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Flood Insurance Systems and Urban Flood Vulnerability: A comparative analysis
of the NFIP (USA) and the CatNat system (France)

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Sebastian Götzer B.Sc.

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Dr. Philipp Marr B.Sc. M.Sc.

Abstract

Floods are the most frequent natural disaster worldwide, posing a substantial threat to populations and structures located in floodplains. Vulnerability to floods is composed of susceptibility to harm and coping capacity. With insurance being a central instrument for financial coping capacity, a variety of systems with differing mechanisms have been established, exerting different implications on flood vulnerability. Research on these designs has been conducted but has largely remained institutional while the quantification of vulnerability is extensive but primarily confined to single countries. This thesis links a comparative analysis with the operationalization of social vulnerability in order to examine how flood insurance systems spatially influence flood vulnerability. Two structurally opposite public systems are compared at the neighborhood level, each anchored to a comparable flood event: the voluntary, risk-based U.S. National Flood Insurance Program (NFIP) in Harris County, Texas (Hurricane Harvey, 2017) and the compulsory, solidarity-based French CatNat regime in Île de France (2016 floods). An equal-weighted Social Vulnerability Index covering demographic, household, physical, and economic dimensions is overlaid with hazard, exposure, and insurance indicators using bivariate mapping and local spatial cluster analysis. In Harris County, flooding was distributed roughly evenly across vulnerability levels, but insurance take-up fell from about 22% to 10% toward the most vulnerable neighborhoods, producing a protection gap driven by the system's design of voluntary uptake, the exclusion of renters, and incomplete hazard mapping. In the Île de France region, flood exposure increased with vulnerability, yet near-universal compulsory coverage converted this exposure into compensated loss, and no comparable protection gap emerged. Insurance design thus determines whether exposure translates into a protection deficit and where that deficit falls, while susceptibility, as operationalized by the SoVI, shapes how severely such a deficit is felt where it does arise. This deficit is governed by coverage in the U.S. system and by exposure in the French one. By demonstrating this at the neighborhood level across two contrasting regimes within a single comparative framework, the thesis shows that the spatial pattern of flood vulnerability is a product of insurance design laid over a given distribution of susceptibility and exposure.

Zusammenfassung

Überschwemmungen sind weltweit die häufigste Naturkatastrophe und stellen eine erhebliche Gefahr für die Bevölkerung und die bauliche Strukturen in Überschwemmungsgebieten dar. Versicherungssysteme gelten hierfür als zentrales Instrument der finanziellen Bewältigungskapazität. Die Forschung zu diesen Systemen war bislang weitgehend auf institutionelle Aspekte fokussiert, während die Quantifizierung von Vulnerabilität zwar umfangreich, aber überwiegend auf einzelne Länder beschränkt ist. Diese Arbeit verbindet einen Ländervergleich mit der Operationalisierung sozialer Vulnerabilität, um zu untersuchen, wie Hochwasserversicherungssysteme die räumliche Ausprägung der Hochwasservulnerabilität beeinflussen. Zwei strukturell gegensätzliche staatliche Systeme werden verglichen und jeweils anhand eines vergleichbaren Hochwasserereignisses untersucht: das freiwillige, risikobasierte U.S. National Flood Insurance Program (NFIP) in Harris County, Texas (Hurrikan Harvey, 2017) und das verpflichtende, solidarisch finanzierte französische CatNat-System in der Île de France Region (Hochwasser 2016). Ein gleichgewichteter sozialer Vulnerabilitätsindex (SoVI), der demografische, haushaltsbezogene, physische und ökonomische Dimensionen umfasst, wird mittels bivariater Kartierung und lokaler räumlicher Clusteranalyse mit Gefahren-, Expositions- und Versicherungsindikatoren überlagert. In Harris County verteilte sich das Hochwasser über alle Vulnerabilitätsstufen hinweg zwar annähernd gleichmäßig, die Versicherungsdichte sank jedoch in den vulnerabelsten Nachbarschaften von rund 22 % auf 10 %, wodurch eine Schutzlücke entstand, die auf die Systemgestaltung, d.h. die freiwillige Inanspruchnahme, den Ausschluss von Mieterhaushalten sowie die unvollständige Gefahrenkartierung zurückzuführen ist. In der Île de France Region stieg die Hochwasserexposition mit der Vulnerabilität, doch die nahezu flächendeckende Pflichtversicherung wandelte diese Exposition in entschädigten Schaden um, sodass keine vergleichbare Schutzlücke auftrat. Die Ausgestaltung des Versicherungssystems bestimmt somit, ob Exposition zu einem Schutzdefizit führt und wo dieses Defizit auftritt. Wo dies der Fall ist, bestimmt die über den SoVI operationalisierte Anfälligkeit, wie schwer es die betroffene Bevölkerung trifft. Im US-amerikanischen System wird dieses Defizit vor allem durch die Versicherungsabdeckung bestimmt, im französischen System hingegen durch die Exposition. Indem dies auf Nachbarschaftsebene über zwei gegensätzliche Regime innerhalb eines einheitlichen Vergleichsrahmens gezeigt wird, macht die Arbeit deutlich, dass das räumliche Muster der Hochwasservulnerabilität ein Produkt der Versicherungsgestaltung ist, die über eine gegebene Verteilung von Anfälligkeit und Exposition gelegt wird.

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List of Abbreviations

BFE	Base Flood Elevation
CatNat system	Catastrophes Naturelles (France's natural hazard insurance system)
CCR	Caisse Centrale de Réassurance
CDC/ATSDR SVI	Center for Disease Control and Prevention / Agency for Toxic Substances and Disease Registry Social Vulnerability Index
DRIEAT	Direction régionale et interdépartementale de l'environnement, de l'aménagement et des transports (Regional and Interdepartmental Directorate for the Environment, Planning and Transport)
EAIP	Enveloppe Approchée des inondations Potentielles (Envelopes approaching Potential Floods)
EMDAT	Emergency Events Database
EPRI	Évaluation Préliminaire des Risques d'Inondation
FEMA	Federal Emergency Management Agency
FIRM	Flood Insurance Rate Map
FSCT	Solidarité en faveur des Collectivités Territoriales (Solidarity in favor of local authorities)
GAO	U.S. Government Accountability Office
HCFCDD	Harris County Flood Control District
IPCC	Intergovernmental Panel on Climate Change
LISA	Local indicators of spatial association
LOMC	Letter of Map Change
LOMA	Letter of Map Amendment
LOMR	Letter of Map Revision
NFHL	National Flood Hazard Layer
NFIP	National Flood Insurance Program (USA)
ONRN	Observatoire National des Risques Naturels (National Observatory for Natural Risks)
PAPI	Programmes d'actions de prévention des inondations (Flood prevention action programmes)
PPR / PPRI	Plans de Prévention des Risques
SFHA	Special Flood Hazard Area
SoVI	Social Vulnerability Index
TRI	Territoire à Risque important d'Inondation (Territory at risk of flooding)
UNDRR	United Nations Office for Disaster Risk Reduction
UN WPP	United Nations World Population Prospects
USACE	United States Army Corps of Engineers
WMO	World Meteorological Organization

1. Introduction

1.1. Background and Context

Natural hazards are becoming an ever-increasing problem globally, threatening the livelihoods of millions of people annually. In the year 2024 alone, the Emergency Events Database [EM-DAT] recorded 393 natural disasters that affected a total of over 167 million people globally, causing 16.753 deaths (CRED, 2025). The total economic losses in 2024 amounted to around USD 320 billion (Munich RE, 2025). Among those events were 142 floods, impacting approximately 48,8 million people with a death tally of 5.883, which was the highest among all natural disasters in 2024 (CRED, 2025). Further consequences including psychological trauma and displacement underline the substantial impacts floods can have on society (Rogers et al., 2025). According to estimations, around 1,8 billion people globally are currently exposed to high risk of flooding, making flood risk management a high priority matter for many regions in the present and especially the future (Rentschler et al., 2022). Rogers et al. (2025) project a steady increase of the population exposed to a 100-year flood hazard (i.e. an event with a 1% statistical probability of annual occurrence) for the 21st century. Ongoing anthropogenic climate change and especially population growth were identified as the main drivers for this development. The United Nations World Population Prospects [UN WPP] (2024) expects the current global population of approximately 8,2 billion (2024) to grow to over 10 billion within the next five to six decades before a decline towards the end of the century is bound to occur. Especially the number of people living in floodplains/flood-prone areas and/or urban regions is seeing a more rapid increase compared to other regions, a trend that will most likely continue in the future (Jongman, 2021). Additionally, the impact of human-induced climate change exacerbates problems when it comes to flood risk. The amplification of severe weather patterns, specifically more frequent occurrences of storms, heavy rainfall etc. paired with higher magnitudes, intensifies risk in many regions globally (IPCC, 2022). The past ten years averaging the highest annual temperatures since the beginning of systematic record-keeping, with 2024 reaching an annual average of around 1,5°C above the pre-industrial levels, underlines this concerning trend (WMO, 2025). While the levels, depending on the flood type and the geographical distribution of these climate effects, vary starkly, the risk increase can predominantly be observed in low-GDP regions (Rogers et al., 2025). The numbers from the EM-DAT reveal the Global South recording more than ten times as many flood events than the Global North with over 900 times as many people affected in 2024 (CRED, 2025). A major reason for this is the rapid urbanization rate in these parts of the globe, where the hopes of an

improved life with better economic opportunities in an urban setting often overshadow the imminent exposure to flood risk (Ermagun et al., 2024). While urban areas are considered vulnerable to flood risk in most regions globally, the highest flood-risk usually can be attributed to the lower-income households (McDermott, 2022; Rogers et al., 2025). This means, poorer communities are often located in low-lying and thus more flood-prone neighborhoods with lacking infrastructure, leading to overall higher risk of human/economic loss in the case of a flooding event (Ermagun et al., 2024; Pralle, 2019).

Consequently, increasing the resilience of urban communities to natural hazard events is and will remain a major global challenge in the upcoming decades (Bixler et al., 2021). On the national and regional scale, changes in policies and a variety of different adaptation measures can induce meaningful change. Among those can be technical solutions such as dams, dikes or drainages, but also more restrictive building codes to people from settling in flood-prone areas to begin with (UNDRR, 2017). To minimize underlying flood risk for a population, a more holistic strategy, involving the people themselves, is required – especially with the mentioned climate change-driven impacts in the future (Ermagun et al., 2024). This primarily means creating awareness among the endangered population and offering them possibilities to resist and cope with natural disasters, as private households generally experience the impact of flooding most severely (Bixler et al., 2021). The main reason for this being the unwillingness or inability of homeowners to voluntarily implement adaptation measures, such as floodproofing their houses or purchasing an insurance policy ahead of a disaster (Kunreuther, 2006). Low-probability, high-consequence events particularly reinforce this observation, as people are especially unwilling to pay upfront adaptation costs for an event with a 100-year return period e.g. under the assumption it will not happen in their lifetime. Natural disasters such as Hurricane Katrina in the USA 2005 have revealed exactly those issues, with large portions of the affected population being unprepared and highly vulnerable to an event of this magnitude. In consequence, the US government paid significant amounts of disaster relief funds from taxpayers' money, which cannot be considered a sustainable course of action going forward (ibid.).

In order to accurately assess potentially endangered areas and consequently implement adequate measures, flood modelling and resulting mapping outputs are crucial tools for policymakers, as well as individuals and communities (Pralle, 2019; Rogers et al., 2025). Especially flood insurance programs, which are widely considered to be a key policy tool for climate change adaptation and the currently best solution for the compensation of economic

losses from natural disasters, are highly reliant on accurate flood maps showcasing the areas and individual property at risk in order to set insurance premiums (Kalfin et al., 2022; Pralle, 2019). The implementation of flood insurance in general varies drastically. Whereas oftentimes handled exclusively by the private insurance sectors, some countries have implemented public systems for flood insurance. Among those are the USA with its National Flood Insurance Program (NFIP) as well as France with its system Catastrophe Naturelle (CatNat). While these two regimes are public, they still embody differing design philosophies, as the NFIP is a voluntary system, based upon risk maps determining the insurance premiums, and the CatNat system relies on compulsory flat premium rates based on the solidarity principle. Considering both systems operate in a similar institutional capacity for over 40 years now and have faced significant flooding episodes in the past decade (e.g. 2016 flooding in France; Hurricane Harvey 2017 in the USA), they offer great comparative opportunities. This especially applies for analyzing vulnerable urban groups and how each system affects them differently in the event of a low-frequency, high-magnitude flood event.

Previous research has applied the framework of hazard/exposure/vulnerability (IPCC, 2022) in the context of urban flood risk, showcasing the importance of social vulnerability when assessing flood risk management on a local scale (e.g. Koks et al., 2015). Moreover, methods for quantifying the concept of social vulnerability have been developed extensively and validated over the past decades (e.g. Cutter et al., 2003; Rufat et al., 2015). A composite social vulnerability index (SoVI), displaying all the primarily socio-economic metrics that are deemed relevant to determine the social vulnerability of a certain population or part of it, is the standard here. These works have predominantly focused on single countries and are rarely linked to insurance-system designs. Similarly, a variety of research analyzing the flood insurance systems themselves in isolation was conducted (e.g. Barraqué & Moatty, 2020; Kousky et al., 2017; Poussin et al., 2013; Pralle, 2019), as well as comparing different systems (e.g. Paudel, 2012). Here, the research is mostly based upon institutional components rather than spatial distribution. A more detailed review of the state of research and connected relevant terminology and frameworks follows in chapter 2.

The intersection between comparative spatial vulnerability analysis of two structurally different flood insurance regimes at the neighborhood scale, anchored in comparable event-level data (2016 floods in Île de France / 2017 Hurricane Harvey in Harris County, TX) is, to my present knowledge, not addressed in the existing literature. This is where the thesis contributes by combining the SoVI methodology with the integrated framework of hazard, exposure and here

flood vulnerability and applying it spatially across two contrasting insurance systems. Thereby, the question raised by de Ruig et al. (2022) "who is protected, where, and under which system design?" is asked spatially rather than only institutionally.

1.2. Research questions

Derived from this research gap, the thesis aims to answer the following research questions:

Main Research Question:

- How do different flood insurance system designs influence spatial patterns of flood vulnerability in urban areas?

Additional Research Questions:

- Which neighborhoods in the two case-study areas combine the highest social vulnerability with the highest flood exposure, and which social vulnerability dimensions characterize these areas?
- How does the spatial coverage of each insurance system (CatNat universality vs NFIP take-up) interact with social vulnerability to produce different protection landscapes in the two case studies?

1.3. Structure of the thesis

The thesis starts by establishing relevant concepts of natural hazard research, flood definitions, adaptation measures including insurance as coping mechanism and the factors influencing adaptation in chapter 2. Following this, chapter 3 builds on these concepts by presenting the previous body of literature, whereby past studies on related topics are discussed briefly, including the groundwork within research for the later construction of this work's social vulnerability index. With this, the exact position of the thesis within the literature is carved out and the baseline knowledge for the analysis established.

Chapter 4 then introduces both the study areas in a mirrored form so that comparability is given throughout. The geographical preconditions are introduced before the specific case study events Hurricane Harvey, 2017 and the floods in France, 2016 are examined. Disaster risk management

in the respective countries follows before the specific flood insurance systems are explored. The chapter is closed by a head-to-head comparison thereof.

The methods and data used for the spatial analysis follow. The general procedure of the analysis, exact datasets and specific processing steps are described in chapter 5 prior to chapter 6 displaying the resulting outputs in a descriptive manner. The discussion chapter 7 then puts these findings and results into context, synthesizes connections and implications and discusses limitations of the analysis as well as criticism and changes since the case study events for each insurance regime. Finally, an outlook is given that encompasses future challenges for natural hazard insurance and both the NFIP and CatNat in particular, followed by potential future research to be conducted on the topic. A concluding chapter rounds up the thesis.

2. State of the Art

Within this chapter general terms and concepts for the analysis are introduced which are taken as established in the subsequent chapters.

2.1. Hazard, Exposure, Vulnerability

The term hazard can manifest itself in many varying forms, as can be seen in figure 1. For the context of this thesis, the Meteorological and Hydrological clusters represent the central element. The Intergovernmental Panel on Climate Change [IPCC] (2022) defines hazard as “the potential occurrence of a natural or human-induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems and environmental resources.” Natural hazards are thereby “predominantly associated with natural processes and phenomena” (UNDRR, 2017).



Figure 1: Classification of 302 Hazards identified by the UNDRR (Combes, 2025).

In order to determine the risk of a natural hazard event and its potentially adverse consequences for society and environment, frameworks for better quantification were established over the past decades. While the Office of the United Nations Disaster Relief Coordinator [UNDRO] first unified hazard, vulnerability, and risk terminology in 1979/1980 (UNDRO, 1980), the modern approach formulates disaster risk in the context of climate change impacts as a function of hazard, exposure, and vulnerability (IPCC, 2022). Exposure hereby encompasses “the presence of people; livelihoods; species or ecosystems; environmental functions, services, and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected”, whereas vulnerability is defined as “the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt” (ibid.). This establishes the concept of a natural disaster not being determined solely by its magnitude but rather the combination of an event occurring with underlying societal factors. By understanding the environmental (such as geological, geomorphological, meteorological etc.) conditions and their interactions as well as improving the societal factors through various different measures

and strategies (see section 2.3.), the overall likelihood of a natural hazard event turning to a disaster can be decreased notably (Gianni et al., 2023).

Within this thesis, particularly the concept of social vulnerability is operationalized in order to assess institutional differences within the flood insurance regimes. Social vulnerability is understood as a measure of societal resistance to hazards (Cutter et al., 2003).

2.2. Floods as hazard

The IPCC (2022) defines a flood as “the overflowing of the normal confines of a stream or other water body, or the accumulation of water over areas that are not normally submerged.” Furthermore, it statutes that floods can be differentiated into categories, including riverine (fluvial) floods, rain (pluvial) floods, coastal floods, and flash floods (ibid.). The often-rapid accumulation of water mostly results from unusually heavy rainfall caused by a storm, for instance. Hereby, fluvial floods occur when the river banks are overtopped and runoff water gets released, flowing from upstream to downstream (IPCC, 2022; Ouma & Tateishi, 2014). Pluvial flooding can happen independently of existing water bodies, as heavy rainfall can overwhelm local infiltration capacities and/or drainage systems (IPCC, 2022). Coastal flooding is understood as the inundation of land areas by seawater, typically driven by storm surges, high tides, or tsunamis. Distinct types of flooding are not mutually exclusive, as they can occur in combination during e.g. compound events (ibid.).

Flooding is the most common natural disaster globally and carries considerable potential for financial and human loss, as was established in the introduction (CRED, 2025). Reasons for the high risk potential and thus notable adverse effects on population and infrastructure include the combination of rapid occurrence and spatial dispersion of impacted areas, complicating adequate flood warning and by that, timely measures and responses (Ouma & Tateishi, 2014; Rogers et al., 2025). Additionally, intense rainfall in flood-prone areas often generates surface runoff considerably faster than water can infiltrate the soil or drain through other pathways (Ouma & Tateishi, 2014). This issue especially comes into play when considering urban areas with high rates of impermeable ground through high population density, economic structures, or infrastructure (ibid.). Alaghmand et al. (2010) synthesizes a correlation between urbanization and hydrological characteristics, which establishes an increase in runoff; as well as an increase in flood frequency and height as direct influences from urban environments. Consequently, areas with high underlying flood risk experience higher levels of physical vulnerability. An

intensification in the face of growing urban populations and impacts of the anthropogenic climate change in the future is expected (Ouma & Tateishi, 2014).

The established concepts of hazard, exposure, and vulnerability from section 2.1. can be applied to flooding directly. Hazard hereby represents the probability of the occurrence of a flood event that may cause adverse effects on the population, structures, ecosystem etc. within a given time period and area. Exposure depicts the mentioned population and assets that could be subject to flooding. Flood vulnerability describes the propensity of the exposed population and assets to be adversely affected by a flood event. It encompasses their susceptibility to harm and their capacity to cope with and recover from flooding and thereby determines whether exposure to the hazard results in actual loss. The operationalization of these concepts for the flood insurance regimes is further described in chapter 5.

2.3. Adaptation strategies

In order to adequately deal with natural hazards and the potentially adverse consequences for vulnerable population and infrastructure, disaster risk management is a necessary step on the decision-maker level (Gianni et al., 2023). By the United Nations Office for Disaster Risk Reduction's (2017) definition, "disaster risk management is the application of disaster risk reduction policies and strategies to prevent new disaster risk, reduce existing disaster risk and manage residual risk, contributing to the strengthening of resilience and reduction of disaster losses." Thereby, three distinct categories of disaster risk management actions are defined based on their individual applications. Firstly, prospective disaster risk management focusses on the avoidance of future disaster risks by implementing adequate policies, building restrictions, or preventive measures in general (e.g. better land-use planning or adjusted water supply systems) (UNDRR, 2017). Secondly, corrective disaster risk management aims at reducing already existing risks by, for example, relocating endangered populations or assets (ibid.). Thirdly, compensatory disaster risk management tackles residual risk of individuals and societies that is not effectively reduceable by strengthening social and economic resilience. Among those are preparedness, response, and recovery activities, as well as financial supporting structures such as insurances (ibid.).

A further differentiation of adaptation strategies is usually made with structural and non-structural mitigation measures. Mitigation in the context of natural hazards is defined as "the lessening or minimizing of the adverse impacts of a hazardous event" (UNDRR, 2017). While

structural measures include any technical or physical construction aimed at improved hazard resistance and resilience in structures or systems, such as the building of dams, dikes or levies, non-structural measures represent the remaining catalogue of adaptations – see figure 2 (ibid.). As these measures can encompass a wide variety, this chapter will primarily focus on those bearing relevance for flooding as a hazard. The most common structural measure private households or businesses can adopt next to the government's infrastructure offering protection, is floodproofing on property level. Hereby, private structures are adjusted to withstand inundation by, for example, sealing openings, constructing water barriers, relocating utilities to upper floors, or elevating the structure itself (Poussin et al., 2015). Considered to be among the most cost-effective non-structural measures for governments, land-use planning and zoning regulations aim to prevent vulnerability accumulation in the first place, rather than mitigating later (Kundzewicz et al., 2018). The exact implementations naturally vary here, depending on the country. In some cases, particularly concerning repeatedly flooded properties, the government makes use of corrective management measures, which can include policy and financial mechanisms for voluntary acquisition of affected lands (Siders, 2019). By then converting the acquired property to open space, exposure can be removed permanently instead of reducing damage per event (ibid.). Additionally, governments can issue flood risk disclosure requirements, by which it becomes mandatory to disclose flood risk in real estate transactions, enabling more risk-informed decisions (Hino & Burke, 2021). Furthermore, monitoring systems used as early warning systems are crucial for the timely recognition of natural hazards, which consequently can lead to more timely reactions in the form of evacuation orders, for instance (Gianni et al., 2023). The rapid occurrence and spatial dispersion of floods, established in section 2.2, further undermines the relevance of these systems. In order to ensure that the full potential of some of these measures is realized, adequate information and communication strategies need to be in place (Gianni et al., 2023). Creating awareness of the possibility that flooding could occur and at what spatial distribution, is of notable importance when wanting to entice population groups to adopt mitigation measures. The strategic and thus varied approach of informing people is seen as mandatory, considering the differences in backgrounds of individuals, which influences their predispositions of being reached and thus adequately informed on underlying flood risk. In detail, this can mean a combination of publicly available data/maps specifically tailored for the public (i.e. accessible for laypeople), educational material, captured footage of natural hazards showcasing the direct impacts, engaging citizens with e.g. gamification elements (ibid.). Based on this awareness, individuals can then make informed decisions on adopting flood mitigation measures, such as floodproofing their

properties or purchasing an insurance policy. Latter can significantly reduce the financial impact of natural disasters, thereby enabling faster recovery of affected individuals, businesses and governments (Pauch et al., 2024). Section 2.4. covers insurance against natural hazards in detail. Finally, appropriate emergency protocols, enabling the access to shelters e.g., especially for vulnerable populations, are a necessity in flood risk management (Ermagun et al., 2024). Figure 2 gives an overview of many of the mentioned flood adaptation measures.

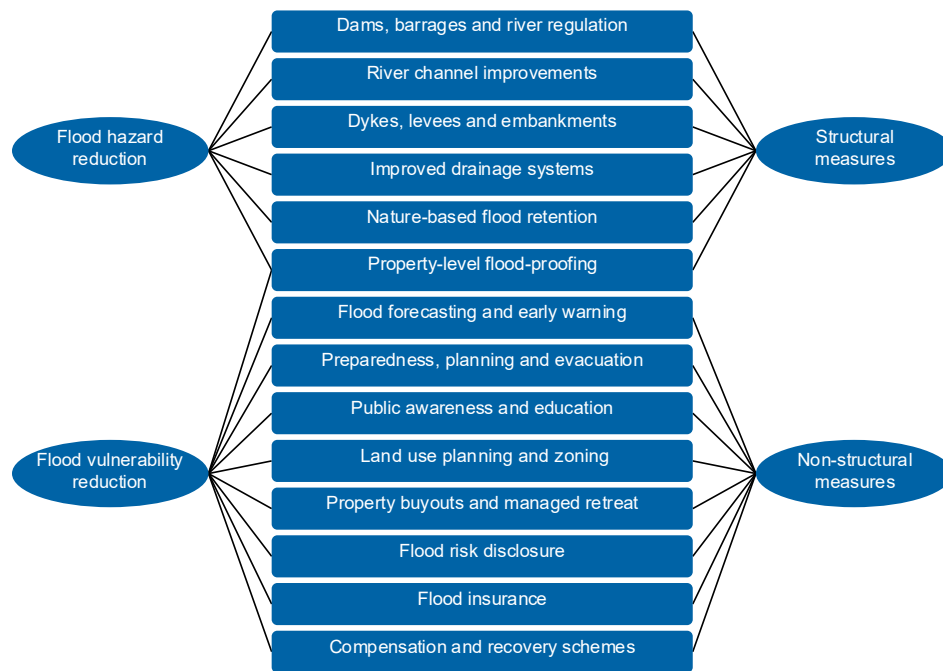


Figure 2: Overview of flood mitigation measures (own illustration based on Meyer et al., 2007).

If adequately implemented, non-structural mitigation actions can substantially decrease flood risk (Poussin et al., 2015). In order to minimize flood risk in general, the combination of structural measures and diverse non-structural measures as a holistic approach is necessary. Recurring flood disasters and a growing body of disaster research have made clear that structural defenses alone cannot eliminate flood risk (Kundzewicz et al., 2018). A comprehensive flood risk management strategy must therefore operate across all three phases of the disaster cycle (i.e. pre-event prevention and preparedness, emergency response, and post-event recovery) with insurance functioning as the principal financial instrument bridging the response and recovery phases by compensating losses that prevention alone cannot avert (Kalfin et al., 2022).

2.4. Insurance as mitigation measure

The concept of insurance is based on transferring the risk each individual carries to an insurer's pool by paying a contractually fixed sum to the insurance company – also called Premium (Gianni et al., 2023). The risk is thereby spread over time, space, and perils where damage costs for the case of a natural hazard event, for example, can be reimbursed in a timely manner afterwards (Oulahen, 2014).

In order for a risk to be considered insurable (i.e. profitable for the insurance company on aggregate), certain idealized conditions must be met, as described by Oulahen (2014) after Crichton (2002) and Kousky (2019): Firstly, a degree of randomness in both the occurrence and the magnitude of losses is required, since events that are certain or inevitable cannot be profitably underwritten. Sea level rise, for example, has resulted in "sunny day flooding" to be a near-certainty in some coastal communities, limiting its insurability. Secondly, risks must ideally be independent, thin tailed (i.e. with a low probability of extreme outliers) and quantifiable, which allows insurers to benefit from pooling. The average claim converges toward the expected value, and the aggregate losses approach statistical normal distribution, so that revenues can be set with high confidence of covering losses over time. This pooling logic in turn requires the insurer to have a sufficiently large "book" of business (i.e. capital to pay for losses), and thus the ability to spread accumulated risk across years, which particularly applies to years with a catastrophic event and claims exceeding yearly revenue when exemplifying natural hazards. Thirdly, losses must be determinable in a non-controversial manner, so that the insurer can establish what is owed and ultimately paid in claims. For natural hazards this means sufficient information and knowledge about potential hazards, vulnerabilities, and exposure. Problems arise when damages stem from multiple perils, only some of which are covered, as illustrated by the wind- versus flood-related damages in homes insured only against wind after Hurricane Katrina in 2005. Fourth, adverse selection and moral hazard must remain limited. Adverse selection arises when insureds hold more information about their own risk than the insurer. In practice, this manifests as a mismatch of incentives, which means that only those in endangered areas are interested in purchasing insurance while insurers only consider low-risk areas as insurable. That, in turn, can cause the market to "unravel", meaning a single blended price is too high for low-risk participants to find worthwhile, yet too low to profitably cover high-risk ones. A common remedy is bundled coverage (i.e. the natural hazard insurance attached to standard homeowner's policy e.g.) that cross-subsidizes risk across the pool, so that policyholders in low-risk areas effectively contribute to claims in high-risk ones. Moral hazard,

by contrast, occurs when insured parties engage in riskier behavior (e.g. not floodproofing homes) because they expect compensation for any resulting losses, and is typically counteracted through deductibles (i.e. a portion of the loss the insured must cover themselves), which leave residual risk with the insured as an incentive to take precautions. Finally, demand must meet supply at a price at which the market clears. Where all five conditions hold, a well-functioning insurance market can exist. Natural hazards, however, frequently violate several of these criteria, whereas the points mentioned under the second condition pose the largest problem. Damages from floods, earthquakes, wildfires etc. are considered fat-tailed, meaning that extreme outlier events occur more frequently than a normal distribution would predict, and the largest losses can be multiples of the second largest. This can ultimately lead to increases for the overall costs of disaster insurance, as the insurer's capital to pay losses becomes insufficient for the frequency of events.

Natural hazard insurance is the presently best solution for recovering from economic losses after a disaster while playing a crucial part in improving overall resilience of people and assets at risk, thus ultimately reducing financial vulnerability and the overall impact of a catastrophic event (Gianni et al., 2023; Kalfin et al., 2022; Kousky, 2019). The guarantee of available funds for recovery from indemnity payouts (i.e. compensation equal to the actual loss suffered), which are usually paid out much faster than potential government aid, can significantly shorten reconstruction processes and positively impact the recovery curve of a community after disaster (Kalfin et al., 2022; Pauch et al., 2024). Kousky (2019) additionally concludes that insurance payouts can serve as extra incentive for hazard mitigation as part of the rebuilding efforts. It is noted though that the impact on risk reduction overall may only be modest. Overall, the recovery and potential mitigation effects of insurance can only be fully realized when embedded into a holistic approach to disaster risk management (ibid.). Hereby, insurance on the government level (i.e. the government as the insured entity) can be a viable addition by helping to manage the emergency and post-disaster periods, as the immediate funds enable swifter emergency responses, such as tents, basic necessities etc., as well as reconstruction efforts (Kalfin et al., 2022). Government disaster assistance in itself, however, can lead to higher levels of vulnerability, as households anticipating disaster relief measures might then neglect insurance in total or proper levels thereof, which is known as "charity hazard" in the literature (Raschky, 2011). Without sufficient insurance, the financial assistance granted often does not meet the needs of the disaster victims, leading to uncovered loss and prolonged recovery periods (ibid.).

The majority of countries globally does not make disaster insurance mandatory (Pauch et al., 2024). Rather than being sold as a standalone product, coverage against natural hazards is typically embedded within standard property insurance policies (e.g. in real estate policy among other perils). Dedicated natural-hazard products are rare and, where they exist, tend to be confined to specific industries with concentrated exposure (e.g. agriculture or energy infrastructure). The basic perils bundled into standard property cover usually include lightning, hail, avalanches, windstorms and earthquakes, while higher-severity or more spatially concentrated risks (most notably floods) are frequently excluded or offered only as optional add-ons (ibid.).

Flood insurance, which is specifically tailored to risks associated with flooding (often mudflows, surface runoff, or land subsidence among others), can be differentiated along two dimensions: Public/Private and Optional/Bundled (Oulahen, 2014). In public models, insurance coverage is either provided or backed by the government, while in private models the responsibility lies fully with commercial insurers. Optional coverage leaves the choice whether to purchase an insurance policy against flood damage up to the individual households, whereas bundled coverage includes flood insurance with the coverage of other perils. A further design choice of flood insurance systems encompasses how premiums are set. Under risk-based pricing, premiums vary according to the actual flood risk faced by the insured property. This generates a price signal that can encourage households to avoid settling in high-risk areas or to undertake mitigation measures in exchange for premium discounts (Kousky, 2017; Tesselaar et al., 2020). Risk-based pricing is also considered to limit moral hazard, although its effectiveness in the context of natural hazard insurance is contested. At the same time, risk-based premiums raise the cost of insurance coverage in areas where exposure is highest, which can discourage take-up among households most in need of protection (Tesselaar et al., 2020). Social equity issues arising from this dynamic are expected to intensify under climate change as risk profiles worsen (Pralle, 2019). The flood insurance systems of the USA and France, both publicly backed but differing in their pricing logic and degree of bundling, are examined in detail in chapter 3.

2.5. Factors influencing mitigation and insurance uptake

The decision to invest in flood protection is shaped by a set of personal, social, and institutional factors that the literature has examined across decades and contexts (Bixler et al., 2021). The findings are sometimes contradictory, but several patterns hold across studies and matter for how compulsory and voluntary insurance regimes reach (or fail to reach) those at risk.

Past experience with flooding is the most consistently identified driver of preparedness. Households who have lived through a previous event tend to associate floods with concrete vulnerabilities rather than abstract probabilities, and are more likely to implement protective measures than those who have not (e.g. Babcicky & Seebauer, 2017). The same pattern is visible on the demand side of insurance take-up, which rises sharply in the year after a flood and erodes over the years back toward pre-event levels (Gallagher, 2014). Perception of risk itself is shaped by experience, social context, and behavioral biases when assessing rare events. Households tend to underestimate or ignore the probability of low-frequency, high-loss events, as they often have no experience with those (Holzheu & Turner, 2018). Additionally, "near misses" may be read as evidence that protection is unnecessary rather than as warnings of possible loss (ibid.). Similarly, the so-called "levee effect" can create a misleading perception of safety for potentially affected population groups as structural mitigation measures built by the government give residents the impression they are fully protected and even induce further settlement and assets accumulation to the area. Breaches/Overtopping of these defenses can eventually result in devastating consequences with correspondingly larger losses, as e.g. Hurricane Katrina in 2005 showed (Di Baldassarre et al. 2018, Kunreuther, 2006). Kunreuther (2006) argues that individual's decision-making often is myopic when upfront cost outlays, whose benefits accrue only over decades, are involved. The immediate expenses weigh more heavily than the eventual return, especially when households do not expect to stay in the home long-term. Budget constraints amplify the effect. For lower-income households, basic necessities crowd out long-horizon protective investments altogether, with clear implications for how vulnerability concentrates spatially (ibid.).

Social capital, i.e. the personal networks, neighborhood cohesion, and shared norms that allow people to act collectively rather than as isolated households further, thereby influencing risk perception and the capacity to act on it (Babcicky & Seebauer, 2017). Communities with denser ties tend to coordinate mitigation more effectively, and social norms shape insurance decisions directly. These interdependencies can lead to a rise in willingness to adopt mitigation measures, following certain tipping dynamics: a few households elevating or floodproofing can shift the

local equilibrium, since being the only protected home in a neighborhood is often understood as oddity rather than prudence and may even depress resale value (Kunreuther, 2006). Flood insurance uptake follows a similar pattern.

Two further factors weigh particularly heavily on insurance specifically. Next to charity hazard, where households expect post-disaster assistance from the government, and thus the economic incentive to insure privately consequently declines (Raschky 2011), financial literacy and consumer education about insurance play crucial roles in mitigation behavior (Holzheu & Turner, 2018). Households might misunderstand the coverage of their existing policies, leading to overall unpreparedness especially in contexts where flood cover must be actively purchased. This gap between perceived and actual coverage translates directly into uninsured loss after an event.

In practice these factors overlap, and the households that lack one usually lack several. Preparedness and thus vulnerability is therefore unevenly distributed in space. In which manner these disparities are handled varies depending on the insurance system in place.

3. Literature Review: Social Vulnerability and Flood Insurance

This section deepens the literature briefly introduced in Chapter 1 by tracing how social vulnerability has been operationalized, reviewing the flood- and insurance-specific evidence base on differing impacts on societies, and grounding the variable selection of the composite Social Vulnerability Index (SoVI) applied in this thesis.

3.1. Social vulnerability: from concept to measurement

The vulnerability paradigm, which emerged as a corrective approach to hazard-centric disaster research, shifted analytical attention from the physical hazard itself to the capacity of population's coping capacity (Wisner et al., 2004). Operationalization of this concept advanced with works such as Cutter et al. (2003) for instance, who introduced the Social Vulnerability Index (SoVI) as a quantitative composite of census-derived socioeconomic variables, establishing the methodological standard for the field. Subsequent variants have adapted the approach to specific contexts: the CDC/ATSDR SVI [Center for Disease Control and Prevention / Agency for Toxic Substances and Disease Registry Social Vulnerability Index] refined the framework for public-health emergency applications (Flanagan et al., 2011), and dedicated flood-specific meta-analyses identified a robust subset of indicators across published

studies (Rufat et al., 2015). The composite approach is not without methodological scrutiny: Index ranks have been shown to be sensitive to variable selection, transformation, weighting and scale of analysis (Tate, 2012). These caveats are taken into account when constructing the social vulnerability index for the case study areas, as explained in chapter 5.

3.2. Flood vulnerability and insurance equity

The empirical record consistently shows that low-income households, renters, the elderly, and households with limited mobility bear a disproportionate share of flood losses, displacement, and recovery delays (Rufat et al., 2015). Koks et al. (2015) provide the integrated framework that anchors this thesis by conducting an urban flood-risk assessment where hazard, exposure, and social vulnerability in a single spatial overlay, directly motivating the cartographic approach taken here.

Both the USA's as well as France's insurance system have been the subject of dedicated research. For the NFIP, researchers have examined participation and take-up patterns, premium pricing, distributional and equity dimensions, and the political processes shaping flood-zone delineation (Pralle, 2019; Kousky, 2017; Amornsiripanitch, 2025). For the French CatNat regime, work has focused on its solidarity-based architecture, the mitigation incentives it generates for households and communities, and the interaction between compensation and risk-prevention instruments (Poussin et al., 2013; Barraqué & Moatty, 2020). The substantive findings of this body of research are taken up in Chapter 4, where each system is described and assessed comparatively. Comparative work between systems exists but remains predominantly focused on institutional or economic characteristics (e.g. Paudel, 2012). More recent contributions have begun to examine flood insurance distribution explicitly in terms of regional inequalities in affordability and uptake (Tesselaar et al., 2020), and to evaluate reform pathways aimed at reconciling risk-based pricing with equity concerns (De Ruig et al., 2022). Yet the geographically explicit comparison of who is protected, and where, under two structurally opposite regimes, remains largely absent. The thesis aims to address that gap with the help of a composite SoVI.

3.3 Variables grounded in literature

The composite index literature converges on a set of socioeconomic and structural variables that are repeatedly identified as relevant predictors of social vulnerability to natural hazards. They can be grouped into four broad dimensions.

Demographic structure: The share of the population below a certain age (e.g. 18) and above a certain age (e.g. 65) is among the most consistently identified predictors. Cutter et al. (2003) include both groups within one demographic factors of the original Social Vulnerability Index, and the meta-analysis of Rufat et al. (2015) confirms age as a leading demographic driver across published flood case studies. Both population groups are considered to be physically more vulnerable to flood impacts, slower to evacuate and more reliant on external assistance during and after events (Flanagan et al., 2011).

Household composition: Households without a car can be associated with reduced evacuation and post-event mobility (Flanagan et al., 2011; Rufat et al., 2015); The renter share of the population is consistently identified as more vulnerable than owner-occupiers across the literature, being linked to weaker post-disaster recovery resources (Cutter et al., 2003; Rufat et al., 2015); Single-person households may serve as a proxy for reduced within-household support capacity, as individuals living alone cannot draw on immediate household members for assistance during disaster preparedness, evacuation, or post-disaster recovery (Arnberg & Melin, 2013).

Physical factors: Construction date of a housing unit functions as a proxy for compliance with modern flood-resistant building codes and structural resistance. Wing et al. (2020), for instance, conducted an empirical analysis of more than two million flood insurance claims in the United States, showing that the age of residential building stock influences flood damage outcomes, with construction period reflecting differences in building standards. The exact time period cutoff varies by national regulatory context; Access to healthcare facilities per inhabitant captures the availability of critical infrastructure for emergency response and is widely used in social-vulnerability indices (Cutter et al., 2003; Rufat et al., 2015).

Financial conditions: Socioeconomic status and thereby income is consistently identified as a notable indicator of social vulnerability across flood-specific research (Rufat et al., 2015). It forms the largest single factor in the original SoVI under the heading of "Personal Wealth" (Cutter et al., 2003); The poverty rate captures the concentration of households below the official threshold and complements median income by foregrounding the lower tail of the distribution. A precise definition of poverty is, however, not directly equivalent across national statistical systems; Unemployment proxies economic precariousness and recovery capacity and is frequently used as a cross-check on poverty (Cutter et al., 2003; Rufat et al., 2015); Educational attainment is correlated with financial resources and is therefore often grouped with socioeconomic-status indicators (Flanagan et al., 2011). Its distinct contribution, however,

lies in the human-capital dimension that income alone does not capture: education is empirically associated with stronger risk perception, more effective preparedness behavior, and faster navigation of recovery and insurance processes (Cutter et al., 2003; Flanagan et al. 2011).

3.4. Position of this thesis

The contribution of this work lies at the intersection of two strands that have largely developed in parallel: flood-specific SoVI research, predominantly applied within single national contexts, and comparative flood-insurance research, predominantly institutional in character. By combining an empirically grounded SoVI with explicit cartographic comparison of two structurally opposite insurance regimes anchored in comparable flooding events, this thesis produces a geographically explicit answer to the question of who is protected, where, and under which system design.

4. Case study areas and underlying systems

This chapter introduces the two case studies on which the comparison rests. Both the United States and France are presented in an identical structure. A general overview of the study area sets it into context by describing the geographical setting, climate, population and land use. Afterwards, the specific flood event that serves as the reference case for the analysis, namely Hurricane Harvey 2017 in Harris County and the 2016 floods in Île de France, is introduced. The underlying disaster risk management framework and the national flood insurance system are examined last, placing the insurance regime within the institutional context in which it operates. A concluding section then compares the two systems side by side. Figures, statistics and mechanisms for the study areas and regimes are predating the reference events where possible. Developments and recent discussion in the time period after 2016/2017 are covered in chapter 7.

4.1. Case study area USA: Harris County

4.1.1. Harris County: Geographic and socioeconomic context

Harris County is located in southeast Texas on the North American Gulf Coastal Plain, approximately 80 kilometers inland from Galveston Bay and the Gulf of Mexico (Figure 3). With a land area of roughly 4.500 km² and approximately 4,6 million inhabitants in 2016, it was and still is the most populous county in Texas and the third most populous in the United States (Statkewicz et al., 2021; U.S. Census Bureau, 2026). Due to the dense network of slow-moving watercourses that traverses the region, Houston is widely referred to as the “Bayou City” (HCFCD, n.d.). The following physical and socio-economic conditions encompass both the flood hazard to which the county is exposed and the social vulnerability that is unevenly distributed across it and thereby motivates its selection as a case study.

Physical conditions

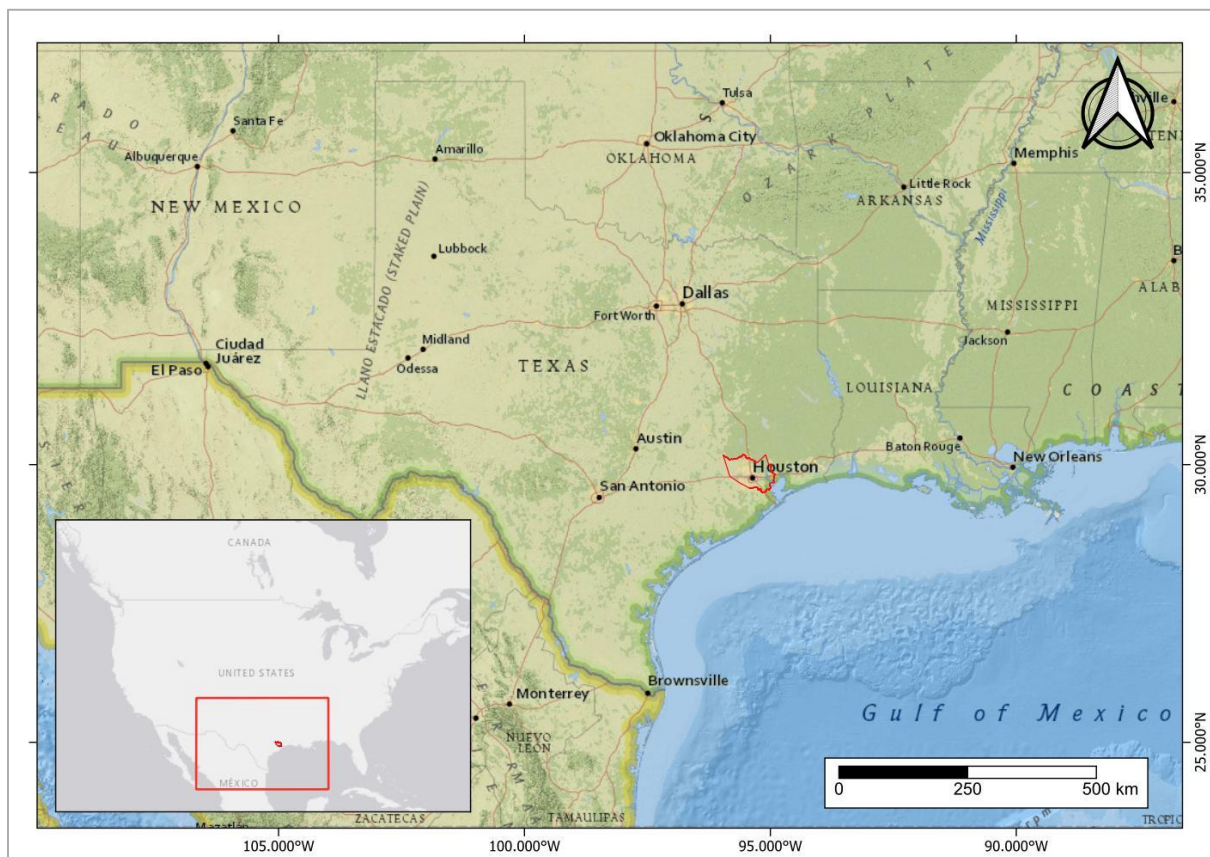


Figure 3: Location of the study area (Harris County, Texas) in the broader Gulf Coast region of the southern United States. Harris County is outlined in red (own illustration from the QGIS basemaps: National Geographic World Map & CartoDB Light All).

The county is characterized by an exceptionally flat, low-lying terrain with little surface relief, such that runoff drains only slowly towards the coast (Statkewicz et al., 2021). The subsurface of the Gulf Coastal Plain consists of unconsolidated sediments in which clay-rich, poorly permeable soils predominate, making infiltration correspondingly limited and rapidly converting rainfall into surface runoff (Kasmarek et al., 2009). The Köppen climate classification Cfa determines the regional climate as humid subtropical with hot, humid summers and mild winters. The mean annual temperature of 21,4°C and mean annual precipitation of approximately 1.316 mm (both based on aggregated 1991-2020 data) that is concentrated in the convective and tropical-cyclone season, underline this (NOAA, n.d.; Statkewicz et al., 2021). The county lies directly within the trajectory of tropical storms and hurricanes making landfall on the Texas coast, and the frequency of extreme single-day rainfall events has increased measurably over recent decades (Statkewicz et al., 2021). Surface drainage is organized into 23 primary watersheds that discharge into Galveston Bay and are administered by the Harris County Flood Control District (HCFCD) (Figure 4).

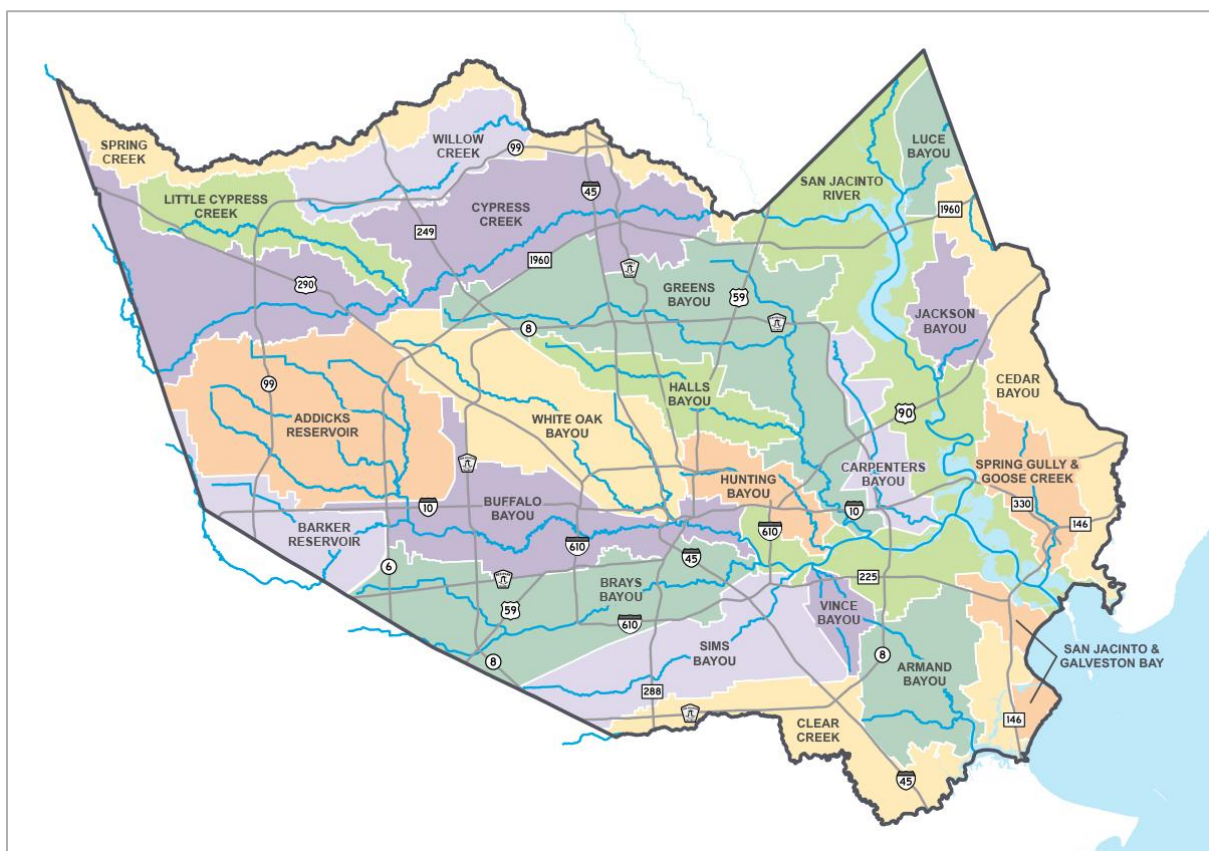


Figure 4: Watersheds in Harris County (HCFCD, n.d.).

This natural disposition towards flooding is further aggravated by land subsidence, as decades of groundwater withdrawal have compacted the fine-grained clay layers of the underlying aquifer system, lowering the land surface and measurably raising how often and how widely the county floods (Kasmarek et al., 2009).

Socio-economic conditions

Harris County has experienced sustained and rapid population growth, reaching a density of 1.083 inhabitants per km² in 2016 with the highest density situated inside the boundaries of Houston (Figure 5).

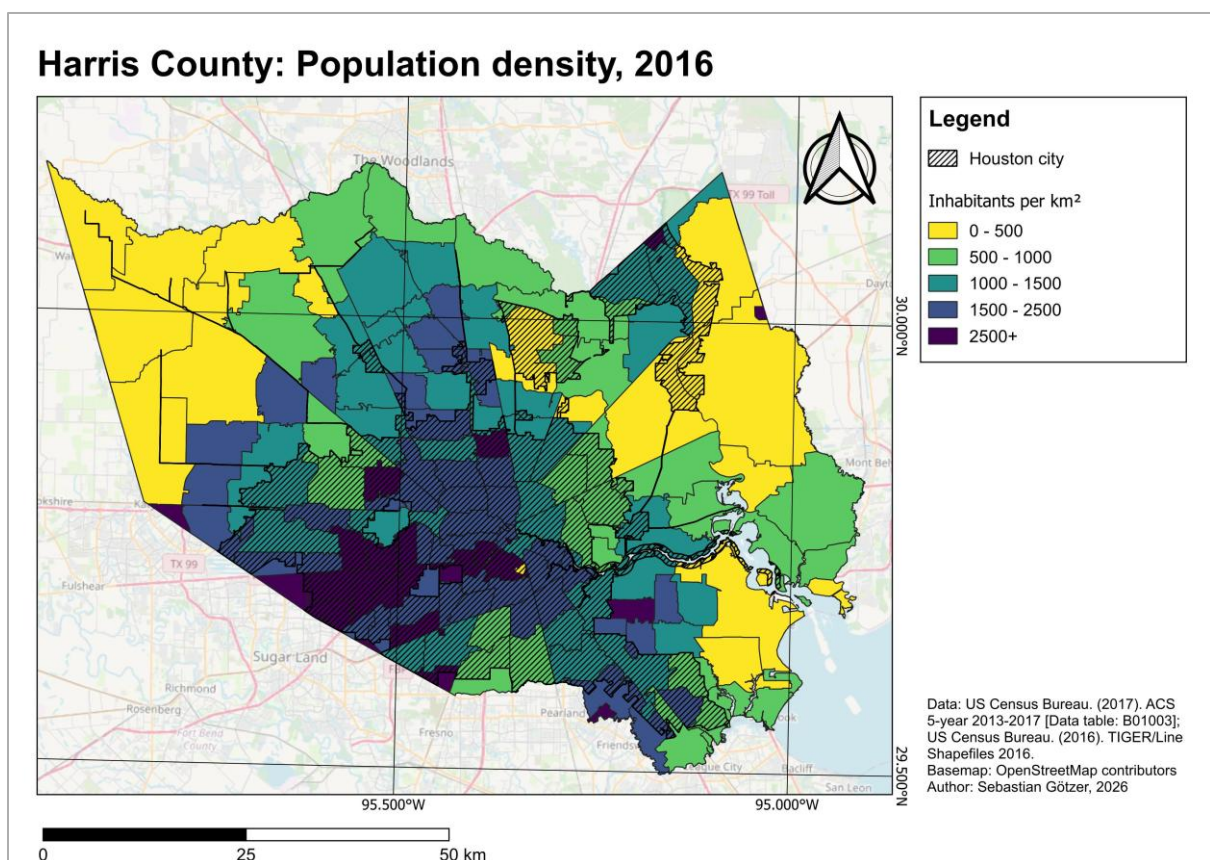


Figure 5: Population density 2016, Harris County (own illustration).

This growth has taken the form of extensive, low-density urban expansion, which has substantially increased the share of impervious surface across the region. The replacement of prairie and wetland by sealed surfaces reduces infiltration, accelerates and increases runoff, and has been shown empirically to raise flood-damage losses in coastal Texas (Brody et al., 2008). Figure 6 shows the extents of the urbanization levels within the county, highlighting the spatial dominance of developed land in the county. Economically, the county is a global center of the

energy and petrochemical industries, organized around the Houston Ship Channel, which is the leading port in the United States by total tonnage, and is further home to the Texas Medical Center and a substantial manufacturing base (Statkewicz et al., 2021). It is at the same time one of the most racially, ethnically, and economically heterogeneous large counties in the country, a heterogeneity that translates into a distinctly uneven distribution of social vulnerability to flooding (Chakraborty et al., 2019).

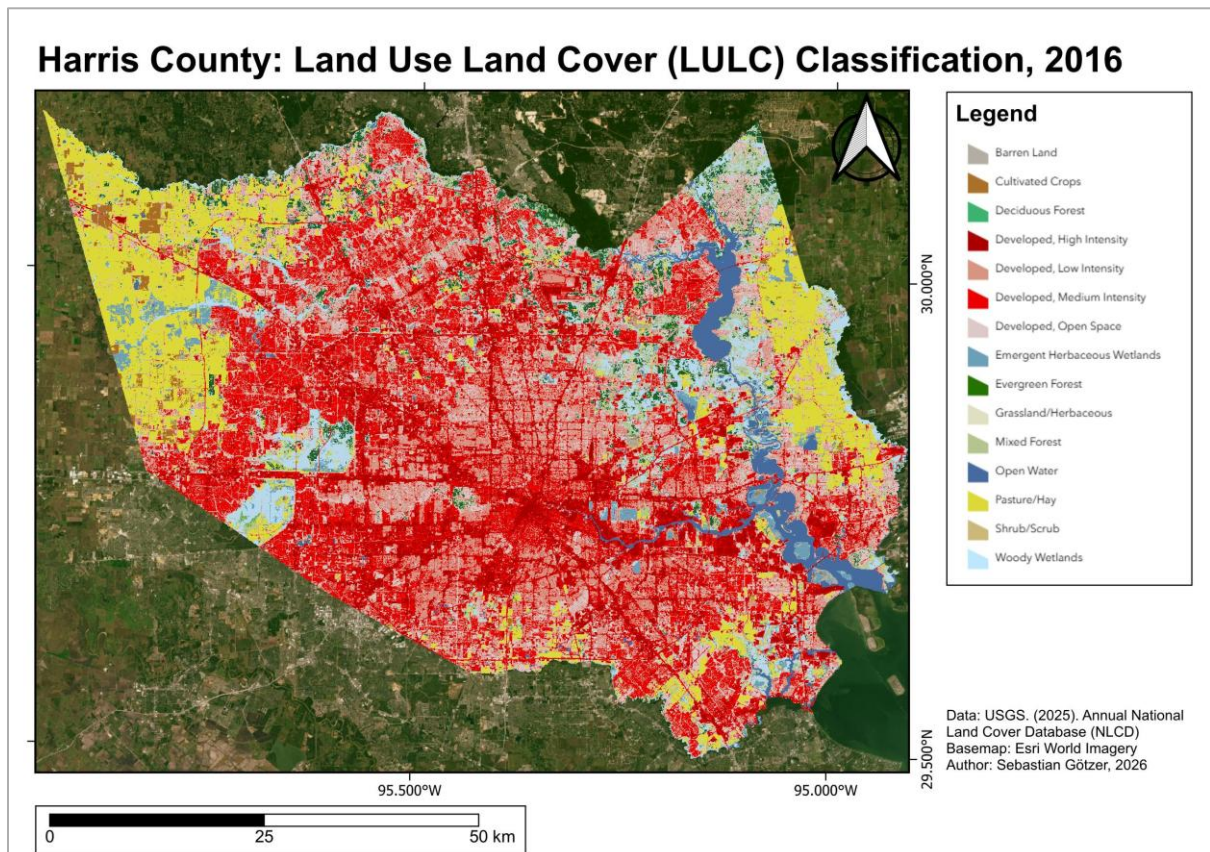


Figure 6: Land Use Land Cover Classification 2016, Harris County (own illustration; data retrieved from USGS).

These characteristics make Harris County a suiting setting for the present analysis. Its flat terrain, intense Gulf-driven rainfall, ongoing subsidence, and rapid sealing of the land surface generate a high and rising physical flood hazard, while its mentioned socio-economic heterogeneity produces spatially uneven patterns of vulnerability to that hazard. The county has thus been struck by a succession of severe flood events in recent years: Tropical Storm Allison (2001), the Memorial Day flood (2015), the Tax Day flood (2016) and, most consequentially, Hurricane Harvey (2017) (HCFCD, n.d.) - the last of which is examined in detail in the following section as the reference event for this case study.

4.1.2. Hurricane Harvey 2017

Hurricane Harvey began as a weak Atlantic tropical storm, dissipated over the Caribbean, and then re-formed over the Bay of Campeche before rapidly intensifying into a Category 4 hurricane and making landfall on the middle Texas coast near Rockport on 25 August 2017 (Blake & Zelinsky, 2018; NESDIS, 2024). What transformed a coastal hurricane into a catastrophic flood event was its near-stationary track after landfall. The system stalled over and near the Texas coast for roughly four days, drawing moisture from the Gulf of Mexico and releasing it as sustained, extreme rainfall over the Houston metropolitan area between 26 and 28 August (van Oldenborgh et al., 2017). In Harris County, Harvey was therefore predominantly experienced as a prolonged precipitation and pluvial flood hazard rather than a wind hazard.

The rainfall totals were without precedent in the modern record. Peak storm accumulations over the four days the hurricane stalled, exceeded 1.524 mm in parts of southeast Texas (Blake & Zelinsky, 2018), and across much of Harris County totals reached 635 to 1.016 mm, with a local maximum of 1.204 mm recorded over four days near Clear Creek (HCFCD, n.d.). The heaviest three-day accumulation, measured at Baytown, reached about 1.043 mm, an amount whose estimated return period in the present climate exceeds 9,000 years (van Oldenborgh et al., 2017). Rapid attribution analysis linked this severity to anthropogenic climate change, estimating that warming had increased the likelihood of such extreme rainfall by roughly a factor of three and its intensity by around 15 percent along the Gulf Coast (ibid.). The resulting inundation extended across large parts of the county, as shown in Figure 7.

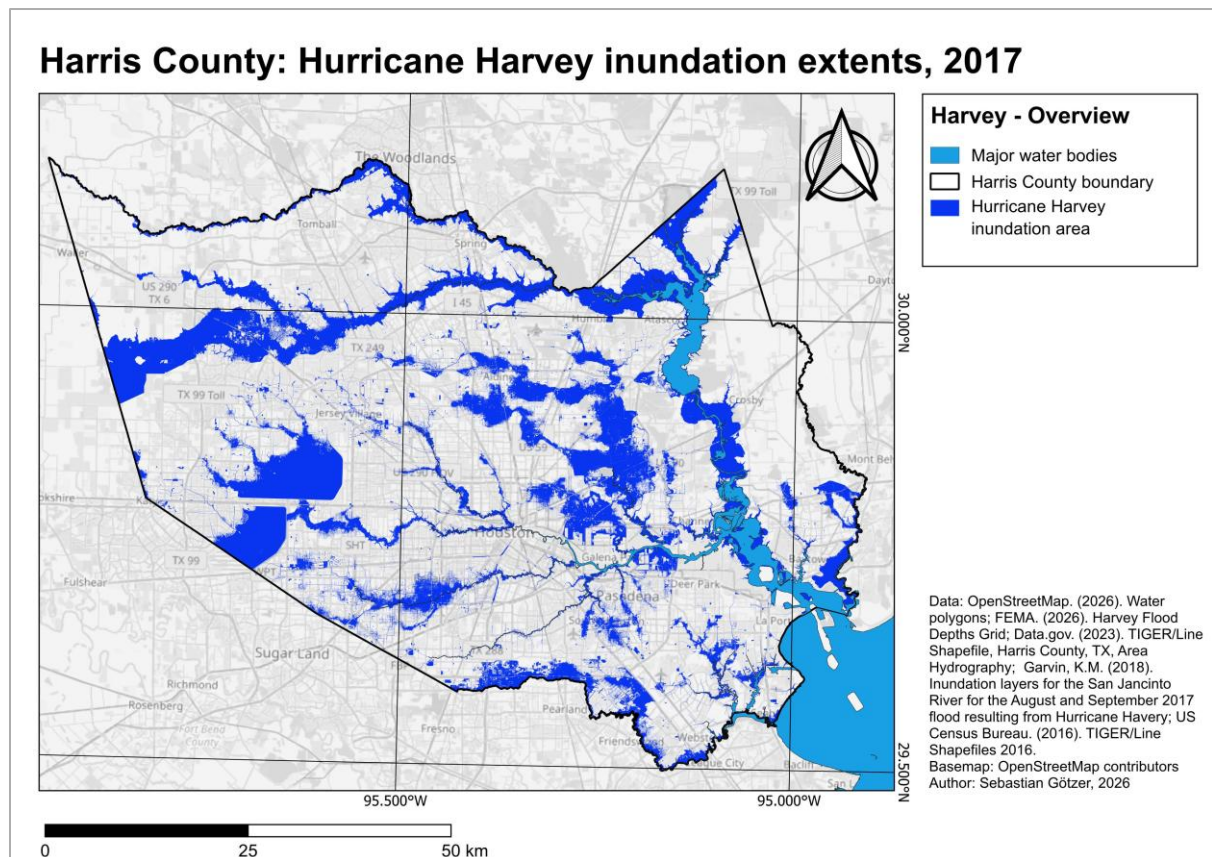


Figure 7: Hurricane Harvey inundation extents 2017, Harris County (own illustration).

Because the disaster was driven by rainfall rather than coastal surge or the overflow of a single river channel, flooding spread well beyond established watercourses and across the developed urban area. The consequences of Hurricane Harvey were severe with 36 deaths in Harris County (HCFCD, n.d.) and at least 68 direct deaths across Texas (Blake & Zelinsky, 2018). An estimated 154.000 homes and around 300.000 vehicles were flooded in the county, and total damages in the United States reached approximately USD 125 billion, placing Harvey among the costliest tropical cyclones in the country's history (HCFCD, n.d.; Blake & Zelinsky, 2018).

Chakraborty et al., (2019) find that the hurricane directly intersected with pre-existing patterns of social vulnerability, a spatial coincidence that this thesis examines directly in Chapter 6 and 7. Insurance coverage against these losses was correspondingly limited, with only around 15% of Harris County homes holding flood insurance when Harvey made landfall.

4.1.3. Disaster risk management in the USA

In the USA, disaster risk management is distributed over several institutions whereas the task of constructing and maintaining structural protection measures against floods mainly falls to the U.S. Army Corps of Engineers (USACE). With the aim of thereby reducing community flood risk, the federal agency's main responsibilities revolve around structures such as levees, dams, and channels (Carter & Lipiec, 2020). The spectrum of tasks has expanded over time by Congress ruling, giving additional responsibility for evaluating non-structural alternatives and more recently nature-based features, such as wetlands or reefs, for instance (ibid.). The case of a disaster event occurring is embedded into the Stafford Disaster Relief and Emergency Assistance Act, which was passed into law in 1988. Within this framework, presidential disaster declarations and federal assistance to states and localities is stipulated. If a natural disaster turns out to exceed the affected state's financial and managing capacities, the governor can request a declaration from the president of the United States, who may then authorize the Public Assistance program (aid for local governments) and/or the Individual Assistance program (aid for affected households) (Kousky et al., 2017). The Federal Emergency Management Agency (FEMA), next to then managing these relief funds, is also responsible for the National Flood Insurance Program (NFIP), which represents the primary federal instrument for ex-ante financial protection of households against floods within the system of flood risk management (De Ruig et al., 2022; Kousky, 2017).

4.1.4. NFIP

The NFIP is a public insurance model based on an optional separate policy that tackles the issue of property coverage not including specific hazards such as flooding, as established in chapter 2 (Kousky et al., 2017). The NFIP, which represents over 95% of the US flood insurance market, has defined program goals of identifying and mapping risk; encouraging floodplain management as well as being an insurance program elevate it beyond just being flood insurance in itself (Amornsiripanitch et al., 2025; Kousky, 2017). It was established in 1968 with the goal of addressing long-standing problems associated with natural hazards in the USA by offering insurance coverage against flooding at partially subsidized premiums (Pralle, 2019; Raschky, 2011). These problems primarily encompassed the combination of most homeowners not being insured against floods with a series of devastating and expensive natural disaster events in the 1960s (Pralle, 2019). In consequence, the NFIP was established as a community-based structure, where the federal government offers flood insurance to property owners and

businesses within communities at risk under certain conditions. In order to participate, a community needs to file an application for the NFIP at FEMA, where an individual flood insurance rate map (FIRM) is then created. This mapping process, indicating flood-prone areas, is the central infrastructure of the NFIP's risk modelling and risk communication efforts (Kousky, 2017). Before Hurricane Harvey struck in 2017, premiums were calculated based on the underlying FIRM zone, where a range of factors including elevation relative to the Base Flood Elevation (BFE), type of property, presence of a basement among others are considered. Two rate classes coexisted: actuarial full-risk rates for structures built after a community's first FIRM (post-FIRM), and explicitly subsidized rates for older pre-FIRM structures. Latter were implemented to avoid penalizing homeowners whose buildings were constructed before the NFIP floodplain was established thus making them unaware of the underlying flood risk – which in turn would lead to high premiums. Through grandfathering (i.e. keeping premiums of an old zone), owners could moreover retain a favorable rate class after being remapped into a higher-risk zone (ibid.). This structure was mid-transition when Harvey made landfall: the Biggert-Waters Flood Insurance Reform Act of 2012 had begun phasing out subsidies toward full-risk pricing, before the Homeowner Flood Insurance Affordability Act of 2014 reinstated grandfathering and capped annual premium increases (Horn & Webel, 2026). Premiums in 2017 were therefore zone-based and only partially actuarial. Within FIRMs, different zones are defined, bearing different meanings and implications. Hereby, specifically the Special Flood Hazard Areas (SFHAs) (areas with 1 percent annual chance of flooding – 100-year floodplains) play a crucial role, as many regulations and requirements are tied to them (Kousky, 2017; Pralle, 2019). Figure 8 showcases the SFHAs (part of FEMA's downloadable National Flood Hazard Layer NFHL) in Harris County before Hurricane Harvey made landfall.

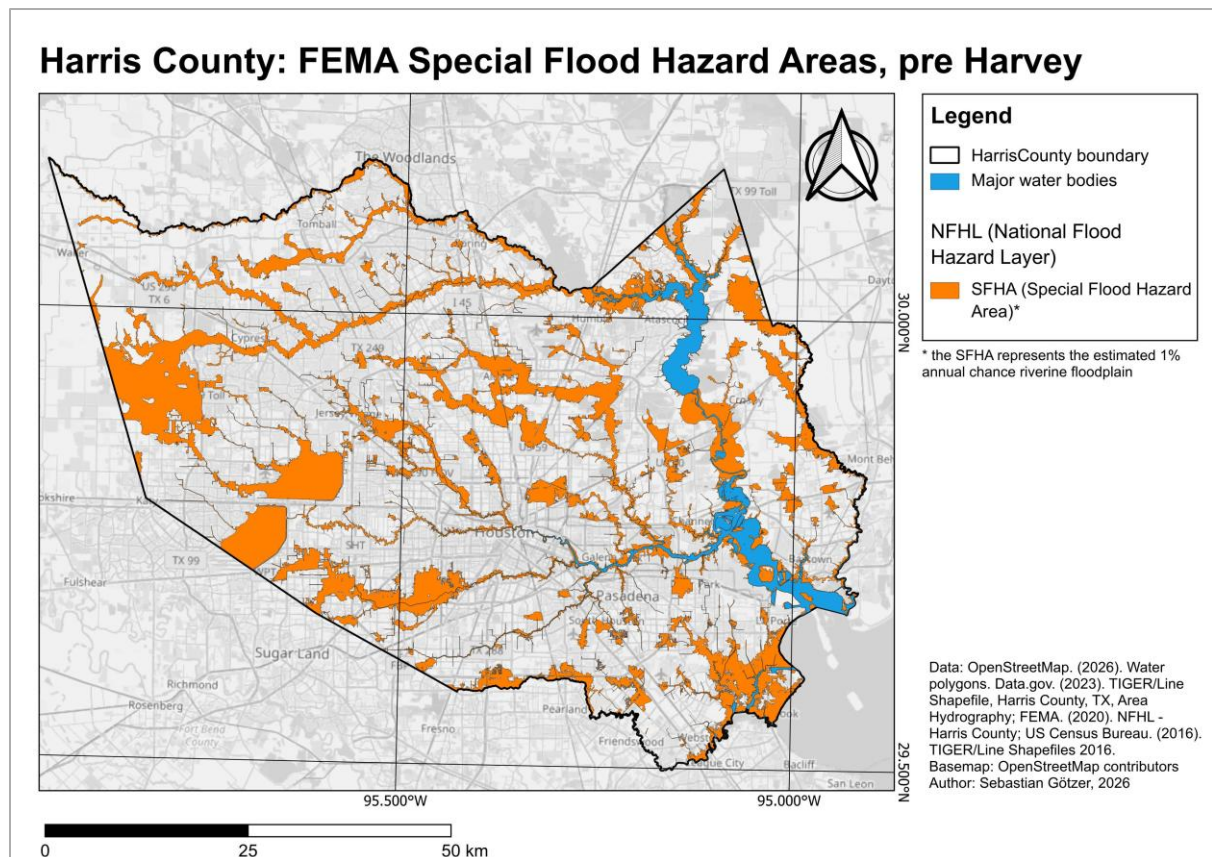


Figure 8: Special Flood Hazard Areas (SFHAs), Harris County (own illustration).

Once an applying community accepts the FIRM created by FEMA, it is eligible for federal disaster assistance, and its households and businesses can purchase flood insurance on a voluntary level. Disaster help within the Individuals Assistance program (IA), such as the Individuals and Households Program (IHP) only becomes available after a presidential disaster declaration. The programs are, however, capped at a comparatively low payout and are only meant to serve as a last resort, whereas insurance coverage claims get paid out independently of any declaration (Kousky, 2017). Furthermore, the community needs to establish and enforce floodplain management and development regulations, designed to reduce overall flood-risk, as a condition for participation in the NFIP (FEMA, 2026b; Pralle, 2019). All property holders within the defined 100-year flood zone (SFHA) of a participating community that have mortgages from federally regulated or insured lenders are required to purchase mandatory flood insurance coverage (FEMA, 2026b; De Ruig et al., 2022). Additionally, households in high-risk areas that received payment from an IA program are required to purchase insurance in order to remain eligible for future federal disaster assistance (Kousky et al. 2017). The flood maps are not static within this system, as any participating community, local government or individual can apply for a Letter of Map Change (LOMC) based on newly obtained information by hydraulic modelling or new geographical circumstances through construction, mitigation

activities, for instance (FEMA, 2024; Pralle, 2019). While some justified concerns on the FIRMs may lead to FEMA adjusting the maps without a LOMC, communities usually must go the way of lodging a Letter of Map Revision (LOMR). Individual property owners can analogously file a Letter of Map Amendment (LOMA) (Pralle, 2019).

The delivery system of the National Flood Insurance Program is based on a network of private insurance companies selling the policies in eligible communities on behalf of the government. Also called “write-your-own” (WYO) companies, these private insurers write policies and then process the claims against payment from FEMA while they are neither involved in setting the premiums nor are they bearing any of the financial risk in the case of a disaster event (Horn & Webel, 2026; Kousky, 2017). The coverage scope is variable with a maximum of USD 250.000 of building coverage and USD 100.000 of contents coverage for individual households to be obtained separate from each other (Kousky, 2017). Hereby, renters occupy a distinct position within this structure, as the mandatory purchase requirement is tied to federally backed mortgages and therefore applies only to property owners, leaving tenants outside any compulsory coverage even within the SFHA. They may voluntarily purchase contents-only policies for their belongings, but building coverage remains the responsibility of the landlord (Horn & Webel, 2026). New policies are subject to a 30-day waiting period before coming into effect in order to avoid purchases in the run-up to a potentially damaging natural hazard event (FEMA, 2026b). In 2016, the NFIP provided an overall USD 1,25 trillion of coverage distributed over more than 5 million policies. Although nominally premium-funded, the NFIP is authorized to borrow from the US Treasury when claims exceed its reserves and had accumulated substantial debt following major events such as Hurricane Katrina in 2005 (Horn & Webel, 2026).

4.2. Case study area France: Île de France region

4.2.1. Île de France: Geographic and socioeconomic context

Île de France is one of eighteen administrative regions of France, located the north-central part of the country, which includes the capital Paris (Figure 9). Covering 12.012 km² with around 12 million inhabitants in 2016 (approx. 18% of France's total population) it is the most populous of the French regions and the country's economic core, generating more than 30 percent of national GDP (INSEE, 2026a; INSEE, 2026b). It is organized concentrically around the department of Paris into a densely built inner ring, the petite couronne (Hauts-de-Seine, Seine-Saint-Denis, Val-de-Marne), and a larger outer ring, the grande couronne (Seine-et-Marne, Yvelines, Essonne, Val-d'Oise).

Physical conditions

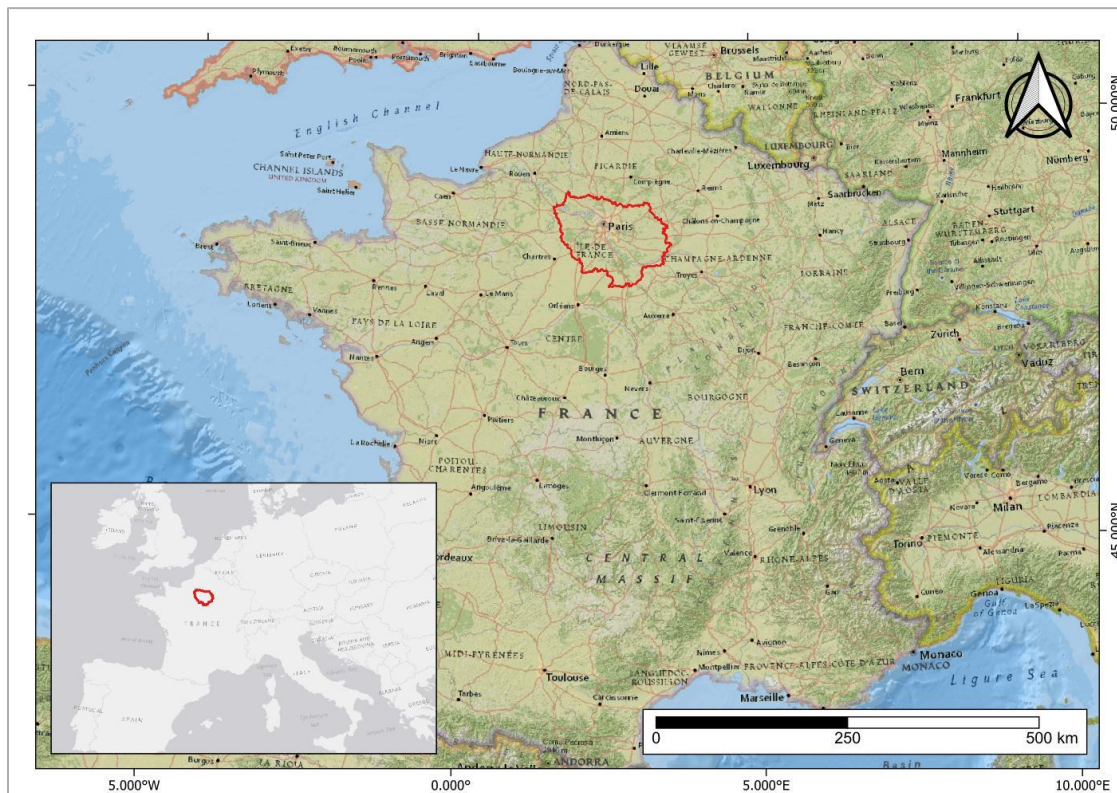


Figure 9: Location of the study area (Île de France) in the broader context of France and Western Europe. Île de France is outlined in red (own illustration from the QGIS basemaps: National Geographic World Map & CartoDB Light All).

The region lies within the Paris Basin, France's largest sedimentary basin, where the Seine and its tributary rivers including the Orge, Marne, Yvette, and Loping form one of Europe's most densely populated river basins. The corresponding valley floors, where built-up areas and critical infrastructure are concentrated, exhibit the most significantly present flood hazard in the region (OECD, 2014). The climate is temperate oceanic (Köppen Cfb): the 1991–2020 normals at

Paris-Montsouris station are a mean annual temperature of 12,8 °C and 634 mm of precipitation, distributed evenly across the year (Météo-France, 2025). Flooding is therefore driven not by convective or tropical-cyclone rainfall but by prolonged, basin-wide rainfall from autumn to spring over a large upstream catchment, producing slow-onset fluvial floods rather than flash pluvial events (OECD, 2014). The drainage network is dominated by the Seine and its main tributaries the Marne, Oise, Yonne and Loing, whose flows converge on the metropolitan area. The Seine itself is low-gradient and slow-flowing, so that major floods build over days rather than hours (ibid.).

Socio-economic conditions

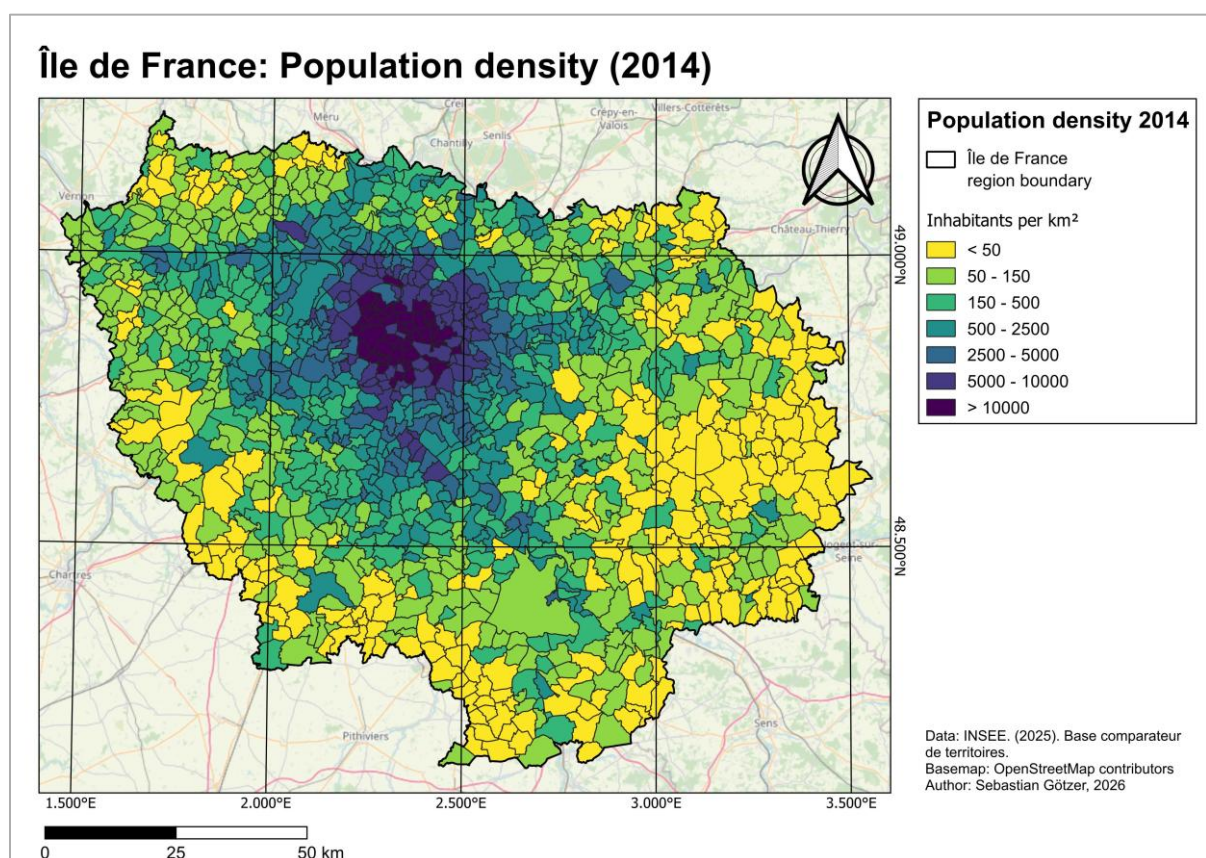


Figure 10: Population density 2014, Île de France (own illustration).

The regional population density average of roughly 1.000 inhabitants per km² masks a steep gradient from the city of Paris (over 20.000/km²) through the petite couronne departments (around 6.600) to the grande couronne (roughly 450), showcasing an overall highly uneven distribution (Figure 10). Land use / Land Cover shows the same contrast: Figure 11 highlights the high concentration of dense urban fabric with Soil Sealing Level (S.L.) of 50 percent and more around the Paris metropolitan area, expanding outwards along the growth axis Seine and

its tributaries. Otherwise Île de France is dominated by arable land and forests, naturally coinciding with low levels of population density. The pattern of urban development progressively extending into the Seine floodplain, concentrating population and assets in the zone most exposed to riverine flooding and thereby creating increased portions of impervious surface directly influences flood risk in the area (OECD, 2014).

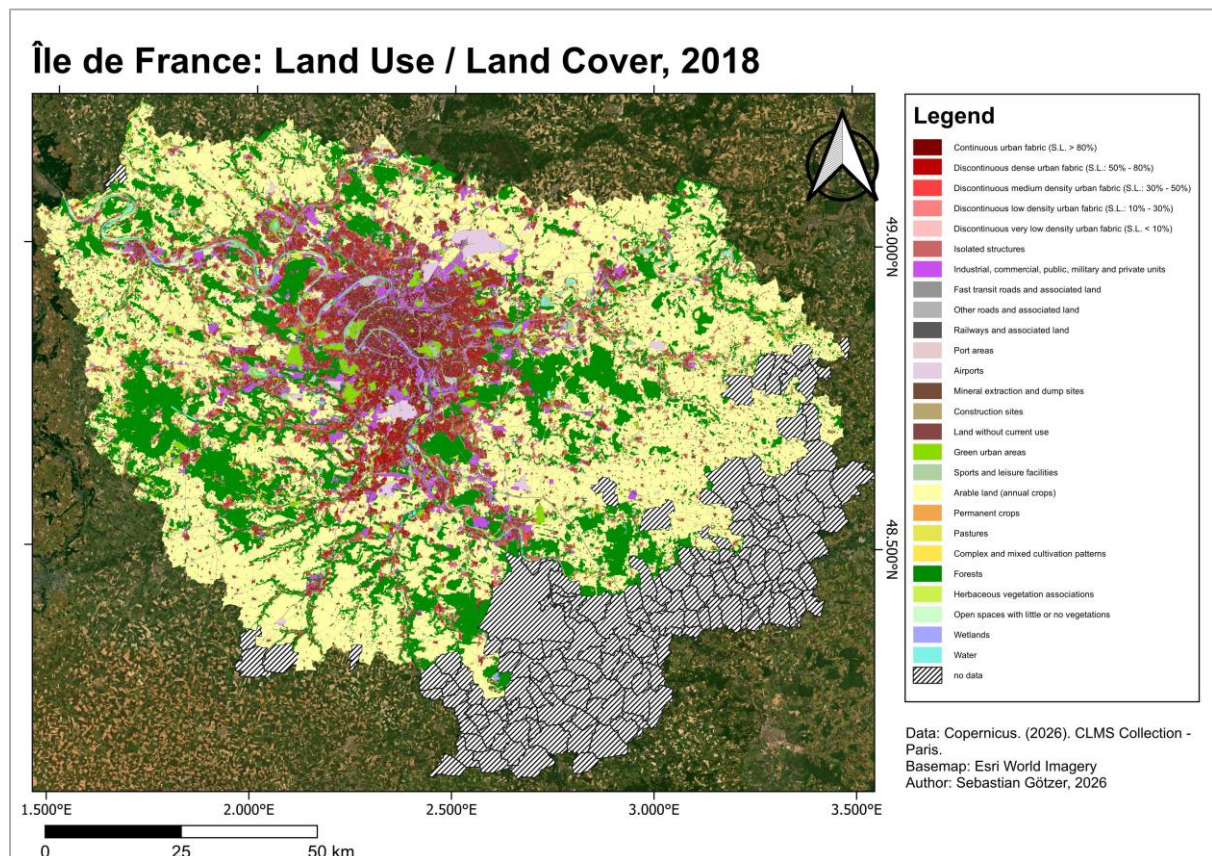


Figure 11: Land Use / Land Cover 2018, Île de France (own illustration).

This concentration is matched by a pronounced socio-spatial inequality. Île-de-France is simultaneously the wealthiest and most unequal French region, with a poverty rate of 15,7 percent in 2016, above the national average (Sagot, 2019). Income levels are sharply differentiated across the region: an affluent western core, with Paris and Hauts-de-Seine among the wealthiest departments, contrasts high levels of poverty concentrated in the north, particularly in Seine-Saint-Denis, which is the poorest department in mainland France (ibid.).

These circumstances make Île de France a suited case study area: a dense concentration of people and assets occupies the slow-rising valleys of the Seine system, while structured social inequality renders vulnerability to flooding spatially uneven. The reference catastrophe of the region is the flood of January 1910, when the Seine reached about 8,6m at Austerlitz and

inundated much of the capital. The river has not overflowed comparably since 1955 however, and before 2016 major floods recurred on average about every twenty years (OECD, 2014; OECD, 2018).

4.2.2. Île de France floods 2016

The heavy torrential rainfalls that caused the 2016 floods began on 26 May, when a low pressure system remained almost stationary over France and Germany and lasted until 4 June (Philip et al., 2018). Across central and north-eastern France, the rain fell as moderate but continuous precipitation over three consecutive days onto soils already saturated by an unusually wet spring. The heaviest three-day total, on 29 to 31 May, is estimated to have had a return period of several hundred years over the Seine basin, a severity that attribution analysis links to anthropogenic warming, which is said to have raised the probability of such rainfall by about a factor of 2,2 (ibid.).

The 2016 event was a fluvial flood which first started at the Seine's tributary rivers (often with reduced warning systems), mainly the Yvette and Loing, in the central Seine and Loire basins, reaching the mainstems only afterwards (Philip et al., 2018). It was anomalous in timing, since almost all significant Seine floods occur in winter: only 2 late spring/summer floods were recorded before in over 500 years of monitoring (ibid.). Consequently, the 2016 flood falls outside the planning frame, as flood-crisis management in the basin, and particularly in Île de France, is organized around the probability of winter flooding (Barroca, 2018; Philip et al., 2018). At Paris-Austerlitz the Seine crested at about 6,10m, a return period of roughly twenty years, well below the level of 8,62m reached in 1910. The damage was therefore primarily driven by tributaries rather than the main stem: the Loing exceeded its hundred-year level and the Yvette reached approximately a fifty-year level (Philip et al., 2018).

The modest crest at Paris is partly explained by the upstream reservoir system. Four large independently operated reservoirs on the Seine and its tributaries, serve a dual purpose: attenuating flood peaks and replenishing low-water levels in the dry season (Van Oldenborgh et al., 2016). This dual function constrained their effect in 2016, as the reservoirs are usually almost empty in December and January, when winter floods are most probable, but are close to maximum capacity through spring in anticipation of typically dry conditions in summer. In 2016 they were all filled to nearly 90% so that a late-spring flood found them in susceptible condition due to little remaining storage (Barroca, 2018). The system protects effectively against frequently occurring floods and significantly lowers the impact of larger floods in winter, is limited in impacting rarely occurring spring events, however (Philip et al., 2018).

While the reservoirs are located in the upstream areas of the Seine basin, the 2016 rainfall occurred mainly downstream of them and upstream of Paris, in catchments such as the Loing that lie outside their reach. Some of these smaller tributaries encountered the worst flooding within the scope of the event: Nemours from the Loing (Fig. 12) and Longjumeau from the Yvette river, for instance (Barroca, 2018; Philip et al., 2018). Consequently, it was impossible to reduce the reservoirs' water levels without worsening the flood situation downstream (Barroca, 2018). Further communes affected by the 2016 floods include Villeneuve-Saint-Georges, Souppes-sur-Loing, and Dammarie-les-Lys.



Figure 12: Flooding of the Loing River in Nemours during the 2016 event . Photo: Nicolas Fillon. Source: actu.fr (Lemonnier, 2026).

In Île de France more than 4.000 people in Nemours and 2.000 in Longjumeau were evacuated while four deaths across France were attributed to the floods (Philip et al., 2018). Insured losses reached more than EUR 1,4 billion across some 182.000 claims, making the event the costliest since the CatNat regime began in 1982 (FFA, 2017).

This exposure is structurally embedded. An estimated 828.100 inhabitants of Île de France were exposed to flooding, largely because the building stock predates the regulations that now restrict construction in floodplains (Faytre, 2011). In a hundred-year scenario nearly 500 km² of the region would be inundated, and roughly 94 percent of the flood zones in Paris and the neighboring departments are already built up (Barroca, 2018). Demographic pressure has sustained home-building in flood-prone urban areas across the region in recent decades, concentrating people and assets in the most exposed zone.

4.2.3. Disaster Risk management in France

Floods represent around 60% of France's natural hazards in total with equal damages, making it the most substantial risk in the country, which is further exacerbated by more than a quarter of the population living in areas endangered by flooding in 2015 (Larrue et al., 2016). French flood risk management is organized around five governance strategies: prevention, defense, mitigation, preparation, and recovery. The system has historically been dominated by the central State, with local authorities acquiring competence through successive decentralization reforms enacted from 1982 onward. It rests on the constitutional principle of national solidarity, which underpins both the compensation regime described in the following subsection 4.2.4. and the prevention measures, and which binds central and local authorities together through the insurance mechanism and the risk-zoning plans (*ibid.*).

The central regulatory instrument of the prevention strategy is the Plan de Prévention des Risques (PPR), created in 1995. Its flood variant, the Plan de Prévention du Risque Inondation (PPRI), is considered the State's principal tool for controlling land use in flood-prone areas (Larrue et al., 2016). A PPRI delineates areas exposed to a reference hazard, typically the 100-year flood or the highest known historical levels where these are higher and imposes either building bans in high-hazard zones or building restrictions elsewhere, such as prohibiting living space or valuables on ground floors (Barraqué & Moatty, 2019). Figure 13 presents the PPRI zoning for Paris as an illustration of this regulatory logic, where the reference hazard is translated into a graded map of prohibition and restriction zones. Drafting of these plans was first decentralized to municipalities in 1982 but recentralized to the prefects' services in 1987, after the plans proved slow and uneven; implementation difficulties have persisted since (Barraqué & Moatty, 2019; Larrue et al., 2016). By the end of 2017, approved flood and mudslide risk plans covered approximately 10.400 communes, meaning that most communes at risk carry at least some building limitation (Barraqué & Moatty, 2019).

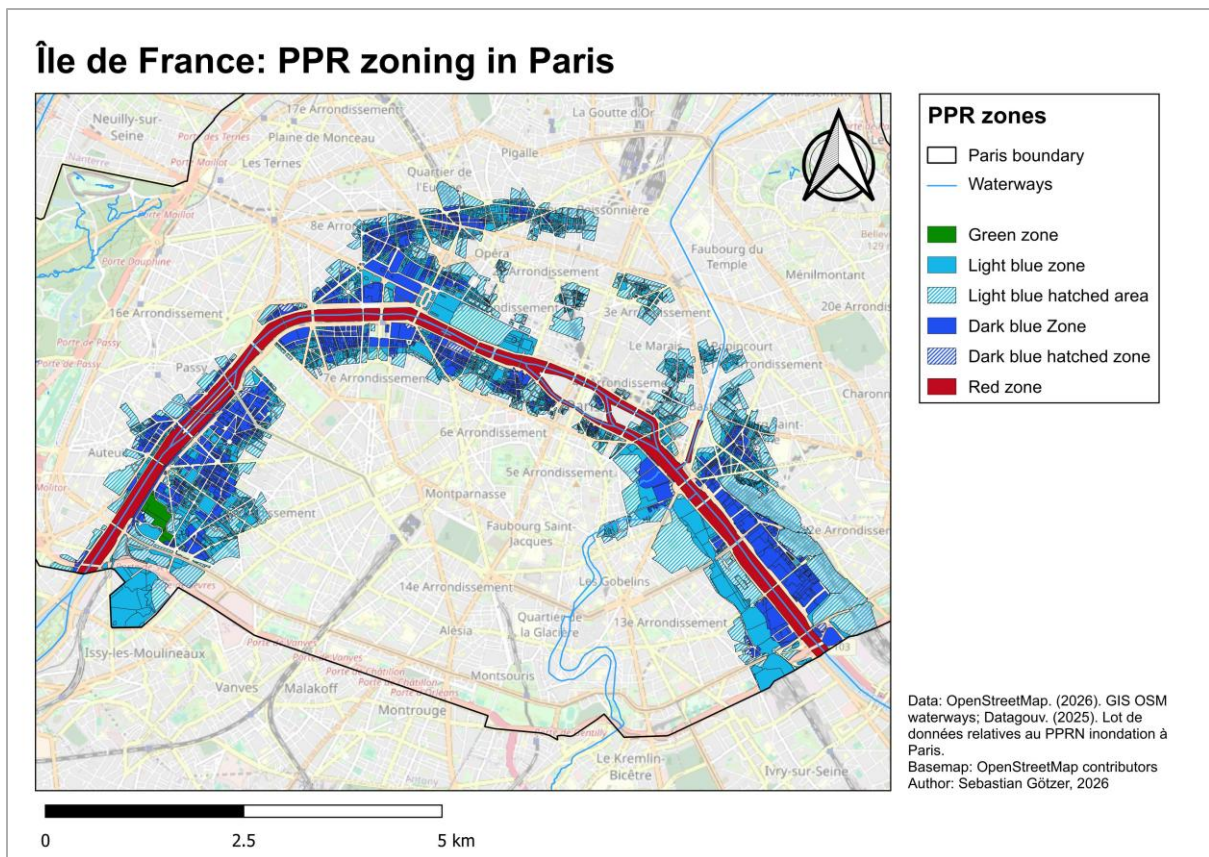


Figure 13: PPR zones in Paris (own illustration). Zones are defined as following: **Green zone** – Area with low flood hazard where development is generally permitted; subject to specific conditions. **Light blue zone** – Urbanized area exposed to moderate flood hazard; development is permitted under prescribed flood-risk mitigation measures. **Light blue hatched area** – Light blue zone subject to additional planning or land-use restrictions due to specific local conditions. **Dark blue zone** – Urbanized area exposed to high flood hazard; construction is strictly regulated to limit vulnerability. **Dark blue hatched zone** – Dark blue zone with additional restrictions reflecting heightened flood risk or strategic flood management objectives. **Red zone** – Area of very high flood hazard intended primarily for floodwater conveyance or storage; new development is generally prohibited.

A second body of instruments derives from the European Floods Directive (2007/60/EC), implemented in France through a tiered process at the scale of the hydrographic districts. This process begins with the Évaluation Préliminaire des Risques d'Inondation (EPRI), the preliminary assessment of exposed people and assets (CEPRI, n.d.; Larrue et al. 2016). The EPRI relies on the Enveloppe Approchée des Inondations Potentielles (EAIP), the spatial dataset used to approximate the extent of extreme potential flooding. It was produced for the entire national territory and covers potential overflow from all watercourses, including small fast-responding and intermittent streams (Géorisques, n.d.; CEPRI, n.d.). The EAIP carries no associated return period and treats protective structures as transparent, and it is informative only, so it may not be used in administrative or regulatory procedures, thereby distinguishing it from the regulatory PPRI (Géorisques, n.d.). Figure 14 maps the EAIP for Île de France, which represents the region-wide hazard envelope used in the analysis.

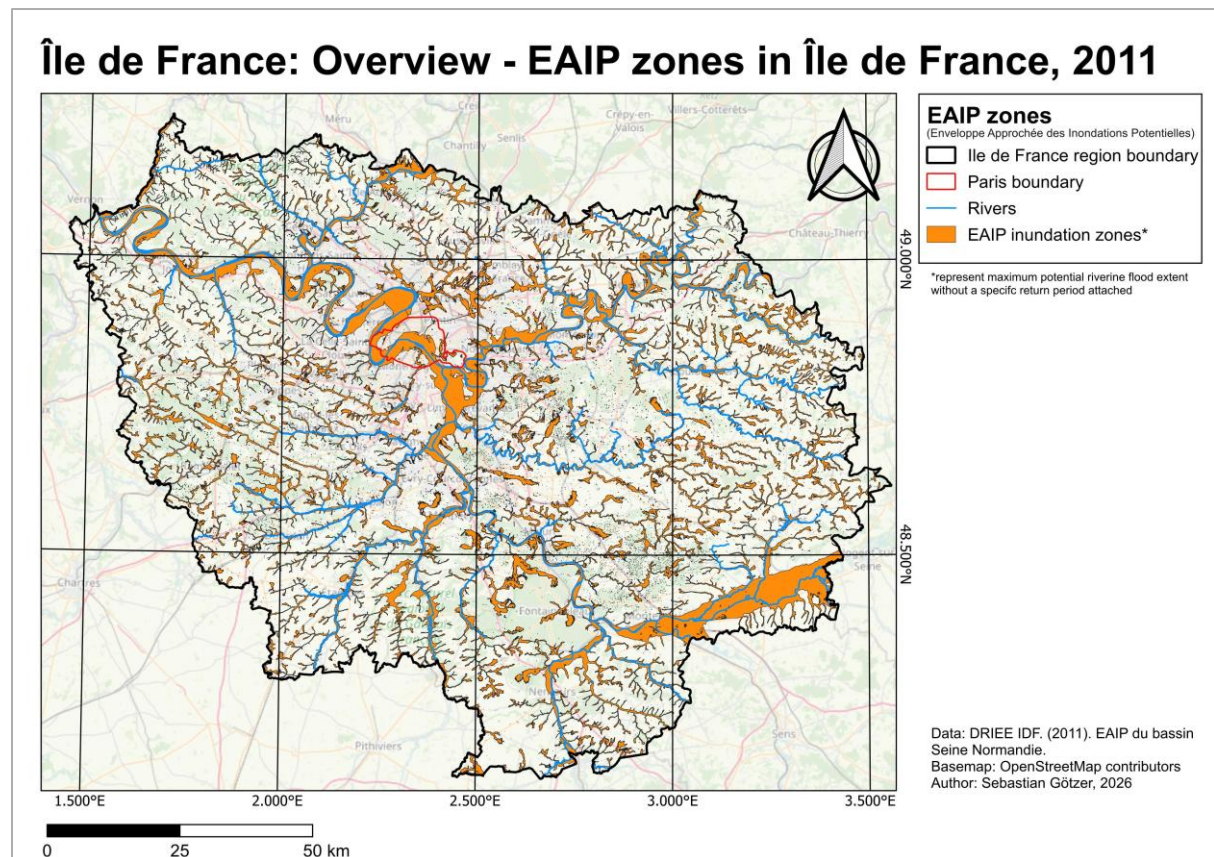


Figure 14: EAIP zones 2011, Île de France (own illustration).

From the EPRI, the State identifies Territoires à Risque important d'Inondation (TRI), the areas where exposed population and assets are most heavily concentrated, and where hazard mapping is subsequently refined (CEPRI, n.d.; Larrue et al. 2016). Figure 15 shows the TRI delineated around Paris. Mapping is complemented by instruments that fund and organize action on the ground. The Programme d'Action et de Prévention des Inondations (PAPI), introduced in 2003, established integrated, catchment-scale flood risk management co-financed by the State and local authorities. It arose from the recognition that drafting a PPR did not in itself reduce the vulnerability of existing buildings (Larrue et al. 2016; Barraqué & Moatty 2019). PAPI projects are financed largely through the Barnier fund (Fonds de Prévention des Risques Naturels Majeurs), created in 1995 and itself fed by a levy on the CatNat premiums (Barraqué & Moatty 2019). The fund subsidizes studies assessing natural disaster risk and prevention and protection works for buildings, and also finances the relocation of homeowners and the demolition of dwellings that are severely damaged or that pose a threat to human life, though its support is largely conditional on a commune having an applied or approved PPR (Poussin et al. 2013). Thereby the CatNat regime, representing the recovery pillar within the flood risk management system, is financially linked to the prevention system.

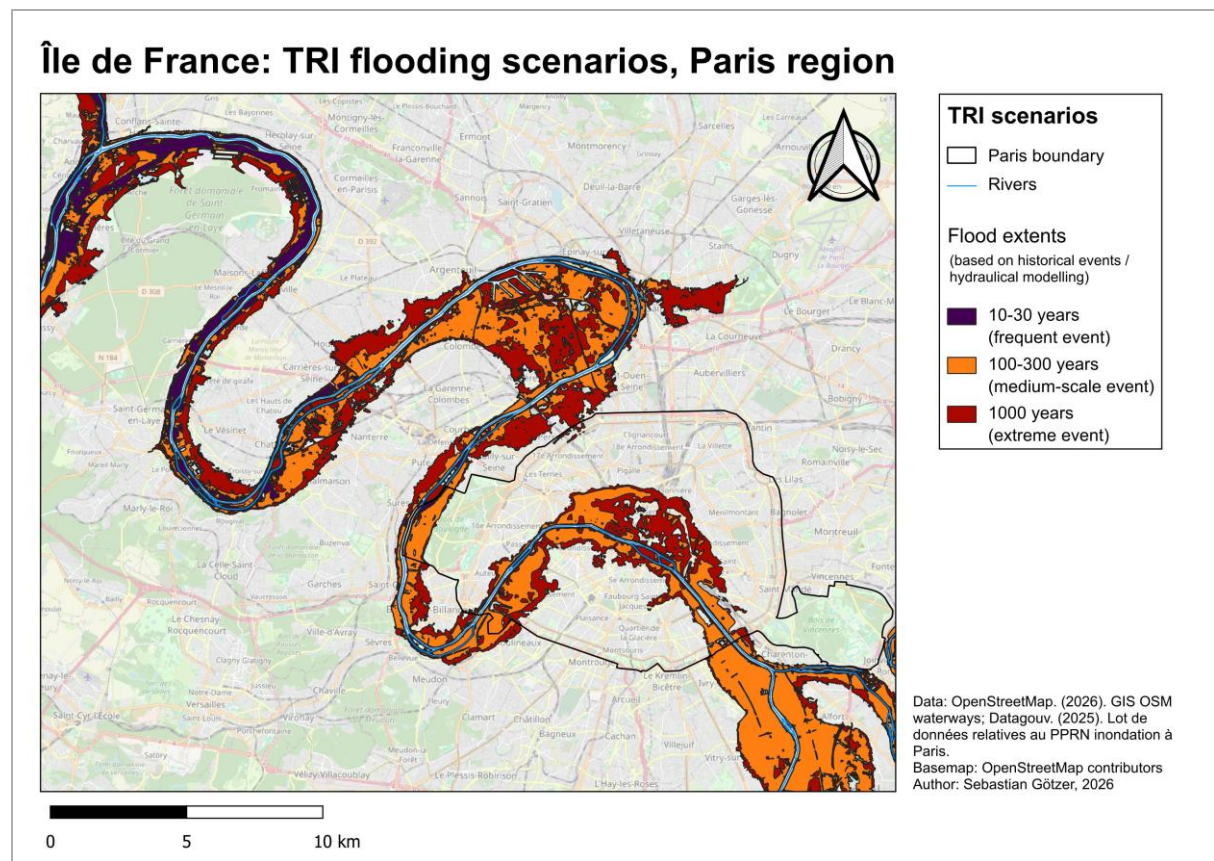


Figure 15: TRI flooding scenarios in the greater Paris region (own illustration).

4.2.4. CatNat

The French natural disaster insurance system, known as CatNat (an abbreviation of *Catastrophe Naturelle*), was introduced in July 1982. It formed part of the broader decentralization reforms of the time, which transferred competence for granting building permits to local authorities and, in parallel, established a national policy for recovery from and reduction of vulnerability to five exceptional natural hazards: floods, landslides, avalanches, earthquakes, and volcanic eruptions (Barraqué & Moatty, 2019). The funding of recovery was deliberately separated from the budget of the river-basin water agencies (Agences de l'eau). Instead, the law mobilized the insurance sector to compensate victims through a dedicated national fund. As a counterpart to this compensation, the same law obliged local authorities in risk areas to draft risk maps, the Plans de Prévention des Risques (PPR), and for floods specifically the PPR-inondation (PPRI) (Barraqué & Moatty, 2019; Poussin et al., 2013). Flood control had until then remained a responsibility of the central government, distinct from the decentralized water-quality institutions created in the 1960s under the polluter-pays principle (Barraqué & Moatty, 2019).

Property insurance in France is generally divided into two arrangements (Poussin et al., 2013). This includes coverage for risks regarded as insurable by the private insurance market, which namely is for property damage attributed to non-catastrophic risks. Home contracts are hereby known as Multi-Risk Habitation (MRH) policies and rely on risk-based premiums, depending on the probability of damage from a hazard, the value of the contents insured, and the options chosen. These are compulsory for tenants and mostly for homeowners as well, leading to household insurance penetration in metropolitan France exceeding 99 % (ibid.). The separate natural disaster protection for damage considered non-insurable, such as flooding, is the public-private compensation system CatNat. Based on a solidarity principle, it provides compulsory natural disaster coverage through a national reserve financed by fixed insurance premiums (ibid.). Private insurers thus have to add a mandatory surcharge to every property and vehicle contract sold. Thereby no differentiation is made according to the actual natural disaster risk faced by the policyholder, meaning the additional charge applies to all policyholders across the country, whether exposed to a hazard or not (Barraqué & Moatty, 2019). The government sets the rate of the surcharge: 12 % of the premium on homes, businesses, and some agricultural assets, and 6 % on automobile contracts, since 2000 (Poussin et al., 2013; Barraqué & Moatty, 2019). Since 1982, insurers have been required to extend every existing property contract (MRH and others) and every vehicle contract to cover damage caused by natural disasters (Poussin et al., 2013). This design of combining the near-universal penetration of MRH contracts with mandatory surcharges for natural disaster insurance from CatNat enables a market penetration rate of close to 100% among the insured population and a large financial reserve at low cost to policyholders. The CatNat coverage comprises a variety of perils ranging from floods and mudslides (classified as one peril), earthquakes and landslides among others with the exception of storms (ibid.). The floods and mudslide perils thereby represents approximately 90% of the CatNat-eligible events (Barraqué & Moatty, 2019). In the international typology of flood coverage systems, CatNat is the standard example of "bundled insurance backed by the State" (Lamond & Penning-Rowsell, 2014, cited in Barraqué & Moatty, 2019).

Compensation under the CatNat system is triggered only when an event is formally recognized as a natural disaster through a decree, the "Arrêté Catastrophe Naturelle", signed by the government (Poussin et al., 2013). Affected municipalities submit a CatNat claim to the prefect, who reports to an inter-ministerial commission deciding on the "naturalness" and "exceptional intensity" of the event. Only once the resulting order is signed, insurers are obliged to mobilize the fund and cover the damage (Barraqué & Moatty, 2019). A decree requires the damage to be

predominantly caused by a natural phenomenon of "abnormal scale", which was equivalent to a 25-year return period in 2016 (Lavarde, 2024). When a decree is granted, the post-disaster coverage under CatNat includes the replacement of damaged infrastructure and buildings, the complete restoration of services, and economic revitalization (Barraqué & Moatty, 2019). For policyholders who are insured, the funds needed to repair their belongings should in theory be obtained within three months. After an event, insurers are in principle not permitted to raise the premiums of the affected policyholders, given the exceptional nature of the disaster (ibid.). Additionally, support through the insurance system can be supplemented by direct subsidies from the state, which are separate from CatNat. These help local authorities provide compensation for uninsured local public assets. The Fonds de Solidarité en faveur des Collectivités Territoriales (FSCT) can be mobilized where damage to a local authority lies between EUR 150.000 and EUR 6 million, and beyond that level, the Fonds de Calamités Publiques can be called upon (France, 2015).

Deductibles (i.e. the fixed sum a policyholder pays out of pocket before compensation applies) for natural hazard coverage are determined by the government, at EUR 380 for an individual property under MRH-type damage contracts in 2013 (Poussin et al., 2013). Since 2000 the deductible can be raised where a vulnerable commune has no PPR, doubling, tripling, or quadrupling after repeated disaster decrees, with the increase suspended once a PPR procedure begins. CatNat compensation is in this way institutionally tied to the PPR system, which regulates land use to limit new construction and reduce exposure in flood-prone areas (ibid.). A flood PPR (PPRI), created in 1995 and approved by prefectorial decree, delimits the area exposed to the highest known historical flood or the 100-year flood, whichever is higher, and maps zones where building is prohibited or permitted under conditions. It thus operates as the local prevention counterpart to nationally funded reconstruction (Barraqué & Moatty, 2019). This link carries a formal enforcement lever: insurers may, with authorization from the Central Tarification Board, decline or discount compensation where a property lies in a non-authorized zone or where compulsory PPR measures have not been implemented in time (Poussin et al., 2013).

The stability of the system relies on state-backed reinsurance. Private insurers can purchase reinsurance at favorable rates from the Caisse Centrale de Réassurance (CCR), a public reinsurer owned by the French government, which allows them to include catastrophe cover within standard home insurance contracts. Above a threshold of damage stipulated in law, the State provides the CCR with an unlimited guarantee of compensation, so that the system as a

whole is ultimately backed by the central government budget (Barraqué & Moatty, 2019; Poussin et al., 2013).

In its design, CatNat combines individual and collective coping within a single national mechanism. Its broad funding base, drawing on all policyholders regardless of their exposure, allows recovery from extreme events without subsequently raising the premiums of victims, which limits the risk of policyholders exiting the scheme. The system is thus credited with preventing many insured households and businesses from facing financial hardship after disaster events, and with financing the physical reconstruction of damaged assets at the national level (Barraqué & Moatty, 2019).

4.3. Direct comparison of the flood insurance systems

Table 1 compares the NFIP and CatNat side by side, listing notable differences and similarities between the two insurance regimes based on selected indicators.

Table 1: Comparison of the two insurance regimes: NFIP and CatNat

Indicator	U.S. (NFIP)	France (CatNat)
Year established	1968	1982
Guiding principle	Risk-based; tied to community floodplain management	National solidarity
Coverage	Voluntary; mandatory only for SFHA properties carrying a federally backed mortgage	Compulsory; attached to every property and vehicle contract
Renter coverage	voluntary and rarely held	Compulsory; tenant MRH covers renters automatically
Relationship to property insurance	Standalone, separate flood policy	Mandatory surcharge bundled into every property (MRH) and vehicle contract
Market penetration	Partial and spatially uneven.	Near-universal (close to 100% of insured property), by design
Official trigger for payout	None; insurance claims are paid regardless of any declaration. Federal disaster aid (e.g. IHP) requires a presidential disaster declaration	Required; an interministerial decree (Arrêté CatNat) must recognise the event before insurers pay
Public sector role	FEMA bears the flood risk, produces FIRMs, sets premiums and floodplain-management conditions, and runs disaster relief	The state supports the system via the CCR, sets the surcharge rate and deductibles, issues the decree, and funds prevention
Private sector role	WYO insurers sell and administer policies and process claims; they bear no underwriting risk	Private insurers underwrite and carry the risk (reinsured by the CCR), issue and administer policies, and collect the surcharge
Hazard covered	Floods, mudflows, collapse or subsidence due to water exceeding certain levels (excludes wind, snow, hail)	Flood and mudslide (single peril); earthquake; landslide; volcanic eruption; avalanche. Excludes storm
Reference return period (zoning)	100-year event (1% annual chance) (the SFHA)	100-year or highest known historical flood (the PPRI)
Damage covered	Building and contents, purchased separately	Property and contents; reconstruction extends to infrastructure and the restoration of services
Limit of indemnity	Statutory caps: USD 250.000 (building) and USD 100.000 (contents) per household	No statutory cap; follows the sum insured in the underlying contract
Premium setting	Zone-based and partially actuarial (mid-transition under Biggert-Waters 2012 and HFIAA 2014); set by FEMA	Flat surcharge: 12% of the property premium and 6% of the vehicle premium; set by the State; not differentiated by exposure
Individual deductibles	Selectable by the policyholder, USD 1.000 to 10.000, set separately for building and contents; a higher deductible lowers the premium	Fixed at EUR 380 (2013), set by the State; can escalate after repeated decrees where no PPR exists
Reinsurance / financial backing	Historically none: deficits borrowed from the US Treasury; private reinsurance introduced 2016/17	Public reinsurance through the CCR, with an unlimited state guarantee above a legal threshold
Risk zoning and risk maps	FIRM / SFHA within the NFHL; regulatory; revised through LOMC	PPRI (regulatory land-use control) plus the EAIP (informative envelope, no return period, non-regulatory); TRI for refined mapping
Integration of prevention / mitigation	Community floodplain-management and building-code requirements (BFE); Community Rating System (CRS) discounts; federal mitigation grant programmes	PPRI building bans and restrictions; the Barnier fund (studies, works, relocation); PAPI catchment programmes
Incentive via premiums	Yes: risk-based premiums, CRS community discounts, and discounts for elevation above the BFE	No: the surcharge is flat and exposure-blind
Incentive via deductibles	Yes: higher chosen deductible lowers premium	Yes: deductibles escalate where a commune lacks a PPR

Note: The comparison is based on the regimes before the respective case study events.

Sources: compiled from Amornsiripanitch et al. 2025; Barraqué & Moatty 2019; De Ruig et al. 2022; FEMA, 2023b; Horn & Webel, 2024; Kousky 2017; Kousky et al. 2017; Lavarde, 2024, Pralle 2019; Poussin et al. 2013.

The comparability of both systems relies on them being state-backed public regimes insuring flood risk. The structural axes they diverge on determine the measurability of flood vulnerability in each study area, thus posing a crucial factor for the methodology of this thesis. The underlying coverage principle is where the most significant difference is seen. While the CatNat system makes it compulsory to have flood insurance (in addition to coverage against other perils) for renters and owners alike through the surcharges on property and vehicle contracts, the NFIP remains mostly on a voluntary level (especially including renters) with the exception of federally backed mortgages. This results in widely differing coverage levels from France's near-universal to the USA's location-based partial level. Premium logic in the NFIP is hereby risk-based and linked to the mapping effort of the FEMA, whereas France's solidary system applies the same rate regardless of exposure to hazards. Hazard zoning and resulting building restrictions exist in both systems, but the French one is not tied directly to insurance coverage.

Another notable distinction is which Hazard are covered and how they are defined respectively. Within the CatNat system, flooding and mudslides form one single defined peril, which is one among other that can be eligible for a CatNat decree to be issued. The markable exclusion hereby are storms. The NFIP on the other hand only covers flooding, mudslides, and perils directly related to this, such as collapse or subsidence near a body of water resulting from a flood (FEMA, 2023b).

Furthermore, the handling of Deductibles varies between the two regimes. While it is a fixed sum in France for affected individuals, households in the USA can preemptively select higher deductibles in order to lower their premium rate. This fixed sum in the CatNat system can however increase when communes lack adequate flood zoning (PPR), making it an incentive for risk reduction. The NFIP incentivizes policyholders via risk-based premiums fundamentally and added discounts for the elevation of structures above base flood elevation (BFE), for instance.

5. Methods

In order to answer the research questions, set out in chapter 1, certain aspects of each system and corresponding metrics are operationalized. The spatial analysis conducted aims to examine how the two comparable yet contrasting flood insurance systems relate to the distribution of social vulnerability within the frame of the case study areas and corresponding flooding events. Particularly, the main difference separating the two regimes, CatNat being compulsory and solidary-based while the NFIP being mostly voluntary and community-based, is utilized as the primary axis of analysis. Since they allocate protection on different principles, they should produce different spatial relationships between vulnerability, exposure, and coverage, which is what the analysis sets out to surface and compare. For the case studies to remain comparable, the data included is primarily from before the respective flood event occurred, where possible (before May 2016 for France; before August 2017 for USA).

5.1. General procedure

The general methodological approach encompasses the creation of a composite measure of social vulnerability (SoVI), which is based on the factors outlined in chapter 3 in particular, for both case study areas, Île de France and Harris County. These respectively comprise the entire Île de France region at commune level (with Paris being split into its arrondissements) accuracy, and Harris County at ZCTA (ZIP Code Tabulation Area) level, which are relatively small spatial units while granting adequate data availability. Spatially aggregated data analysis within this thesis is therefore exclusively handled at these levels. It is to be noted that, in contrast to communes in France, ZCTAs are purely statistical units and do not have specific names. In addition, several datasets for insurance coverage, flood planning and exposure as well as spatial extents for the flood events are utilized in combination with the SoVI. This enables synthesizing a connection on a spatial level between social vulnerability and exposure to hazards, thus facilitating analysis on which communes/ZCTAs are most affected and corresponding shortfalls in protection. The exact procedure is outlined in section 5.3 while the results are described in chapter 6 and further discussed in chapter 7.

Preceding the core spatial analysis of the thesis is a comprehensive literature review which chapters 1 to 4 rely on and that ultimately represents the base which the methodology is grounded on. Relevant literature encompasses the two distinct fields of vulnerability research, as well as flood insurance research, including country-specific flood policies. Thereby, the

inclusion criteria were kept relatively broad, prioritizing publications from 2010 onwards in order to reflect the current state of methods and data. Mostly peer-reviewed articles in scientific journals represent the foundation of the literature work. Geographically, the search prioritized work on the USA, France or comparative studies including either. Since this work is a comparative GIS-based analysis, built entirely on secondary data without including the collection of primary data, several public and official sources were drawn on for country-specific insurance policies and data. Grey literature for the analysis was retrieved directly from the respective institutional sources, which include the IPCC (SREX, AR6 WG2), the UNDRR, Munich Re's NatCatSERVICE as well as CRED / EM-DAT. The statistical and spatial datasets used in the analytical parts of this thesis are documented separately in the next section 5.2.

The analytical design follows established approaches in social vulnerability and flood risk research, whereby the methodology of the SoVI is anchored primarily in Cutter et al. (2003) and the adaptation of the concept to flood exposure is anchored primarily in Koks et al. (2015). Deviations and exact realization are described in section 5.3.

QGIS (version 3.40.7) was the primary tool used for spatial data handling, spatial joins, zonal calculations, classification and visualization of the final results among other procedures. Python (libraries included: pandas, geopandas, requests) served as the main tool for the acquisition and cleaning of data that was not already in a spatial format. Microsoft Excel in combination with Python scripting was further used to filter and prepare tabular datasets for usage in QGIS as well as the creation of result tables. Claude AI served as a tool for assisting in language smoothing, the organization of research notes, Python scripting and debugging and guidance in QGIS algorithms and workflows. The research design, data selection and interpretation as well as the written argument remain the author's own.

5.2. Data used

The three tables outlined in this section give an overview of the datasets that were used for the analysis. Table 2 presents the respective variables used for the SoVI in both case study areas. All datasets specific to the USA are in table 3, whereas the French equivalents can be found in table 4. Processing steps are laid out in the next section 5.3.

Table 2: Operationalization of the social vulnerability indicators: data variables and sources for the French (commune level) and U.S. (ZCTA level) case studies.

Indicator	France (commune level)		United States (ZCTA level)	
	Variable	Source	Variable	Source
Income	Median standard of living, 2015	INSEE, 2015	Median household income, 2016	U.S. Census Bureau, 2016 (Table S1903)
Poverty	Poverty rate, 2015	INSEE, 2015	Poverty status in the past 12 months, 2016	U.S. Census Bureau, 2016 (Table S1701)
Age	Number of people aged 65 or over and 14 or under, 2014	INSEE, 2017	Number of people aged 65 or over and 14 or under, 2016	U.S. Census Bureau, 2016 (Table S0101)
One-person households	Number of one-person households, 2014	INSEE, 2017	Number of one-person households, 2016	U.S. Census Bureau, 2016 (Table S2501)
Single parents	Number of single-parent families, 2014	INSEE, 2017	Number of householders with own children under 18 years, 2016	U.S. Census Bureau, 2016 (Table DP02)
Education	Number of households where the reference person is an executive or holds a higher intellectual profession, 2014	INSEE, 2017	Number of householders with a bachelor's degree or higher, 2016	U.S. Census Bureau, 2016 (B25013)
Unemployment	Number of people unemployed, 2015	Paris Region Institute, 2016	Unemployment rate, people over 16 years, 2016	U.S. Census Bureau, 2016 (Table S2301)
Rent	Number of owners vs. tenants, 2016	INSEE, 2019	Number of owners vs. tenants, 2016	U.S. Census Bureau, 2016 (Table S2501)
Households without a car	Number of households without a car, 2016	INSEE, 2019	Households with no vehicle available, 2016	U.S. Census Bureau, 2016 (Table B08201)
Housing: time period of construction	Houses constructed in 1990 or earlier, 2016	INSEE, 2019	Year structure was built (1980 or earlier), 2016	U.S. Census Bureau, 2016 (Table S2504)
Healthcare facilities in proximity	Number of healthcare facilities in the municipality, 2012	INSEE, 2014	Number of healthcare facilities in each census tract, 2016	Melendez et al., 2024

Note. Count-based indicators are expressed relative to the total number of households in each spatial unit. Years indicate the reference period of the underlying data. Healthcare facilities in US: clinics/physicians, pharmacies, all resident care facilities, mede equipment; Healthcare facilities on France side: `etablissement_sante_court_sejour`; `etablissement_sante_moyen_sejour`; `etablissement_sante_long_sejour`; `urgences`; `centre_de_sante`; `pharmacie`, `ambulance`, `hospitalisation_a_domicile`.

Table 3: Datasets used for Harris County

Dataset	Source
TIGER/Line Shapefiles (administrative boundaries)	U.S. Census Bureau, 2016
TIGER/Line Shapefile, Harris County area hydrography	U.S. Census Bureau, 2023
Water polygons (coastline-derived)	OpenStreetMap contributors, 2026
National Flood Hazard Layer (NFHL)	FEMA, 2018
FEMA OpenData (Policies, Claims, IHP applications)	FEMA, 2026a
Hurricane Harvey flood-inundation maps	Watson et al., 2018
Harvey flood depths grid	FEMA, 2023a

Note: FEMA OpenData datasets retrieved via API; NFIP Policies filtered to latest date being 24 August 2017; Claims and IHP applications filtered to Hurricane Harvey -specific data.

Table 4: Datasets used for Île de France

Dataset	Source
GIS OSM Waterways	OpenStreetMap contributors, 2026b
CatNat declarations, GASPAR database (Géorisques API)	Géorisques, 2025
ONRN commune-level flood indicators (five files)	ONRN, 2026
Flood surfaces by type and scenario (Directive Inondation, TRI)	DRIEAT ÎdF, 2016
Progress of/Approved flood risk prevention plans (PPRI)	DRIEAT ÎdF, 2018
Flood risk prevention plan (PPRN inondation), Paris	DRIEAT Îdf, 2025
Approximate envelope of potential floods (EAIP)	DRIEAT ÎdF, 2011
Flood delineation and damage assessment, France (EMSN028)	Copernicus EMS, 2016a
Flood in the Loing basin (EMSR165)	Copernicus EMS, 2016b

Note: The five ONRN (Observatoire National des Risques Naturels) files are ONRN_CoutCumulative_INON_9521, ONRN_CoutCumulative_INON_Hab_9521, ONRN_Frequency_INON_9521, ONRN_Reco_INON_8224 and ONRN_SsurP_INON_9521 (cumulative losses, losses to dwellings, event frequency, CatNat recognitions, and claims-to-premium ratio). DRIEAT datasets accessed via datagouv. The EAIP envelope was requested directly from the DRIEAT.

5.3. Processing steps

All spatial processing is carried out in projected coordinate reference systems (CRS) suited to each case area, EPSG:32615 (UTM zone 15N) for Harris County and EPSG:2154 (Lambert-93) for Île de France. Every layer is reprojected to the respective CRS before any area, distance, or overlay operation. Data are held as GeoPackages throughout. The tabular joins and the SoVI computation, including the crosstabulations, were conducted in the QGIS DB Manager using SQL queries, the spatial operations through the Processing toolbox, the Bivariate mapping via the “Bivariate QGIS Plugin” (by Hemed Lungo, version 0.0.3) and the cluster analysis through the “Hotspot Analysis v3” plugin (by Abimael Cereda Junior, version 4.0.0). The processing steps were kept identical where possible in order to grant comparability across the study areas. Filtering within the attribute table and summary functions within QGIS were primarily used to identify visually noticeable ZCTAs/communes for further examination. Limitations in this context are discussed in chapter 7. All final visualizations were conducted via QGIS.

Social Vulnerability Index

The SoVI is built identically for both case areas, so that the two results stay comparable. Each input variable is first transformed by percentile ranking within its own study area, following the CDC/ATSDR Social Vulnerability Index (Flanagan et al., 2011). Under this approach every commune or ZCTA receives, for each variable, its rank as a percentile of that area's distribution, so a value expresses relative standing within the area, rather than an absolute level. Percentile ranking is robust to outliers and skew and keeps the index interpretable. Because each variable is normalized within its own study-area distribution, the two composites can be read against one another. For the variables median income/standard of living, healthcare provision, and higher education, the ranking is reversed, so a higher score consistently means greater vulnerability. The ranked variables are then combined by equal weighting in two stages. Within each of the four domains, age, household, physical, and economic, the variable percentiles are averaged into a domain score. The four domain scores are then averaged into the composite including the respective indicators from table 2.

$$\text{SoVI} = \{ \text{age} [(\text{Age}) / 1] + \text{household} [(\text{One-Person households} + \text{Single parents} + \text{Renters} + \text{Households without a car}) / 4] + \text{physical} [(\text{Housing: time period of construction} + \text{Healthcare facilities in proximity}) / 2] + \text{economic} [(\text{Income} + \text{Poverty} + \text{Education} + \text{Unemployment}) / 4] \} / 4.$$

Equal weighting with percentile ranking is preferred here over the factor-analytic construction of the original index, as it is transparent and has been shown to be robust relative to more complex alternatives such as principal component analysis (Tate, 2012). Missing values (NULL) are handled inside the SQL so that each domain score is averaged only over the variables that are present, rather than a single missing variable blanking out the whole domain and, with it, the unit's entire SoVI. This means not all ZCTAs/communes have all the 11 variables factored. This limitation is further discussed in chapter 7. The finished composite is classified into quintiles for a clean visualization (see Figure 16 & Figure 27 in chapter 6).

Harris County

The United States side begins by assembling all indicators onto a single ZCTA-level layer for Harris County. The NFIP policy and claim records and the IHP registrations are retrieved from the OpenFEMA API through a Python script that handles keyset pagination, cleaned with pandas, aggregated to the ZCTA level, and joined to the ZCTA polygons, which are clipped to the county boundary. The socio-economic inputs and the take-up denominator come from the American Community Survey five-year estimates for 2012 to 2016 (U.S. Census Bureau, 2026) which were also used for the construction of the SoVI. The extent of Hurricane Harvey's flooding consists of a spatial merger of the FEMA flood-depth grid (FEMA, 2023a) and the inundation maps of Watson et al. (2018), from which the share of each ZCTA inundated is derived. The calculations for the population density map among others were conducted via functions within the QGIS Processing Toolbox (Statistics by Category, Intersection, Difference).

The link between vulnerability and coverage is shown through bivariate three-by-three choropleths that pair the SoVI with the take-up rate, with the premium burden, and with the share of claims outside the SFHA. The two axes of each map are classified into three classes and combined in a nine-class matrix. The Bivariate QGIS Plugin supplied the bivariate scheme and visualization matrix therefore. Additionally, spatial clustering is then tested with the bivariate Local Moran's I (Anselin et al., 2002), showing local indicators of spatial association (LISA), to identify clusters of combined social vulnerability and exposure. Computed in the Hotspot Analysis v3 plugin, this bivariate Local Moran's I pairs the SoVI with the take-up rate, at a 0,05 pseudo-significance threshold, and returns the four local cluster types. The cluster that combines high vulnerability with low coverage is of central interest, as it marks where the least-protected population coincides with the thinnest insurance coverage. Finally, a cross-tabulation

(Table 5) computed from the assembled layer's attribute table via the QGIS DBManager summarizes the US indicators across the five SoVI quintiles.

Île de France

The French side follows the same procedure of creating one master layer on commune-level for Île de France where most of the data is combined. The CatNat decrees are retrieved from the Géorisques API, and the ONRN/CCR (Observatoire National des Risques Naturels/Caisse Centrale de Réassurance) commune indicators are downloaded from the ONRN file server and filtered from the national files to the eight Île-de-France departments by INSEE code, which leaves 1.287 communes. These are joined to the commune polygons, clipped to the region, on the INSEE code (which is the equivalent to the ZCTA). The EAIP envelope, the Copernicus inundation extents (EMSN028 and EMSR165), the PPRI status, and the INSEE socio-economic data complete the layer. The ONRN indicators, all cumulative over 1995 to 2021, are the total inundation cost, the cost per inhabitant, the claim frequency, and the S/P ratio (Sinistres/Primes = Claims/Premiums). The S/P ratio and the cost per inhabitant are supplied with five pre-defined category strings, which must first be converted into ranks so they can be used in the bivariate maps and the cross-tabulation (see Fig. 32 and Appendix A 1). The S/P axis uses fixed thresholds of EUR 0 to 50, 50 to 100, and above 100 and the cost per inhabitant map EUR <100, 100 to 1.000, 1.000 and more for display. The EAIP coverage is the share of each commune lying within the envelope, the same areal measure as the US SFHA share. Calculations were conducted identically as for the US side.

These indicators are mapped in the same way as for Harris County as well. The SoVI appears in quintiles, and the descriptive indicators, the S/P ratio, cost per inhabitant, claim frequency, decree count, EAIP coverage each as its own map. The flood zoning maps and specific commune example maps were created by spatial overlays in QGIS. The bivariate three-by-three choropleths pair the SoVI with the EAIP coverage, the S/P ratio, and with the cost per inhabitant (Appendix Fig. A 2). The bivariate Local Moran's I is computed exactly as on the US side, here pairing the SoVI with the EAIP coverage. The cross-tabulation (Table 6) sets the five SoVI quintiles against the French indicators, again processed in the QGIS DBManager via an SQL query.

6. Results

This chapter describes the output resulting from the procedure depicted in chapter 5 before chapter 7 synthesizes the connections and implications of these results.

6.1. Results Harris County

While mentioned ZCTAs (Zip Code Tabulation Areas) will mostly be designated in the figures, a mapped overview of all ZCTAs within the study area can be found in the appendix figure A 3. One ZCTA in the south-central part of the county (marked as insufficient data) is excluded from all the maps tied to socio-economic factors due to being mostly covered by industrial and logistical facilities.

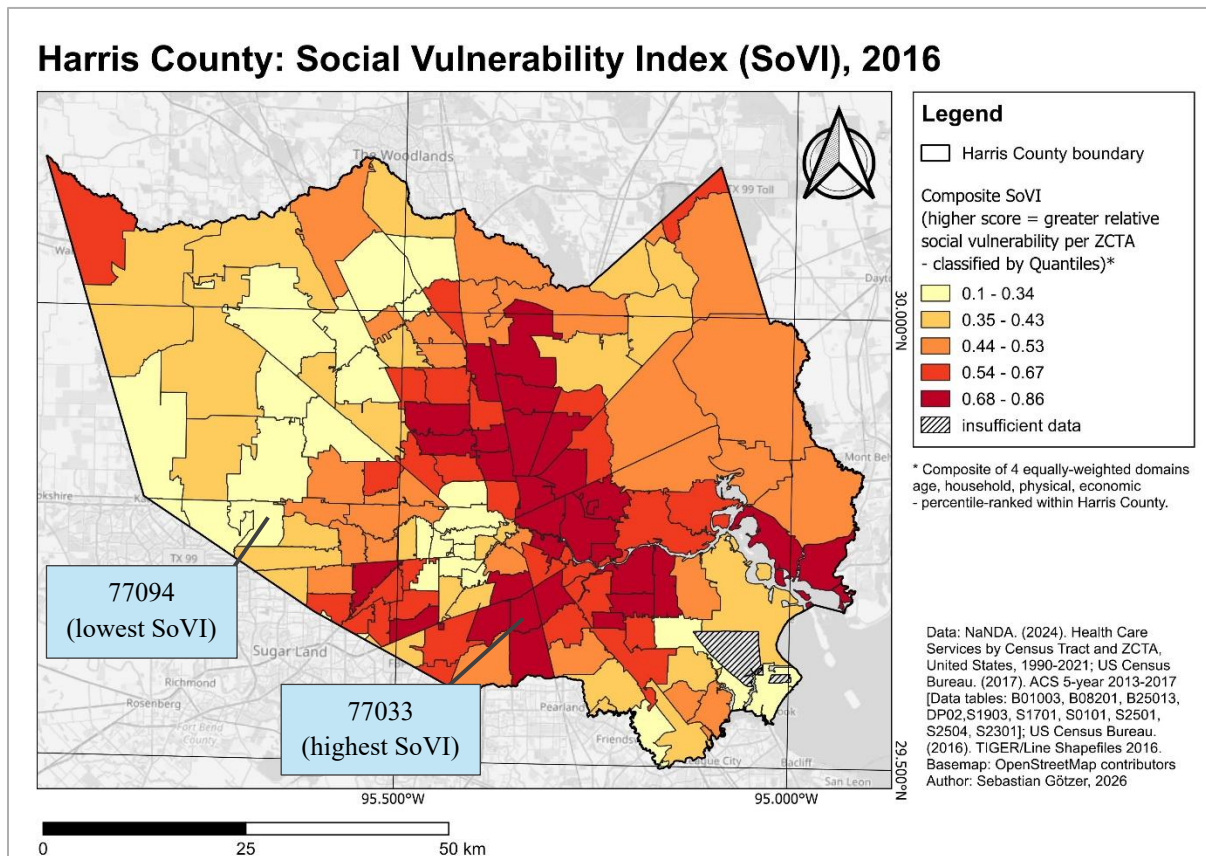


Figure 16: Composite SoVI scores per ZCTA 2016, Harris County (own illustration).

Figure 16 shows the composite Social Vulnerability Index (SoVI) for the 138 ZCTAs included in the Harris County analysis, classified into quintiles, where a higher score denotes greater relative social vulnerability. The highest-scoring ZCTAs are concentrated across the central and

eastern parts of the county, covering the highly urbanized area around the city core and a corridor running east and southeast toward the Houston Ship Channel. The most vulnerable units sit in the inner northeast and south-central areas, including ZCTAs 77033, 77016, and 77028. The lowest scores can generally be observed in the western and northwestern suburban fringe together with a pocket along the southeastern edge, with 77094 and 77493 in the west and 77505 toward the southeast among the least vulnerable. A spatial pattern of the upper quintiles being predominantly grouped into a broadly continuous zone rather than scattered as isolated units is noticeable.

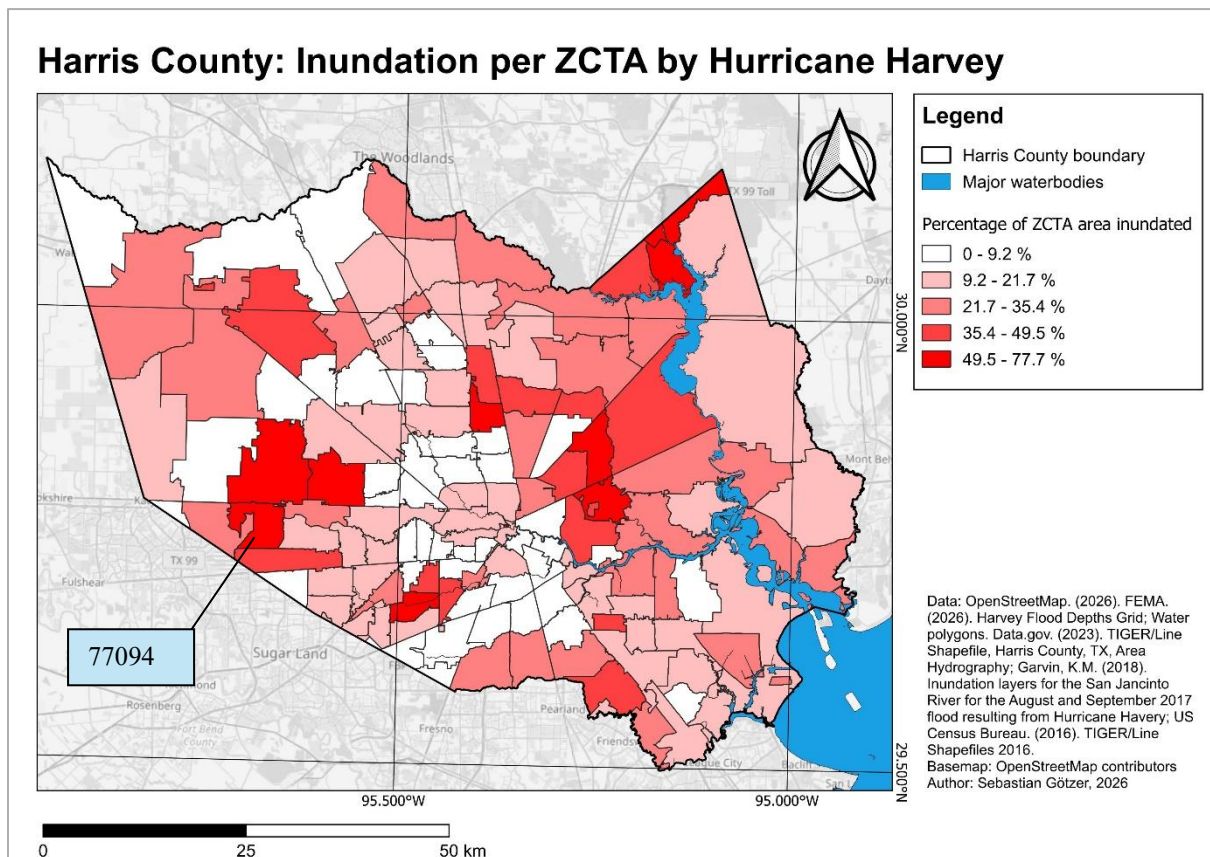


Figure 17: Inundation percentage per ZCTA from Hurricane Harvey 2017, Harris County (own illustration). Note: Classified by natural breaks.

Figure 17 shows the share of inundated areas in each ZCTA during Hurricane Harvey. The majority recorded low to moderate flooding percentages, and the most severe inundation was confined to scattered pockets. The most extensively flooded units lie in the southwest of the county, where 77094 saw 77,7% of its area flooded, flanked by adjacent ZCTAs at roughly 60% and 54%. Beyond this western cluster, notable inundation occurred in the eastern urban core as well as in the northeastern tip close to the San Jacinto River. The two ZCTAs showing the highest SoVI rank in the lowest inundation class hereby (77033, 77016). Much of the city center

and its surroundings, together with most of the northwestern part of Houston, fall in the lowest inundation classes. The heavily inundated ZCTAs also lie away from the major water bodies, spread across the county rather than concentrated along them.

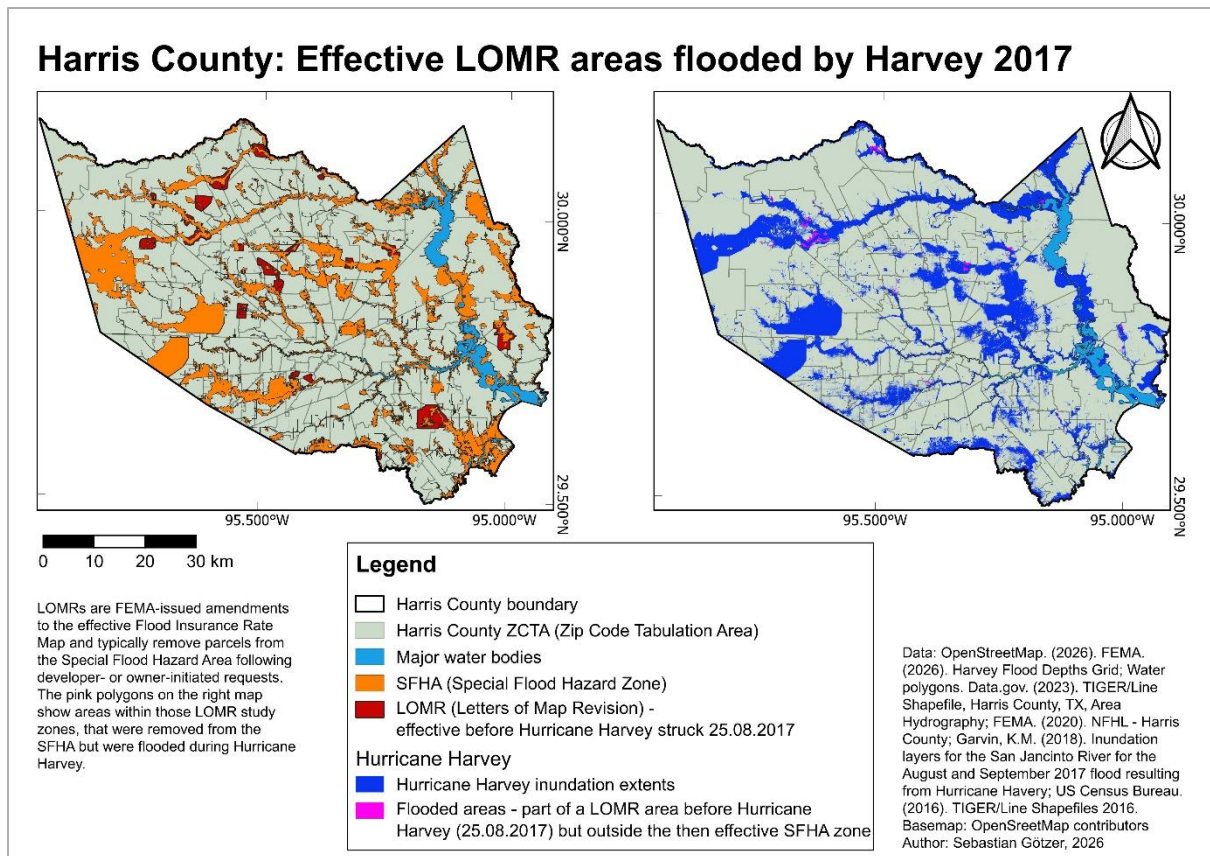


Figure 18: Effective LOMR areas flooded by Hurricane Harvey 2017, Harris County. Right panel: Effective LOMR areas and SFHA zone before Hurricane Harvey 2017; Left Panel: Hurricane Harvey inundation extents with spatial overlap from LOMR areas (own illustration).

Figure 18 revisits the effective SFHA and the Harvey inundation extent introduced in chapter 4, now placed side by side so that the mismatch between the regulated flood zone and the area that actually flooded becomes visible. The left panel sets the effective SFHA against the LOMR revision footprints effective before Harvey made landfall in August 2017. The SFHA geometry already incorporates the effect of all effective LOMRs, so the orange shows the regulated floodplain after revision rather than before it, and the dark red footprints mark where FEMA reanalyzed the map rather than the resulting zone. Generally, these footprints are distributed across the county, with a visible concentration in the northwestern area. The pink polygons on the right panel isolate land that lies within a pre-Harvey LOMR footprint, sat outside the then-effective SFHA, and was inundated by Harvey. These are areas the regulatory map treated as

outside the high-risk floodplain following a revision, and which flooded during the event. They mostly converge around the Cypress neighborhood in the northwest (ZCTA 77429).

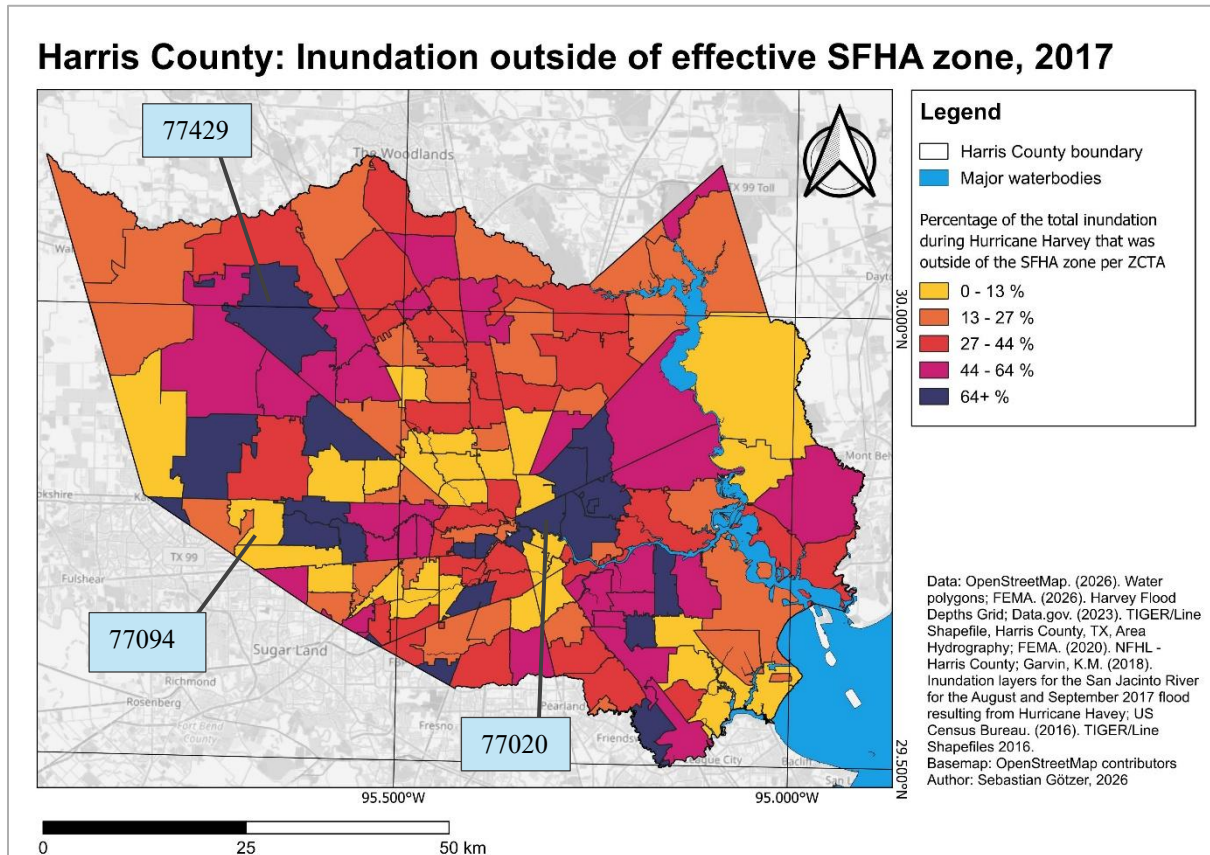


Figure 19: Inundation outside of the effective SFHA zone 2017, Harris County (own illustration). Note: Classified by Quintiles.

Where the previous map (Figure 17) measured how much of a ZCTA flooded, figure 19 measures how much of that flooding lies beyond the zone FEMA had designated as high-risk. This map can be understood as a proxy for the part of the flood exposure that fell outside the officially mapped floodplain. The pattern is relatively heterogeneous across the county, with pockets of high shares of inundation outside the SFHA zone observable to the east of the city center and the northwest of the county. These same areas experienced considerable amounts of flooding in general, as can be seen in Figure 17.

The figure must be read in accordance with the inundation and SFHA-extent maps, because a high share does not by itself indicate extensive flooding. Several ZCTAs in the highest class flooded only slightly, so their out-of-zone share rests on a small base and is amplified where little of the ZCTA was mapped as SFHA to begin with. 77020 is the clearest case, with 94% of its inundation outside the SFHA but only 6,4% of the ZCTA flooded and just 1,5% of its area inside the SFHA. The opposite case is 77094, the most extensively flooded ZCTA in the county

where only 7% of the flooding fell outside the SFHA, consistent with 73% of the ZCTA lying within it. The combination that carries the most weight is high inundation alongside a high out-of-zone share, seen in 77429, which flooded across 46% of its area with 65% of that flooding outside the SFHA.

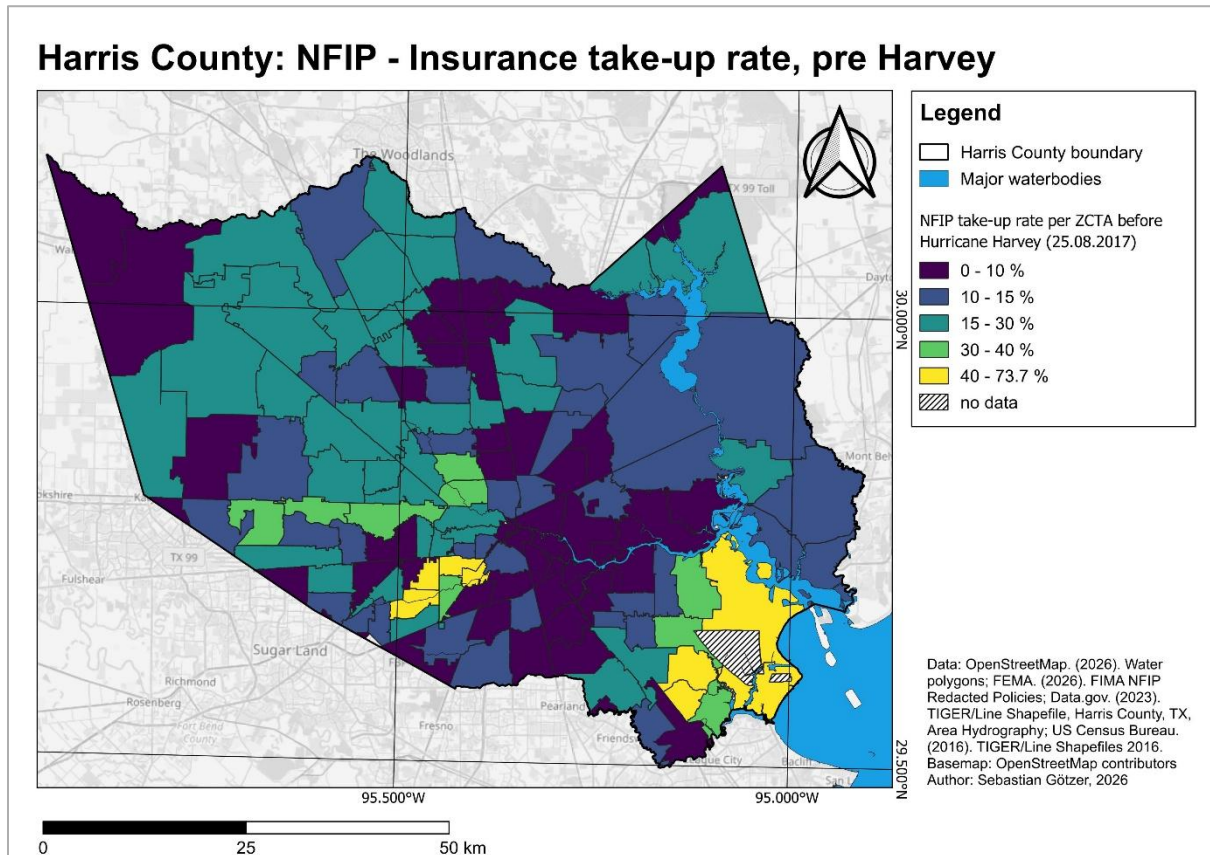


Figure 20: NFIP take-up rate right before Hurricane Harvey struck in August 2017 (own illustration). Note: Classified by natural breaks and then slightly adjusted class boundaries; Calculated using total NFIP policies before Harvey and total occupied housing units (table DP04); the ZCTA showing “no data” represents the industrial area where insufficient policies and households are present.

Figure 20 shows the NFIP take-up rate per ZCTA before Hurricane Harvey. The visualization is inverted so that the darkest shades mark the lowest percentages of insurance take-up. Generally, coverage across most of the county is low. The two lowest classes hold the majority of ZCTAs, with the county-wide rate of roughly 15%, so high take-up is the exception. The highest take-up concentrates along the southeastern bay and coastal margin toward Galveston Bay and the Ship Channel, with a secondary band of moderate take-up running roughly east to west through the west-central county. The lowest take-up forms a large and broadly continuous zone across the central and inner county, joined by scattered northern ZCTAs. Take-up is measured as policies over occupied housing units, and renters cannot hold an NFIP building policy.

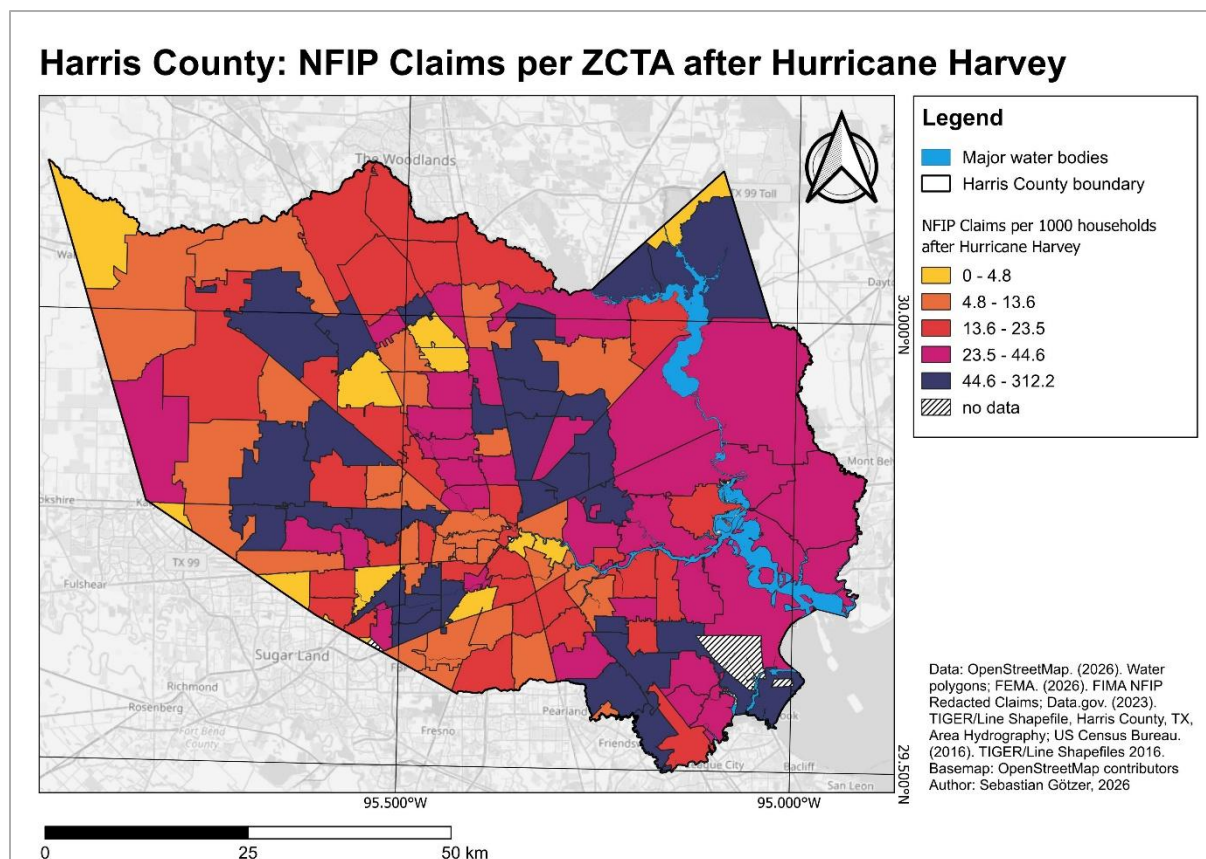


Figure 21: NFIP Claims per 1.000 households after Hurricane Harvey 2017, Harris County (own illustration). Note: Classified by Quintile; “no data” ZCTA represents industrial area.

Figure 21 shows NFIP claims filed after Hurricane Harvey per 1.000 households in each ZCTA. The higher classes cover much of the central and eastern county, with the western and northwestern ZCTAs more often in the lower classes. The top class includes a wide margin, while only six ZCTAs exceed 100 claims per 1.000 households, so most ZCTAs lie well below the upper bound. 77401 is the single highest at 312, where 46% of the ZCTA flooded almost entirely within the SFHA, with only about 0,5% of its inundation falling outside the zone, on a low-vulnerability and high-income base (SoVI 0.33, median household income around USD 170.000). The high-vulnerability, high-exposure ZCTAs east of the city center mostly fall between 50 and 100 claims per 1.000 households, inside the same top class but short of its extreme. The amount actually paid per claim follows a different geography, running higher in the northern and western ZCTAs, which are among the higher-income parts of the county, and is mapped in the appendix figure A 4.

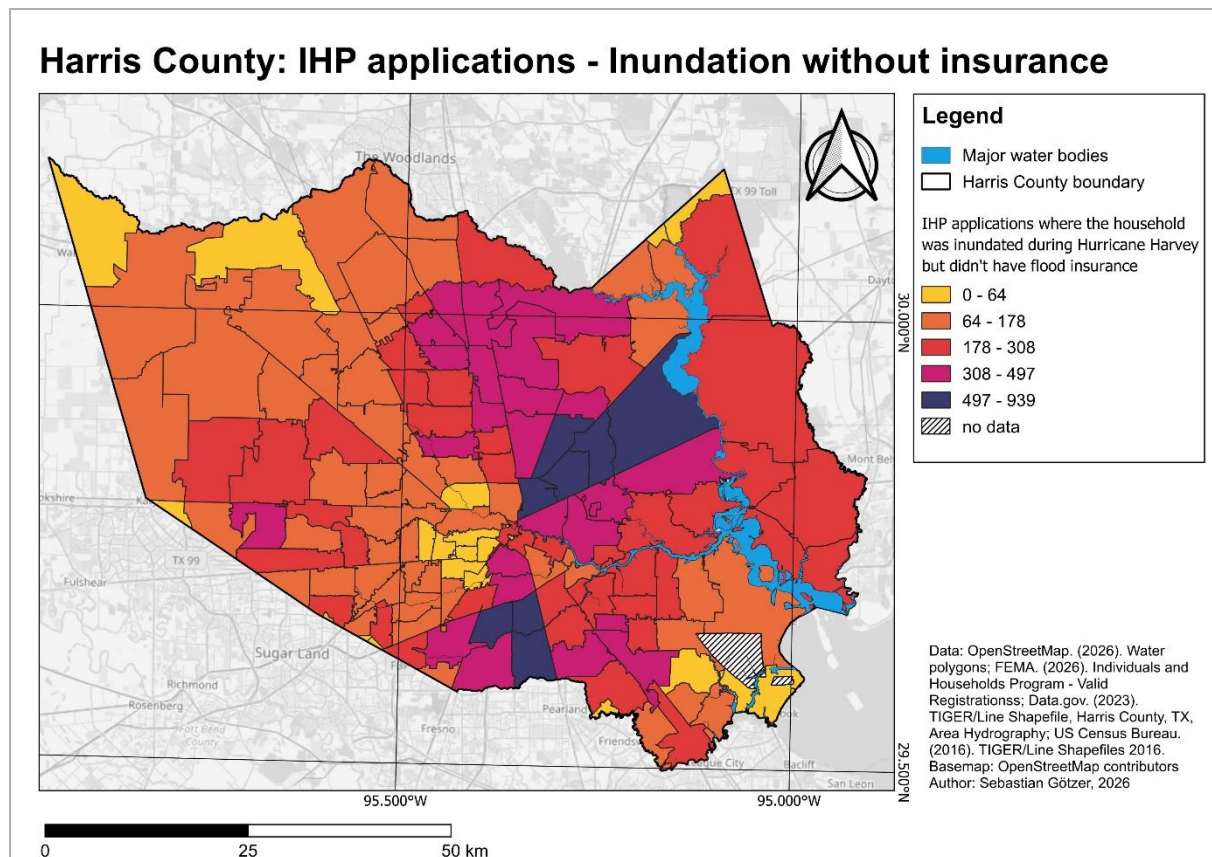


Figure 22: Applications for the Individuals and Households program (IHP) after Hurricane Harvey from household that experienced inundation but did not at the time hold a NFIP policy (own illustration). Note: Classified by Natural Breaks.

Figure 22 shows the number of IHP applications in each ZCTA from households that were inundated during Harvey but held no flood insurance. A clear concentration of the higher classes in the central and eastern county can be observed. Especially the ZCTAs east of the city center with high social vulnerability and low take-up rates (Fig. 16 & Fig. 20) stand out, carrying high counts of applications from uninsured households, whereas the western and northwestern ZCTAs sit mostly in the lower classes. This pattern mirrors the take-up map. The central and eastern areas that recorded the lowest coverage now show the highest uninsured-applicant counts, while the better-covered west shows fewer. Read together with the overall IHP applications in appendix figure A 6, the western applications skew comparatively more toward insured households, while the eastern concentration is driven by uninsured ones.

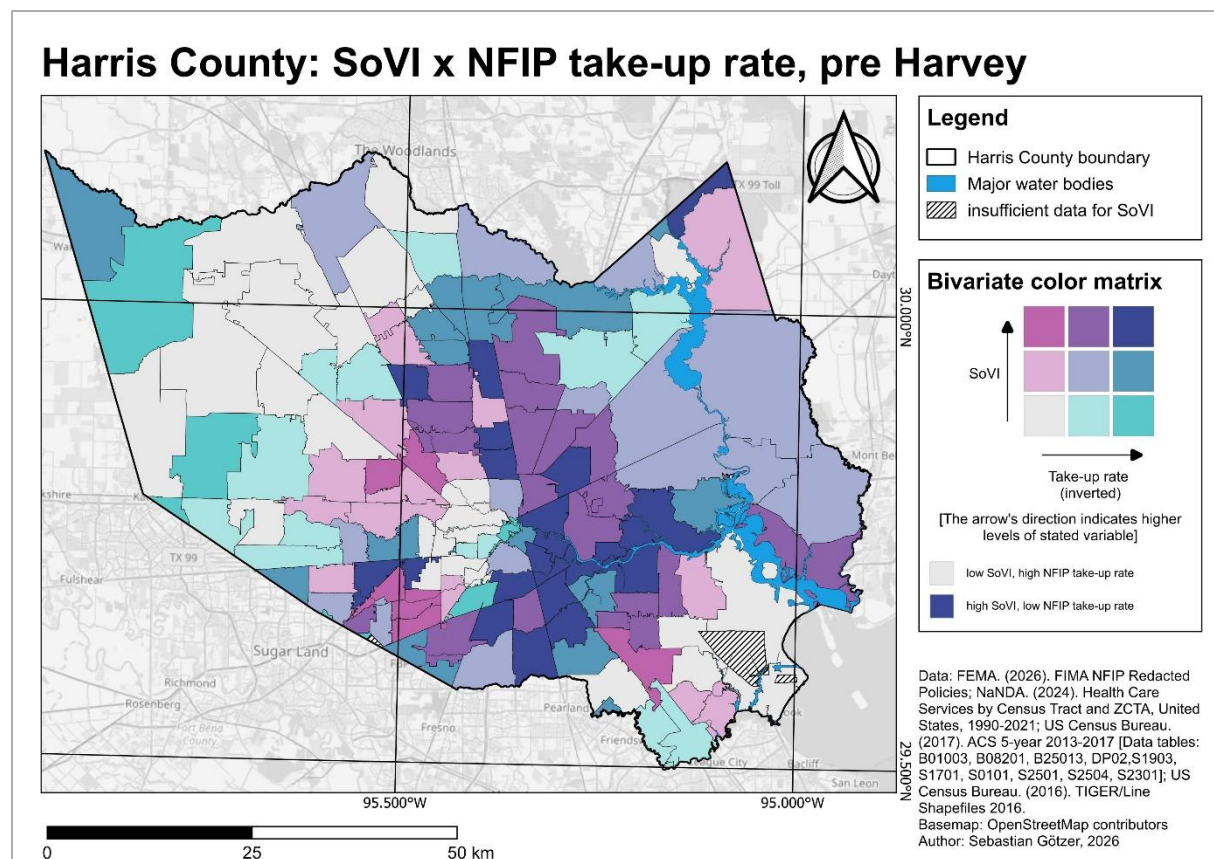


Figure 23: 3x3 Bivariate choropleth with SoVI x NFIP take-up rate before Hurricane Harvey 2017, Harris County (own illustration). Note: Classified by quantiles; Take-up rate is inverted to showcase the negative impact thereof.

Figure 23 maps SoVI against the NFIP take-up rate per ZCTA before Hurricane Harvey. The SoVI represents the vertical axis of the matrix and the take-up axis is inverted, so the saturated indigo-colored corner combines high vulnerability with low coverage, and the pale grey corner combines low vulnerability with high coverage. The indigo and purple cells dominate the central and inner county, so high SoVI and low take-up fall in the same place across the urban core. The pattern of the ZCTAs east of the city center carries through here, holding most of the high-vulnerability, low-coverage units. This overlap consequently coincides with where SoVI peaked and take-up was lowest on the single-variable maps. The opposing combination, low vulnerability with high take-up, sits on the western and northwestern fringe.

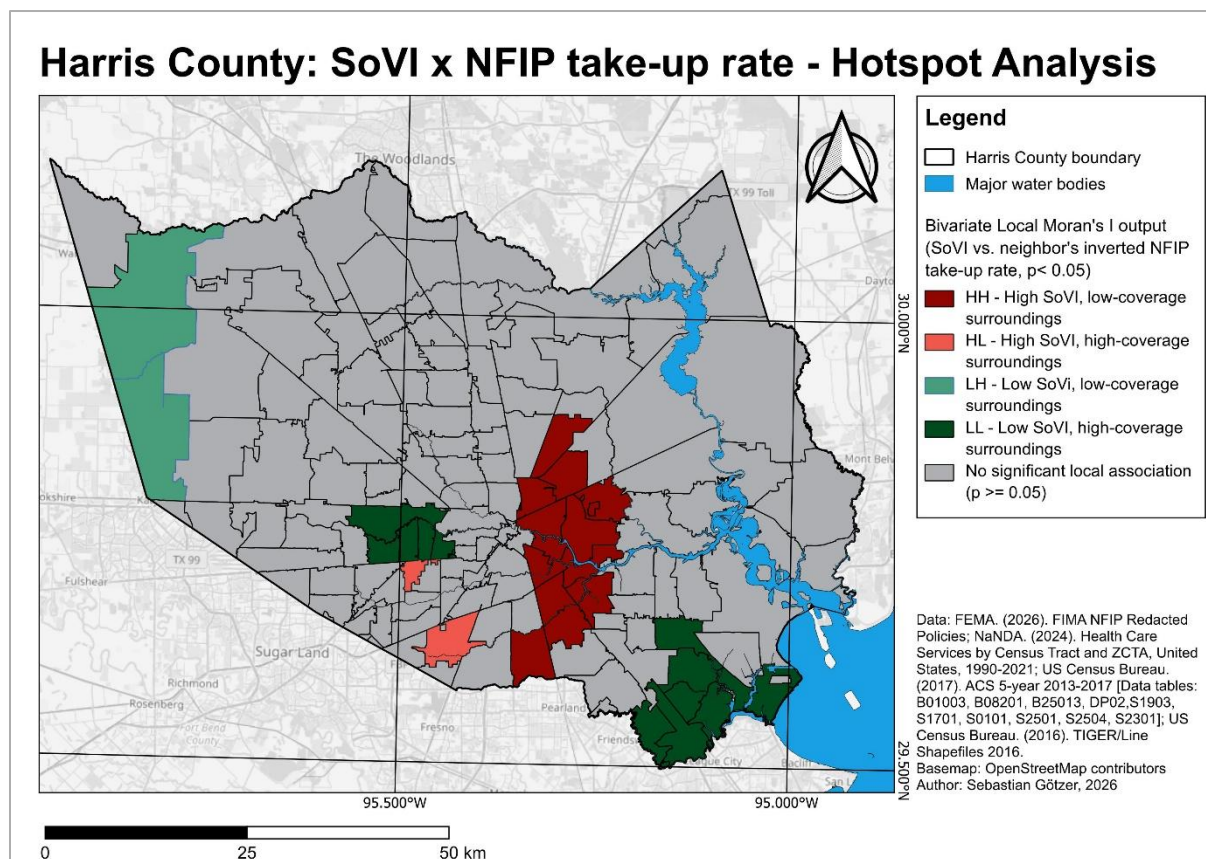


Figure 24: Bivariate Local Moran's I for SoVI x NFIP take-up rate before Hurricane Harvey 2017, Harris County (own illustration). Note: take-up rate inverted; method searches for local associations of the two variables with statistical significance of $p \geq 0.05$.

Figure 25 shows the formal clustering test, a bivariate Local Moran's I run with queen contiguity and 999 permutations and mapped only where significant at $p < 0.05$. The second axis is the spatial lag of inverted take-up, so "low-coverage surroundings" means neighbors with low take-up. One significant high-high (HH) cluster, high SoVI in low-coverage surroundings, covers the central and inner county and extends east of the city center, marking the most significantly vulnerable ZCTAs in that broad area. A significant low-low (LL) cluster, low SoVI in high-coverage surroundings, sits along the southeastern bay margin toward Galveston Bay, with a smaller pocket in the west-central county. HL and LH clusters are few, a low SoVI and low-coverage block in the far northwest and two small high SoVI and high-coverage pockets in the west-central county, while most of the county shows no significant association. Taken together, these clusters confirm the bivariate pattern and show that the central overlap of high vulnerability and low coverage is spatially clustered rather than incidental.

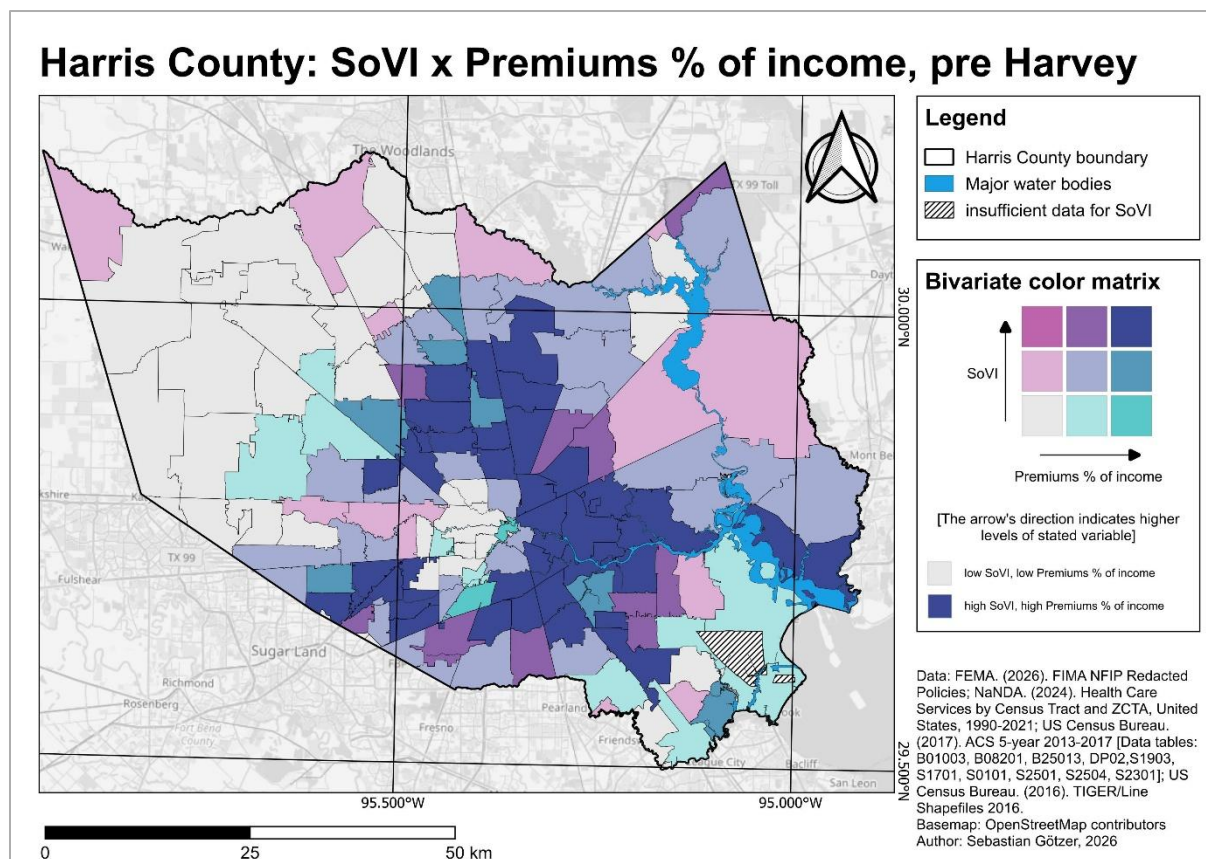


Figure 25: 3x3 Bivariate choropleth with SoVI x the share NFIP premiums represent of a household's income before Hurricane Harvey 2017, Harris County (own illustration). Note: Classified by Quantiles.

Figure 25 maps SoVI against insurance premiums as the percentage of median income per ZCTA. This can be understood as the financial dimension of vulnerability, as it measures the affordability of insurance. A higher value on the horizontal axis of the matrix means coverage consumes a larger share of income and is thus less affordable. The underlying premium costs are mapped in appendix figure A 5. The indigo and purple cells fill the central and inner county, so the pattern around the city center becomes clear, with high SoVI coinciding with a high premium-to-income ratio across the urban core. That is the same core that carried the lowest take-up and the same area picked out by the take-up clusters, so the least affordable coverage and the lowest uptake fall together. The combination, low SoVI with low financial burden can predominantly be observed in the western and northwestern suburban fringe. High SoVI with low burden appears only scattered with no ZCTA recording the combination of highest SoVI score with lowest Premiums as percentage of income.

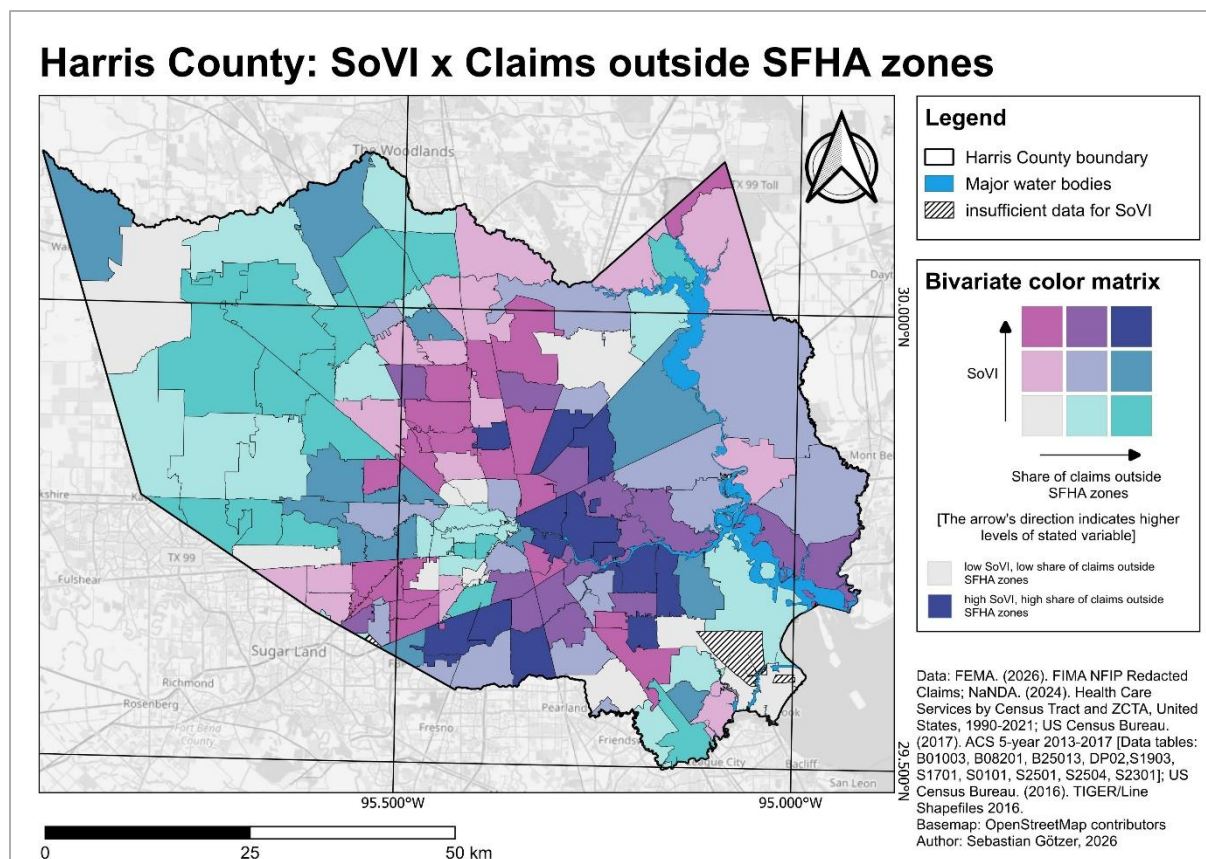


Figure 26: 3x3 Bivariate choropleth with SoVI x NFIP Claims outside the SFHA zones after Hurricane Harvey 2017, Harris County (own illustration). Note: Classified by Quantiles.

Figure 26 maps SoVI against the share of NFIP claims filed outside the SFHA per ZCTA, the zoning dimension of the analysis. The share of claims outside the SFHA is the proportion of a ZCTA's NFIP flood claims filed for properties beyond the Special Flood Hazard Area, so a higher value means a larger part of the flood losses NFIP actually paid fell outside the mapped high-risk zone. The underlying out-of-zone claims pattern is mapped in appendix figure A 7. The high-high cells concentrate across the central and south-central county, the same ZCTAs that carried the lowest take-up, so the core overlap recurs here. Unlike the take-up and premium-burden maps, though, the high-share side is not confined to that core, since a high out-of-zone share also fills the low-vulnerability western and northwestern suburbs. Out-of-zone claims were therefore a broadly distributed feature rather than a localized one.

Table 5: Crosstabulation of selected variables by SoVI quintile for Harris County

SoVI quintile	SFHA share (%)	NFIP take-up (%)	Premium /Income (%)	Inundation (%)	Claims per 1,000 hh	Median paid claim (USD)	IHP apps per 1.000 hh	n
Q1 (least vulnerable)	24,0	22,4	0,55	21,2	37,4	\$69.935	152,5	28
Q2	22,8	18,1	0,88	20,0	25,7	\$69.832	193,9	27
Q3	19,5	15,0	0,85	19,6	28,6	\$76.256	291,0	28
Q4	21,0	12,5	1,51	21,3	36,1	\$54.723	297,5	27
Q5 (most vulnerable)	17,4	10,1	2,11	20,9	35,2	\$43.734	451,0	28

Note: Own calculations based on the variables are introduced throughout this chapter; n is the number of ZCTAs per quintile.

Table 5 is a crosstabulation of selected variables across the five SoVI quintiles. Two variables show no clear gradient across the levels of vulnerability: The inundated share of the ZCTA stays close to 20 to 21% throughout, and claims per 1.000 households range from 25,7 to 37,4 with no clear connection to vulnerability. The remaining variables differ more distinctly. The share of the ZCTA within the SFHA is broadly lower toward the most vulnerable quintiles, falling from 24,0% in Q1 to 17,4% in Q5. The NFIP take-up rate declines steadily across the gradient, from 22,4% in the least vulnerable quintile to 10,1% in the most vulnerable. The NFIP premium as a percent of median household income moves in the opposite direction, rising from 0,55% in Q1 to 2,11% in Q5, with the steepest increase in the two most vulnerable quintiles. Applications to the Individuals and Households Program per 1.000 households rise in the same way, from 152,5 in Q1 to 451,0 in Q5. The median sum paid per insurance claim holds near USD 70.000 in the two least vulnerable quintiles and peaks at USD 76.256 in Q3, before falling to USD 54.723 in Q4 and USD 43.734 in Q5, so the lowest payouts fall in the two most vulnerable quintiles. The spatial distributions behind these indemnity figures are shown in appendix figure A 5.

6.2. Results Île de France

The results of the Île de France side follow below. Due to the size of the region, a separate map showing the location of all the communes mentioned throughout the thesis can be viewed in the appendix figure A 8.

For the communes designated with “insufficient data” in Fig. 27 (SoVI), Fig. 33 (SoVI x EAIP), Fig. 35 (SoVI x S/P ratio) a majority of the SoVI variables used had no data records, which would have created a skewed weighting of single factors. Since these communes are predominantly in rural areas and have small population numbers they are left out of the analysis.

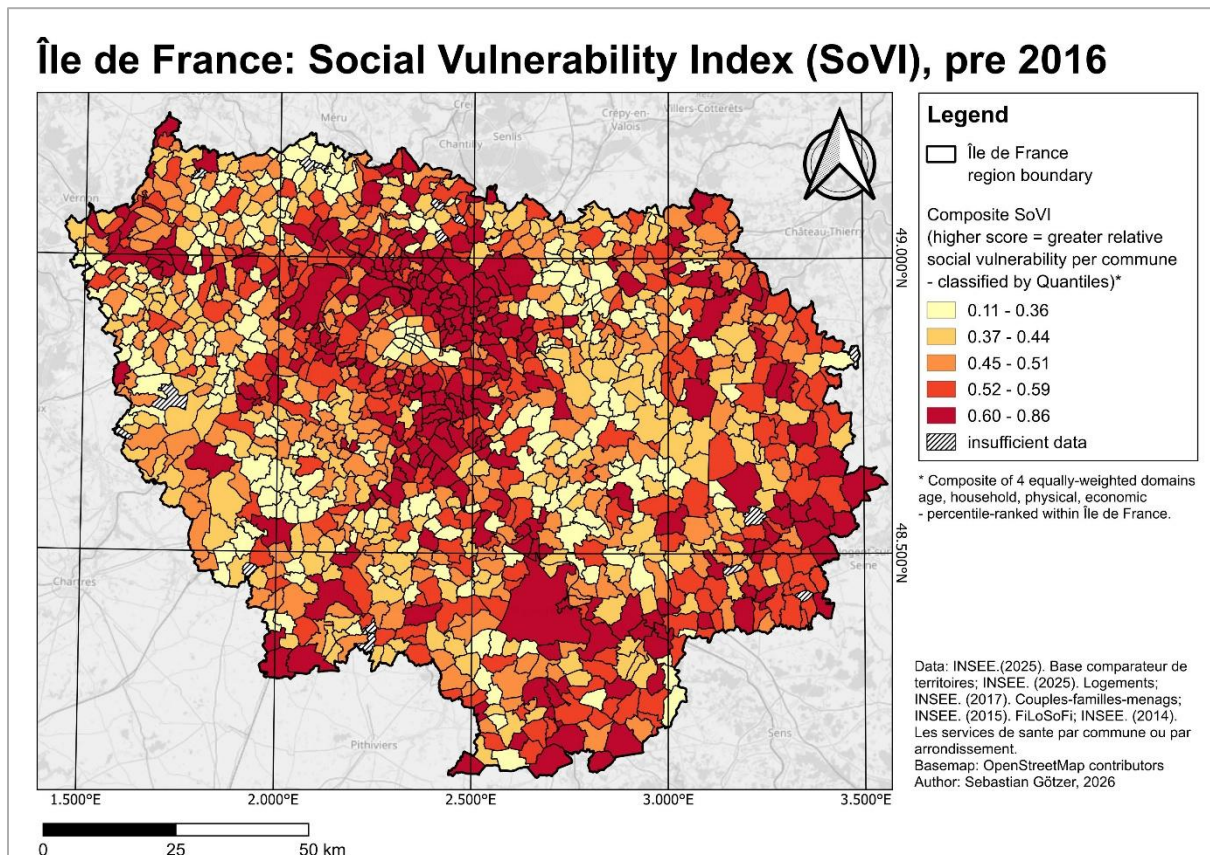


Figure 27: Composite SoVI scores per commune before the 2016 floods, Île de France (own illustration).

Figure 27 maps the composite SoVI for the 1287 communes of Île de France before the 2016 flood event. The highest scores concentrate around Paris, especially to the northeast and southeast of the capital. Saint-Denis, Aubervilliers and surrounding communes anchor the northeastern cluster, where most communes score above 0.70. To the southeast, Villeneuve-Saint-Georges, Vitry-sur-Seine, and Longjumeau in the south show values of roughly 0.65 to 0.70. Beyond this suburban ring, high scores appear as isolated pockets across the outer region.

Nemours and Souppes-sur-Loing in the south and Dammarie-les-Lys further upstream along the Seine are two such cases. The inner core of Paris sits at the opposite end of the range. There, the central arrondissements fall in the lowest classes, around 0.30 and below.

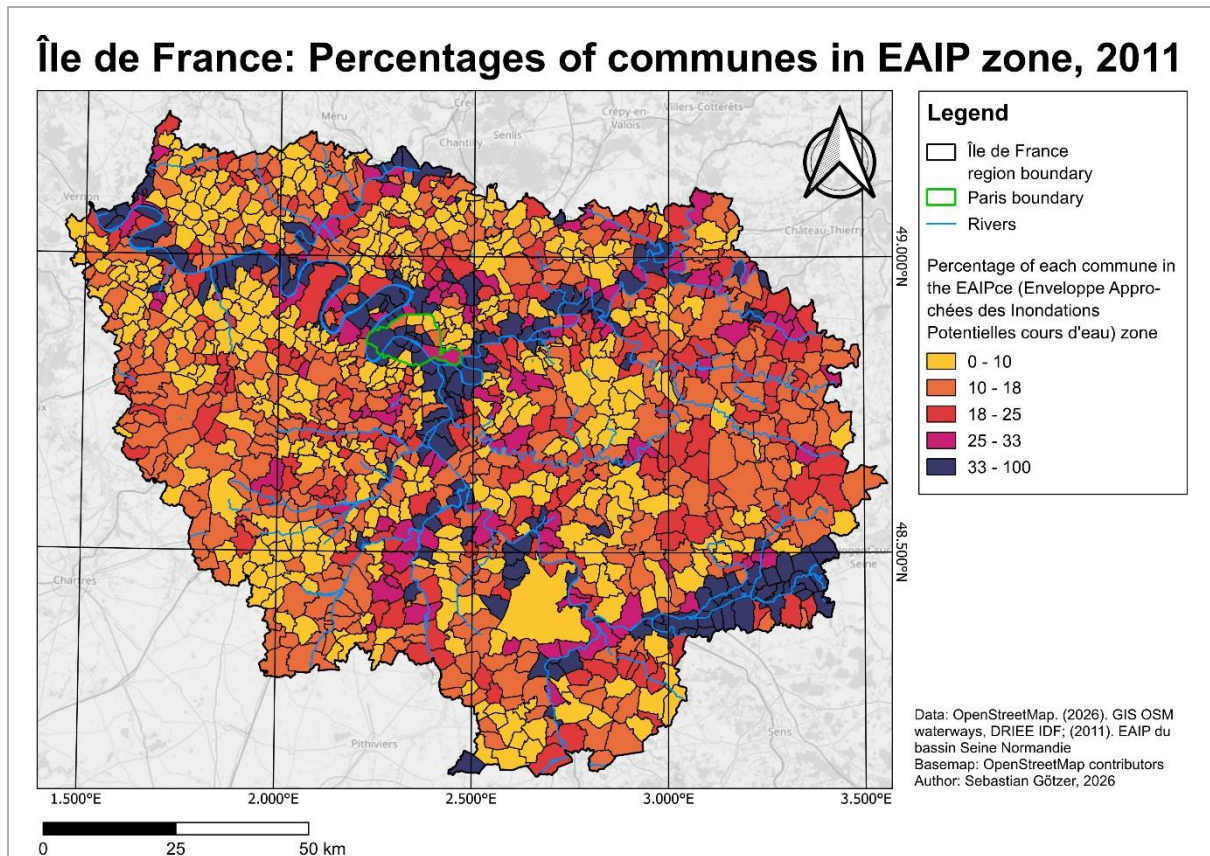


Figure 28: Percentage within the EAIP zone per commune 2011, Île de France (own illustration). Note: Classified by Natural Breaks and slightly adjusted class boundaries.

Figure 28 maps the communes based on the share of their total area within the EAIP zone. It provides potential flood areas without a specific return period attached, as introduced in subsection 4.2.3. Naturally, the highest concentrations occur in the river corridors of the region with the river Seine being the most influential one. The Seine corridor upstream of Paris to its southeast showcases the highest percentages as can be seen in Ablon-sur-Seine (75%+) or Villeneuve-Saint-Georges (73%+), for instance. Furthermore, the inner core of Paris, many communes downstream of the capital to the northwest as well as the Seine corridor in the very southeast of Île de France display percentages of around 70% or more. Apart from these clusters, communes within the highest class here lie scattered around the region, as in the Marne corridor northeast of Paris or single communes further south.

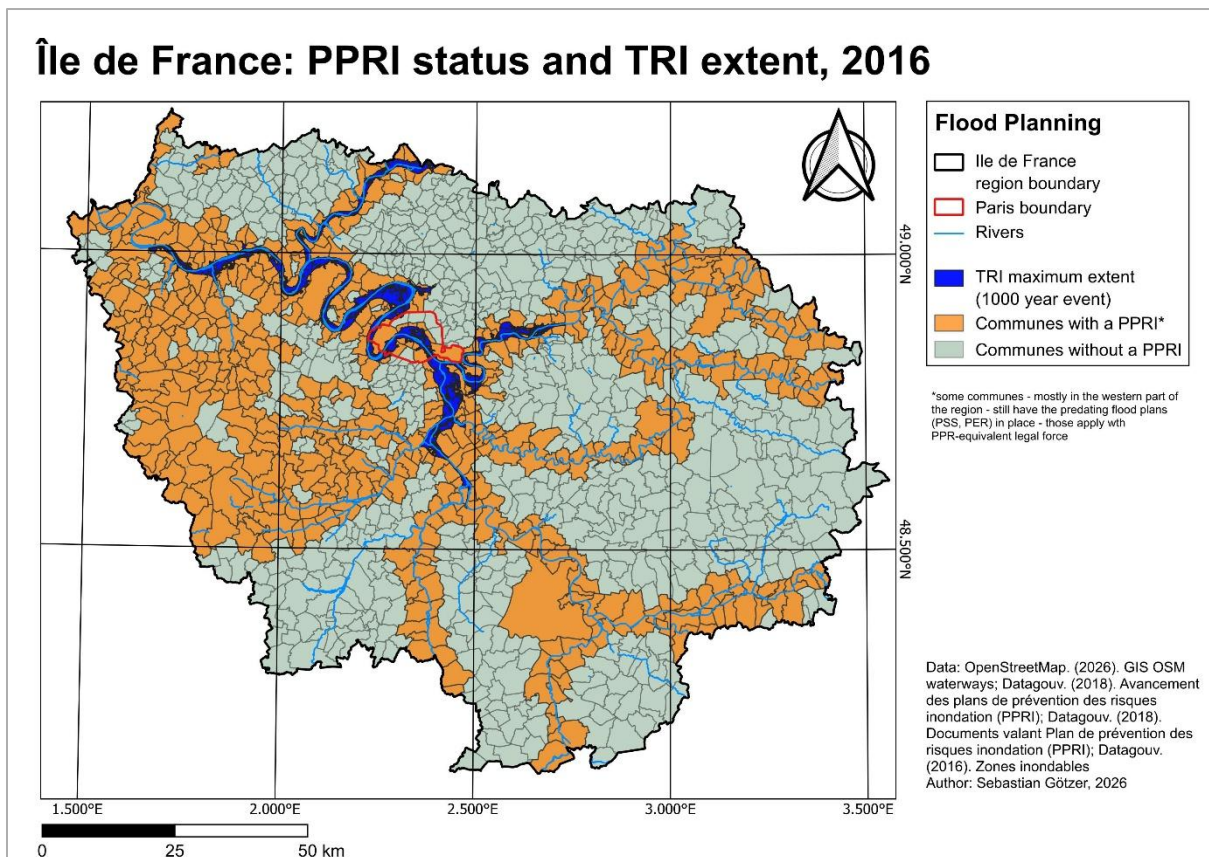


Figure 29: PPR status and TRI extent before the 2016 floods, Île de France (own illustration). Note: PPRI status is binary at commune level, and the orange class includes communes covered by predating prevention plans with PPR-equivalent force; Provenance is the data.gouv.fr PPRI progress and documents-valant-PPRI layers (2018) and the Zones inondables extent (2016).

Figure 29 shows the regulatory flood-zoning context for the region, combining PPRI status by commune with the maximum TRI extent before the 2016 floods. The conceptual basis for both instruments is set out in section 4.2. Communes with a PPRI (orange) follow the river corridors closely. The zoning concentrates along the Seine and the Marne and their tributaries across the region. Many of the orange communes in the west do not hold a PPRI in the strict sense, as they operate under flood plans predating the PPR, which however carry PPR-equivalent legal force and are counted here as covered, as the figure note records. The dark blue marks the maximum TRI extent, the low-probability 1.000-year envelope from the detailed modelling. That modelling was produced only for the designated TRI territories, mainly the central Seine and Marne corridors, so it does not extend across the whole region. Large parts of the periphery away from the main corridors carry neither a PPRI nor TRI-level modelling.

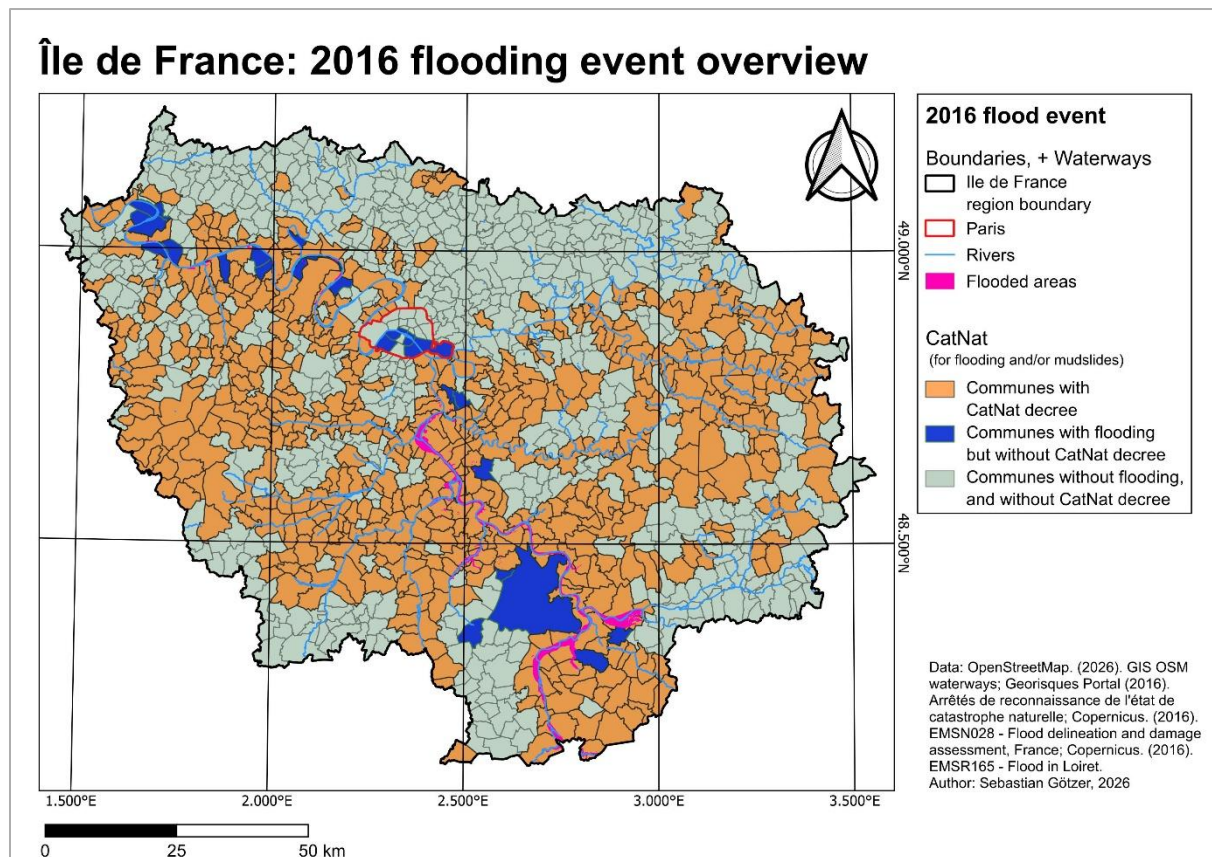
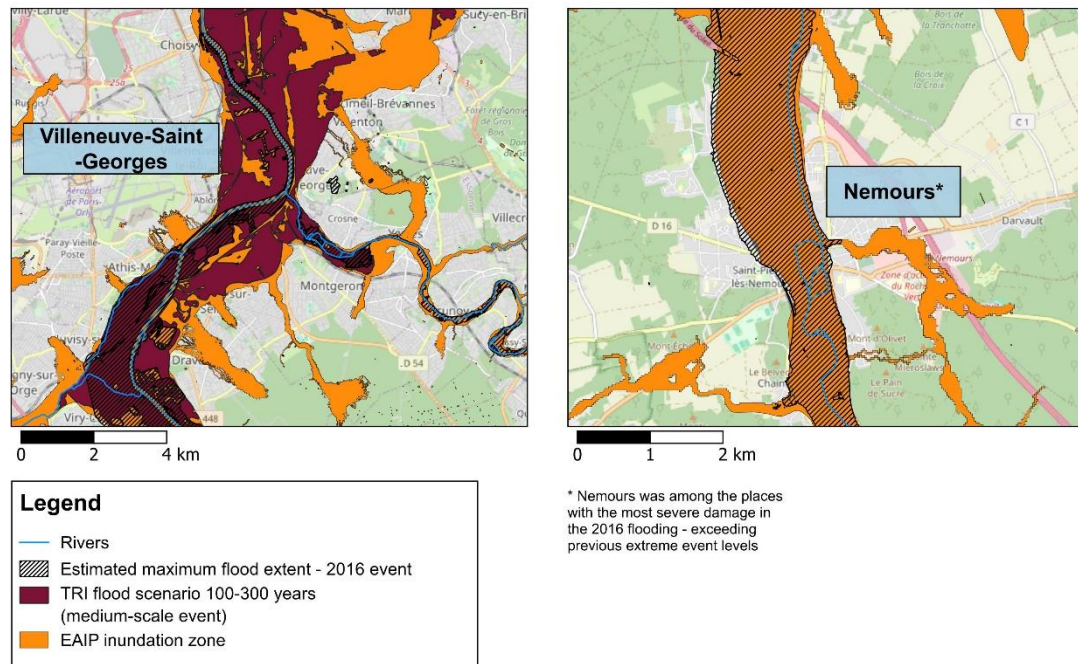


Figure 30: Overview of the 2016 flooding event showcasing CatNat decrees in orange, confirmed flooding extents in pink, and communes with any amount of flooding and no CatNat decree in 2016, Île de France (own illustration).

Figure 30 provides an overview of the 2016 event across Île de France. The mapped flooded areas follow the Seine and are most extensive in the corridor upstream of Paris, where most of the 2016 inundation occurred. This layer derives from two Copernicus activations, EMSN028 and EMSR165, which cover only parts of the region. It therefore does not capture the full extent of inundation across Île de France. The flooding status (i.e. all communes with “Flooded areas” present) is consequently only displayed as a binary attribute indicating those communes that recorded any flooding but have not received a CatNat decree. The decrees are issued for flooding and mudslides, so a decree can reflect flooding, flood-related mudslides, or both. Large parts of the communes covered by a PPRI (Fig. 29) show an overlap with CatNat decrees received in 2016. Especially the eastern part of the region and the southwestern area next to the Seine corridor show relevant portions of CatNat decrees where no PPRI or TRI modelling existed prior.

Île de France: Exemples - Places affected by 2016 flooding



Data: OpenStreetMap. (2026). GIS OSM waterways; Datagouv. (2016). Zones inondable; Copernicus. (2016). EMSN028 - Flood delineation and damage assessment, France; Copernicus. (2016). EMSR165 - Flood in Loiret; DRIEE IDF. (2011). EAIP du bassin Seine Normandie
 Basemap: OpenStreetMap contributors
 Author: Sebastian Götzer, 2026

Figure 31: Affected communes in Île de France – examples . Left Panel: The EAIP zone, TRI medium flooding scenario and actually realized flooding extents in Villeneuve-Saint-Georges; Right panel: The EAIP zone and actually realized flooding extents in Nemours from the 2016 event (own illustration).

Figure 31 examines two of the communes previously mentioned more closely. Appendix figure A 8 shows the exact location within the region of both communes. Villeneuve-Saint-Georges lies in the high-SoVI, high-EAIP-percentage Seine corridor southeast of Paris where extensive TRI modelling was conducted. More than 52% of the commune’s area is susceptible to flooding in the medium TRI scenario (100 - 300-year return period). While the realized flooding in 2016 did not notably exceed the modelled scenario, as can be seen on the “Estimated maximum flood extent – 2016 event” layer, this figure shows the exposure of this commune to flooding. In the time period of 1982 – 2024, 14 separate CatNat decrees, representing “catastrophic flooding” were issued here, making it one of the most frequently flooded communes in the entire region (Fig. A 9). Similarly, Nemours, located near the southern tip of the region, shows high exposure to floods with 7 unique CatNat decrees in the mentioned period while showing elevated levels of social vulnerability. As no TRI modelling was conducted here, the estimated maximum flood extents from 2016 is laid over the EAIP zone, which shows the maximum potential flood extents. It becomes apparent that Nemours experienced significant levels of flooding, most likely exceeding a 100 – 300-year return period markedly.

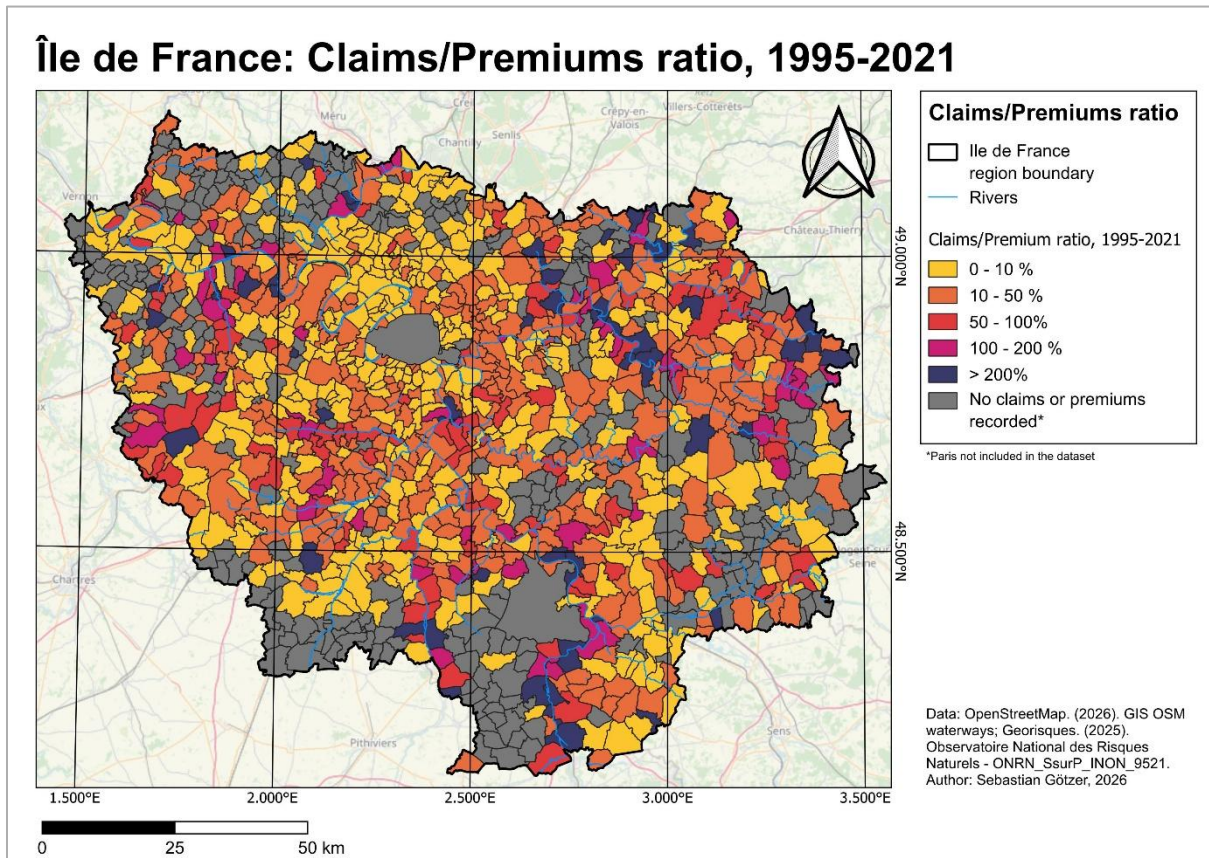


Figure 32: Claims/Premium (S/P – Sinistres/Primes) ratio cumulated from 1995-2021, Île de France (own illustration). Note: Visualized based on the predefined categories the datasets comes in. A separate grey class covers communes with no recorded claim or premium value, which is not the same as a low ratio. Paris is not included in the dataset and falls in this grey class.

Figure 32 maps the claims-to-premiums ratio (S/P) per commune for the flood peril under the CatNat regime, accumulated over the period 1995 to 2021. The ratio sets the flood indemnities paid in a commune for all the Claims against the CatNat premiums collected there over the same window. As established in subsection 4.2.4, the premium is a flat national surcharge, set as a fixed percentage of each property contract and not differentiated by location or flood risk. A value below 100% means premiums collected within a commune exceeded its indemnities paid over the period while a value above 100% means claim indemnities paid exceeded premiums collected. High values thus show higher flood exposure in a commune. The ratio is cumulative across the full window and does not isolate the 2016 event.

The two lowest bands, below 10% and 10% to 50%, cover most communes across the region. The higher bands, from 50% to over 200%, appear as individual communes scattered throughout. The mentioned examples Villeneuve-Saint-Georges and Nemours both fall into the highest category, underlining their status as communes with high flood risk.

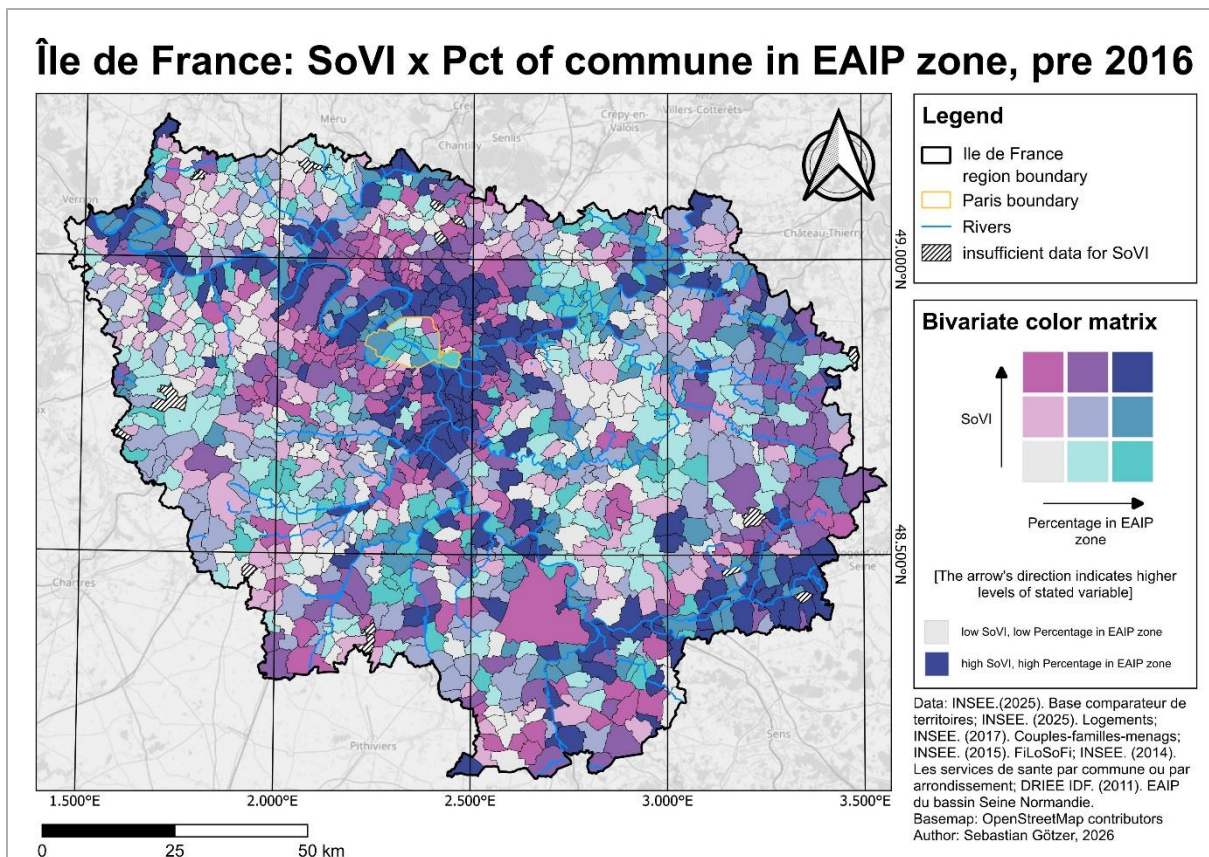


Figure 33: 3x3 Bivariate choropleth with SoVI x the percentage of a commune in the EAIP zone before the 2016 floods, Île de France (own illustration). Note: Classified by Quantiles.

Figure 33 crosses the composite SoVI with the share of each commune that lies within the EAIP zone. The grey corner marks communes that are low on both, low vulnerability and a small EAIP share. The dark blue corner marks communes that are high on both, high vulnerability and a large EAIP share. This map highlights those communes that combine high social vulnerability with notable flood exposure provided by the EAIP share functioning as a proxy thereof.

The most pronounced accumulation of these communes follows the Seine corridor southeast of Paris. Mentioned examples such as Villeneuve-Saint-Georges, Vitry-sur-Seine, Longjumeau, and Nemours all fall into this category. Paris sits in the low-SoVI row of the matrix, with EAIP shares relatively high along the rivercourse. The same low-SoVI pairing recurs across scattered rural communes elsewhere, in both its low-share grey form and its high-share teal form.

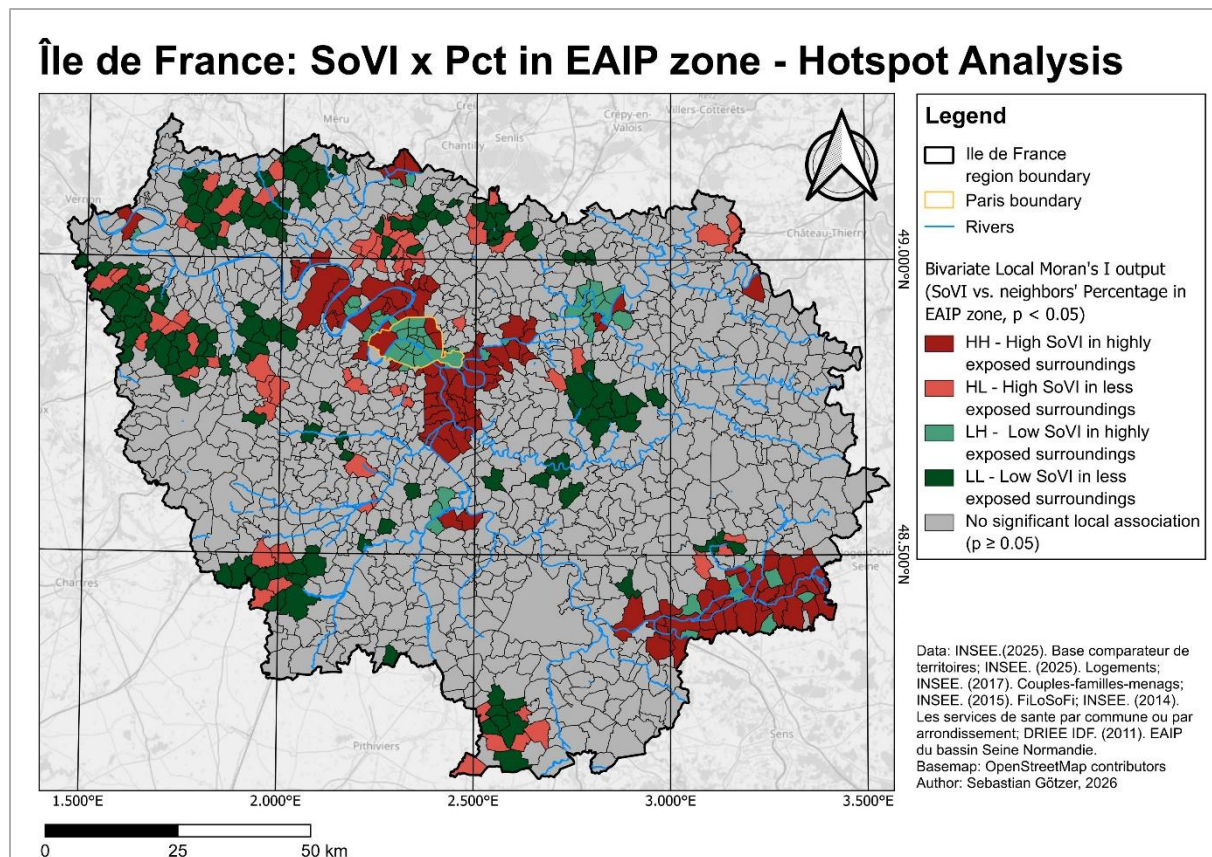


Figure 34: Bivariate Local Moran's I for SoVI x Percentage of a commune in the EAIP zone before the 2016 floods, Île de France (own illustration). Note: Method searches for local associations of the two variables with statistical significance of $p \geq 0,05$.

Figure 34 shows the bivariate Local Moran's I for the SoVI against the surrounding EAIP exposure. The test pairs the SoVI of each commune with the EAIP share of its neighboring communes. Each cluster class describes a commune's own vulnerability relative to the exposure of the area around it. Only communes with a statistically significant local association at $p < 0.05$ receive a class. All other communes show no significant association and appear in grey. Four cluster types are mapped. HH marks high SoVI in highly exposed surroundings. HL marks high SoVI in less exposed surroundings. LH marks low SoVI in highly exposed surroundings. LL marks low SoVI in less exposed surroundings.

Most communes show no significant local association and appear in grey. The significant clusters stand out against this background. The HH cluster is the most prominent. It concentrates along the Seine corridor south and southeast of Paris, in line with the accumulation seen in the preceding figure 33, and forms a second cluster in the southeast of the Île de France region. Paris and a group of communes to its northeast fall in the LH class, low vulnerability in highly exposed surroundings. The HL and LL communes appear as scattered units across the region and do not form tight clusters.

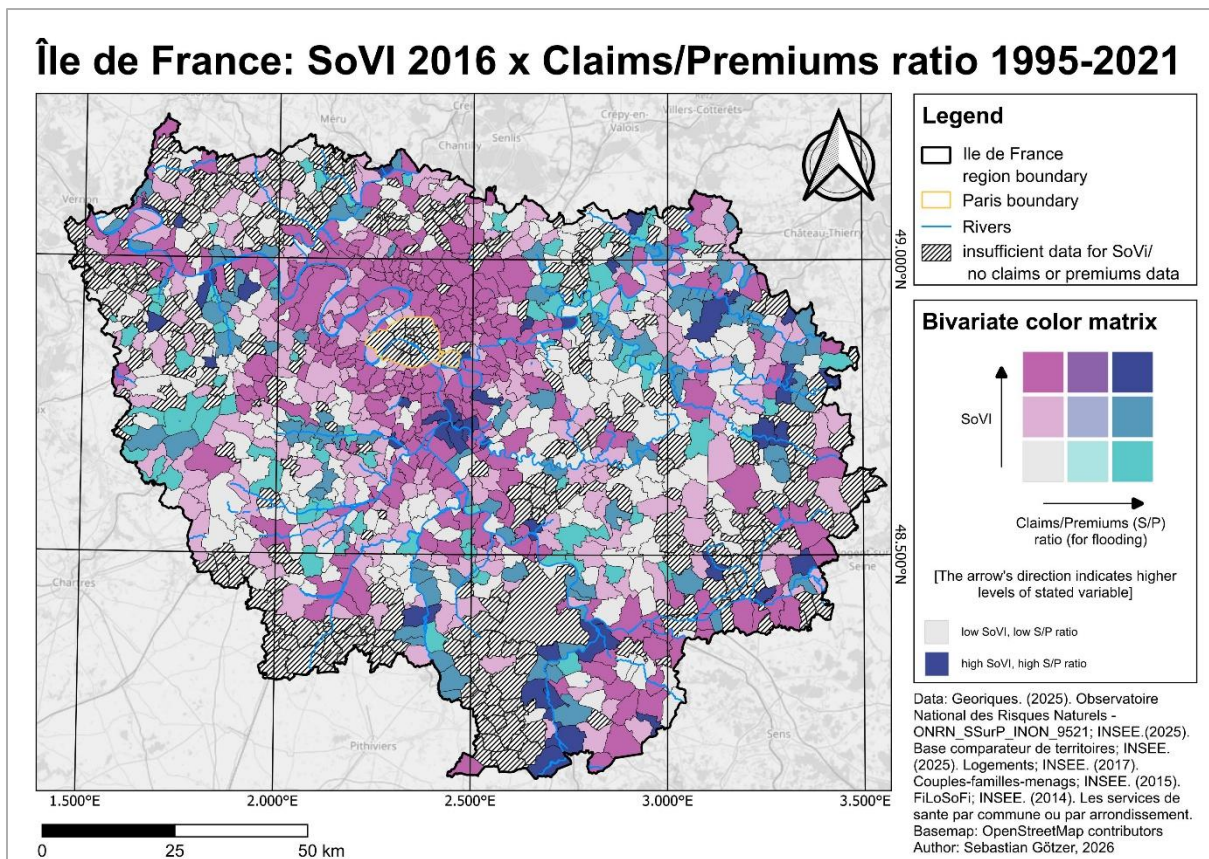


Figure 35: 3x3 Bivariate choropleth with SoVI 2016 x Claims/Premiums (S/P) ratio 1995-2021, Île de France (own illustration). Note: SoVI classified by Quantiles while S/P ratio comes in predefined categories and is a long-run variable.

Figure 35 crosses the composite SoVI with the claims-to-premiums (S/P) ratio for floods under the CatNat regime introduced earlier in this chapter. SoVI increases upward and the S/P ratio increases to the right, where a value above 100% means indemnities paid exceeded premiums collected over 1995 to 2021. The grey corner marks communes that are low on both. The dark blue corner marks communes that are high on both, high vulnerability combined with a high S/P ratio. Hatched communes lack sufficient SoVI data or carry no claim or premium value, with Paris being among them.

The communes with a high SoVI score and a low S/P ratio cover most of the region around Paris, indicating comparatively low flood losses over the stated time period. The dark blue communes, high on both axes, appear mostly as individual units scattered across the region with small accumulations in the recurring Seine corridor southeast of Paris and the southern tip of Île de France. The remaining classes don't show any notable accumulations. A companion bivariate that crosses SoVI with cumulative flood indemnities per inhabitant over the same period shares the flood claims numerator with the S/P ratio and shows a closely related spatial pattern. It is provided in appendix figure A 2.

Table 6: Crosstabulation of selected variables by SoVI quintile for Île de France

SoVI quintile	EAIP share (%)	PPRI coverage (%)	2016 decree (%)	Cost per cap. (rank)	S/P ratio (rank)	n
Q1 (least vulnerable)	17,1	35,0	36,0	1,77	2,00	258
Q2	16,1	41,0	44,0	1,83	2,15	257
Q3	17,6	49,0	50,0	1,79	2,08	257
Q4	21,6	46,0	51,0	1,81	2,12	257
Q5 (most vulnerable)	24,5	53,0	45,0	1,39	1,68	258

Note: Own calculations based on the variables are introduced throughout this chapter; n is the number of ZCTAs per quintile; Cost per inhabitant and S/P ratio are displayed in rank due to their predefined data categories – lower rank equals lower variable value.

Table 6 is a crosstabulation of selected variables across the five SoVI quintiles, with n being the number of communes included for each. The two hazard and zoning variables are broadly higher toward the most vulnerable quintiles. The share of the commune within the EAIP zone rises from 17,1% in Q1 to 24,5% in Q5, with the increase concentrated in the two most vulnerable quintiles. PPRI coverage is higher toward the upper quintiles as well, from 35,0% in Q1 to 53,0% in Q5, with a small dip in Q4. The share of communes with a 2016 CatNat decree does not follow this pattern. It rises from 36,0% in Q1 to a peak of 51,0% in Q4, then falls to 45,0% in Q5. The two claim variables are reported as mean ordinal ranks, where a higher rank marks a higher band. The mean cost-per-inhabitant rank stays close across the first four quintiles, between 1,77 and 1,83, and falls to its lowest value of 1,39 in Q5. The mean S/P ratio rank follows the same shape. It holds between 2,00 and 2,15 across the first four quintiles and falls to 1,68 in Q5. Across the table, the exposure and zoning measures rise toward the most vulnerable quintile, while the cost-per-inhabitant and S/P ranks do not. The spatial patterns behind the EAIP share and the S/P ratio are shown in the bivariate maps above, and the cost-per-inhabitant distribution in appendix figure A 1.

7. Discussion

This chapter combines the findings of the Results chapter, synthesizes the meaning and implications thereof and discusses limitations of the analysis as well as criticism and changes for both flood insurance regimes.

7.1. Interpretation of the results and implications

7.1.1. USA, Harris County

The levels of flooding caused by Hurricane Harvey in 2017 were relatively evenly distributed across Harris County. This is shown by figure 18 where no clear clustering of inundation in just one area of the county can be observed, the spatial distribution of NFIP claims per 1.000 households (Figure 21), as well as in Table 5 where it becomes apparent that flooding affected all five SoVI quintiles roughly on an equal level. The ZCTAs showing the highest social vulnerability, however, are almost exclusively located in the urban core of Harris County, east of Houston's city center, whereas those with the lowest SoVI scores are found in the city center and towards the northwest. Flood risk consequently is a question of coverage rather than pure exposure to hazard in this case.

The benefits of insurance coverage when it comes to financial recovery after a natural disaster are established in section 2.4. With a roughly equal distribution of exposure and levels of flooding across the county, take-up rates become a determining factor for how severe certain neighborhoods are affected by an event. Especially the Bivariate (Figure 23) and LISA (Figure 24) maps for SoVI x Take-up showcase the corresponding spatial relationship for this in the central-eastern core. NFIP take-up rates decline monotonically with the SoVI score rising (from 22,4% for the least vulnerable quintile to 10,1% for the most vulnerable quintile), whereas the applications for the federal aid program IHP, especially those from households not holding a policy, almost triple in the high-vulnerability urban cluster east of the city center. IHP payout, however, is significantly lower than NFIP claim indemnities are, thus further impeding financial recovery. A main driver for these low take-up rates is the financial burden of the premiums (i.e. the share of the household income that is paid in NFIP premiums annually), representing 2,11% for the most vulnerable ZCTAs whereas the least vulnerable ZCTAs only pay 0,55% of their income per year. A potential lack of awareness of the underlying danger, given the low frequency of events posing a threat to livelihoods, underlines the financial decision not to purchase coverage.

The Special Flood Hazard Area (SFHA), created and maintained by FEMA, represents areas susceptible to 100-year fluvial floods and carries corresponding building-restrictions and mandatory purchase requirements, as established in section 4.1. Figure 19 shows certain ZCTAs had large shares of the inundation caused by Hurricane Harvey occurring outside of the designated zone. This is supported by roughly 47% of NFIP claims county-wide coming from outside the SFHA. The least vulnerable SoVI quintile had the highest share of 24,0 % in the SFHA zone while the most vulnerable quintile had only 17,4%. With the levels of inundation being similar across the county, this indicates a protection gap for the vulnerable core – hereby meaning it is under-mapped. One significant reason for this is the pluvial nature of Hurricane Harvey, whereas the FEMA maps only indicate fluvial flood risk. There are, however, at least three different architectural gaps within the NFIP system causing protection gaps, as described below based on example ZCTAs (Figure 36):

a) Market gap – The insurance uptake is mostly voluntary when a ZCTAs is characterized by a low share of SFHA zones. This example (ZCTA 77028) is located in the high-SoVI, low coverage urban core and experienced inundation of 44% during Harvey (71 % of that outside of the SFHA zone). Due to the coverage being mostly voluntary while this being a lower-income neighborhood, a large protection gap arose.

b) Mandate gap – The area is accordingly mapped but the mandatory purchase requirements fall through. The example ZCTA (77026) shares a border with 77028, but in contrary only had roughly 9% of its inundation occurring outside of the SFHA zone with similar take-up rates. Hereby a large share of renters, mortgage-free homeowners and informally financed structures most likely pose the coverage problem, as these are exempt from mandatory NFIP policies. Similarly to a), the financial burden of flood insurance might be in contest with everyday necessities, thus being neglected.

c) Mapping gap – The SFHA zone is drawn too narrowly or got reduced via LOMC (Letter of Map Change). ZCTA 77429 (Cypress) lies in the low-SoVI, relatively high-coverage western part of the county, resulting mostly from land development in recent decades. The levels of inundation outside of the SFHA zone partly trace back to LOMCs (LOMRs here mostly) narrowing down the mandatory purchase zone and further regulations driven by land developers. This phenomenon is also displayed in Figure 18, which shows that several map revisions took place in the years before Hurricane Harvey in this area.

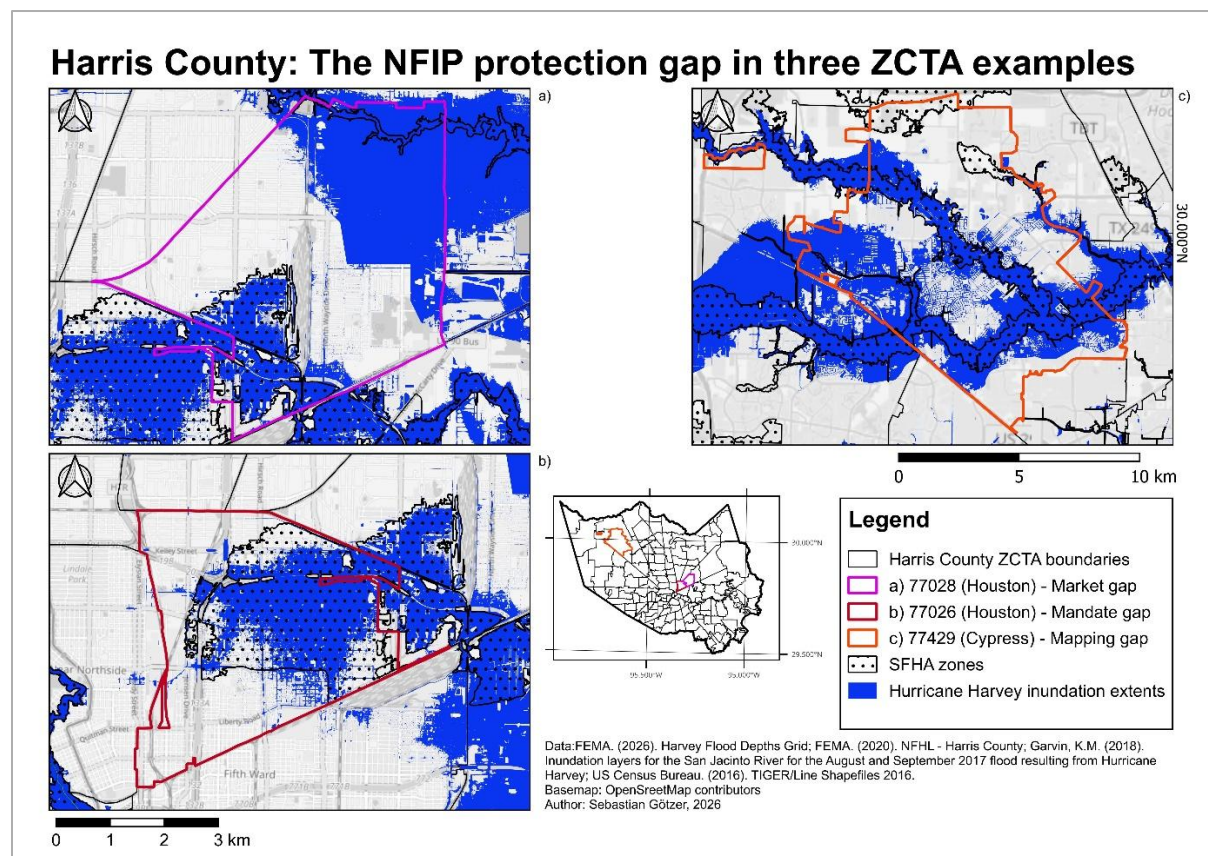


Figure 36: ZCTAs within Harris County showcasing different protection gaps, exemplified by Hurricane Harvey 2017 (own illustration). Note: specific ZCTAs were chosen based on exceptional values from certain variables.

The mechanisms behind these protection gaps within the NFIP are based on the voluntary system including the ability to shrink the mandatory zone. The exception of renters by design exacerbates this. Thereby, low-income neighborhoods where the financial burden for insurance is high for infrequent disaster events see low take-up rates, which in turn means high dependence on federal aid and ultimately high financial vulnerability. More affluent areas experience different problems with the shrinkage of the SFHA zone potentially causing a false sense of security and generally higher financial losses due to the higher property valuations.

7.1.2. Île de France

The spatial distribution of social vulnerability in the Île de France region mirrors the pattern observed in Harris County, with the highest SoVI scores concentrated in the area around Paris and a scattering of high-vulnerability communes further out. The confirmed inundation of the 2016 event, by contrast, was more spatially concentrated with the heaviest flooding occurring in the southern tributary valleys of the Yvette and Orge and on the Loing further to the southeast,

rather than regionwide. It is to be noted that this case study area is notably larger in size than its counterpart in the U.S.

The EAIP zone is taken as a proxy for flood exposure across the region since the TRI scenarios do not cover the entirety of Île de France, as shown in Figure 29 and region-wide inundation extents are not openly available. The share of commune area within the EAIP envelope rises with social vulnerability, from 17,1% for the least vulnerable quintile to 24,5% for the most vulnerable (Table 6). The Bivariate SoVI x EAIP (Figure 33) as well as the corresponding LISA map (Figure 34) show that exposure and vulnerability are tied together here, most visibly in the corridor southeast of Paris around communes such as Villeneuve-Saint-Georges, which combine high SoVI scores with a large share of EAIP area and saw notable inundation in 2016. This relationship is not absolute, however, since Paris itself carries a high EAIP share while recording among the lowest SoVI scores in the region, showing that exposure alone is not the determining factor for social flood vulnerability. The general tendency in the region and especially in the belt around Paris for many of the high-SoVI communes is to occupy flood-prone river corridors.

The question of coverage is largely settled in France with the mandatory surcharge attached to every property insurance. The CatNat system's near-universal reach, encompassing renters and owners alike, entirely removes coverage as a source of spatial variation, and thereby shifts the focus towards flood exposure and to the redistribution of the surcharge itself (i.e. the S/P ratio).

This flat structure of the surcharge consequently renders a bivariate map of social vulnerability against premium burden obsolete. While there naturally is an increased financial burden for lower-income households, there would be no differentiation to an income map. This is a direct expression of the principle of national solidarity. The ratio of claims to premiums at commune level (S/P ratio) captures this redistributive mechanism and can thus be seen as a measure of the solidarity cross-subsidy. While it shows no clear gradient across the vulnerability quintiles, it is lowest for the most vulnerable quintile, indicating that these communes in general are contribute more to the system than what they receive, as can be seen in Table 6. The dense and comparatively more vulnerable ring around Paris thus pays a large share into the pool while the heaviest claims accrue to the more heavily damaged communes upstream and along the tributary corridors. The redistribution consequently tracks hazard and realized damage rather than social vulnerability. The regulatory layer reinforces this decoupling, as PPRI coverage rises with social vulnerability, from 35,0% to 53,0% across the gradient (Table 6), meaning regulatory attention is present, which does not gate access to insurance, since a CatNat decree indemnifies

affected communes regardless of their PPRI status. A flooded commune without a PPRI is therefore not a coverage gap in the French system.

The CatNat system in Île de France pairs uneven vulnerability with a flat and universal cover, leading to the financial consequences of a flood/mudflow event being held collectively rather than falling on the individual household. Hence, the most vulnerable communes are protected regardless of being net contributors to the pool rather than net recipients of it. This protection carries its own equity questions, since the same universality that covers the vulnerable also cross-subsidizes affluent households that have settled in flood-prone river corridors. The absence of a risk-based price signal can encourage continued development in exposed areas, particularly where the PPRI and its building restrictions are out of date or not yet refined. The single risk-based exception is the suspension of CatNat cover for buildings constructed in a zone designated as unbuildable by a PPR after its publication. Coverage is also conditional in practice on holding the underlying insurance contract, which the vast majority of households do, and on the recognition of the event through a CatNat decree, to which a fixed deductible of EUR 380 (in 2016) for residential property is attached.

7.1.3. Comparison and synthesis

As established in chapter 2, flood risk is understood here as a function of the hazard, exposure to flooding, and flood vulnerability. The latter consists of susceptibility and coping capacity (IPCC, 2022). Naturally, how a flood insurance system is designed determines neither the hazard, the population and assets exposed to it, nor the susceptibility, meaning where the socially vulnerable live in this case. What the system design does determine is the financial protection within the frame of a population's or system's coping capacity. It thereby acts on one dimension of flood vulnerability and influences whether the potential harm implied by exposure and susceptibility gets converted into a protection deficit, and where that deficit occurs spatially. Over longer horizons, however, risk-based pricing and its flat-rate counterpart also potentially shape exposure itself through location and development incentives.

In both case study areas, social vulnerability concentrates around the urban core with exposure to flooding present. While the exposure based on the actual inundation percentages remains flat throughout the five SoVI quintiles in Harris County, the French communes with the highest SoVI scores experience the greatest flood exposure as shown by the commune share in the EAIP zone. Even though the USA's SFHA shows a gradient in the opposing direction, it is only partly

representative for exposure, as it regularly is subject to change and the Hurricane Harvey inundation extents far exceeded its boundaries. Since no region-wide actual inundation extents exist for France and the EAIP represents maximum potential flood extents, the argument rests on differing measures that show existing exposure on a broader level, nonetheless.

The mechanism distinguishing both systems rests on the connection between coverage and financial burden thereof. The NFIP's risk-based premiums represent a barrier for lower-income neighborhoods, as the share of the premium costs on the annual income increases markedly between the ZCTAs with the highest SoVI scores compared to those with low scores. The result is a protection gap precisely where social vulnerability is highest and accordingly take-up generally lowest. This means that susceptibility is directly tied to coping capacity in the American system. The CatNat's flat compulsory surcharge on the other hand represents the general funding mechanism instead of an obstacle. While mandatory payments and deductibles in the case of a flooding event might still affect socially vulnerable households financially, coverage is guaranteed under the condition that a CatNat decree is issued. The fact that the redistributive ratio (S/P ratio) at commune level reaches the most vulnerable quintile least even though it shows the highest exposure does not translate into reduced protection either, since coverage does not depend on being a net beneficiary of the pool within the CatNat system. Susceptibility and coping capacity are decoupled here.

The relationship between the regulatory flood hazard layers and insurance coverage within the systems follows a similar logic. In the NFIP, the mapped zone and the insurance mandate are tied together, so that the SFHA both designates hazard and determines who is required to hold a policy. This coupling is what allows the under-mapping of the vulnerable core, where the SFHA share is lowest at 17,4%, to translate directly into a coverage gap. In the French system the corresponding layers are decoupled from coverage entirely. Even though the share of commune area within the EAIP envelope and within the PPRI rises with social vulnerability, neither layer gates access to insurance, since a CatNat decree, apart from rare exceptions, indemnifies a commune regardless of its mapped status. A flooded commune outside any prevention plan is therefore exposed to a planning shortcoming but not to a coverage gap, which is the inverse of the American case.

The core difference between the two regimes lies in which component binds the spatial pattern of the protection deficit. In the NFIP it is coverage (i.e. coping capacity), while it is exposure in the CatNat system. In the ZCTAs east of Houston's city center with low NFIP take-up rates, flood vulnerability is driven by social vulnerability through the coverage gap consisting of the

premium burden as well as renter exclusion for mandatory purchase requirements. In the low-SoVI northwestern areas of Harris County, by contrast, flood impact stems from exposure the SFHA fails to designate, often a consequence of land development. At the same time, greater coping capacity, partly through private insurance, can be assumed there. Overall, coverage with its direct link to social vulnerability, remains the primary factor within the NFIP. In France's system, coping capacity as a source of spatial variation drops out mostly due to the near-universal coverage independent of social vulnerability. Consequently, exposure becomes the determining factor for where residual flood risk concentrates. While exposure rises with social vulnerability, the universal insurance coverage converts exposure into indemnified loss rather than into uncovered gaps.

The three protection gaps discussed in subsection 7.1.1 consequently do not arise in the CatNat system. The surcharge is flat and compulsory (a), it attaches to standard multi-risk policies held by renters and owners alike (b), and indemnification does not depend on flood mapping (c). A high-SoVI, flood-prone commune in Île de France was, on this dimension, better protected from the 2016 floods than its counterpart ZCTA in Harris County was protected from Hurricane Harvey in 2017.

7.2. Limitations of the Analysis

The interpretations within this chapter rest on data that differs in quality and availability between the two case studies, making this the central limitation of the analysis. The openly accessible flood and insurance data for Île de France is considerably more limited than the equivalent data for Harris County, especially in temporal precision. This asymmetry partly reflects the two systems themselves, since a centralized solidarity regime and a decentralized risk-based one collect and publish different information. For this thesis in particular, it imposes concrete constraints on what can be mapped and compared. The two regulatory flood layers illustrate this with the SFHA being a statistically defined zone representing the 100-year fluvial flood, regulatory in function, and openly available through FEMA (chapter 3), while the French EAIP is conceptually different, as it represents a maximum potential flooding extent with no associated return period. Additionally, it is informational rather than regulatory, and has not been openly distributed since around 2015, thus having to be obtained directly from the Regional and Interdepartmental Directorate for the Environment, Planning and Transport [DRIEAT] Île de France for this thesis. While the mapped TRI scenarios represent a more accurate coverage of flood extents with three distinct return periods attached, they could not be

used for the analysis due to limited coverage, particularly in the heavily affected areas in the south of the region, as can be seen in Figure 29.

The more consequential limitation concerns the flood extent data for the 2016 event itself. No continuous inundation surface comparable to the one used for Hurricane Harvey is openly available for Île de France. The available remote sensing data comes from two separate Copernicus activations, EMSN028 and EMSR165, which only cover certain parts of the region. While the most detailed coverage is the Seine upstream area in the south where the inundation was most severe, several heavily affected areas fall outside it. The valleys of the rivers Orge and Yvette around Longjumeau were among the most heavily affected in 2016 yet are not represented in the openly available extent data, and the parts of the upstream catchments of the Seine and the Loing are likewise under-represented. Figure 37 illustrates this gap, showing the remotely sensed 2016 flood extents alongside the area of the Yvette and Orge convergence which was heavily affected but for which no openly available inundation data exists. The 2016 event could consequently only be represented as a binary indicator of confirmed flooding rather than as a continuous measure of inundation, which is only operationalized briefly in figure 30, showing the relation to issued CatNat decrees. Therefore, no equivalent realized exposure measure to the Hurricane Harvey inundation extents could be built for the 2016 floods. This also is the reason the French bivariate analysis relies on long-run and structural indicators while the American analysis is anchored to the event itself.

Île de France: Flooding data limitations for 2016 event

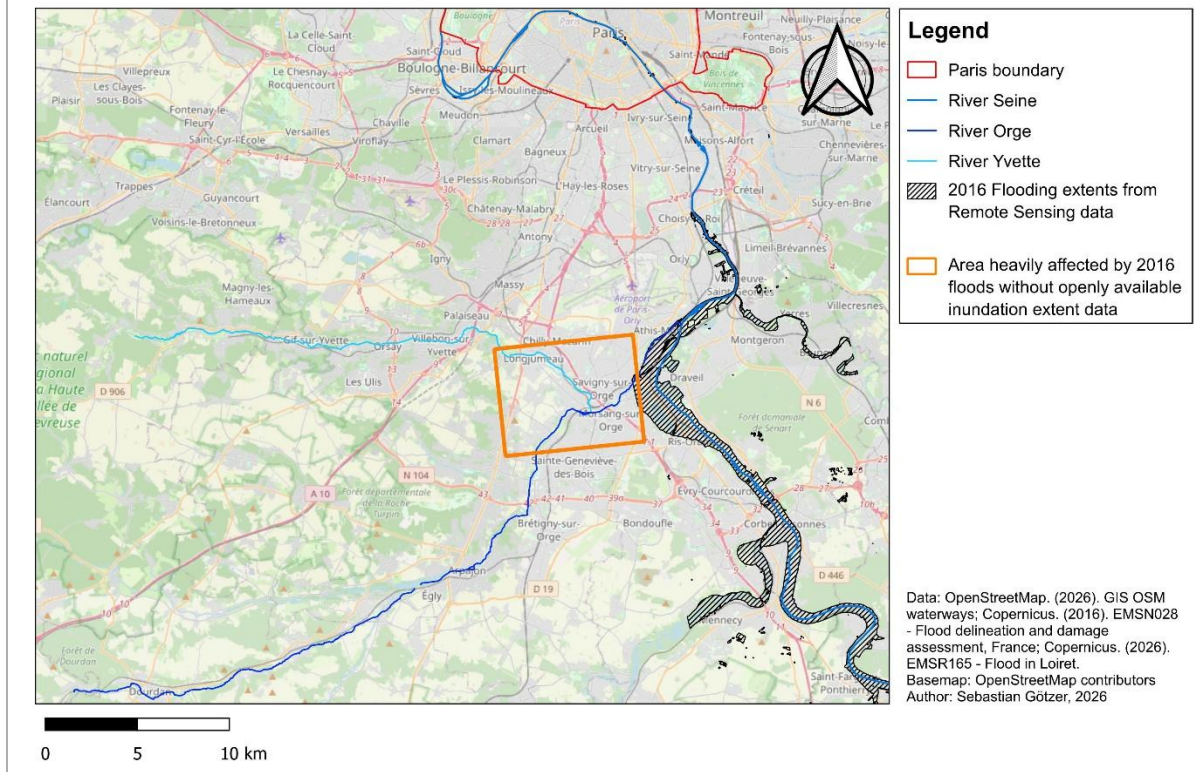


Figure 37: Limitations of openly available flooding extents for the 2016 event, Île de France (own illustration).

The most significant difference between the data availability of the two systems is the absence of openly available commune level insurance data for France. The comparability within this thesis rests on the French solidarity principle, granting uniform coverage nationwide. While insurance indicators for claim frequency, the claims-to-premiums (S/P) ratio, and inundation costs per inhabitant among others are available from the ONRN at commune level, they carry the temporal limitation of not being specific to 2016 but rather being cumulative values covering 1995 to 2021. The count of CatNat decrees on the other hand covers a different window again, from 1982 to October 2024. These indicators describe the long-run behavior of the system rather than the response to a single event, and the mismatch between their reference periods is a slight limitation when they are read alongside one another. Additionally, the data arrives in predefined categories rather than as continuous values and was converted to ordinal ranks, which restricts the precision of the resulting maps. The claims-to-premiums (S/P) ratio in particular rests on an allocated estimate of CatNat premiums apportioned by peril rather than on a directly observed series, so it is best read as an approximation of the redistributive mechanism rather than an exact measure of it. Furthermore, the PPRI layer combines modern prevention plans with older instruments now serving an equivalent function and is recorded

only as a binary indicator of commune coverage. Generally, the absence of a CatNat decree does not mean that no flooding occurred, since the decree results from an administrative procedure that institutionally weaker communes may struggle to complete. Consequently, this layer reflects administrative capacity next to hazard and was only used in Figure 29.

The data for Harris County is more complete but carries limitations of its own. The insurance figures exclusively cover the NFIP while private flood insurance, which is more common in higher-income areas, is not captured. Thereby, the take-up rates presented here understate the true extent of coverage, especially in more affluent neighborhoods. The effective National Flood Hazard Layer (NFHL) that holds the SFHA zones used in this study dates from January 2018 but rests on hydrological studies that predate Hurricane Harvey, so the mapped floodplain reflects an earlier baseline than the storm conditions themselves. Moreover, the take-up denominator is the number of occupied housing units, which includes renters who cannot hold NFIP structure coverage, so neighborhoods with high shares of renters show depressed take-up for structural reasons.

The construction of the vulnerability index involves choices that constrain the comparison. By construction, the equal-weighted percentile SoVI treats all domains and variables as equally important, so the analysis identifies the spatial concentration of vulnerability but cannot determine which individual variable contributes most to it. Moreover, the index deliberately excludes any variable for ethnicity or migration background, even though such variables feature prominently in the social vulnerability literature (Cutter et al., 2003; Rufat et al., 2015), because they are not measured comparably across the French and American statistical systems and are not consistently available for the French case. Other variables carry related caveats. Education functions partly as a proxy for the willingness to undertake mitigation but is measured differently in the two areas and is therefore folded into the economic domain rather than treated separately. The availability of healthcare facilities uses different establishments, as described in chapter 5, while not incorporating the number in neighboring communes/ZCTAs thereof. While every variable used on the American case study can be dated to 2016 (based on statistical estimations for the ACS variables), the Île de France side mixes different years predating the 2016 event. Due to the composite weighted SoVI method, this limitation can be neglected. The processed data should, however, be viewed as regional estimates rather than exact neighborhood measures. The two spatial units, communes and ZCTAs, also differ in their typical population size, so comparisons of absolute values between the regions should be read with the caution. Finally, not every variable for every commune in Île de France has a valid

value (predominantly rural communes with low populations counts), causing slight imbalances in the SoVI scores in a slight minority of cases. This is balanced by the weighted domains as well, though.

7.3. Criticism and Changes

NFIP

The NFIP has been criticized on several related points over the past decades. The first is moral hazard, whereby the combination of the program's affordable coverage with an implicit expectation of federal aid after a disaster, is argued to understate how expensive it actually is to live in a floodplain, and it has not done enough to restrain building in exposed areas (Holladay & Schwartz, 2010; Knowles & Kunreuther 2014). While it is not fully agreed upon what drives this continued development, the possible reasons range from the moral hazard itself to the weak enforcement of the program's own floodplain regulations, to a general tendency of individuals to underestimate rare but severe hazards (Knowles & Kunreuther, 2014). A second point of criticism concerns the program's finances, as it generated roughly USD 60 billion in premium income across its first five decades while accumulating costs of about USD 96 billion (FEMA, 2025). This gap is generally attributed to its pricing approach being based on national averages rather than on the risk of a specific location, to continued construction in exposed areas, and to a rate structure that gave homeowners little incentive to protect their own property with other structural/non-structural mitigation measures (Kousky, 2017). Third, the maps are based on historical records and only represent fluvial flooding, the regulated zone tends to lag behind both present and future conditions (ibid.). The Harvey claims that occurred outside the SFHA, as shown in previous chapters 6 and 7, illustrate this. This is worsened by a tendency to map already developed land before open land, so that in many cases mapping comes after development rather than directing it, leading to some areas being built up with inadequate regard for their flood exposure (Pralle, 2019). These weaknesses are not distributed evenly, however. The process for challenging a map designation favors those who can afford it, whereas premiums based on risk weigh most heavily on lower-income households and minority communities (Tesselaar et al., 2020). At the local level, the attention given to insurance costs tends to dominate the discussion and to displace the equally central question of actually reducing flood risk, which can leave communities poorly prepared for future flood events (Pralle, 2019).

The most notable change since Hurricane Harvey, 2017 is the so-called Risk Rating 2.0, the first fundamental revision of NFIP pricing since the 1970s. It was introduced in two phases across 2021 and 2022 and sets each building's premium according to its individual flood risk and its rebuilding cost, instead of the previous approach that relied on the property's zone and elevation on a flood map (FEMA, 2025). Its stated goal is to align premiums with actual risk and to improve the program's finances (ibid.). A report analyzing the changes to the NFIP by the U.S. Government Accountability Office [GAO] (2023) concludes that FEMA's new Risk Rating 2.0 methodology improves actuarial soundness by aligning premiums more closely with underlying flood risk and expected claims. However, the median premium would still need to increase by almost 90% before eventually reaching the full-risk level. Amornsiripanitch et al. (2025) find that underinsurance remains disproportionately concentrated in lower-income communities, where it represents a substantially larger share of household income, further exacerbating these concerns. The reform therefore most likely deepens the protection gap observed in Harris County rather than reducing it, since the financial burden that has already lowered take-up rates in the vulnerable core is likely to increase further.

CatNat

The CatNat system is criticized on different grounds, most of which arise from the very feature that makes it equitable. Because the surcharge is uniform and does not account for risk, it gives households little incentive to reduce their own exposure. The funds it provides have been found to primarily finance reconstruction as before rather than adaptation to future flood risk (Barraqué & Moatty, 2019). The main instrument intended to counteract this is a deductible that increases for communes without an approved prevention plan (PPR), but it has little effect. It is linked only to whether such a plan has been applied for, rather than to its approval and the measures that this approval requires. Even at its maximum the deductible remains small compared to the potential cost of a flood, so that it puts only weak pressure on reluctant municipalities (Poussin et al., 2013). This is connected to a broader difficulty in restraining development, as the plans are slow to draw up, local elected representatives tend to protect the development prospects of flood-prone land instead of working to lower flood risk, and the state tends to downplay how much floods affect private property, or to leave the matter to the insurers (Barraqué & Moatty, 2019). The Barnier fund, which was created in part to finance prevention, only supports measures that an approved plan makes mandatory, so that it never reaches communes without such a plan, and it is considered both too small to improve resilience in the most exposed areas and difficult to access, while a portion of it goes unused from one year to

the next (Barraqué & Moatty, 2019). A final tension concerns equity within the solidarity principle, as policyholders in lower-risk areas increasingly object to paying the same rate as those in the most exposed areas, a sentiment that the 2025 increase is likely to intensify (Lavarde, 2024).

The most notable change since 2016 is the increase of the CatNat surcharge from 12% to 20%, along with an increase from 6% to 9% on vehicle insurance, which came into effect in January 2025 and represents the first adjustment of the rate in twenty-five years (Lavarde, 2024). It followed a persistent deficit that had existed since 2016 and had almost depleted the reserves of the public reinsurer. Its purpose is to stabilize the insurance system rather than to change the way it works. This last aspect is the relevant one for the comparison, as the reform raises the level of the flat contribution but leaves its structure unchanged, so that the surcharge remains uniform across the country and undifferentiated by risk (ibid.). France thus has responded to rising losses by strengthening national solidarity rather than by moving towards the individualized risk-based pricing adopted in the United States. Faced with the same increasing flood losses, the two systems have moved in opposite directions, reinforcing their respective approach to flood insurance.

8. Outlook

8.1. Climate change impacts on flood insurance

Global warming is projected to further intensify flooding in the future through sea-level rise and shifting precipitation patterns globally. While this increased impact falls sharpest on coastal areas, inland regions also face heavier and more frequent rainfall, threatening a rise in pluvial and fluvial flooding events (IPCC, 2022). This presents notable challenges for the conventional instruments of planning and risk-management, with property insurance among them, as climate change driven risks are often without precedent and thereby prior experience. According market and institutional adjustments pose a crucial role in shaping future levels of flood risk and thus socioeconomic welfare (Kousky et al., 2024). Where levels of flood exposure are high, insurance markets struggle, as insurability of objects in these regions is not given anymore. The inability to profitably insure perils leads to price increases and insurance companies exiting, thereby pushing risk onto public programs with direct implications for the housing markets and vitality of local economies (ibid.).

Demand for flood insurance falls when premiums climb faster than households adjust their perception of flood risk. Because climate change steadily raises actual risk, households anchor their willingness to pay to a perceived threat that lags the real one, so the premium required for solvency increasingly outruns what they will accept (Tesselaar et al., 2020). Risk-based insurance models will see progressively rising premiums in the future, especially under the high-emission IPCC RCP8.5 (i.e. representative concentration pathway with radiative forcing value of 8,5 W/m² by 2100), most likely causing flood insurance demand to diminish as affordability and thus take-up rates decrease (ibid.). Consequently, the question of who bears redistributed risks of climate change-driven developments becomes highly relevant with adequate policies needed therefore (Kousky et al., 2024). This again raises a debate about equity and thus the fair distribution of increased future risk and costs thereof, with lower-risk groups potentially subsidizing flood coverage for structures built deliberately in higher-risk areas (Pralle, 2019). While risk-based premiums as in the NFIP reflect the risk from natural hazards, the price signal is mostly based upon measures from the past or present rather than trajectories of future risk (Kousky et al., 2024). The principle of setting adequate premium rates, however, runs into the dilemma of penalizing lower-income communities whereas suppressing prices conceals actual risk and raises the danger of a market shock in the case of a natural disaster. Prices should therefore optimally reflect future risk while the system provides support for lower-income households (ibid.). This is applicable to both the NFIP's approach, where price in theory directly mirrors underlying risk which in turn has adverse effects on the coverage of the socially vulnerable, as well as the CatNat system, where the price signal in the form of the flat surcharge does not reflect flood risk, thus masking potential danger.

The financial stability of the NFIP under future climate conditions remains uncertain. Model projections suggest that without structural change the program's debt would grow by roughly 60%, from USD 20,5 billion to USD 32,8 billion, whereas premiums that fully reflect individual risk would limit this increase to 28% (De Ruig et al., 2022). With Risk Rating 2.0, the program has already moved in this direction by tying premiums to property-level risk. This transition, however, sharpens the equity dilemma outlined in section 7.3, since premiums fall for many households but rise steeply for subgroups in high-risk areas (GAO, 2023). Proposed remedies therefore include targeted vouchers that covers a portion of an actuarially-priced premium a household cannot afford while leaving the price signal intact. This can be paired with low-cost loans that let poorer households fund risk reduction measures such as flood-proofing. Relocation or managed retreat remains as a possible last resort (De Ruig et al., 2022, Kousky et al., 2024). Pricing reform alone is nonetheless insufficient, as the highest societal benefit

arises when risk-based premiums are combined with proactive public investment in large-scale flood protection, as such infrastructure reduces the unaffordability that pure risk pricing creates while complementing rather than blunting the price signal (De Ruig et al., 2022).

The CatNat system approaches the same dilemma from another direction. Its solidarity-based surcharge has been raised repeatedly since the scheme's inception, from 5,5% initially to 12% in 2000 (Barraqué & Moatty, 2020) and further to 20% in January 2025 (Lavarde, 2024), thereby reinforcing flat pricing instead of introducing a risk signal. An accumulation of extreme events could nevertheless exceed the system's means. Already in 2016, compensation paid to flood and drought victims exceeded premium income by 4,5%, with a wider deficit the following year (Barraqué & Moatty, 2020). The reform debate consequently centers less on pricing and more on the balance between compensation and prevention. Considered measures include financing interim housing for victims and reimbursing vulnerability-reduction costs within damage settlements, yet financial means directed toward prevention and resilient recovery through the Barnier fund are then unavailable for compensating losses once they occur (ibid.). A further aspect of the French debate points toward spatial rather than financial reform. Zoning that walls developable land off from flood-prone ground captures only part of the real exposure. The alternative is to weave rivers back into the urban fabric, so that the way a district is designed becomes decisive for the risk it carries (Barroca, 2018).

Generally, where premiums track individual risk, as in the NFIP, affordability has to be restored separately. Vouchers or means-tested support (i.e. assistance tied to low income) can cover the portion of a risk-based premium a household cannot pay while leaving the price itself intact, so the incentive to reduce risk survives (De Ruig et al., 2022; Kousky et al., 2024). CatNat needs no such instrument, since its flat surcharge distributes cost across all policyholders within the system and never generates a premium distinguishing between different risks to begin with. Mandatory or near-universal participation assembles a risk community large enough to keep a scheme viable, a logic that can equally inform recovery planning for the poorest and most exposed households (Holzheu & Turner, 2018). Beyond these instruments, the role of insurance itself is shifting. Lasting solutions have to drive risk down at source rather than merely conceal or displace it, which calls for adaptation across all sectors and casts insurers not only as payers of claims but as active drivers of risk reduction (Kousky et al., 2024).

8.2. Future research

The comparative spatial approach developed in this thesis opens several avenues for future research. The method could be applied to additional insurance regimes, such as the British Flood Re scheme or the voluntary German market for instance, thereby testing how specific design features translate into spatial patterns of vulnerability across a broader range of institutional settings. A second avenue could conduct analysis based on a more recent temporal scale and eventually compare results from before and after the described reforms. With Risk Rating 2.0 in the United States and the raised surcharge alongside proposed relocation and vulnerability-reduction measures in France, repeating the neighborhood-level analysis at a later point would reveal whether these reforms actually shift the spatial distribution of vulnerability. Third, the vulnerability surfaces produced here are static and could be coupled with climate projections to map future rather than present conditions, connecting the method to the scenario-based modeling literature. Beyond these extensions, the spatial associations found here reveal where vulnerability and insurance features coincide, but not whether one causes the other. Testing that would mean isolating individual design features, such as mandatory versus voluntary uptake or flat versus risk-based pricing, to see whether insurance design itself produces the vulnerability patterns observed. Furthermore, a variable-level analysis, testing which individual socio-demographic indicators carry the greatest weight in predicting flood exposure or realized loss could extend to implemented weighted composite SoVI approach. Finally, the data asymmetry documented in this thesis would constitute a research agenda of its own. Harmonizing event-based and structural indicators, claims records and decree data, or hazard envelopes defined without and with return periods would substantially improve the comparability of flood insurance systems across national data infrastructures, enabling more precise conclusions to be drawn and to potentially be applied to other systems.

9. Conclusion

The aim of this thesis was to examine how the design of a flood insurance system influences the spatial patterns of flood vulnerability in urban areas. For this purpose, a composite Social Vulnerability Index (SoVI) was combined with hazard, exposure and insurance indicators representing the coping capacity aspect and applied at neighborhood level in two case study areas with structurally opposite insurance regimes. Harris County was examined under the NFIP with Hurricane Harvey 2017 as the reference event, and Île de France under the CatNat system with the floods of 2016. The question of who is protected, where, and under which system design was thereby asked spatially rather than only institutionally.

Regarding the first additional research question, both case study areas show a comparable distribution of social vulnerability. The highest SoVI scores concentrate in the urban core around the respective central city, east of Houston's city center in Harris County and in the suburban ring northeast and southeast of Paris in Île de France, while the lowest scores lie in the western and northwestern fringe of Harris County and in the central arrondissements of Paris next to scattered rural communes. The constructed composite SoVI weights all four domains age, household, physical, and economic equally, thus describing general dimensions of flood vulnerability and where vulnerability concentrates. The high-scoring units are characterized by a combination of economic disadvantage (lower incomes, higher poverty and unemployment) that constrains the financial capacity to prepare for and recover from flooding, age structures skewed toward the young and elderly who are less mobile in an evacuation and more reliant on outside assistance, household compositions (single-person households, single parents, renters, those without a car) that lack internal support and evacuation resources, and an older building stock predating modern flood-resistant construction standards combined with more limited access to healthcare facilities, hindering emergency response. High vulnerability in these areas is therefore driven less by any one factor than by heightened susceptibility across all four dimensions. The exposure side differs between the two areas, however. The inundation caused by Hurricane Harvey remained roughly equal across all five SoVI quintiles (around 20 to 21%), whereas the share of commune area within the EAIP envelope in Île de France rises with social vulnerability, from 17,1% in the least vulnerable quintile to 24,5% in the most vulnerable one. The latter is used as an exposure proxy since no region-wide inundation extents are available for the 2016 floods in Île de France. Exposure and vulnerability are consequently tied together spatially in the French case but not in the American one based on the present

analysis. Paris itself, combining a high EAIP share with the lowest SoVI scores of the region, shows at the same time that exposure alone does not determine social flood vulnerability.

The second additional research question concerned the interaction between insurance coverage and social vulnerability, and it is here that the two systems diverge most clearly. In Harris County, NFIP take-up declines steadily with rising vulnerability, from 22,4% in the least vulnerable quintile to 10,1% in the most vulnerable, while the premium burden rises in the opposite direction from 0,55% to 2,11% of median household income. Applications for federal aid from uninsured flooded households almost triple across the same gradient, and the median paid claim falls from close to US\$ 70.000 in the least vulnerable quintiles to US\$ 43.734 in the most vulnerable one. Since IHP payouts are capped well below NFIP indemnities and are intended only as a last resort, this shift from insurance to federal aid translates directly into weaker financial recovery precisely where vulnerability is highest. Coverage in the NFIP thereby thins exactly where social vulnerability peaks. Three architectural gaps were identified as the mechanisms behind this pattern, a market gap through the mostly voluntary purchase, a mandate gap through the exemption of renters and mortgage-free owners, and a mapping gap through SFHA zones drawn too narrowly or reduced via LOMCs. In Île de France, the compulsory surcharge attached to every property and vehicle contract removes coverage as a source of spatial variation almost entirely. The tenant insurance obligation closes the renter gap that widens the American deficit, and none of the three gap types arise. The premium burden map that revealed the affordability gradient in Harris County was not constructed for Île de France at all, since the surcharge is a fixed national percentage without any differentiation by location or risk, expressing the solidarity principle spatially. The claims-to-premiums (S/P) ratio, the one indicator of the redistributive mechanism available at commune level, shows no gradient across the vulnerability quintiles but is lowest for the most vulnerable one. The cross-subsidy consequently follows realized damage rather than social vulnerability. Protection is not reduced by this, however, since coverage under CatNat does not depend on being a net beneficiary of the pool.

These findings allow the main research question to be answered. The design of a flood insurance system determines neither where the socially vulnerable live nor where flooding occurs. What it determines is whether exposure and susceptibility are converted into a protection deficit, and where this deficit is located. Coverage is the binding axis in the NFIP. The voluntary, risk-based structure produces a protection gap that maps directly onto the vulnerable urban core, tying susceptibility to coping capacity. Exposure is the binding axis in the CatNat system. The

compulsory, solidarity-based structure removes coverage as a variable, so that the exposure rising with vulnerability across the region is converted into indemnified loss rather than into uncovered gaps, and susceptibility and coping capacity remain separated. The NFIP pairs a spatially uneven distribution of vulnerability with an equally uneven coverage. The CatNat system pairs the same uneven vulnerability with a flat and near-universal coverage. The spatial pattern of flood vulnerability that results is consequently a product of the insurance design laid over a given distribution of social vulnerability and exposure, neither of which the design itself sets. Confronted with the same rising flood losses, the two systems have since moved in opposite directions. Risk Rating 2.0 carries the NFIP further toward individualized risk-based pricing, while the increase of the CatNat surcharge from 12% to 20% in 2025 reinforces flat, solidarity-based funding. Each reform thus deepens the very design principle that produces the respective protection pattern documented here.

The contribution of this thesis lies in demonstrating this relationship at neighborhood level and across two contrasting national systems within a comparative frame. The asymmetry in data availability between the two cases, event-based and openly accessible on the American side, cumulative and considerably harder to obtain on the French side, turned out to be a comparative finding of its own, as it reflects the different information infrastructures the two regimes generate. The method itself is transferable, as it could be applied to further insurance regimes, or repeated once the discussed reforms in both systems are researched more closely. This would show whether the protection gap observed in Harris County deepens and whether the raised CatNat surcharge changes the relationship between solidarity and exposure documented here.

Climate change sharpens this trade-off from both sides: under risk-based pricing, rising hazard levels translate into premiums that increasingly exceed what vulnerable households can afford, while under flat pricing they accumulate as unpriced risk that strains the solvency of the collective pool. This tension is already visible in the deficits both programs have accrued. Both regimes therefore face the same underlying question of how to absorb growing losses without either pricing out the most vulnerable or concealing the risk they face. The design of a flood insurance system is in the end also a decision about which neighborhoods carry the remaining risk once a flood exceeds what prevention can mitigate.

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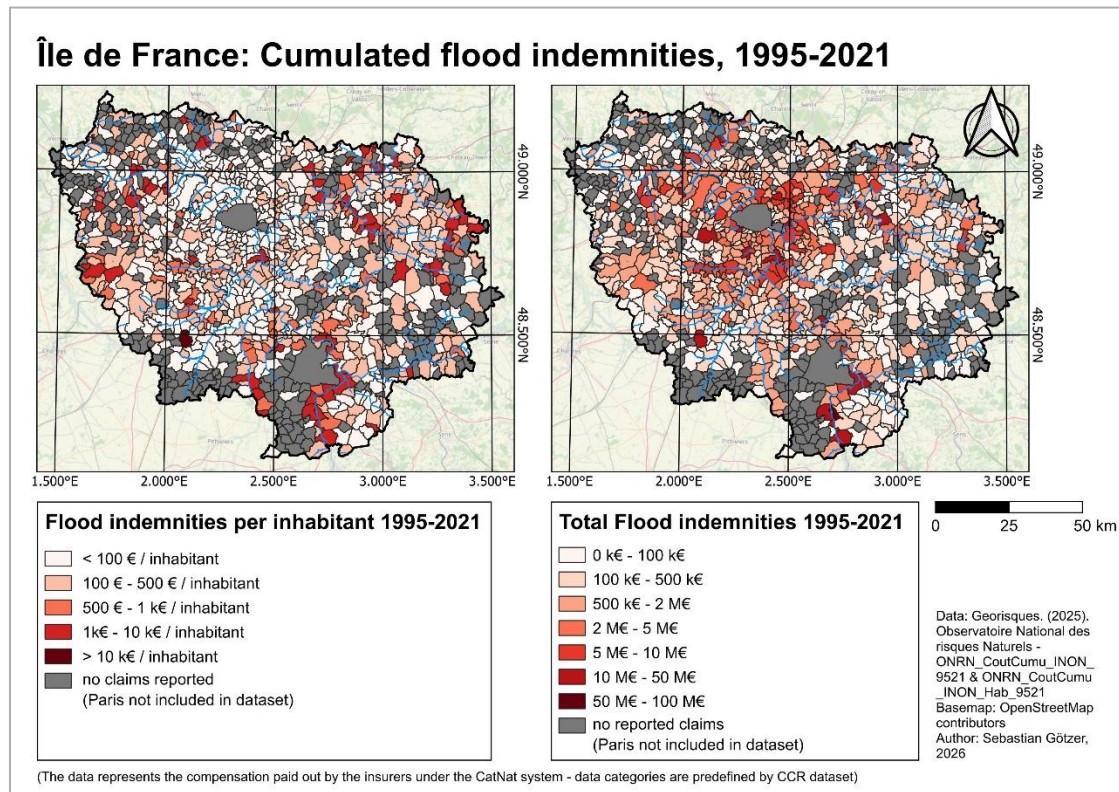
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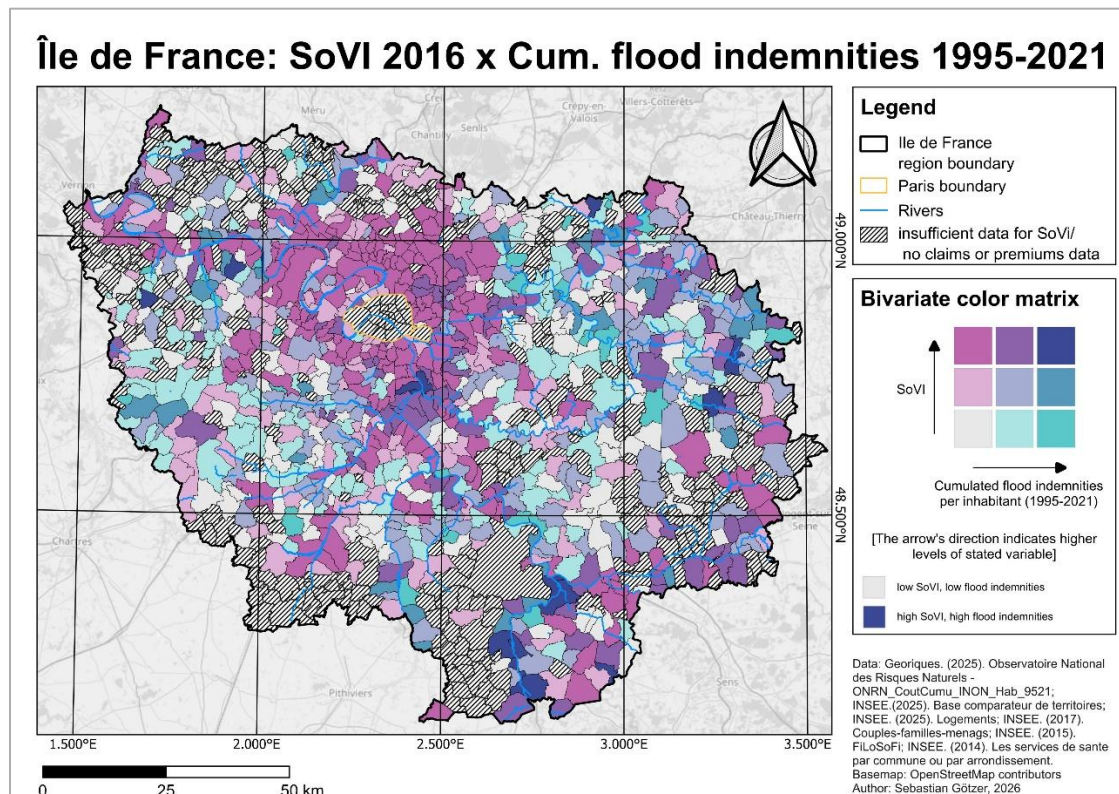
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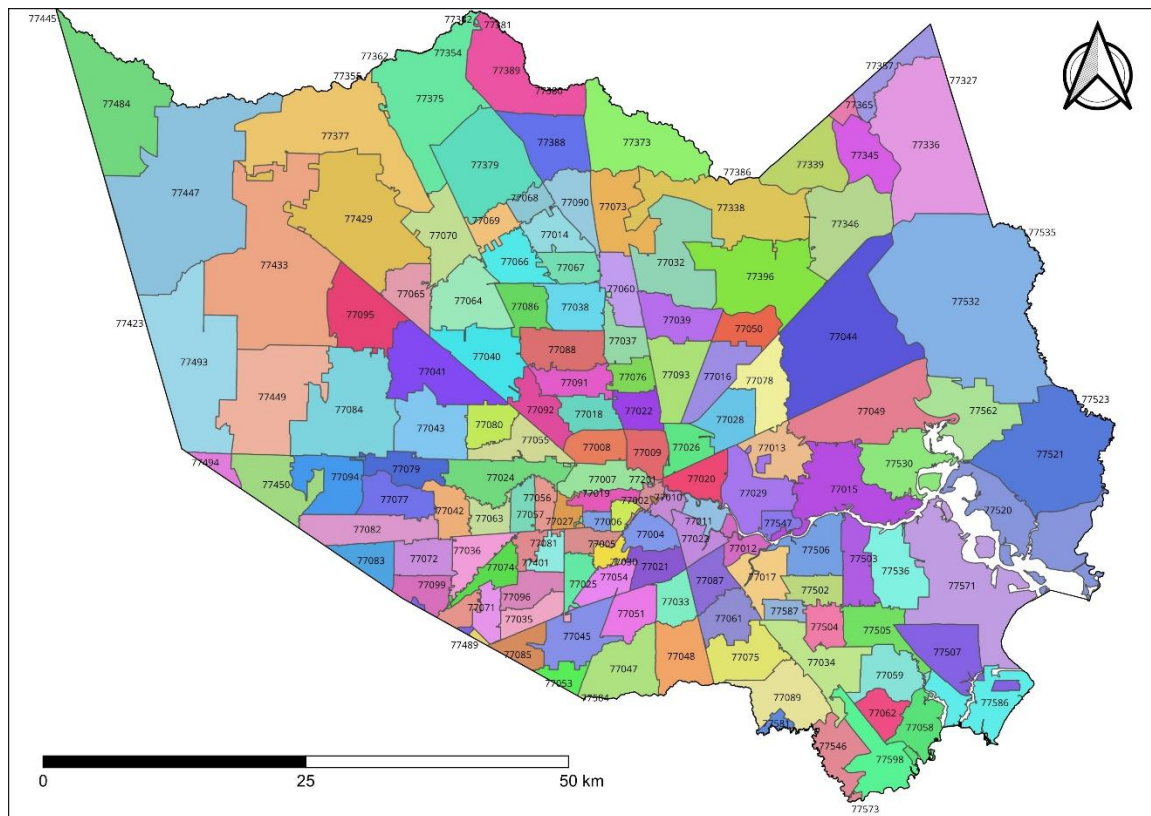
A Appendix: Additional Figures



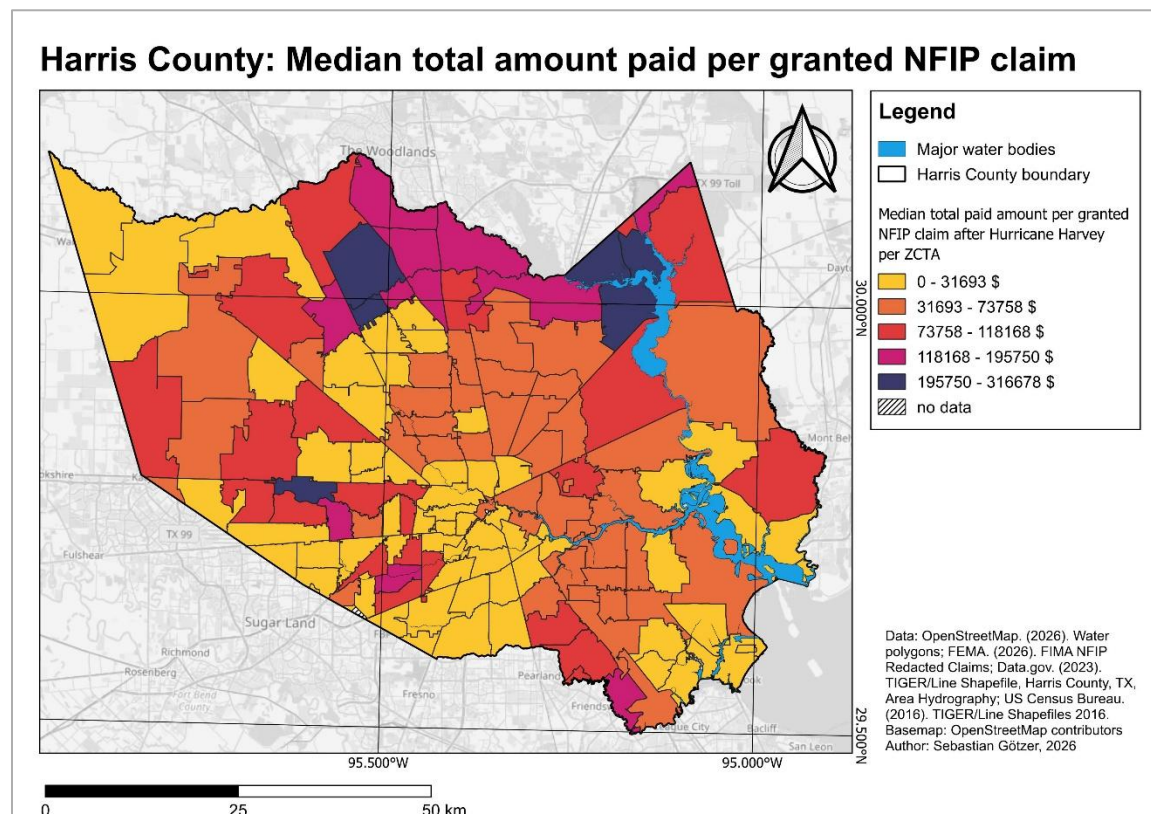
A 1: Cumulated flood indemnities per inhabitant & Total 1995-2021, Île de France (own illustration).



A 2: Bivariate choropleth with SoVI 2016 x Cumulated flood indemnities 1995-2021, Île de France (own illustration).

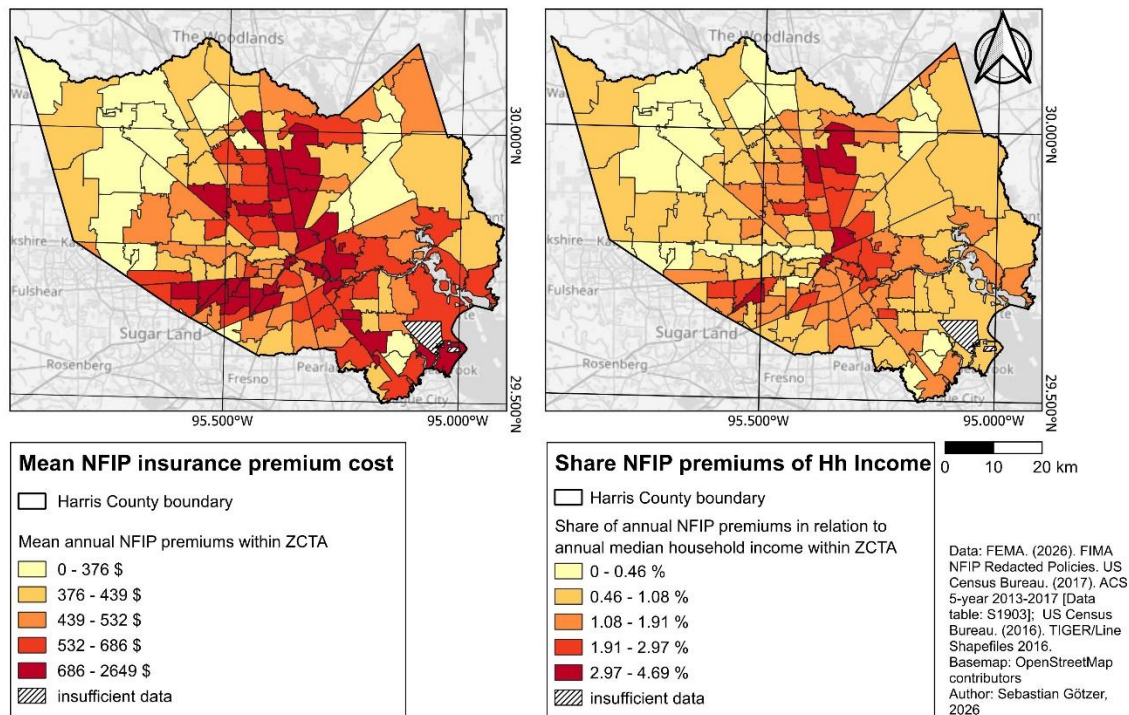


A 3: Overview of ZCTAs in Harris County (own illustration based on TIGER/Lines from U.S. Census Bureau 2016)



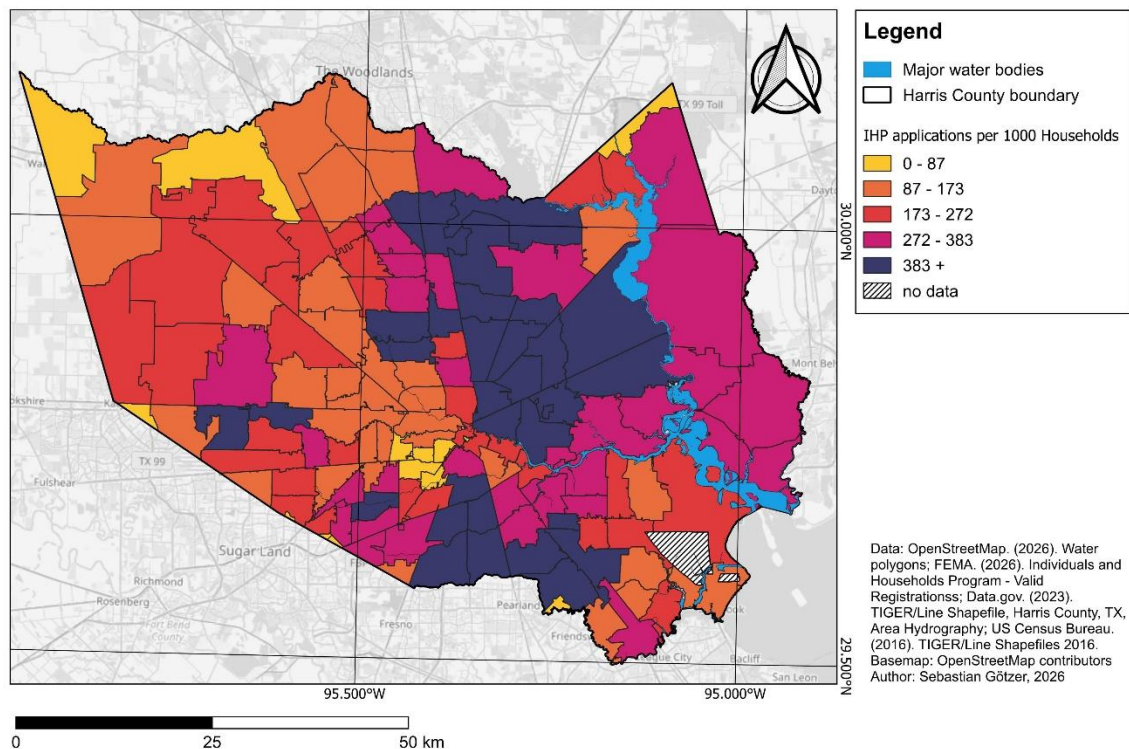
A 4: Median total amount paid per NFIP claim after Hurricane Harvey 2017, Harris County (own illustration). Note: Classified by Natural Breaks.

Harris County: Annual costs of NFIP premiums, pre Harvey



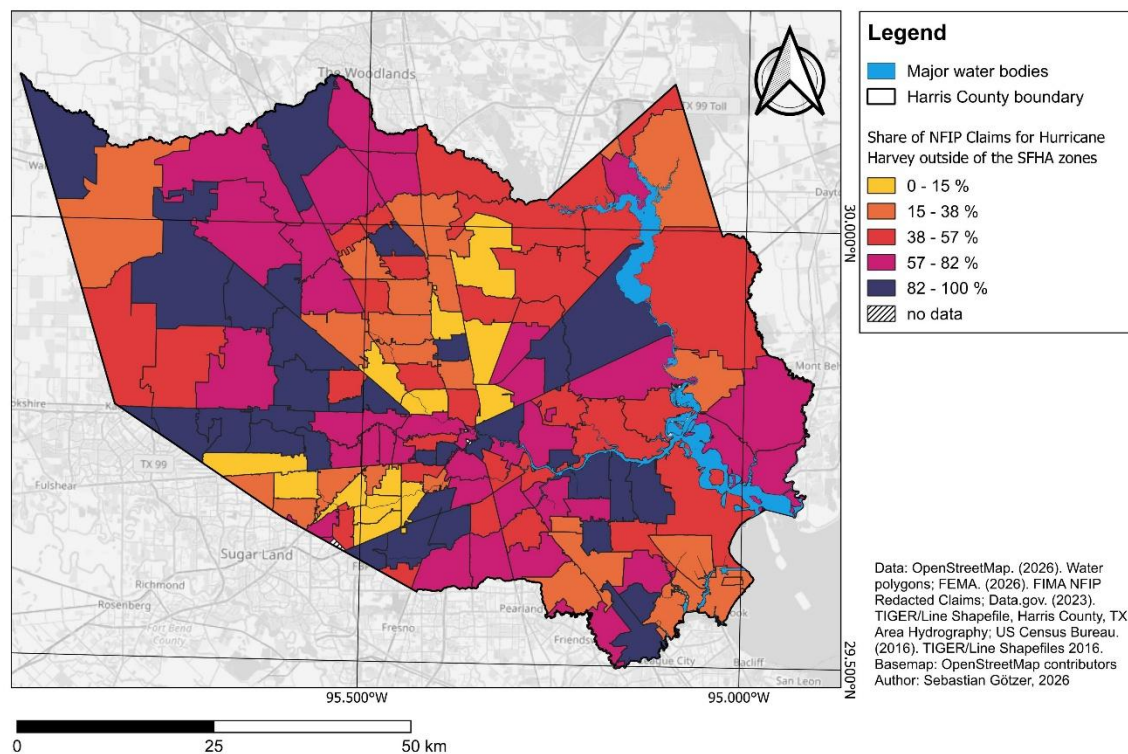
A 5: Annual NFIP premium cost before Hurricane Harvey 2017, Harris County ; Left panel: Mean annual costs of NFIP premiums (Quantiles); Right panel: Share of NFIP premiums from household income (Natural Breaks) (own illustration).

Harris County: IHP applications after Hurricane Harvey

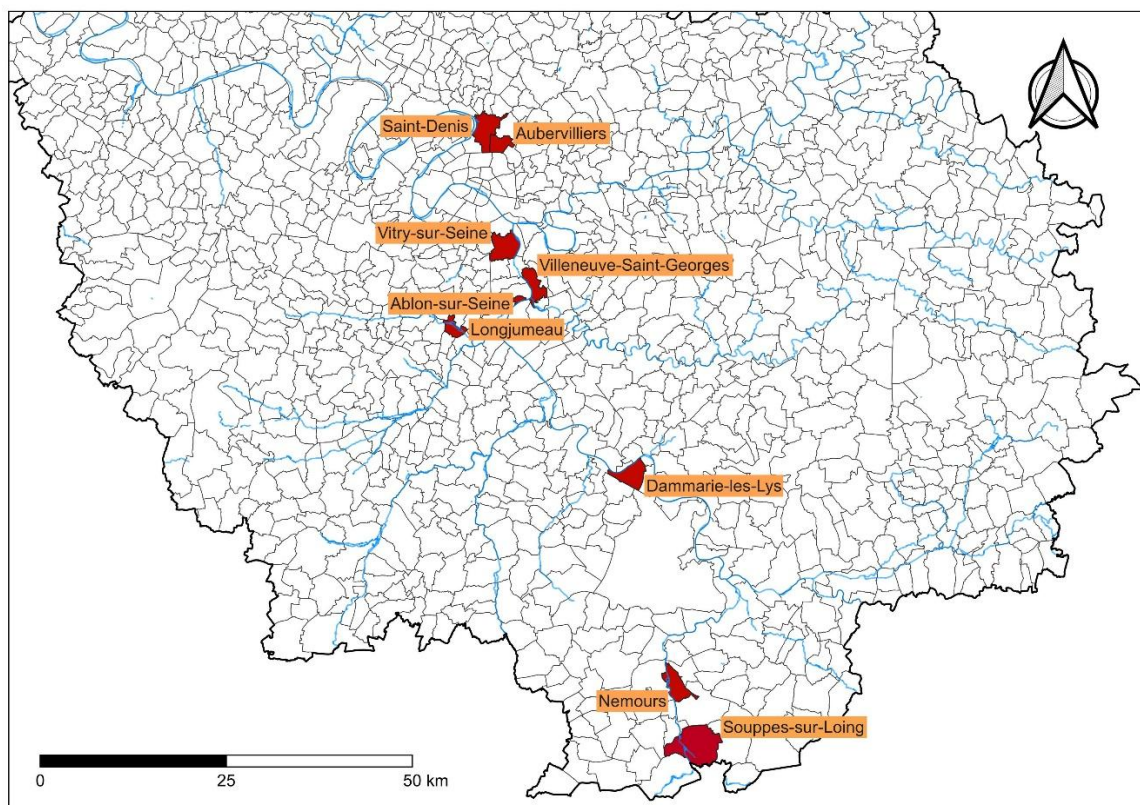


A 6: Individual and Households Program (IHP) applications per 1.000 households after Hurricane Harvey 2017, Harris County (own illustration). Note: Classified by Quintiles.

Harris County: Share of NFIP claims outside of the SFHA zones

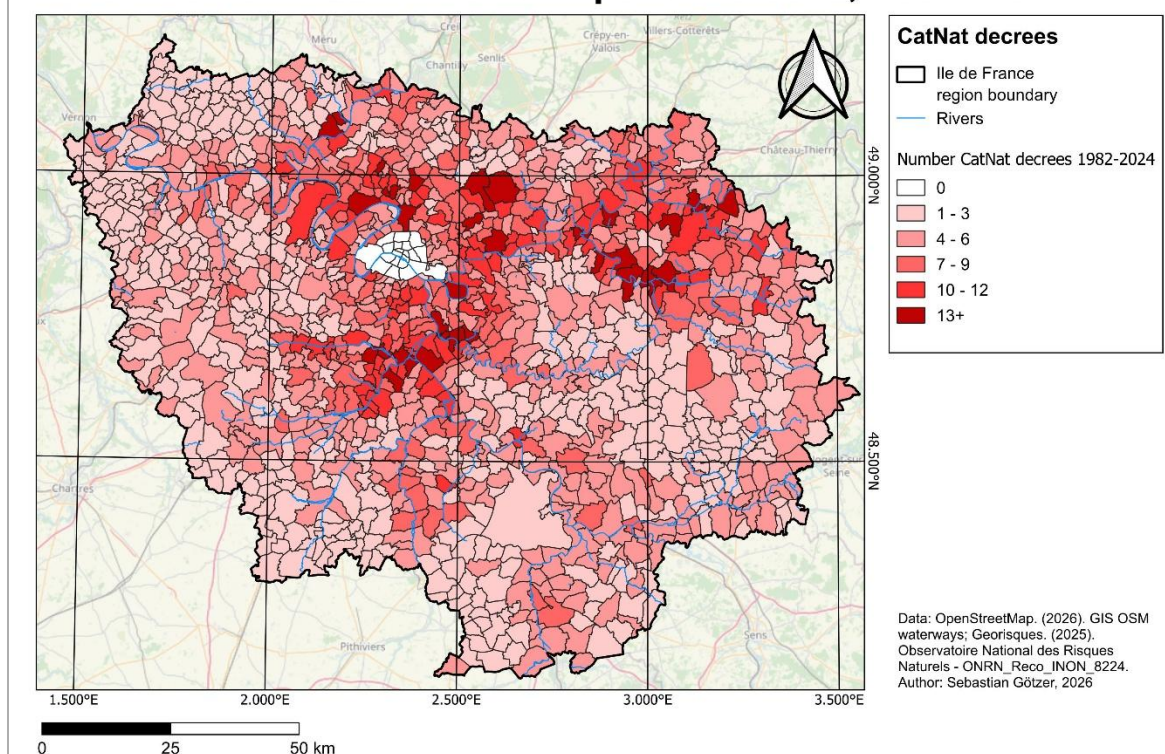


A 7: Share of NFIP claims outside of the SFHA zones due to Hurricane Harvey inundation 2017, Harris County (own illustration).



A 8: Overview of mentioned communes within the context of Île de France (own illustration).

Île de France: CatNat decrees per commune, 1982-2024



A 9: Cumulated amount of CatNat decrees per commune 1982-2024 (own illustration).