse)
library(ggplot2)
library(cowplot)
library(corrplot)
library(ggrepel)

setwd("F:/01_Data_analysis_Thesis_2022/Cities comparison/Exposure comparison")

y5 <- read.csv2("5yrs.csv", head=T)
y10 <- read.csv2("10yrs.csv", head=T)
y50 <- read.csv2("50yrs.csv", head=T)


names(y5)[9] <- "percent_f"
names(y5)[3] <- "vul_s"
names(y10)[9] <- "percent_f"
names(y10)[3] <- "vul_s"
names(y50)[9] <- "percent_f"
names(y50)[3] <- "vul_s"


#Specify labels
#make a new field in your dataframe
#y5

y5$outliers <- NA

y5[c(which(y5$vul_s > 0.75), which(y5$vul_s < 0.2)),"outliers"] <-
as.character(y5[c(which(y5$vul_s > 0.75), which(y5$vul_s < 0.2)),"name"])

y5[c(which(y5$percent_f > 14), which(y5$percent_f < 0)),"outliers"] <-
as.character(y5[c(which(y5$percent_f > 14), which(y5$percent_f < 0)),"name"])


#r F&C 5 yrs}
# Plot F 5
##percent plot
percent <- ggplot(data= y5, mapping=aes(y = percent_f,x = vul_s, color= City, pch=City))+
geom_point()+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
                   label.size=NA,
                   label.padding = 0.1,
                   label.r=0)+
  theme_bw()


percent2<- print(percent + ggtitle("5-yrs return period")+labs(x= "", y="% of area
flooded"))


##Max plot
y5$outliers <- NA

y5[c(which(y5$vul_s > 0.75), which(y5$vul_s < 0.2)),"outliers"] <-
as.character(y5[c(which(y5$vul_s > 0.75), which(y5$vul_s < 0.2)),"name"])

```

```
y5[c(which(y5$X_max > 6), which(y5$X_max < 0)),"outliers"] <-
as.character(y5[c(which(y5$X_max > 6), which(y5$X_max < 0)),"name"])
max <-ggplot(data= y5, mapping= aes(x = vul_s, y = X_max, color= City, pch= City)) +
  geom_point()+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
                   label.size=NA,
                   label.padding = 0.2,
                   label.r=0)+
  theme_bw()
max2<- print(max +labs(x= "", y="max water depth (m)"))
#Mean plot
y5$outliers <- NA
y5[c(which(y5$vul_s > 0.75), which(y5$vul_s < 0.2)),"outliers"] <-
as.character(y5[c(which(y5$vul_s > 0.75), which(y5$vul_s < 0.2)),"name"])
y5[c(which(y5$X_mean > 0.6), which(y5$X_mean < 0)),"outliers"] <-
as.character(y5[c(which(y5$X_mean > 0.6), which(y5$X_mean < 0)),"name"])
mean <- ggplot(data= y5, mapping= aes(x = vul_s, y = X_mean, color=City, pch =City)) +
  geom_point()+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
                   label.size=NA,
                   label.padding = 0.2,
                   label.r=0)+
  theme_bw()
mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))
fivey <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)
fivey
 #rPlot 10 yrs return period}
 ##percent plot
 percent <- ggplot(data= y10, mapping=aes(y = percent_f,x = vul_s, color= City,
pch=City ))+
   geom_point()+
   theme_bw()
 percent2<- print(percent + ggtitle("10-yrs return period")+labs(x= "", y="% of area
flooded"))
 percent2
 ##Max plot
 max <-ggplot(data= y10, mapping= aes(x = vul_s, y = X_max, color= City, pch= City)) +
   geom_point()+
   theme_bw()
 max2<- print(max +labs(x= "", y="max water depth (m)"))
 #Mean plot
 mean <- ggplot(data= y10, mapping= aes(x = vul_s, y = X_mean, color=City, pch =City)) +
   geom_point()+
   theme_bw()
```

```

mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))



teny <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)


teny


#r Plot 50 yrs return period}

##percent plot
y50$outliers <- NA

y50[c(which(y50$vul_s > 0.75), which(y50$vul_s < 0.2)),"outliers"] <- as.character(y50[c(which(y50$vul_s > 0.75), which(y50$vul_s < 0.2)),"name"])

y50[c(which(y50$percent_f > 14), which(y50$percent_f < 0)),"outliers"] <- as.character(y50[c(which(y50$percent_f > 14), which(y50$percent_f < 0)),"name"])


percent <- ggplot(data= y50, mapping=aes(y = percent_f,x = vul_s, color= City, pch=City ))+
  geom_point()+
  geom_label_repel(aes(label = outliers),
                  na.rm = TRUE,
                  min.segment.length = 0,
                  max.overlaps = Inf,
                  label.size=NA,
                  label.padding = 0.2,
                  label.r=0)+
  theme_bw()

percent2<- print(percent + ggtitle("50-yrs return period")+labs(x= "", y="% of area flooded"))


##Max plot
y50$outliers <- NA

y50[c(which(y50$vul_s > 0.75), which(y50$vul_s < 0.2)),"outliers"] <- as.character(y50[c(which(y50$vul_s > 0.75), which(y50$vul_s < 0.2)),"name"])

y50[c(which(y50$X_max > 6), which(y50$X_max < 0)),"outliers"] <- as.character(y50[c(which(y50$X_max > 6), which(y50$X_max < 0)),"name"])


max <-ggplot(data= y50, mapping= aes(x = vul_s, y = X_max, color= City, pch= City)) +
  geom_point()+
  geom_label_repel(aes(label = outliers),
                  na.rm = TRUE,
                  min.segment.length = 0,
                  max.overlaps = Inf,
                  label.size=NA,
                  label.padding = 0.2,
                  label.r=0)+
  theme_bw()

max2<- print(max +labs(x= "", y="max water depth (m)"))


#Mean plot
y50$outliers <- NA

y50[c(which(y50$vul_s > 0.75), which(y50$vul_s < 0.2)),"outliers"] <- as.character(y50[c(which(y50$vul_s > 0.75), which(y50$vul_s < 0.2)),"name"])

y50[c(which(y50$X_mean > 0.6), which(y50$X_mean < 0)),"outliers"] <- as.character(y50[c(which(y50$X_mean > 0.6), which(y50$X_mean < 0)),"name"])
```

```


mean <- ggplot(data= y50, mapping= aes(x = vul_s, y = X_mean, color=City, pch =City)) +
  geom_point()+
  geom_label_repel(aes(label = outliers),
                   na.rm = TRUE,
                   min.segment.length = 0,
                   max.overlaps = Inf,
                   label.size=NA,
                   label.padding = 0.2,
                   label.r=0)+
  theme_bw()

mean2<- print(mean +labs(x= "CI Vulnerability Score", y="mean water depth (m)"))



fivtyy <-plot_grid(percent2, max2, mean2, labels=c("A", "B", "C"), ncol=1, nrow=3)


fivtyy

```

Appendix 5: All districts with ID and concept and IVI scores (First Cologne then Frankfurt)

Cologne

ID	Name	economic	age	gender	natio	fam	educ	snp	house	infras	IVI score
101	Altstadt-Süd	0,27	0,16	0,44	0,20	0,02	0,33	0,47		0,97	0,36
102	Neustadt-Süd	0,21	0,09	0,46	0,14	0,10	0,11	0,47		0,99	0,32
103	Altstadt-Nord	0,26	0,12	0,17	0,25	0,00	0,30	0,47		0,82	0,30
104	Neustadt-Nord	0,17	0,17	0,44	0,15	0,09	0,07	0,47		0,88	0,31
105	Deutz	0,22	0,20	0,49	0,20	0,16	0,32	0,47		0,67	0,34
201	Bayenthal	0,15	0,36	0,48	0,23	0,28	0,27	0,37		0,80	0,37
202	Marienburg	0,18	0,43	0,48	0,27	0,32	0,39	0,37		0,72	0,39
203	Raderberg	0,32	0,27	0,55	0,26	0,35	0,54	0,37		0,93	0,45
204	Raderthal	0,23	0,51	0,69	0,13	0,34	0,52	0,37		0,87	0,46
205	Zollstock	0,23	0,34	0,69	0,20	0,24	0,51	0,37		0,94	0,44
206	Rondorf	0,17	0,53	0,61	0,18	0,39	0,62	0,37		0,77	0,45
207	Hahnwald	0,00	0,61	0,36	0,12	0,40	0,14	0,37		0,00	0,25
208	Rodenkirchen	0,11	0,62	0,83	0,12	0,29	0,30	0,37		0,81	0,43
209	Weiß	0,15	0,63	0,69	0,07	0,46	0,45	0,37		0,79	0,45
210	Sürth	0,13	0,47	0,65	0,13	0,43	0,42	0,37		0,67	0,41
211	Godorf	0,40	0,43	0,00	0,38	0,38	0,96	0,37		0,59	0,44
212	Immendorf	0,28	0,51	0,50	0,26	0,48	0,80	0,37		0,76	0,50
213	Meschenich	0,71	0,45	0,06	0,59	0,56	0,96	0,37		0,91	0,58
301	Klettenberg	0,08	0,43	0,82	0,03	0,27	0,08	0,58		0,92	0,40
302	Sülz	0,12	0,24	0,77	0,06	0,18	0,06	0,58		0,92	0,37
303	Lindenthal	0,07	0,30	0,81	0,07	0,14	0,00	0,58		0,91	0,36
304	Braunsfeld	0,12	0,37	0,76	0,09	0,21	0,03	0,58		0,82	0,37
305	Müngersdorf	0,20	0,45	0,51	0,21	0,35	0,32	0,58		0,76	0,42
306	Junkersdorf	0,13	0,41	0,49	0,11	0,33	0,07	0,58		0,63	0,34
307	Weiden	0,25	0,54	0,66	0,29	0,26	0,39	0,58		0,86	0,48
308	Lövenich	0,09	0,57	0,69	0,09	0,35	0,19	0,58		0,75	0,41
309	Widdersdorf	0,09	0,59	0,53	0,23	0,68	0,30	0,58		0,78	0,47
401	Ehrenfeld	0,31	0,14	0,48	0,23	0,19	0,35	0,38		0,96	0,38
402	Neuehrenfeld	0,26	0,32	0,55	0,17	0,28	0,35	0,38		0,96	0,41
403	Bickendorf	0,46	0,38	0,53	0,37	0,48	0,73	0,38		0,94	0,53
404	Vogelsang	0,28	0,50	0,54	0,18	0,44	0,60	0,38		0,79	0,46
405	Bocklemünd/Mengenich	0,60	0,59	0,65	0,40	0,67	0,88	0,38		0,92	0,64
406	Ossendorf	0,37	0,32	0,42	0,40	0,63	0,69	0,38		0,73	0,49
501	Nippes	0,19	0,29	0,70	0,17	0,28	0,23	1,00		0,98	0,48
502	Mauenheim	0,27	0,42	0,57	0,22	0,36	0,58	1,00		0,93	0,54
503	Riehl	0,15	0,60	0,82	0,18	0,25	0,33	1,00		0,93	0,53
504	Niehl	0,34	0,43	0,60	0,37	0,36	0,65	1,00		0,61	0,54
505	Weidenpesch	0,31	0,40	0,59	0,29	0,28	0,64	1,00		0,92	0,55
506	Longerich	0,22	0,55	0,58	0,21	0,35	0,65	1,00		0,77	0,54
507	Bilderstöckchen	0,48	0,42	0,53	0,48	0,51	0,76	1,00		0,90	0,63
601	Merkenich	0,20	0,41	0,38	0,22	0,36	0,78	0,39		0,68	0,43
602	Fühlingen	0,19	0,43	0,43	0,14	0,38	0,61	0,39		0,73	0,41
603	Seeberg	0,61	0,59	0,61	0,70	0,67	0,90	0,39		0,95	0,68

604	Heimersdorf	0,18	0,65	0,75	0,22	0,34	0,68	0,39		0,81	0,50
605	Lindweiler	0,49	0,64	0,65	0,39	0,63	0,87	0,39		0,85	0,61
606	Pesch	0,15	0,72	0,59	0,23	0,35	0,69	0,39		0,74	0,48
607	Esch/Auweiler	0,17	0,57	0,47	0,19	0,40	0,54	0,39		0,72	0,43
608	Volkhoven/Weiler	0,38	0,39	0,53	0,57	0,59	0,78	0,39		0,73	0,54
609	Chorweiler	0,79	0,62	0,76	0,81	0,87	0,92	0,39		1,00	0,77
610	Blumenberg	0,28	0,31	0,46	0,68	0,60	0,80	0,39		0,85	0,55
611	Roggendorf/Thenhoven	0,45	0,50	0,50	0,36	0,66	0,83	0,39		0,82	0,56
612	Worringen	0,32	0,52	0,52	0,20	0,51	0,94	0,39		0,81	0,53
701	Poll	0,29	0,49	0,55	0,21	0,33	0,53	0,46		0,82	0,46
702	Westhoven	0,21	0,53	0,34	0,23	0,22	0,44	0,46		0,72	0,39
703	Ensen	0,32	0,49	0,47	0,31	0,38	0,66	0,46		0,85	0,49
704	Gremberghoven	0,81	0,45	0,19	0,70	0,55	0,89	0,46		0,49	0,57
705	Eil	0,37	0,51	0,62	0,39	0,45	0,82	0,46		0,74	0,55
706	Porz	0,43	0,48	0,61	0,49	0,40	0,71	0,46		0,90	0,56
707	Urbach	0,42	0,54	0,56	0,42	0,45	0,81	0,46		0,87	0,57
708	Elsdorf	0,17	0,59	1,00	0,29	0,52	0,57	0,46		0,82	0,55
709	Grengel	0,40	0,52	0,36	0,35	0,51	0,82	0,46		0,79	0,52
710	Wahnheide	0,36	0,45	0,38	0,27	0,37	0,81	0,46		0,81	0,49
711	Wahn	0,37	0,45	0,41	0,33	0,54	0,69	0,46		0,77	0,50
712	Lind	0,42	0,53	0,21	0,24	0,32	0,78	0,46		0,78	0,47
713	Libur	0,11	0,42	0,37	0,06	0,49	0,56	0,46		0,80	0,41
714	Zündorf	0,23	0,61	0,69	0,21	0,38	0,54	0,46		0,81	0,49
715	Langel	0,18	0,58	0,45	0,07	0,48	0,72	0,46		0,74	0,46
716	Finkenberg	1,00	0,70	0,59	0,85	0,64	0,98	0,46		0,89	0,76
801	Humboldt/Gremberg	0,61	0,34	0,35	0,53	0,37	0,76	0,23		0,98	0,52
802	Kalk	0,76	0,27	0,23	0,57	0,34	0,75	0,23		1,00	0,52
803	Vingst	0,69	0,51	0,64	0,61	0,75	0,87	0,23		0,98	0,66
804	Höhenberg	0,67	0,36	0,45	0,52	0,40	0,82	0,23		0,98	0,55
805	Ostheim	0,73	0,50	0,47	0,60	0,70	0,79	0,23		0,91	0,62
806	Merheim	0,29	0,47	0,48	0,42	0,50	0,64	0,23		0,86	0,49
807	Brück	0,19	0,59	0,70	0,12	0,38	0,55	0,23		0,81	0,45
808	Rath/Heumar	0,17	0,54	0,55	0,12	0,31	0,48	0,23		0,76	0,40
809	Neubrück	0,59	0,67	0,65	0,61	0,59	0,86	0,23		0,93	0,64
901	Mülheim	0,63	0,32	0,32	0,46	0,38	0,71	0,00		0,97	0,47
902	Buchforst	0,61	0,40	0,50	0,51	0,50	0,83	0,00		0,98	0,54
903	Buchheim	0,56	0,41	0,46	0,50	0,48	0,71	0,00		0,94	0,51
904	Holweide	0,45	0,43	0,61	0,34	0,50	0,76	0,00		0,86	0,49
905	Dellbrück	0,22	0,51	0,69	0,09	0,35	0,54	0,00		0,82	0,40
906	Höhenhaus	0,38	0,56	0,56	0,24	0,52	0,74	0,00		0,85	0,48
907	Dünnwald	0,47	0,52	0,55	0,28	0,61	0,80	0,00		0,86	0,51
908	Stammheim	0,44	0,55	0,59	0,39	0,49	0,78	0,00		0,87	0,51
909	Flittard	0,41	0,56	0,55	0,23	0,46	0,79	0,00		0,85	0,48
	Cologne total	0,33	0,40	0,55	0,29	0,34	0,53	0,42		0,87	0,47

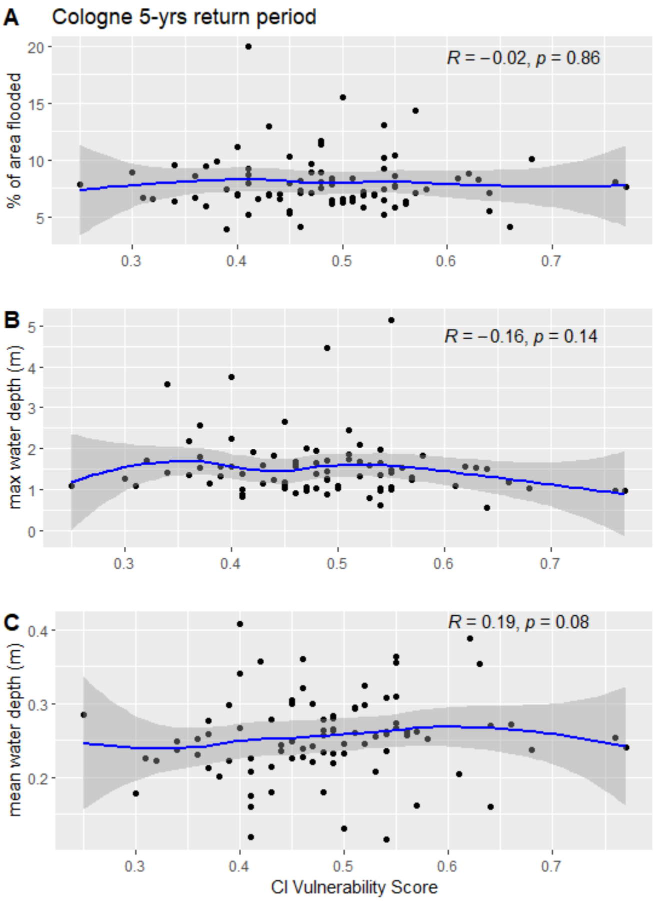
Frankfurt

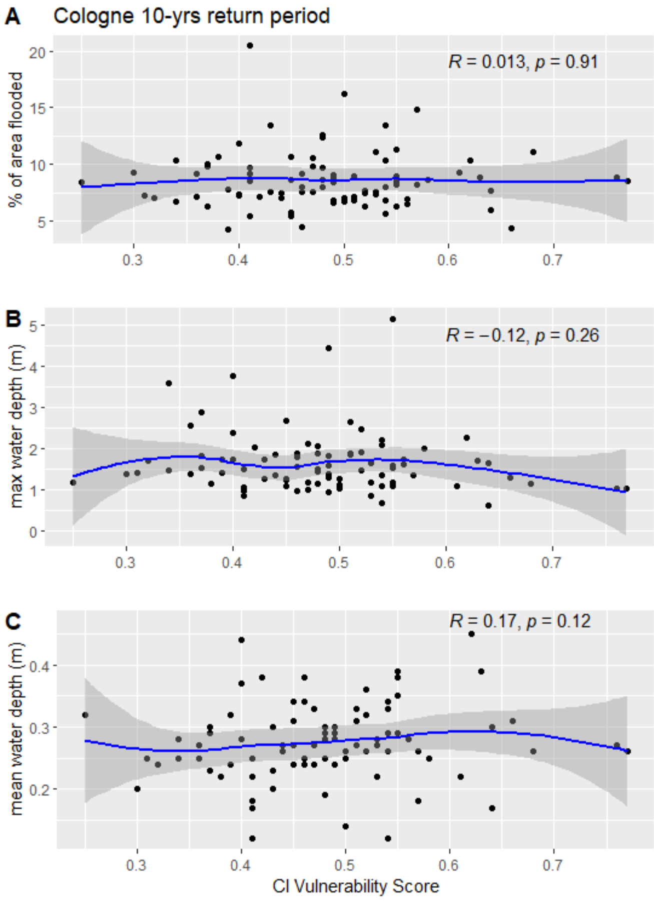
ID	Name	economic	age	gender	natio	fam	educ	snp	house	infras	IVI score
1	Altstadt	0,49	0,38	0,57	0,57	0,30	0,33		1,00	0,94	0,57
2	Innenstadt	0,58	0,26	0,49	0,58	0,05	0,71		1,00	0,50	0,52
3	Bahnhofsviertel	0,70	0,00	0,32	0,50	0,00	0,70		1,00	0,85	0,51
4	Westend-Süd	0,00	0,47	0,65	0,34	0,26	0,39		0,71	0,66	0,44
5	Westend-Nord	0,21	0,47	0,81	0,50	0,41	0,49		0,71	0,99	0,57
6	Nordend-West	0,16	0,42	0,48	0,23	0,26	0,37		0,79	0,96	0,46
7	Nordend-Ost	0,26	0,37	0,46	0,23	0,30	0,36		0,79	1,00	0,47
8	Ostend	0,37	0,42	0,51	0,41	0,23	0,52		0,98	0,68	0,51
9	Bornheim	0,41	0,52	0,54	0,36	0,37	0,46		0,98	0,99	0,58
10	Gutleutviertel	0,75	0,31	0,37	0,51	0,09	0,42		1,00	0,77	0,53
11	Gallus	0,52	0,33	0,53	0,71	0,45	0,59		1,00	0,29	0,55
12	Bockenheim	0,35	0,37	0,56	0,49	0,34	0,50		0,71	0,90	0,53
13	Sachsenhausen-Nord	0,25	0,43	0,52	0,34	0,37	0,40		0,64	0,86	0,48
14	Sachsenhausen-Süd	0,23	0,62	0,57	0,33	0,30	0,50		0,64	0,80	0,50
16	Oberrad	0,75	0,54	0,64	0,56	0,43	0,71		0,64	0,92	0,65
17	Niederrad	0,58	0,45	0,57	0,58	0,38	0,67		0,64	0,86	0,59
18	Schwanheim	0,71	0,70	0,77	0,57	0,64	0,64		0,57	0,92	0,69
19	Griesheim	0,81	0,47	0,69	0,77	0,46	0,84		0,57	0,91	0,69
20	Rödelheim	0,60	0,53	0,58	0,50	0,43	0,62		0,55	0,86	0,58
21	Hausen	0,57	0,61	0,95	0,70	0,45	0,68		0,55	0,99	0,69
22	Praunheim	0,62	0,72	0,76	0,55	0,56	0,68		0,55	0,92	0,67
24	Heddernheim	0,64	0,64	0,79	0,56	0,69	0,55		0,45	0,91	0,65
25	Niederursel	0,65	0,68	0,88	0,68	0,58	0,68		0,45	0,94	0,69
26	Ginnheim	0,61	0,55	0,77	0,66	0,61	0,56		0,62	0,93	0,66
27	Dornbusch	0,36	0,65	0,69	0,39	0,37	0,51		0,62	0,96	0,57
28	Eschersheim	0,41	0,56	0,65	0,32	0,36	0,54		0,62	0,91	0,55
29	Eckenheim	0,71	0,60	0,80	0,65	0,56	0,64		0,31	0,91	0,65
30	Preungesheim	0,54	0,54	0,68	0,62	0,69	0,58		0,31	0,93	0,61
31	Bonames	0,74	0,65	0,81	0,67	0,55	0,70		0,31	0,93	0,67
32	Berkersheim	0,58	0,63	0,80	0,55	0,73	0,49		0,31	0,85	0,62
33	Riederwald	0,89	0,65	0,75	0,58	0,69	0,96		0,43	0,94	0,74
34	Seckbach	0,69	0,68	0,64	0,39	0,48	0,69		0,43	0,88	0,61
35	Fechenheim	1,00	0,53	0,80	0,77	0,74	0,80		0,43	0,85	0,74
36	Höchst	0,87	0,40	0,68	0,74	0,60	0,77		0,57	0,85	0,68
37	Nied	0,76	0,57	0,75	0,71	0,53	0,80		0,57	0,89	0,70
38	Sindlingen	0,77	0,61	0,73	0,65	0,58	0,80		0,57	0,91	0,70
39	Zeilsheim	0,78	0,70	0,81	0,62	0,74	0,73		0,57	0,90	0,73
40	Unterliederbach	0,69	0,59	0,68	0,67	0,67	0,72		0,57	0,87	0,68
41	Sossenheim	0,91	0,60	0,86	0,78	0,63	0,80		0,57	0,92	0,76
42	Nieder-Erlenbach	0,29	0,70	0,58	0,03	0,57	0,32		0,05	0,84	0,42
43	Kalbach-Riedberg	0,17	0,57	0,70	0,58	0,84	0,41		0,00	0,89	0,52
44	Harheim	0,30	0,68	0,61	0,07	0,61	0,44		0,05	0,87	0,45
45	Nieder-Eschbach	0,63	0,67	0,82	0,62	0,54	0,63		0,05	0,82	0,60

46	Bergen-Enkheim	0,42	0,70	0,64	0,26	0,46	0,56		0,43	0,89	0,55
47	Frankfurter Berg	0,60	0,56	0,74	0,69	0,64	0,64		0,31	0,87	0,63
Frankfurt am Main	Total	0,54	0,52	0,64	0,52	0,45	0,59		0,57	0,87	0,59

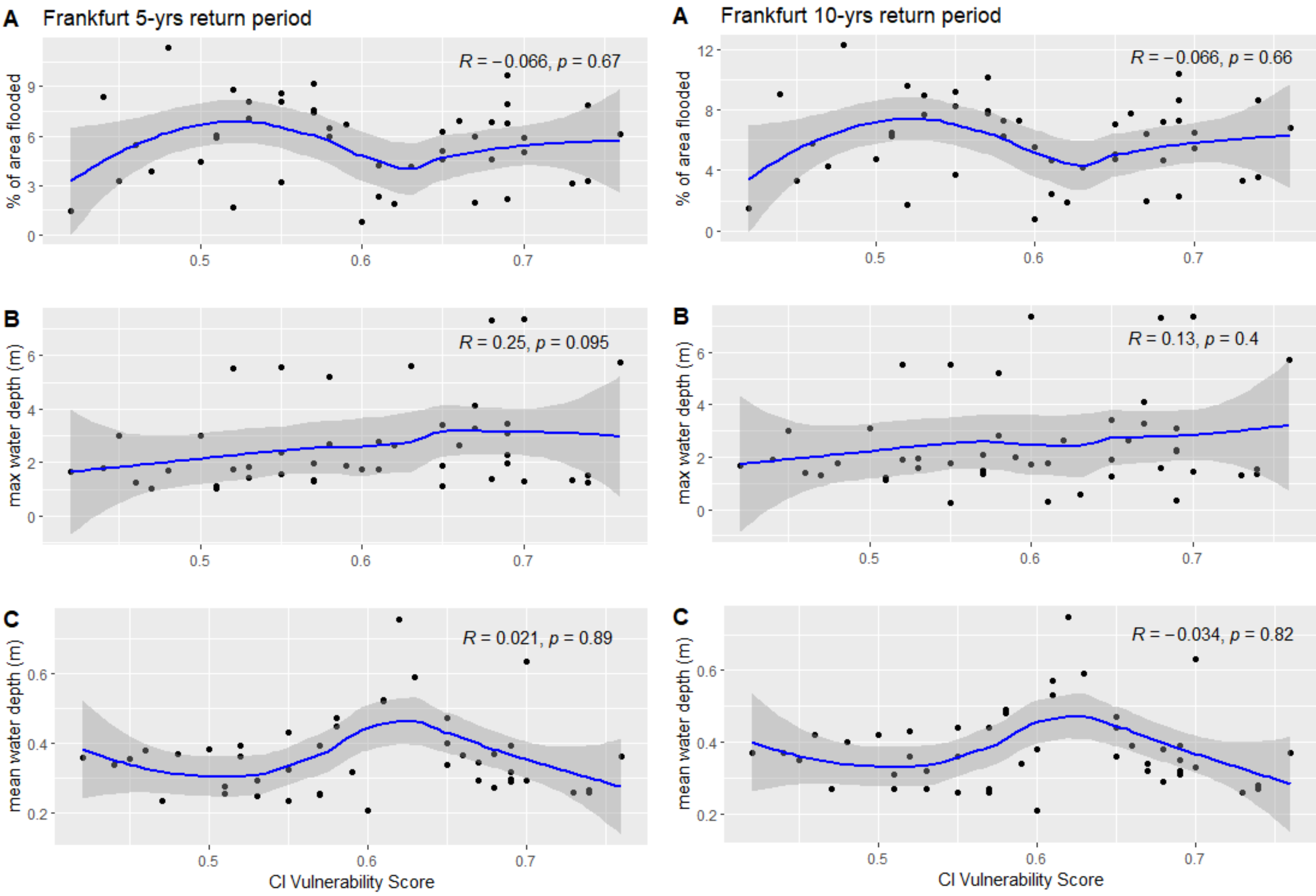
Appendix 6: Flood exposure relative to the IVI for return periods 5yrs and 10yrs

Cologne:

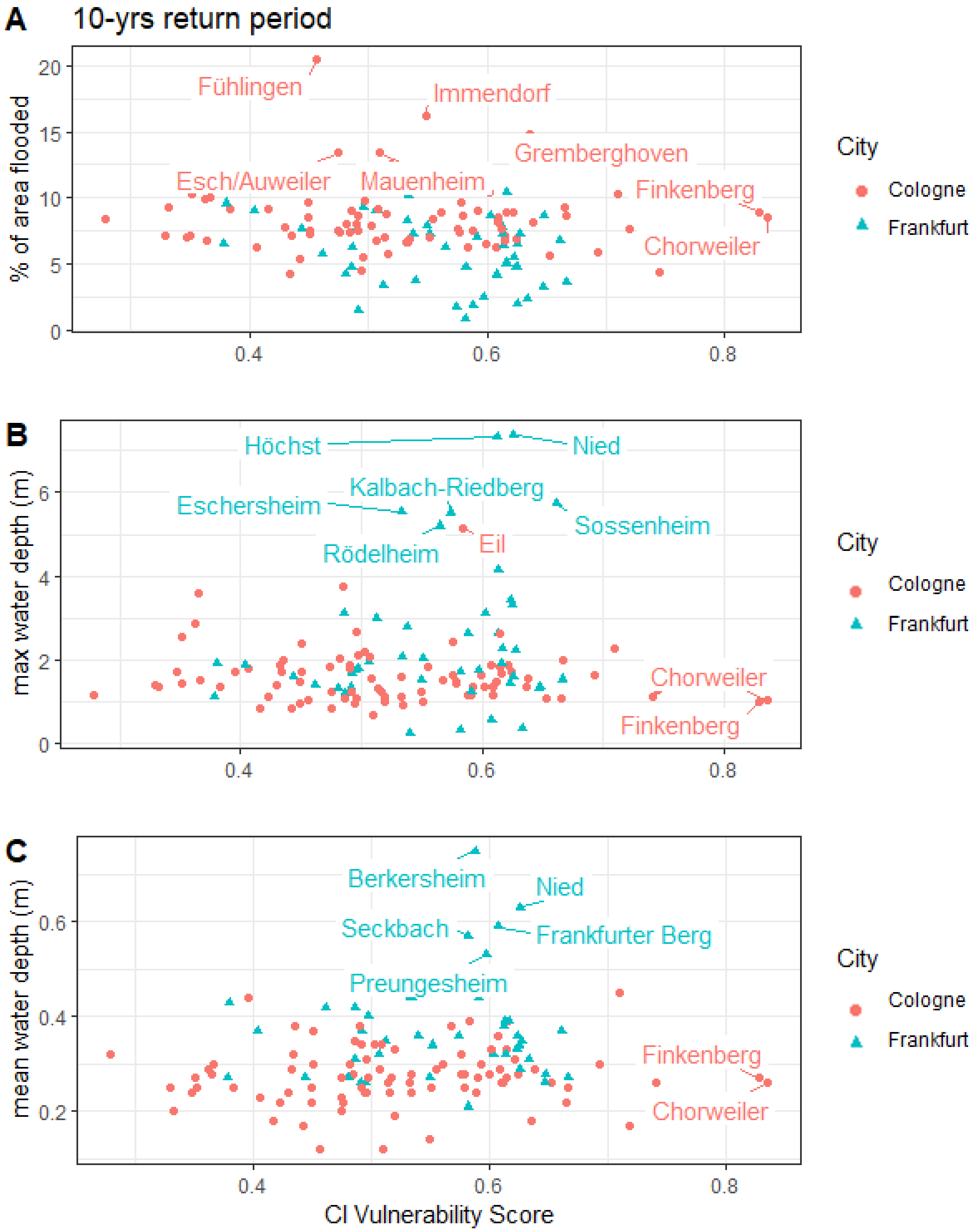




Frankfurt


A
Frankfurt 5-yrs return period
R = −0.066, p = 0.67
% of area flooded
A
Frankfurt 10-yrs return period
R = −0.066, p = 0.66
% of area flooded
B
R = 0.25, p = 0.095
max water depth (m)
B
R = 0.13, p = 0.4
max water depth (m)
C
R = 0.021, p = 0.89
mean water depth (m)
CI Vulnerability Score
C
R = −0.034, p = 0.82
mean water depth (m)
CI Vulnerability Score

Appendix 7: Flood exposure relative to the IVI for Frankfurt and Cologne. Return period: 10yrs



Appendix 8: Cologne and Frankfurt IVI scores relative to one another: Districts beyond 1 Std Dev of the mean IVI Score

	Group	District	IVI Score
1	high vul C	Chorweiler	0,836357239
2	high vul C	Finkenberg	0,829304047
3	high vul C	Vingst	0,745438189
4	high vul C	Seeberg	0,740547749
5	high vul C	Neubrück	0,719330965
6	high vul C	Ostheim	0,710116895
7	high vul C	Bocklemünd/Mengenich	0,693615678
8	high vul C	Meschenich	0,666514767
9	high vul C	Lindweiler	0,664874909
10	high vul C	Buchforst	0,652432114
11	high vul C	Höhenberg	0,638162077
1	high vul F	Riederwald	0,666686595
2	high vul F	Sossenheim	0,66138257
3	high vul F	Fechenheim	0,64780258
4	high vul F	Zeilsheim	0,6469575
5	high vul F	Niederursel	0,633605119
1	low vul C	Bayenthal	0,406318689
2	low vul C	Klettenberg	0,395231939
3	low vul C	Altstadt-Süd	0,383133904
4	low vul C	Braunsfeld	0,366780171
5	low vul C	Deutz	0,364390136
6	low vul C	Sülz	0,362234972
7	low vul C	Junkersdorf	0,351446892
8	low vul C	Lindenthal	0,350668341
9	low vul C	Neustadt-Süd	0,347401759
10	low vul C	Altstadt-Nord	0,332108527
11	low vul C	Neustadt-Nord	0,329333262
12	low vul C	Hahnwald	0,278822834
1	low vul F	Nordend-Ost	0,480967648
2	low vul F	Nordend-West	0,461993417
3	low vul F	Gutleutviertel	0,443869645
4	low vul F	Westend-Süd	0,404134442
5	low vul F	Innenstadt	0,380171427
6	low vul F	Bahnhofsviertel	0,378276225