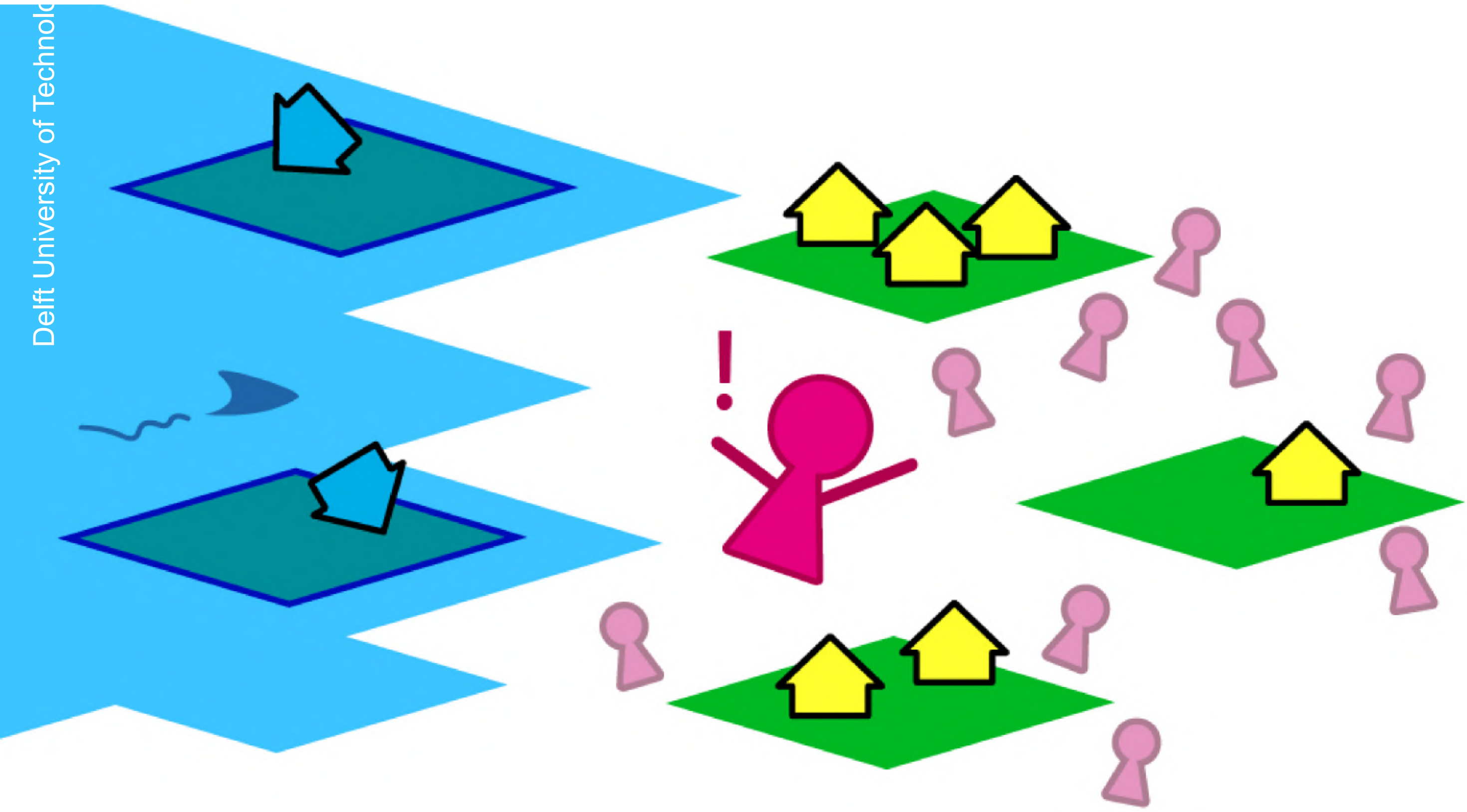
'Underwater' Real Estate

Exploring housing market dynamics under severe flooding in Rotterdam

MSc. Engineering and Policy Analysis Thesis

Sherman Lee



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Exploring housing market dynamics under severe flooding in Rotterdam

by

Sherman Lee

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Cover:	“Pawns fleeing from flood in housing market” (own work)
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Executive Summary

Climate change will lead to more extreme climate and weather phenomena, and this includes the increased risk and severity of flooding. Flooding is one of the most destructive and common natural hazards globally, and rising sea levels and extreme precipitation mean that many human settlements will be situated in climate-sensitive areas.

However, the increased threat of floods in coastal cities is not currently sufficiently represented in the housing markets. Contemporary property prices are shaped by the locational advantages of coastal cities, and have a tendency to underestimate or ignore flood risk, even after experiencing a flood themselves. This increases the possibility of structural shifts in housing markets when the flood risk is realised by the public, leading to a depreciation of real-estate property values, and may cause cascading effects in other aspects of the economy, such as the collapse of the regional housing market and reduced economic attractiveness to the region. The Netherlands, for example, is arguably the best-protected delta in the world from flooding. Still, it is vulnerable to the "safe development paradox", where public flood protection measures motivate the continued investment and expansion of flood-risky areas. While Dutch safety standards are very high, they cannot guarantee absolute protection from floods; the country is still at risk from rare-but-severe flooding, or the occasional minor flood, both of which can influence the Dutch housing markets.

The deep uncertainty of future flood risk means that empirical research alone cannot sufficently describe possible responses to housing market shocks from flooding. Therefore, modelling and simulation is useful in testing potential variants of a housing market system, such as testing different dynamics of housing market actors and potential policy levers in various flood scenarios. This is further supported by an increase in publicly-available rich datasets, that allow for spatial and empirical representation of the housing market and climate-induced flood scenarios.

In this thesis, the city of Rotterdam is used as a case study, to explore the usage of empirical data and to model a housing market shocked by various plausible flood scenarios. This is done in two steps: firstly via a data exploration effort in publically-available datasets for the Netherlands, and then consolidating the data into a stylised agent-based model, simulating the transactions of the housing market while several districts experience flooding shocks from different flood scenarios.

Firstly, I have conducted the data exploration aspect using Dutch open data for flood scenarios, housing, local demographics, and empirically-estimated flood discounts. The data was judged on the suitability of the datasets to be incorporated into an empirical model, and on the presence of data gaps while linking between different data. The exploration highlights the potential of modelling the housing market using empirical demographic data based on income level, but only missing certain data to characterise how homebuyers would acquire mortgage financing. Additionally, on the flood damages side, I show the possibility of characterising flood discounts as a function of flood depth, and the depth-damage relation for the Netherlands.

In the modelling part of the thesis study, I have consolidated the data into an agent-based model with a stylised set of relationships for the housing market. The model was designed based on the empirical stylised trends regarding housing markets dynamics, like declining flood risk discounts in property prices over time. In short, the model simulates the purchase transactions of homebuyers, who are discouraged from flood-affected properties, thus leading to a growing demand and price premium for flood-safe properties. This model was then tested with a simple series of experiments, for single flooding and multiple flooding scenarios, based on empirically-grounded severe flood scenarios on Rotterdam. While the model results are limited in terms of prediction for policy purposes directly, the modelling process as a whole illustrates the value of exploratory modelling to refine the understanding of a system. Via this exploration, it was highlighted that there is a need to further characterise flood discounting behaviour around the action of housing market actors.

Acknowledgements

This thesis study can be described as a personal marathon for me, mostly a blur and a lot of sweat. Even though this thesis is a personal endeavour, I've gotten plenty of assistance towards shaping this thesis. Therefore, I want to mention my gratitude to the following people.

Firstly, my graduation committee. I want to thank Tatiana for her boundless patience, pragmatism, and confidence in me. Without her practical scheduling and pragmatic expectations, I doubt I would've completed the thesis in a more coherent and managed manner. Her work in the multidisciplinary intersection of floods, housing markets, economies, and household adaptation was enlightening and inspirational. Next, I want to thank Igor for his incisive feedback, and inspiring me towards understanding and modelling complex adaptive systems. The candour and levity in his teaching and supervision was essentially a shortcut towards understanding these phenomena. Thirdly, I want to thank Alessandro for his patient support and his interest in my code creations; I was personally inspired to do this thesis because of his extensive agent-based model on regional economies being eroded by flooding. Lastly, I want to thank Kees, for his invaluable assistance in demystifying Dutch flood data and water management terminologies, and linking me to domain experts within Deltares. His idea of using individual flood scenarios likely singlehandedly improved the empirical power of this study.

My friends, from the EPA community and the Malaysian community. Particularly, I want to thank Tim and Yasin for providing emotional and practical support from their experiences in their own thesis studies. I also want to mention Auriane, David, Marya, Hidde, and Elias, as EPAs-in-arms concluding our theses later than others.

I also want to thank my family, as a source of lively distraction from the daily grind. They may not fully understand what goes on in the marathon, especially from the other side of the globe, but they certainly understand the work that has gone into this thesis. The submission of this thesis also coincides with the anniversary of my grandfather's passing; he and my other grandparents may not comprehend what this thesis is about, but they would be happy for me nonetheless.

Concurrent with this thesis was my formal diagnosis with attention-deficit disorder (ADD), which started my journey in adapting to my neurodivergence. This thesis was the crucible for me to hone my habits, such that they work to my strengths, and mitigate my shortcomings. Here, I want to thank Skye for her own journey with ADHD and her thesis, because without her experience, I would not have realised that I'm simply wired differently.

Last, but certainly not the least, to my girlfriend, Jet, who's also running her own thesis marathon. I am blessed to have her as a perpetually-available, direct line of support when the going gets tough. Her companionship makes the arduous climb a less lonely task.

Sherman Lee
Delft, 17 November 2022

Contents

1 Problem Context

As of writing, there is widespread scientific consensus that anthropogenic greenhouse gas emissions is causing climate change, leading to various tangible effects in the climate and weather systems, such as sea level rise and more severe and frequent weather extremes (IPCC, 2022). One of these climate effects is flooding, one of the most destructive and frequent natural disasters in Europe (EEA, 2017). In fact, some very recent instances of major flooding, such as the 2022 Bangladesh and Pakistan floods, and the 2021 European floods, have already caused significant damage and disruption. (Taherkhani et al., 2020). Already, projected sea level rise suggests that without coastal protection or adaptation, an increase of 52% of the global population would be at risk of flooding by 2100 (Kirezci et al., 2020).

These flood events highlight the need for flood protection for coastal and riverine settlements, entailing added infrastructure such as dikes and storm surge barriers, and early warning systems (Hallegatte et al., 2013; Taherkhani et al., 2020). On the other hand, they also allude to the need to also adapt to the changing climate, which is arguably only starting to take hold in high level decisionmaking, such as the recent discourse on loss and damage in the recent COP27 summit (UNFCCC, 2022). Increasingly, incremental adaptation that rely on well-established measures may eventually become insufficient, thus starting the discourse on *transformational climate change adaptation*, such as managed retreat initiatives(IPCC, 2022; Kates et al., 2012; Olsthoorn et al., 2008; Scott et al., 2020).

As a sizeable portion of the world's population inhabit coastal and delta areas, the increased coastal and pluvial flood risk threatens the security of these settlements and economies (Kirezci et al., 2020). Broadly speaking, persistent flood risk reduces the attractiveness of these areas, and may lead to socio-economic tipping points (SETPs), such as reduced economic investment and development, human capital flight, and potentially climate gentrification (de Koning & Filatova, 2020; van Ginkel et al., 2020). One of these SETP dominos is the housing market, which is a key driver in national economies (Zhang, 2019). A severe flood threatening a large city is likely to shock the housing market in the region, creating a severe depression of prices and may influence further SETPs (Caloia & Jansen, 2021; de Koning, 2019; Juhola et al., 2022; van Ginkel et al., 2021). Therefore, it is crucial that urban planners understand and prepare for potential housing market dynamics in light of the accelerating flood risk due to climate change and urbanisation.

1.1. Flooding and housing markets: the state-of-the-art

In spite of the destructive and disruptive nature of flooding, a reliable body of research suggests that flooding causes house price discounts in coastal and riverine housing markets. However, the effect is usually temporary, and has a tendency to neglect or underestimate future flood risks. This is illustrated in two themes, intuitively described by Pryce et al. (2011) as follows:

- Amnesia: past floods are forgotten over time, leading to temporary price discounts for homes.
- Myopia: existing or future flood risks are neglected due to their small likelihood, leading to flood risk not being sufficiently captured.

From an empirical perspective, this *flood risk discount* mean that housing prices are lower in floodplains than comparable real-estate in safe areas. The exact value is dependent on variables such as flood severity and location (inland or coastal), for example, the meta-analysis by Beltrán et al. (2018) posits a narrow range of 4.6% to 6.9% for average initial flood discounts, while Bin and Landry (2013) found a range of discounts from 6% to 20% for Hurricane Fran and Floyd in 1996 and 1999 respectively. This flood risk discount is either negligible before the flood, and only surfaces after a flood event. However, immediately after the flood event, the price discounts reduce over time, essentially disappearing within a range of 5 to 12 years (Bin & Landry, 2013; Mutlu et al., 2022).

In this section, we will start with the theoretical framework of Pryce et al. (2011) for why flood risk discounts are temporary, followed by possible indications of new norms, where housing markets start to factor into account increasing climate risk. Next, we then explore how sudden “tipping” into new norms of flood risk discounts exposes current societal vulnerabilities and uncertainties, and then leading into the usage of simulation models in understanding potential futures.

1.1.1. Status quo: Amnesia and Myopia

Amnesia in the housing markets can be broadly attributed to several reasons: either from market information asymmetries leading to new residents who are not aware of flood risk, or ignoring flood risk as a result of the levee effect, where residents believe that the approval of goverenmant or regulatory bodies to construct homes indicates that the area is flood-safe (Pryce et al., 2011).

This amnesiac phenomena can be seen in studies by Atreya et al. (2013), Bin and Landry (2013), and Mutlu et al. (2022), that found varying property discounts that disappear about or within a decade. While these studies are from flooded housing markets of the previous decades, the market amnesia theme is still applicable in recent times, especially in housing markets where climate change or flood awareness are still low.

Myopia in housing markets can be broadly attributed to cognitive biases and heuristics, such as the availability heuristic, where individuals tend to discount information that is inconsistent with prior experience(DellaVigna, 2009). This is particularly insidious given that areas that are perceived safe may be insufficiently protected, or that flood risk is deemed acceptable in exchange for the added amenity that water access provides. For example, a meta-analysis by Beltrán et al. (2018) highlights the diversity in flood discounts due to difficulty in disentangling current flood risk and prior flood experience, They also note that coastal flood risk discounts are unreliable, due to the lack of controlling for perceived added attraction[1] (Biagi et al., 2021). Worryingly, Filippova et al. (2020) finds that even the disclosure of projected coastal erosion risk maps for New Zealand property markets had a negligible effect on house prices.

1.1.2. Shifting tides: indications of possible new norms

However, it is highly likely that households and housing markets will react and adapt given the new knowledge of flood risk, thus leading to an erosion of the status quo dynamics (Cheung & Yiu, 2022; Haer et al., 2017; Koks et al., 2015). The increase in frequency and severity of flooding events may cause more lasting changes to decision-making rationale in housing markets, for example when the attraction of coastal or riverine amenities becomes less preferred over the risk of flood damage (Cheung & Yiu, 2022; Pryce et al., 2011). Three recent findings below illustrate the presence of changing paradigms.

Firstly, Seo et al. (2021) finds that while disclosure of flood risk has a negligible effect on home prices, South Korean homebuyers tend to weigh flood risk discounts higher in districts with severe past flood experiences. Notably, this suggests that cultural differences in decision-making may lead to difference outcomes in housing markets, and supports a proposition by Pryce et al. (2011) that path dependency[2] affects the local norms in the housing market.

Next, Cheng et al. (2019) compared Taiwanese house prices based on their earthquake-resistance characteristics, and found that homebuyers were capable of creating a nuanced characterisation of risk from the disclosed risk information. As a result, housing prices for "more safe" properties returned to normal at a faster rate than "less safe" properties, or properties that were closely located to the risk area. Compared to Filippova et al. (2020), it suggests that risk disclosure alone is insufficient in inducing housing markets to capture flood risks in prices.

Lastly, Fu and Nijman (2021) compared between districts Miami-Dade and Pinellas in Florida, and found higher price discounts for properties in the Miami-Dade district, associated with the flood exposure levels. However, they also note that other elements, such as non-primary ownership and affluence of owners may distort market signals, thus may delay market

[1] also known as "utility"
[2] Path dependency describes how prior sequence of experiences affects the decision-making of agents.

adaptation to the increasing exposure risk of coastal properties. These observations thus imply how demographical composition of home owners in a region may affect the pace and trajectory of climate adaptation, in this case how financial mobility and flexibility can mask climate risk.

These examples serves to reinforce the importance of awareness, culture and demographical influences on decision-making in housing markets. However, it also raises another concern: what effects could be seen from drastic shifts?

1.1.3. Tipping points: potential dangers

For housing markets unaccustomed to flood risk, it is possible that established norms may tip, leading to a paradigm shift where at-risk areas suddenly lose attractiveness in a state of panic (de Koning & Filatova, 2020; Pryce et al., 2011). The sudden nature of this change can likely come with negative social and economical effects, as markets and social norms reorient. The nature and magnitude of the effects are currently debated in recent research, but there are several aspects to consider:

1. Erosion of agglomeration effect of economies, leading to out-migration and the loss of employment (Chen et al., 2013)
2. Erosion of insurability and mortgage financing of homes, leading to a mass devaluation of household wealth, and/or a depletion of capital (Caloia & Jansen, 2021; Pryce & Chen, 2011)
3. Climate gentrification, where low-income households are priced out of low-risk areas, and are thus forced to stay in risky or low-resilience areas (de Koning & Filatova, 2020; Gould & Lewis, 2021; Shokry et al., 2020; Taylor & Aalbers, 2022)

Studying the impact of these tipping points require a multi-disciplinary approach encompassing the intersections of different domains, for example including flooding, economics, land use, and social studies, but as of writing, this intersection of domains is still at a nascent stage, mostly as different disciplines contributing in piecemeal fashion, and not integrated.

1.1.4. Simulation models: towards understanding potential futures

The prior subsections established that we are currently underprepared to face the future effects of increased flood risk on housing markets, specifically that we do not know how housing markets would react to a realisation of flood risk. Prior empirical research, while crucial towards understanding fundamental mechanisms in a housing market system, cannot inform on how it would behave under a changed structure.

As a result, there is an increasing effort to explore housing market systems in these potential new states via simulation models, to understand potential future system behaviours. There are several subjects of interest that are targeted in modelling approaches:

1. Modelling of decision-making ability in system actors, such as bounded rationality (de Koning, 2019; Hemmati et al., 2021)

2. Inclusion and integration of empirical knowledge and data (Caloia & Jansen, 2021; Moradi & Nejat, 2020)
3. Experimentation of potential system configurations, such as cultural risk tolerance, or housing market structure (Bankes, 1993)
4. Capturing non-linear behaviour such as feedback loops and hysteresis, which traditional statistical models or equilibrium models are limited in (Evans et al., 2021; Glavatskiy et al., 2021)
5. Spatial representation of flooding and housing markets (Evans et al., 2021)

These subjects of interest can be categorised into themes (depicted Figure 1.1), where most recent studies usually capture a subset of all themes, but never in entirety due to the complexity of the problem. The themes are described as follows:

1. Flooding: floods can be expressed in various methods and detail, either in high detail such as simulating flood propagation, or using quantified flood risk data or flood scenario data, depending on the research question.
2. Housing market actors: examining the (potential) role of actors in housing markets, and how they can adapt or facilitate adaptation of the system (or lack thereof).
3. Multi-system linkages: as housing markets are interlinked with the macroeconomy, a shocked housing market is likely to have knock-on effects on, e.g. labour availability, investment, or unemployment.
4. Temporal scope: studies may either study the current risk of flooding (such as flood risk disclosures) or the effect of an experienced flood on housing markets.
5. Individual-level logic: individuals can behave differently based on lived experience and culture, and at an aggregate level this may lead to different outcomes.

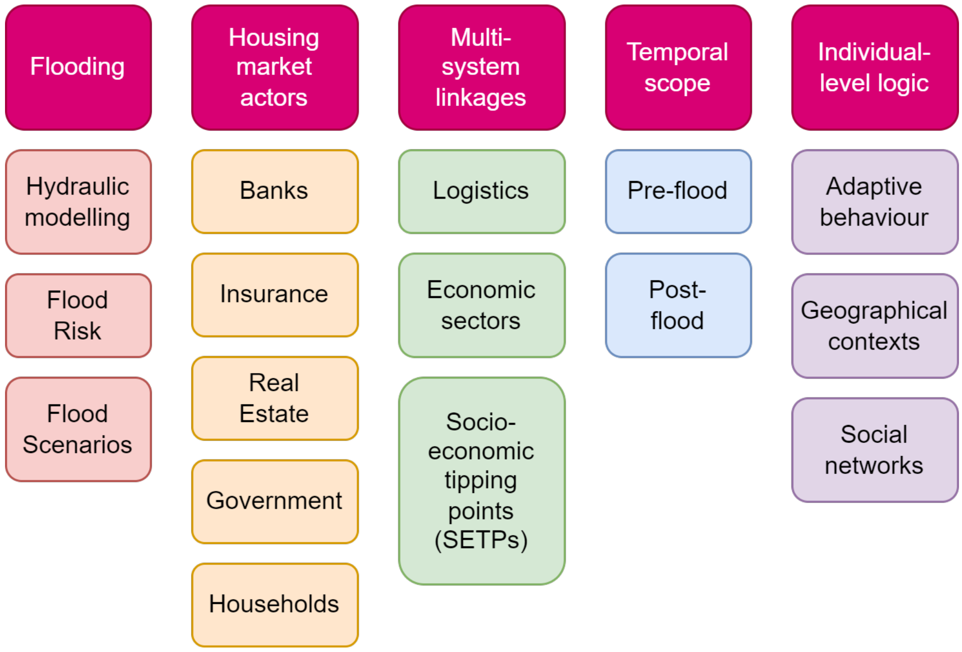


Figure 1.1: Current research themes (non-exhaustive), addressing future flood risk on housing market behaviour

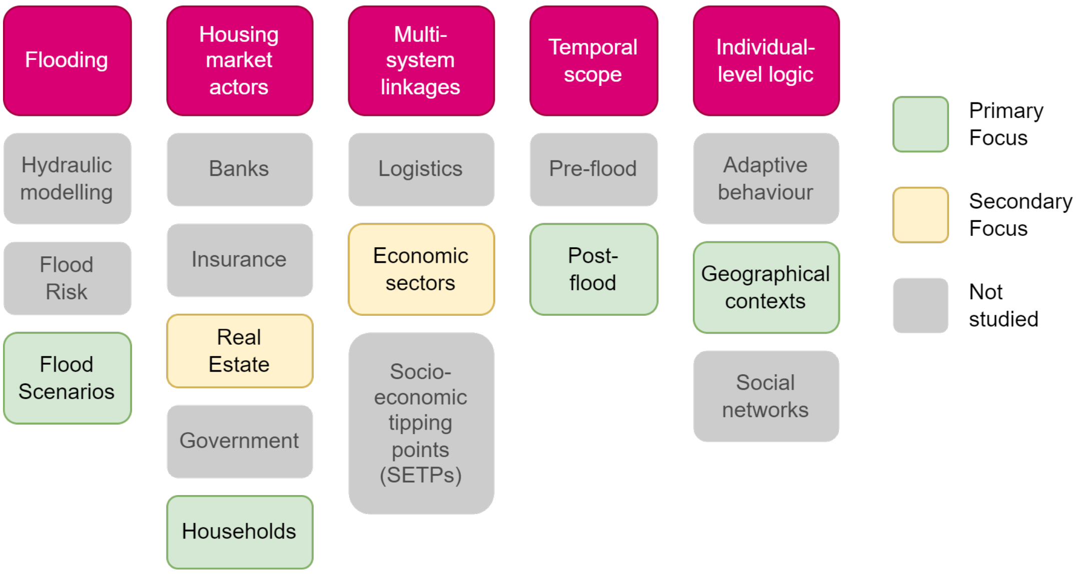


Figure 1.2: Research focus for this study. Primary focus themes are included in the simulation model, while the secondary focus themes are only limited to the data exploration aspect of the study.

1.2. Research Gap

Given these severe effects, we thus arrive at a research gap for this thesis study. Recent research are only beginning to explore the direct and indirect social costs of disruptions to the housing market, and the effect of individual adaptation to flood risk (Haer et al., 2017; Taberna et al., 2020). Additionally, flood risk is usually quantified at a high aggregate level (see Caloia and Jansen (2021) and Bosker et al. (2019)), which can lose sight of local-level dynamics. A connective framework is needed to link flood events, the housing market, and low-level adaptation in order to explore possible outcomes, especially for the more severe indirect social costs such as climate gentrification.

Therefore, this thesis positions itself as a building block towards this multi-disciplinary effort, by studying the impact of specific flood events on a city-sized housing market via a simulation model. The research question is framed as such:

What trends in urban house prices could be seen,
under various empirical and plausible severe flood scenarios?

This research question would be answered by the following subquestions:

1. What research methods should be employed?
2. What data sources are available, and how can they be adapted to a model representation of a housing market?
3. What key mechanisms should be captured in a model of the housing market system shocked by floods?
4. What phenomena could be seen from the model experimentation?
5. What insights could be derived from the model results and behaviour?

In relation to Figure 1.1, the research focus for this study is described in Figure 1.2, as an overview of the research work done for this thesis study. The primary focus themes are included in the full study (data analysis and simulation modelling), while the secondary focus themes are only limited to the data exploration chapter (Chapter 3) and are not integrated into the simulation model due to practical limitations to the thesis study.

The subsequent topics in this thesis document is broken down into 4 chapters: Chapter 2 discusses the methods used in this study, Chapter 4 describes the model design, data integration aspect, and experiment design. Chapter 5 discusses the experiment outcomes for single floods and multiple floods, Lastly, Chapter 6 discusses the findings and concludes the thesis document.

2 Research Strategy

This chapter outlines the research strategy conducted in this study, serving as an introduction to the later chapters.

Given the deep uncertainty surrounding the convergence of flood risk and housing markets, an exploratory modelling approach was chosen to explore the key dynamics in a housing market impacted by flooding. An exploratory model can be described as an ’incomplete’ representation of a system, with a shallow level of empirical or analytical validity due to the uncertainties of key aspects of the system (Bankes, 1993). Exploratory models are distinct because does not seek to make predictions, but rather to model incomplete knowledge to gain insights into the system of interest (Bankes, 1993; Marchau et al., 2019). A key distinction of gaining insights from exploratory models lie with transparently reflecting on the assumptions made, and the model’s limitations. Such a reflection can identify further questions of interest or added necessity for validation or empiricalisation, sharpening future research efforts and complementing the other research strands in climate resilience of settlements (Bankes, 1993).

The study could be described as two methods:

- the inclusion of empirical flood scenario data and housing market data in a case study, using different quantified flood scenarios to shock a stylised Rotterdam housing market.
- the modelling of the housing market system in agent-based modelling (ABM), simulating individual decision-making homebuyers choosing and purchasing homes in a housing market.

2.1. Case study of Rotterdam and data sources

For this thesis study, the Dutch city of Rotterdam is chosen as the subject of the case study. The city of Rotterdam is a coastal port city to the west of the Netherlands. It is the 2nd-largest city in the Netherlands, and 10th-largest in the European Union. Its close access to the North

Sea and inland waterways through the Rhine, Meuse and Scheldt ((Rijn, Maas, en Schelde)), compounded with its low-lying terrain, means the city has a high likelihood of flooding (Koks et al., 2015). De Bruijn and Klijn (2009) classified Rotterdam as 'hazardous and vulnerable', both having a high likelihood of severe flooding and a high potential of severe damages due to its population density.

In spite of the flood risk, the Netherlands currently has a housing availability crisis, and plans to build 900,000 more houses by 2030. This plan has raised some concerns, given the planned constructions would be situated at high-risk and climate-sensitive regions, further compounding future damages in the event of flooding (Deltaprogramma, 2021; Haer et al., 2020) . In terms of flooding damages, Caloia and Jansen (2021) predicted that while the financial system can handle flooded homes in unprotected areas, severe flooding in the more densely-populated western Netherlands can lead to a drastic increase in capital depletions.

Given the high risk of flooding in the Netherlands, the country has invested heavily into water management, and extensive datasets open data are available for flood modelling for Rotterdam. As on overview, the following datasets were employed in this study:

1. Flood maps from dike breaches, for different scenarios. These describe the areas flooded, and the depths of flooding (Rijkswaterstaat, n.d.).
2. Flood depth-damage functions for Dutch infrastructure. These describe the extent of damage per depth of flooding, used for calculating flood damages (Slager & Wagenaar, 2017).
3. District boundaries. These are used to filter the flood maps for only Rotterdam districts (CBS, 2020).
4. Surface terrain heights. These are used to filter the flood maps to only include landed terrain (AHN, 2020).

Additionally, the national Dutch Statistics Bureau (CBS) and local Rotterdam open data repository also offer a broad array of general statistics that could be employed in this study, such as:

1. Number of households per district (OBI Rotterdam, 2020b).
2. Population migration per district (OBI Rotterdam, 2020a, 2020c).

As empirical modelling becomes more extensive with rich data, added transparency in the data handling process is required for reproducibility and scientific rigour (Laatabi et al., 2018). Therefore, the data and its integration efforts are elaborated in its own chapter in Chapter 3, detailing the data exploration, processing and integration into the agent-based model. Additionally, not all data that was found was integrated into the model, and the chapter elaborates on the data or knowledge gaps causing this. Further details on the data acquisition procedure for specific datasets are provided in Appendix B.

2.2. Modelling and simulation with agent-based modelling

A model is a representation of a system. Due to computational limitations, models are usually more simplistic than the actual system itself. The model designed in this study falls under the formalism of a ”dynamic simulation model”, where it simulates abstracted mechanisms within the model; essentially, the model consists of many smaller components, such as the simulation of homebuyer decisionmaking. Due to the uncertainties surrounding this policy problem, the design of the model aims to achieve modularity and flexibility, in which components can be swapped, activated or deactivated in the model.

Reiterating the earlier section 1.1.4, there are several subjects of interest that need to be captured in a housing market model. These are further expanded upon below:

1. **Simulation of individual-level decision-making.** Homebuyers are individualistic entities that make decisions based on various environmental criteria, and aggregate homebuyer interactions drives housing market dynamics (Parker & Filatova, 2008). These homebuyers also make their decisions in a bounded-rational behaviour, which means their decision-making process are not based on perfect information or memory (Glavatskiy et al., 2021; Haer et al., 2017).
2. **Heterogeneity in demographics participating in housing markets.** Homebuyers are demographically heterogenous and are likely to have different decision-making attributes, based on financial ability and preference (Gilbert et al., 2009).
3. **Non-linear system behaviours such as shocks and feedback loops.** Housing markets are characterised by cyclical, non-equilibrium behaviour, even in the absence of flooding (Axtell et al., 2014; Parker & Filatova, 2008) Combined with other elements such as flooding and social networks, the importance of feedback loops and compounding effects are important aspects to be captured in models.
4. **Modularity in system configurations.** This modularity allows for possible reuse or expansion of the model, to account for example different housing market structures, different decision-making logic, or different spatial layout.

Agent-based models (ABMs) satisfy the above criteria, as they primarily focus on modelling the decision-making rationale of individuals (in this case, homebuyers). As a primer, agent-based models (ABMs) are a population of decision-making agents interacting with each other and/or the environment they inhabit (Epstein, 1999). These agents possess a decision-making behaviour that can be influenced by the state of themselves, other agents, or the environment. The cumulative effect of made decisions and interaction forms the basis of bottom-up emergent phenomena, such as the patterns in the transmission of infectious diseases.

The model used in this study can be described as “medium-complicated” according to Sun et al. (2016); it contains empirical inputs from flood scenarios, but uses simplistic agents in the model, where the agents do not have lasting memory or learning behaviours. A detailed description of the model design is done in Chapter 4, and an outline of the model code structure and design assumptions are listed in Appendix A.

2.2.1. Employment of ABMs

ABMs have increased in usage in recent years, due to the ability to generate non-linear phenomena via individual decision-making (Parker et al., 2003). Economics and housing markets in general found that ABMs describe real-life dynamics better than equilibrium models, such as house price cycles (Baptista et al., 2016; Glavatskiy et al., 2021), herding behaviour (Glavatskiy et al., 2021), and also simulating the 2008 housing market bubble (**axtellAgentBasedModelHousing**)

In more recent literature, there is increasing focus on climate adaptation, climate resilience and social justice in housing markets, such as residential income segregation (Pangallo et al., 2019), climate gentrification (de Koning & Filatova, 2020), bottom-up climate adaptation (de Koning et al., 2019; Hemmati et al., 2021), climate resilience of cities (Taberna et al., 2021), and climate effects of sea-level rise on coastal communities (Karanci et al., 2017).

3

Analysis of Empirical Data

This chapter describes the data acquisition, exploration, and processing work, which forms the input for the agent-based model subsequently described in Chapter 4. Given that the modified empirical data from the Rotterdam case study informs the model design process, an explicit description would allow for reproducibility in further research. The data exploration phase serves several overarching goals:

- Identify relevant datasets for the Netherlands on flood scenarios, the Dutch/Rotterdam housing market, Rotterdam socio-demographics, and linkages in between that are required for modelling
- Identify limitations or gaps in the open data
- Describe the characteristics of the data, and processing the raw data into a model-ready format.

In the later sections of this chapter, the Secondary Focus section describes promising data sources that were not employed in the modelling phase, due to limitations, data gaps, or practical limitations. These serve as potential areas for improved data and future research. Each key data item is described in a discrete section, in the following order:

1. Overview: spatial boundaries
2. Data: Flood scenarios
3. Data: Flood depth-damage functions
4. Data: Housing market demographics: number of households per district, number of moving households per district.
5. Data: House price discount and recovery
6. Secondary focus: Household consumption, mortgage debt, household income percentiles, economic

An emphasis was made to acquire open-source data for the study, and identify possible areas where added open data is required for more detailed study. However, not all necessary data was found, and are replaced by workarounds. All data sources are linked to their respective URLs in the references.

3.1. Spatial boundaries

The municipality of Rotterdam has different administrative borders compared to the city itself, including outlying districts and industrial districts. Given that this study focuses on housing market in the city itself, the following districts are excluded from this study:

1. port-, industrial-, and business-specific districts (*haven- en industriegebieden*), as they have very few residences: Botlek-Europoort-Maasvlakte, Spaanse Polder, Nieuwe Mathenesse, Waalhaven-Eemhaven, Vondelingenplaat, Rotterdam Noord-West, Bedrijventerrein Schieveen, and Rivium.
2. districts that are ”disconnected” from the city of Rotterdam: Rozenburg, Hoek van Holland, Hoogvliet and Pernis. These districts are closer to other districts in the province of South Holland than the city itself, and it is assumed that any flood events affecting the city of Rotterdam would motivate other citizens to move to other parts of the city, instead of to these districts.

The included and excluded districts in this study are depicted in a map in Figure 3.2.1.

3.2. Flood scenarios

The flood scenarios represent plausible events where specific areas in Rotterdam are flooded. The following datasets are referenced to in this section:

1. **Flood scenario data**, from the Landelijke Informatiesysteem Water en Overstromingen (Rijkswaterstaat, n.d.). This data repository contains various datasets on flood risk per area in the Netherlands, based on hydraulical modelling from Deltares. The data is usually given in a GIS raster format, containing metadata on the coordinate systems, spatial resolution and map projection.
2. **Terrain data**, from Actueel Hoogtebestand Nederland (AHN, 2020). This data describes the terrain height in a Digital Surface Model (DSM), which includes the top of buildings. This is also given in a GIS raster format, similar to the flood scenario data by LIWO.
3. **Country, province, district and neighbourhood boundary geometries**, from the Centraal Bureau voor de Statistiek (CBS, 2020). This dataset contains the vector geometries for all administrative borders in the Netherlands. It is provided in a GIS vector tabular shapefile, containing the vector geometries of each area, the associated GIS metadata, and identification information for each area.

Map of Rotterdam, with included/excluded districts

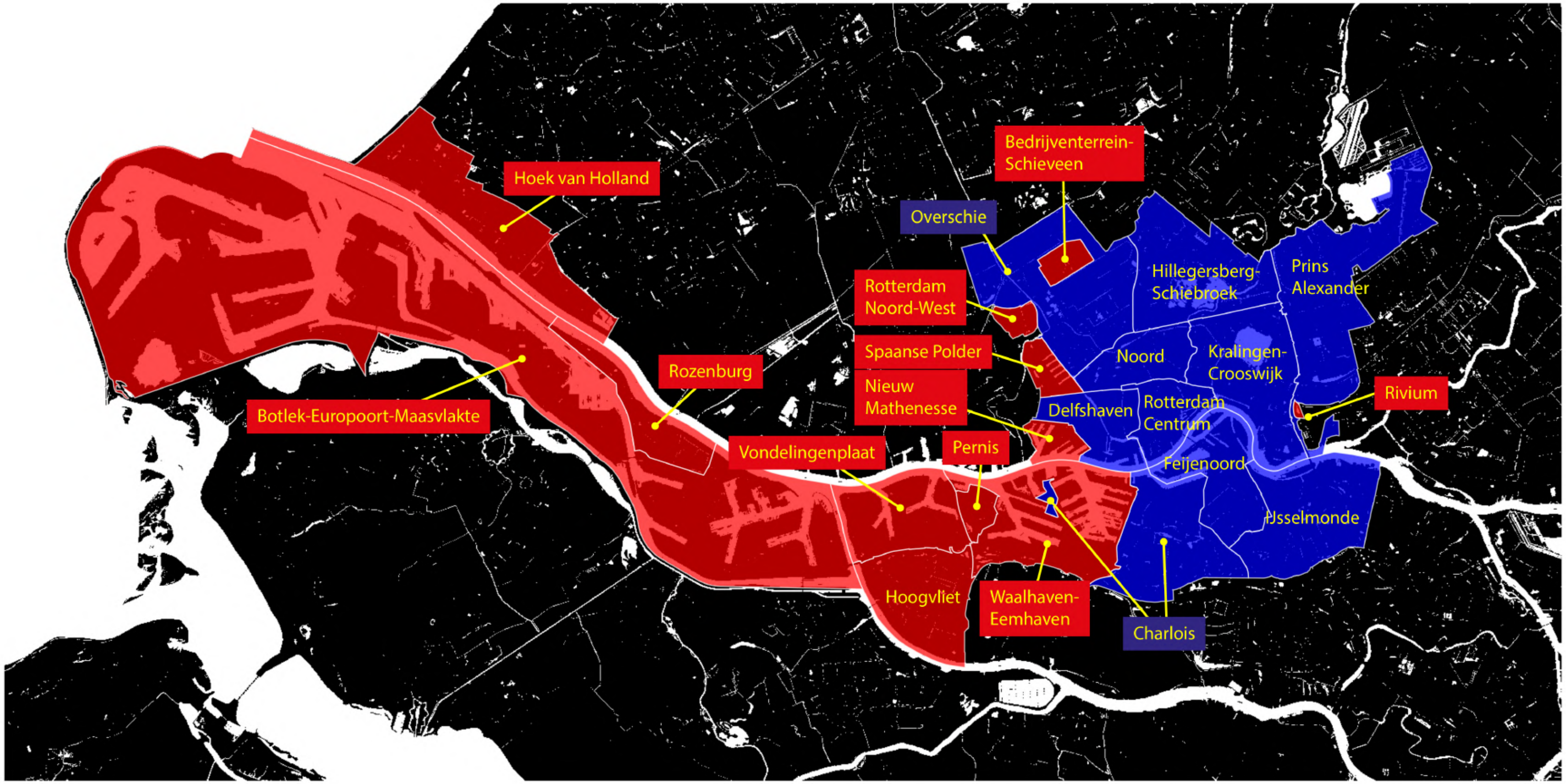


Figure 3.1: Map of Rotterdam districts, where blue are included districts, and red are excluded districts.

3.2.1. Exploration

The flood scenario data from LIWO contains several comprehensive datasets on flood risk or expected flood damage in the Netherlands. A hallmark of these datasets are their spatially-explicit nature, characterising the flood hazard or exposure for any area in the Netherlands. There are 3 classes of data investigated in this study:

1. The expected flood return rate, per individual parcels of land (Figure 3.2)
2. The maximal expected flood depth per tile, per grade of flood return rate (Figure 3.3)
3. The expected flood depth, per scenario where there is a failure in flood mitigation structure (Figure 3.4)

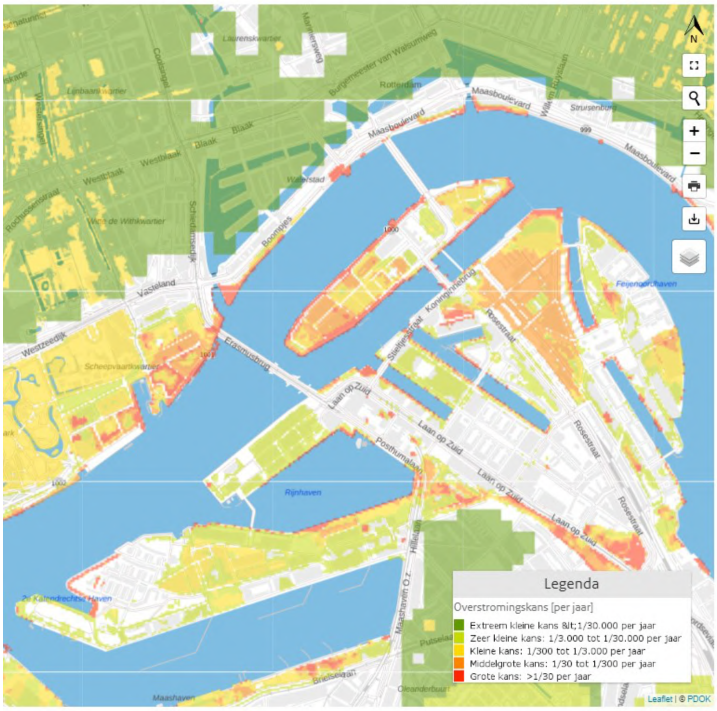


Figure 3.2: Example of expected flood return rate per tile (Rijkswaterstaat, n.d.). The coloured tiles represent areas that have a non-negligible flood risk, where red means a high likelihood of flooding. Likelihood is described as a probability of 1 flood event per N years (also known as 'flood return rate').

Datasets 1 and 2 are unsuitable because they describe the flood risk (likelihood or expected flood depths) of all land parcels in the Netherlands by combining the effects of various flooding scenarios. While they are useful to analyse the existing risk per land parcel, the aggregation of flood risk limits their utility as flood scenarios for housing market shocks, because it an unrealistically-large proportion of Rotterdam would be flooded. As a result, a more scenario-focused approach is thus preferred.

The third dataset contains individual flood scenarios for breaches in individual dikes or sluice gates, and provide a localised depiction of flood depths. As a result, 6 severe flood scenarios (hereinafter: "flood maps") from the 3rd dataset were hand-chosen as flood scenario inputs for the study, with the criterium that the floods severely impact parts of Rotterdam. These

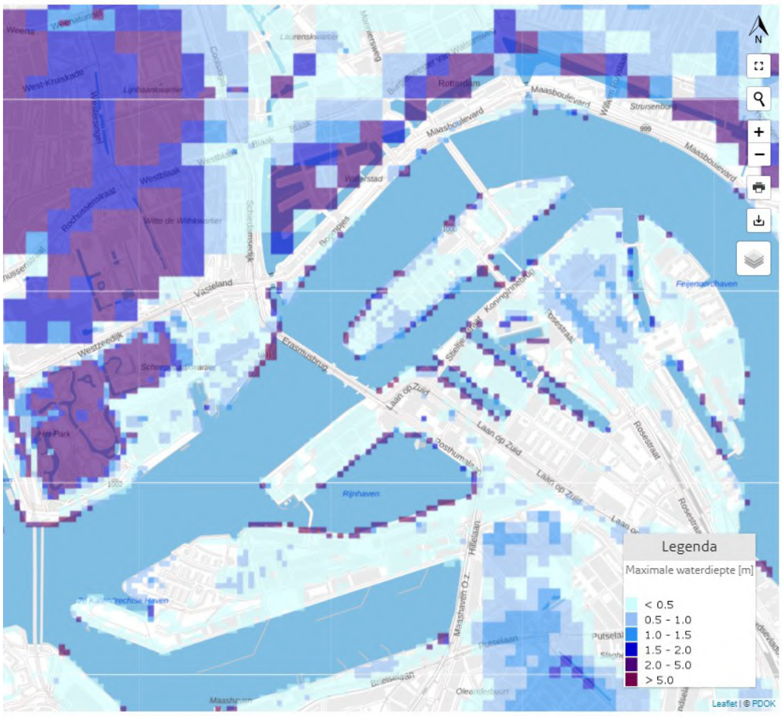


Figure 3.3: Example of max expected flood depth per tile from all possible flood events, per grade of severity (Rijkswaterstaat, n.d.). Deeper-coloured tiles represent more severe flooding, which can be more than 5 metres deep. However, it is unlikely that all tiles would be flooded simultaneously.

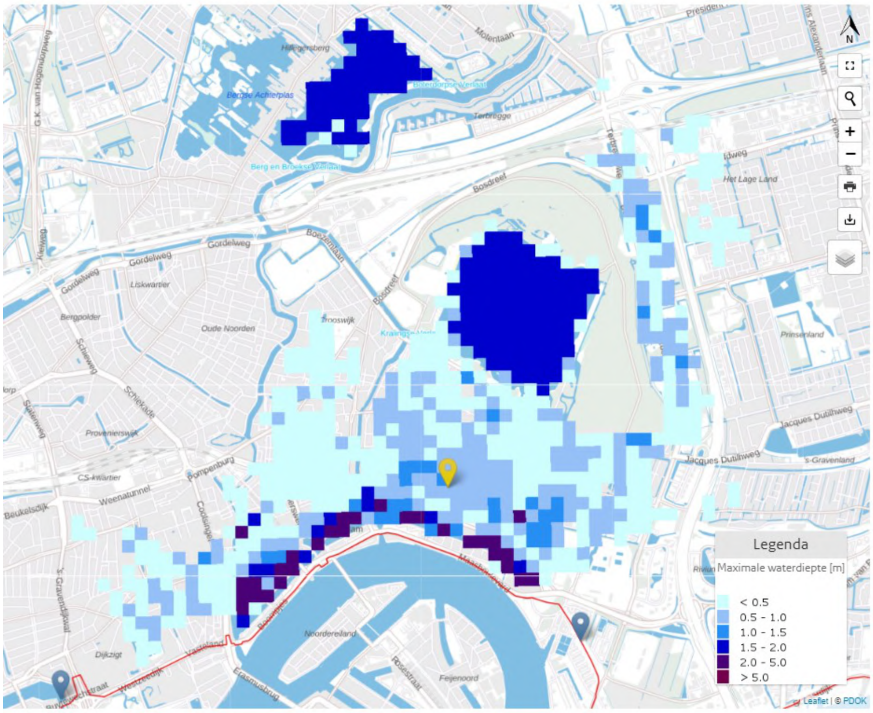


Figure 3.4: Example of expected flood depth per dike/sluice gate failure scenario (Rijkswaterstaat, n.d.). The areas close to the failure point (yellow pin) experience worse flooding (in deeper shades of blue), and may propagate inland. Notably, inland water bodies, such as the two ponds in the top half of the image, are classified as flooded.

flood scenarios are described in Table 3.1 and illustrated at the end of this chapter in Figure 3.9. Further information on the data acquisition method is elaborated in Appendix B for the sake of reproducibility.

An ethical concern arises here; as the three datasets are capable of describing the flood risk of all flood-vulnerable areas in the Netherlands, albeit at a spatial resolution of a hectare. As this research domain aims to test various hypothesis about housing market behaviours post-flooding, policy analysts would need to exercise caution when drawing conclusions from the exploration of more severe scenarios. As home purchases have an emotional component attached (Pryce & Chen, 2011), the disclosure of simulated and hypothetical flood damages may cause public and political discontent.

Flood Scenarios

Flood Scenario	Return Rate	Flood coverage [ha]	Mean Flood Severity [m]	90th Percentile Flood Depth [m]	Max Flood Depth [m]
maashaven34.6_4e5	1/400,000	367	0.226	0.502	0.922
boerengatsluis_1e6	1/1,000,000	584	0.563	1.031	3.938
capelle_1e6	1/1,000,000	1462	1.338	1.615	5.177
parksluizen_1e6	1/1,000,000	2459	1.096	2.243	9.079
maashaven36.1_4e5	1/400,000	2638	0.584	1.028	1.909
nieuwe_maas_4e5	1/400,000	3876	1.043	1.800	2.898

Table 3.1: Table of severe flood scenarios used for the model experiments, consisting of varying combinations of flood coverage and flood severities. For example, scenario "maashaven36.1_4e5" affects a wide area, but only has a lower maximum depth value of under 2m. It is likely that the maximum flood depths seen in several scenarios are imperfections from the data cleaning section, as they might not correctly clear the flooding in inland water bodies.

3.2.2. Data processing

The flood maps do not distinguish between the districts of Rotterdam, and they also classify inland water bodies as flooded terrain (see the dark blue tiles in Figure 3.4), even though no houses would be sited there. The inclusion of district boundaries is necessary in the integration with the housing market, as there are different population densities per district.

The flood maps are provided in raster format (*.tiff* format) embedded with GIS [1] metadata specifically for the Netherlands. Most are at a spatial resolution of 100m x 100m (or a hectare), but may differ per data source.

For every flood map, the inland water bodies are excluded using the terrain map[2] (AHN, 2020). Next, flood tiles that are less than 1cm high are also excluded, as that is assumed to be an unthreatening level of standing water. The flood maps are then divided into districts via

[1] Geographic Information System Mapping
[2] Preferably, land use data would also be employed to also filter out non-residential terrain, but this was not publically available.

rasterio[3] over the vector geometry of the district boundaries. Districts where flooding is less than 1% of the total area are excluded.

From the divided flood maps, flooded districts are preserved and compiled into a "combined flood risk profile" (e.g. Figure 3.6), where the tiles are spatially-linked to the respective flood maps per district. This implementation is to ensure two things:

- that tiles that are vulnerable to multiple flood events are correctly represented.
- that tiles that are flooded repeatedly by the same flood event are consistently flooded by the same flood depth.

However, the current implementation cannot concurrently handle different spatial resolutions. It strictly requires the same spatial resolution to function adequately, and that the total number of tiles (flooded and unflooded) per district must be exactly the same. A future iteration might utilise an explicit GIS approach, for example using location coordinates to check the membership of a location in multiple flood scenarios, to ensure that different spatial resolutions can be combined.

Given the combined flood risk profile, it is used as a model input to assign flood risk to houses being placed in vulnerable districts. In the model, houses are placed randomly, and not according to empirical locations or land-use guidelines. When a house is placed in a flood-risky district, it has a non-zero possibility of choosing a tile that will be flooded by any scenario.

3.3. Flood depth-damage functions

The flood depth-damage functions describe the damage level per depth of flooding, where usually an increasing depth of flooding leads to increasing damage for a structure or the contents within. Two sources of flood depth-damage functions are available for the Netherlands:

1. Slager and Wagenaar (2017), with curves for a wide variety of structures, such as offices, shops, industrial buildings, single-family homes, apartments, and traffic infrastructure. The data is specific to the Netherlands.
2. Huizinga (2007), with curves for general residences, infrastructure and industry. The document specifically has a focus on countries in the European Union.

Both curves are illustrated in Figure 3.7, specifically the structural damage curve for single-family homes in Slager and Wagenaar (2017) and residences damage curve in Huizinga (2007). For this study, only the structural depth-damage curve for single family households from Slager and Wagenaar (2017) is used, due to its recency and that it represents a more severe curve than Huizinga (2007).

In the model, the depth-damage curve is an input parameter into the ABM model, and can be modified with other depth-damage curves. For future research, the depth-damage curves for apartments and home internal contents may be interesting for a more detailed and heterogeneous representation of household flood damage.

[3] *rasterio* is a Python library for the processing of GIS raster data files

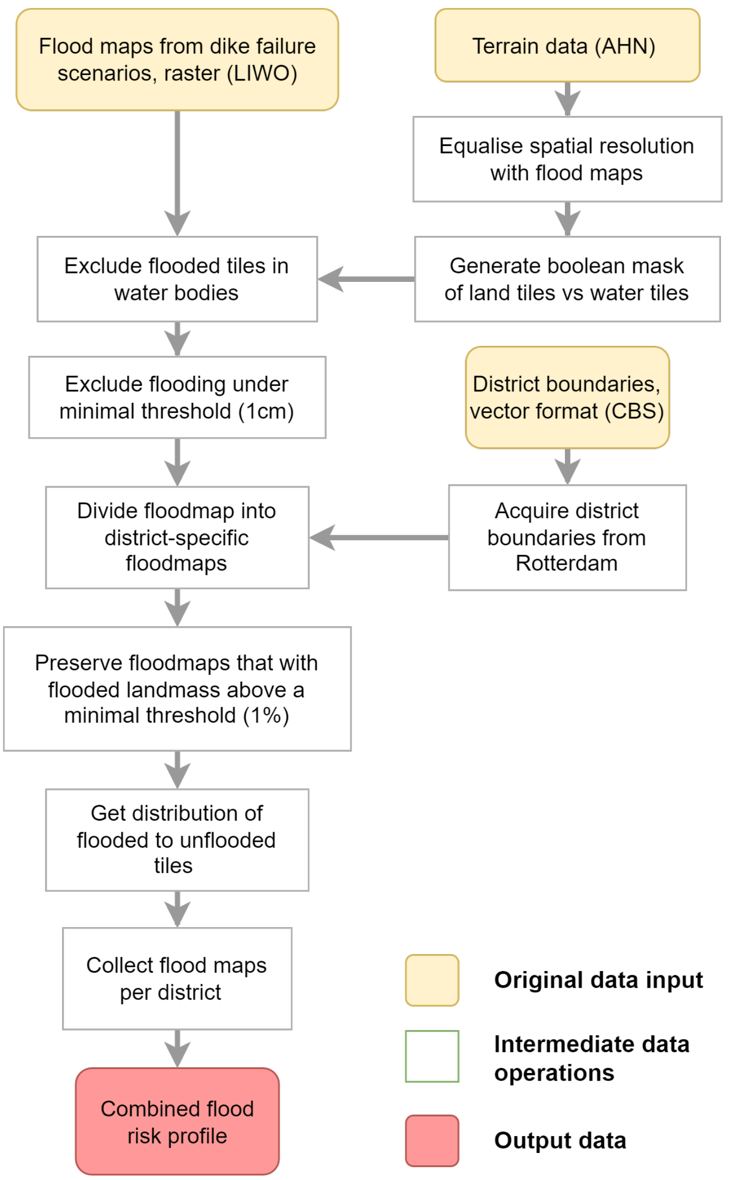


Figure 3.5: Flow diagram of the flood scenarios data cleaning processes

3.4. Housing market demographics

The original datasets used are as follows, sourced from the Rotterdam municipality's Research and Business Intelligence[4] (OBI) statistics:

1. Number of inhabited addresses, per district (OBI Rotterdam, 2020b). This is used to establish the number of houses in a district[5].
2. Total number of residents per district (OBI Rotterdam, 2020a) . This is used in conjunction with the total number of emigrating residents per year, to estimate the number of house transactions per year.
3. Total number of emigrating residents per year, per district (OBI Rotterdam, 2020c). This is used as a proxy for establishing how many houses listings are generated per year.

An overview of the data used is shown in Table 3.2.

Rotterdam Demographics, per district

Districts	Number of inhabited addresses	Population size	Emigrants per year	Percentage leaving
Rotterdam Centrum	18,445	36,039	4,288	11.9%
Delfshaven	33,975	76,774	5,694	7.4%
Overschie	8,276	19,201	870	4.5%
Noord	26,164	52,479	4,171	7.9%
Hillegersberg-Schiebroek	19,833	44,730	2,136	4.8%
Kralingen-Crooswijk	26,699	54,466	5,319	9.8%
Prins Alexander	44,626	95,926	4,688	4.9%
Feijenoord	34,134	76,539	4,298	5.6%
IJsselmonde	27,615	61,340	3,966	6.5%
Charlois	32,123	69,377	5,024	7.2%

Table 3.2: District demographics for the districts in Rotterdam, for 2020

For all datasets, the values for 2020 were used for consistency, and to discount the effect of the COVID-19 pandemic on demographics. The number of inhabited addresses per district represents the *distribution of houses* in the model, as different districts have different population densities. In the model, the number of houses in the model are set to a lower number than in reality due to computational limitations, so the dataset is converted into ratio of houses per district. A simplifying assumption made here is that all houses are considered to be owned houses, and does not distinguish rental properties, as the study focuses on the house prices

[4]Dutch name: Onderzoek en Business Intelligence

[5]OBI distinguishes between "number of households" (aantal huishouden) and "inhabited addresses" (bewoond adressen). They are identical in terms of available spatial levels and units of measurement, but the presence of multi-family homes means that multiple households may live under the same address, and thus the inhabited addresses numbers are usually lower than the number of households per district. For this study, the "inhabited addresses" dataset was used such that the number of houses are correctly represented. However, for a socio-demographic study, using the "number of households" dataset may be more representative.

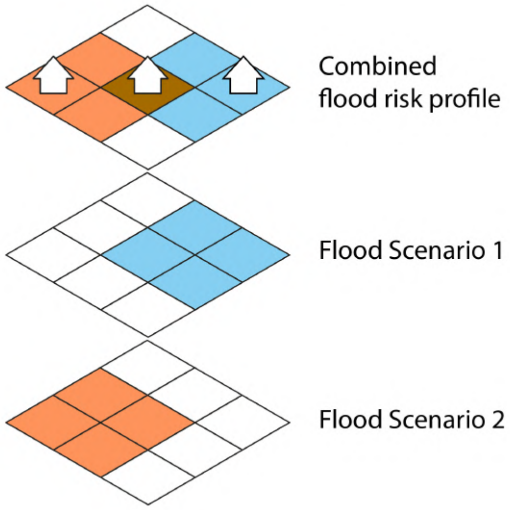


Figure 3.6: Combined flood risk profile, from the superimposition of multiple flood maps

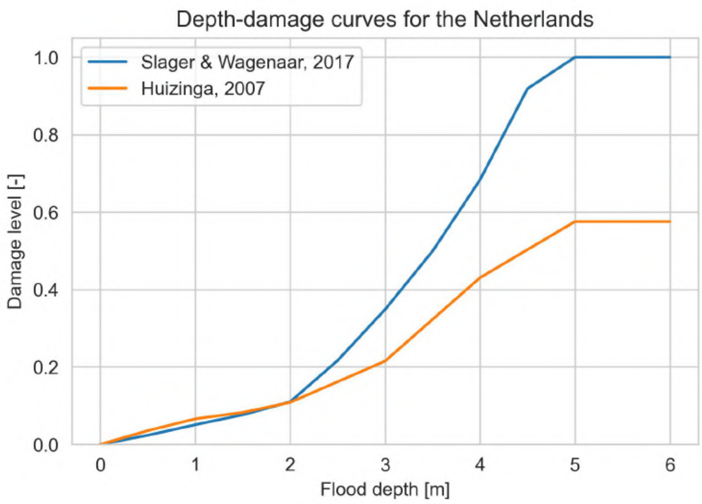


Figure 3.7: Depth damage curves for the Netherlands. This study uses the curve from Slager and Wagenaar (2017) due to its recency and its more severe effect.

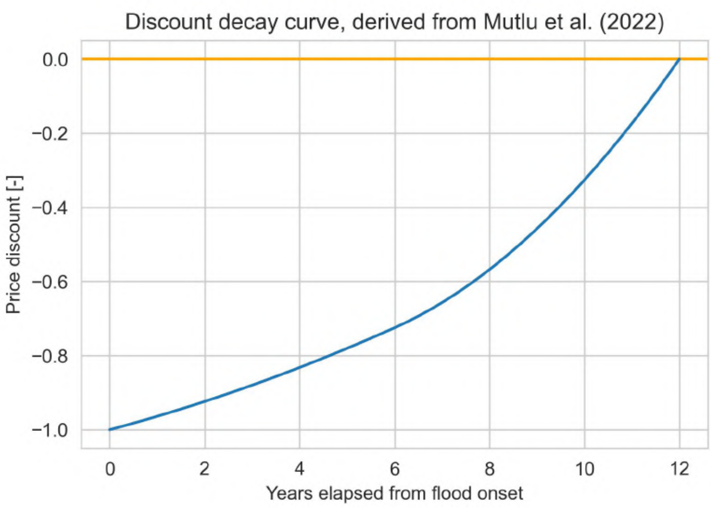


Figure 3.8: Discount decay curve, derived from Mutlu et al. (2022). The regression points are converted into dimensionless ratio form for use in the contemporary Rotterdam housing market.

only, and less on demographic migration.

The emigrating residents per year is used as a proxy for the number of housing market transactions per year. This is due to the number of house listings per year not being publically available, while the number of housing market transactions done per year is very low due to the high proportion of rentals in central Rotterdam (OBI Rotterdam, 2019). As the emigrating residents dataset is in a different unit of measurement than the number of inhabited addresses (i.e. number of persons versus number of addresses), the dataset is converted into dimensionless ratio form, by dividing over the total inhabitants. This gives the *fraction of emigrating households per year, per district*, ranging between 12% to 4%. In the model, the fraction of emigrating households defines the number of listings in the housing market and also the number of potential buyer agents.

3.5. House price discount and recovery

When a house is flooded, it would suffer a discount in their valued price. In the model, the price trends are modelled after the status quo, where prices for flood-risky homes would drop and recover within a decade, as the housing market forgets about the flood (Pryce et al., 2011). This uses two inputs, the price discount values:

1. Price discount per damage level (hereinafter: ”damage-discount ratio”). The price discount value in this study refers to a percentage value of discount in house price per percentage of house damaged.
2. Time series price discount data, from Mutlu et al. (2022). This describes the discount in house prices sold in the years after the flooding in Limburg in 1993 and 1995.

The damage-discount ratio is referenced in some US-based hurricane literature, such as a low bound of -1.28% from Rezakhani (2022) and 6-8% for Peacock et al. (2014). However, the damage-discount ratio for flooding-specific scenarios was not found. Given this uncertainty, the damage-discount ratio was assumed to be 1%, thus meaning that 1% of damage linearly corresponds to 1% of discount.

Flood discount regression points from Mutlu et al. (2022)

Time [yr]	Modelled Discount (Mutlu) [%]	Converted Ratio [%]
(pre-existing)	-1.02	*n.a.*
-3 - 0	-5.63	*n.a.*
1 - 4	-10.9	-100.0
5 - 8	-9.07	-83.2
9 -12	-6.19	-56.7
13 - 16	-0.529	0.0

Table 3.3: Excerpt from Mutlu et al. (2022). This study uses the ratio of values compared to the onset of the flood, in the “Converted Ratio” column.

The time series price discount data is described in Table 3.3. For this study, only the shape of the price discounts over time is used, as discounts from Limburg in 1993 and 1995 are not applicable to contemporary Rotterdam. Additionally, the discounts before the floods are not included, assuming that the Rotterdam housing market as ”naïve” to flood risk, thus meaning a discount of 0% before flooding. The discount regressions are converted into ratio form, by dividing the discounts over the starting value (10.9%), leading to the values in the ”Converted Ratio” column in Table 3.3. As the price discount already starts reducing within 1 year after a flood event, as seen in Peacock et al. (2014), the discounts were set to be at maximum at the onset of the flood and will start decreasing afterwards, instead of staying at 100% until the 4th year. The data points are fed into a 1D quadratic interpolation scheme, such that the gradient around the data points are quasi-continuous, which gives the *discount decay curve* seen in Figure 3.8. The coarse nature of the data points mean that a higher degree of fit would not yield any useful insight.

Reflecting on the data exploration process, modelling the price discount mechanisms raises several questions on the amnesiac behaviour in housing markets:

- Is this forgetting behaviour affected by increasing severity of flooding?
- Does visible devastation and unrepaired damage affect how quickly the forgetting process begins? For example, would a quick recovery in property damage mean that forgetting trends
- Does population density affect the severity of discount or the temporal trends?
- At what point would the housing market start remembering the discounts, for example, in a hysteretic[6] manner?
- Which actors affect the price discount?
- How do housing market system structures, such as financing, insurance, and risk disclosure, amplify or mitigate flood-forgetting behaviour?

In the model, the damage-discount ratio and the discount decay curve are set as input parameters to the model, thus allowing for possible variation of both inputs, such as the regression curves from Atreya et al. (2013). The current discount decay curve can be modified along its temporal axis and its magnitude axis, making it possible to stretch or compress the discount decay phase.

3.6. Secondary focus

This section describes the other datasets that were discovered in the data exploration effort, but were not incorporated into the model. Nonetheless, they serve as a starting points for future research efforts, and may highlight potential limitations of current open data.

[6]Hysteresis/hysteretic behaviour refers to history-dependent behaviour, where the state of the system is based on its history. An example is when a spring is pulled beyond its elastic regime and does not return to its original form when released.

3.6.1. Neighbourhood-level spatial data

In most of the datasets (for example in the Rotterdam OBI statistics), there is the possibility of using spatial data at the neighbourhood (*buurt*) or district (*wijk*) level. This study uses the district-level spatial level due to the coarse resolution of the flood maps, and for easier verification while conducting data exploration and modelling. However, the data processing and modelling process is designed to be agnostic to the spatial level of the model, as long as the input data is processed to the same spatial level. These input data elements include the divided flood maps, number of houses per area, and the annual transactions per year.

3.6.2. Household incomes, income distribution per district

One possibility in the thesis study was to empirically characterise the household incomes and its distribution across different districts. This data is drawn from two data sources:

1. The lowest 40% percentile and highest 20% percentile in income, per district (OBI Rotterdam, 2018a). This describes the proportion of inhabitants with the lowest 40% and highest 20% percentiles of national income distribution. By inference, the middle 40% can be derived with this data.
2. The national income distribution for the Netherlands (CBS, 2022c). This tabular data describes gross income, disposable income, primary income and standardised income (controlled for household size). They are sorted according to income brackets, or as deciles.

With these two datasets, it is possible to generate an empirical population of households with heterogeneous income levels, with disposable incomes (required for characterising household consumption) and gross incomes (required for establishing mortgage financing). However, this was not implemented due to the limitations with characterising house pricing and mortgage financing.

3.6.3. Mortgage loan determination, mortgage debt statistics, average home values

The Netherlands has one of the highest proportions of population with mortgage debt, with 61% of the population with mortgage debt, and a high loan-to-value and loan-to-income rates (DNB, 2021). The high mortgage debts in Dutch housing markets becomes a significant vulnerability in light of flood risk, as many citizens would then suffer from ”underwater mortgages”, where the mortgage debt is higher than the value of the home. On the other hand, the ability to borrow is a key factor in home purchases, thus an understanding of the linkage between household incomes and mortgage eligibility is important in characterising the purchasing decision-making for potential homebuyers. In this study, two datasets were found related to the mortgage financing in the Dutch housing market:

1. Tabular data for advised loan-to-value and loan-to-income, based on the interest rate and gross income (NIBUD, 2021).

2. Aggregate mortgage debt statistics, describing the loan-to-value and loan-to-income for home-owners in the Netherlands, in annual statistics (CBS, 2022b). It can be filtered by categories such as total households, migration background, quartiles based on disposable income, and quartiles based on home value. However, it is deemed too aggregated and low in resolution for linking household incomes to mortgage debt.
3. Average home values , at the district or neighbourhood level (OBI Rotterdam, 2018b). This dataset is deemed too aggregate for use, because it does not describe the distribution and range of the home values in the area.

The dataset by NIBUD is the most interesting, as it prescribes different loan-to-income values, given a homebuyer's gross income and interest rate. However, a key element in household decisionmaking is the required monthly mortgage payments, which, at a simple level, is a function of the total mortgage debt (home value, V_{home}, and added interest μ) and mortgage repayment duration, $12 \cdot N_{year}$:

$$C_{monthly} = \frac{V_{home} \cdot (1 + \mu)}{12 \cdot N_{year}} \tag{3.1}$$

The monthly repayments can be described as a fraction of gross monthly income:

$$C_{monthly} = I_{gross,monthly} \cdot \epsilon_{mortgage} \tag{3.2}$$

The preferred mortgage repayment duration is not present in the NIBUD or the CBS dataset, which limits the modelling the decision-making of potential households seeking to finance a house. Ideally, either the preferred mortgage repayment duration or the preferred mortgage proportion of household income would be able to describe a potential homebuyer's budget.

3.6.4. Household consumption

Another research possibility is to link the effect of flood damages on household consumption, and then to the regional economy. The hypothesis is that households that experience damage and disruption from flooding, which necessitates using a portion of their income to repair the damage. This has two interesting potential effects:

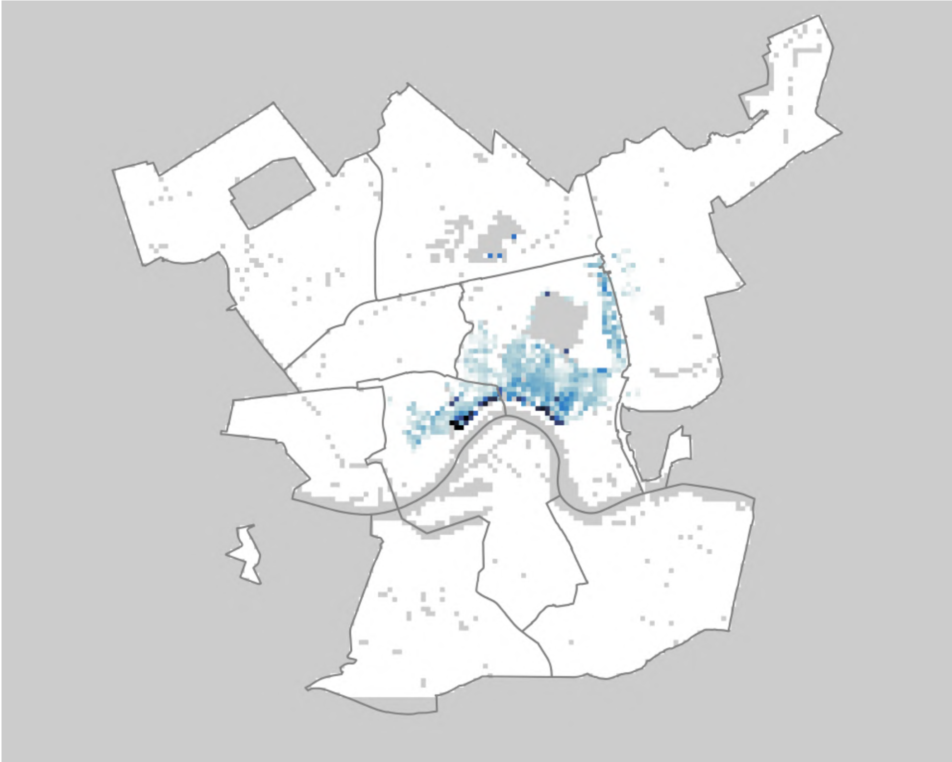
1. That household recovery may be governed by the disposable income of households, which may disadvantage poorer households
2. That the change in consumption behaviour may lead to a boost or depression in certain areas of the economy, such as in construction, retail services

In CBS data, there is a dataset for household consumption, divided according to income deciles, and includes various categories of consumption (CBS, 2022a):

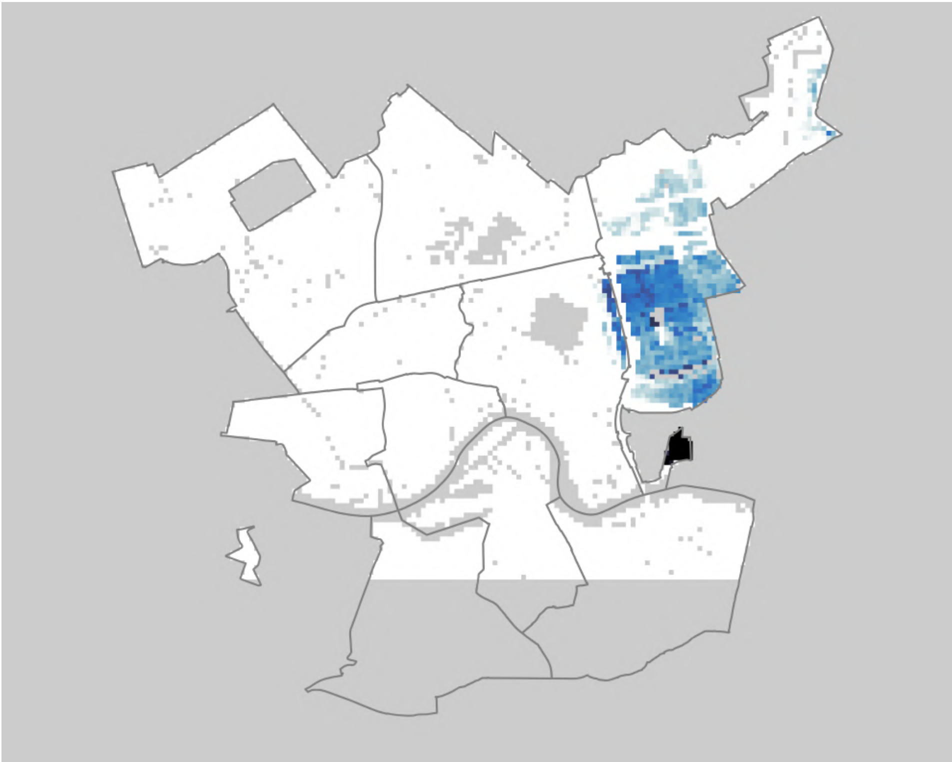
1. Food and alcohol-free drinks (*Voedingsmiddelen en alcoholvrije drank*)
2. Alcoholic drinks and tobacco (*Alcoholhoudende dranken, tabak, en verdovende middelen*)

3. Clothes and shoes (*Kleding en schoenen*)
4. Accommodation, water, electricity and energy (*Huisvesting, water, elektriciteit, gas en andere brandstoffen*)
5. Household upholstery, appliances, and daily maintenance (*Stoffering, huidhoudelijke apparaten en dagelijks onderhoud van de woning*)
6. Healthcare (*Gezondheid*)
7. Transport (*Vervoer*)
8. Communication (*Communicatie*)
9. Recreation and Culture (*Recreatie en cultuur*)
10. Education (*Onderwijs*)
11. Restaurants and hotels (*Restaurants en hotels*)
12. Diverse goods and services (*Diverse goederen en diensten*)
13. Consumption-related taxes (*Consumptiegebonden belastingen*)

This dataset would be a foundation towards estimating the change in consumption behaviour of households as a result of flood damage, and investigate the net effect of this change in consumption behaviour in the regional economy.

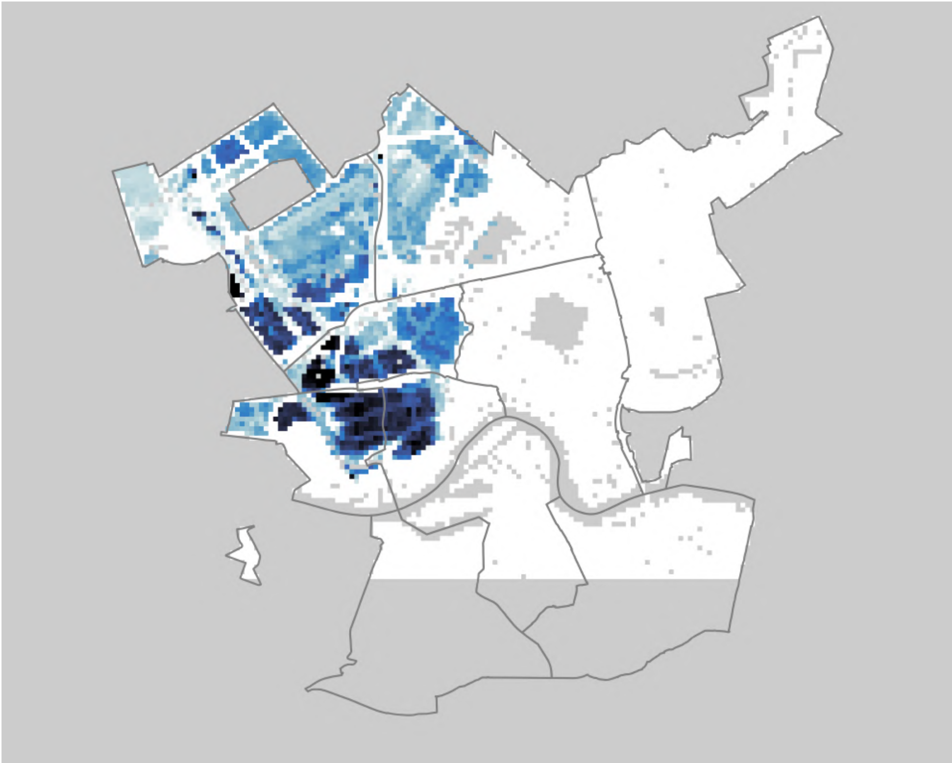


(a) Boerengatsluis (1/1mil.)

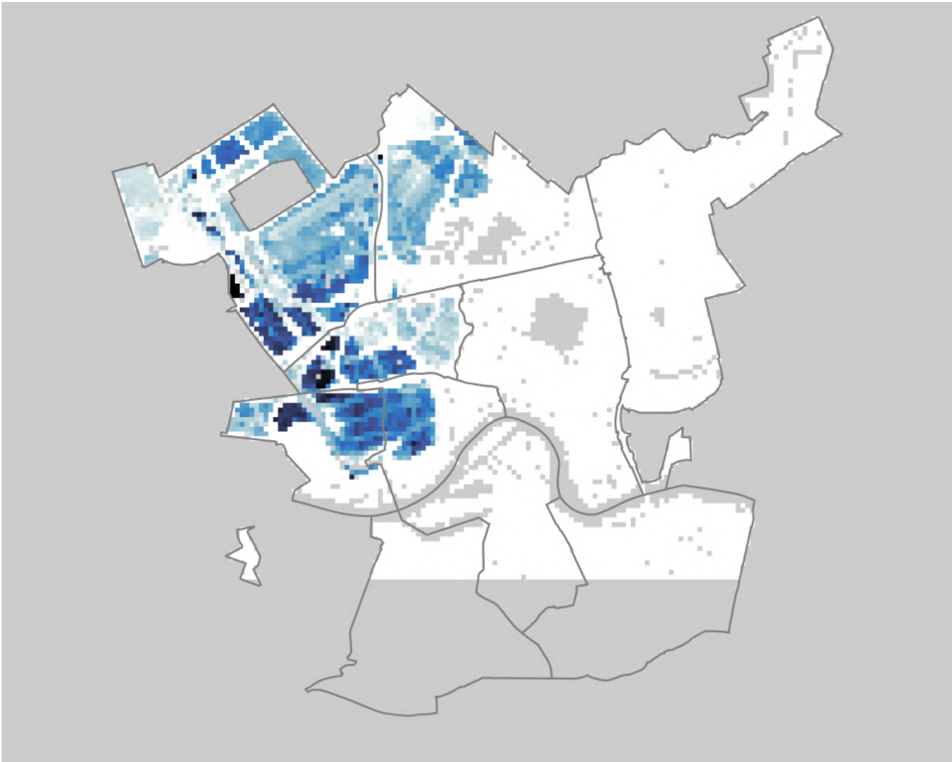


(b) Capelle aan de IJssel, West Nijverheidstraat (1/100k)

Figure 3.9: Flood depth maps for the chosen flood scenarios, with dark blue being deeper water depths. The flood return period are described in brackets, denoting the likelihood of the flood event per N years. The district borders are drawn in dark grey, excluded/water tiles in grey, and land tiles are in white. For each flood map, not all land tiles in the district are represented, hence the visible cutoff.

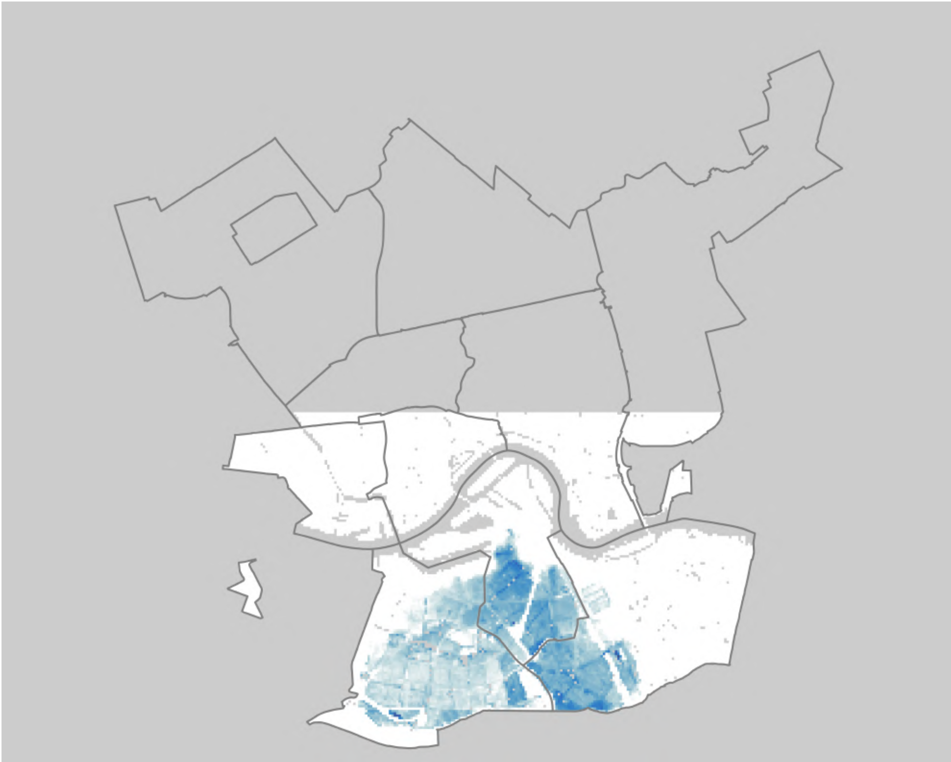


(c) Parksluizen (1/1mil.)



(d) Parksluizen (1/1000)

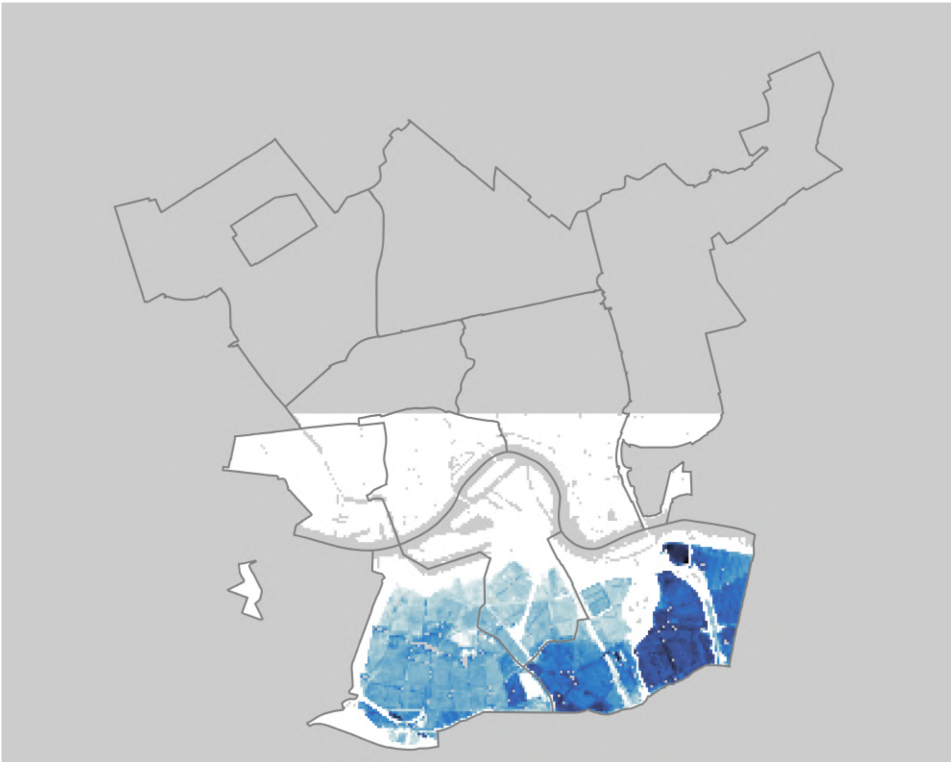
Figure 3.9: Flood depth maps for the chosen flood scenarios, with dark blue being deeper water depths. The flood return period are described in brackets, denoting the likelihood of the flood event per N years. The district borders are drawn in dark grey, excluded/water tiles in grey, and land tiles are in white. For each flood map, not all land tiles in the district are represented, hence the visible cutoff.



(e) Maashaven, KV2 (1/400k)

(f) Maashaven (1/400k)

Figure 3.9: Flood depth maps for the chosen flood scenarios, with dark blue being deeper water depths. The flood return period are described in brackets, denoting the likelihood of the flood event per N years. The district borders are drawn in dark grey, excluded/water tiles in grey, and land tiles are in white. For each flood map, not all land tiles in the district are represented, hence the visible cutoff.



(g) Nieuwe Maas, km41.2 (1/400k)

Figure 3.9: Flood depth maps for the chosen flood scenarios, with dark blue being deeper water depths. The flood return period are described in brackets, denoting the likelihood of the flood event per N years. The district borders are drawn in dark grey, excluded/water tiles in grey, and land tiles are in white. For each flood map, not all land tiles in the district are represented, hence the visible cutoff.

4

Model Design

This section describes the housing market simulation model that serves as a base for computational experiments. The processed data from the Model Data section are consolidated here as inputs to the housing market model, and this chapter further expands on the internal relationships driving the housing market model.

As mentioned in the Research Strategy chapter, the model paradigm chosen for this study is an agent-based model (ABM), which simulates decisions of individual homebuyer agents, which leads to emergent behaviour at the housing market level.

4.1. Model Overview

Before diving into the details of the agent-based model, a high-level description of the model is presented here.

In the model, time is represented in terms of steps, like a board game, where each player makes a move. In an ABM, a player is an ”agent”, because they have some form of agency and decision-making capacity. During a time step, all agents follow a set of instructions, such as observing the agents' own situation, and make a decision based on the information. While each agent may have similar instructions, their decision-making outcomes may be different, due to different attributes (such as available budget, or the decisions they can make), or them being placed in different situations. A visual overview of the model operations is provided in Figure 4.1.

In terms of time, the model simulates the housing market of Rotterdam in timesteps of quarters of a year (i.e. 4 steps per year). This temporal resolution was chosen for potential future model extensions, such as macroeconomic simulation or post-flood recovery. However, the model can accept different timestep sizes (such as in years or in months) with minor adaptation[1]. As for the total duration, the model is simulated for a total of 26 years.

The aforementioned ”components” in the model can be described as relationships in the system. The key relations are as follows:

- placement of houses and how they are flooded
- how the prices of houses are affected due to their flooding history
- generation of house sellers and buyers
- how flooded houses discourage homebuyers from buying houses in that district, thus encouraging them to consider other houses in other districts
- how homebuyers value and bid for houses
- how prices are updated in the housing market system

The agents in the model are potential homebuyers entering the Rotterdam housing market. They have numerous choices, and they prefer houses that are not flooded. If a district is (partially) flooded, the district becomes less attractive to the agent, and thus agents are more likely to prefer houses in safer districts. The agent then chooses a random house, and enters the bidding process. A flooded house will be valued less, and will receive a lower bid depending on how severe the house was flooded in recent history. For a house listing, the more agents in the bid queue, the higher the price of the house. The transactions prices and price index of these houses are recorded and analysed.

In terms of flooding, the model is assigned one or more flood scenarios at the start, and the housing market is created with a small group of houses that will be flooded in the simulation. At specific time steps, the model ”experiences” a flood event, which causes houses to be flooded and subsequently discounted in price. After the flood, the flood discounts gradually reduce as the housing market ”forgets” about the flooding, until they are forgotten totally.

The model is used to simulate various scenarios in the form of ”experiments”. In these experiments, the flood scenarios and their timing are varied, while the housing market initial setup was kept constant. Two main categories of experiments was done, one for 1 flood and another for 2 floods; the 1-flood experiments are to analyse the effect of different flood scenarios on the housing market, and the 2-flood experiments are to analyse the effect of different flood intervals on the housing market. The experiment setup is described in this chapter at Section 4.5, and the results are discussed in the next chapter.

4.2. Translation of theory to model

This section describes the application of the theory described in Chapter 1. As described by Pryce et al. (2011), housing markets tend to underestimate or forget about floods, via myopic

[1]The model uses a constant to signify how many steps should be taken in a year, which is used to reduce variables that have a yearly temporal unit. However, this is not linked with the Mesa *step()* function in the current implementation, so changes to the timestep must be matched with the corresponding number of simulation steps to be done.

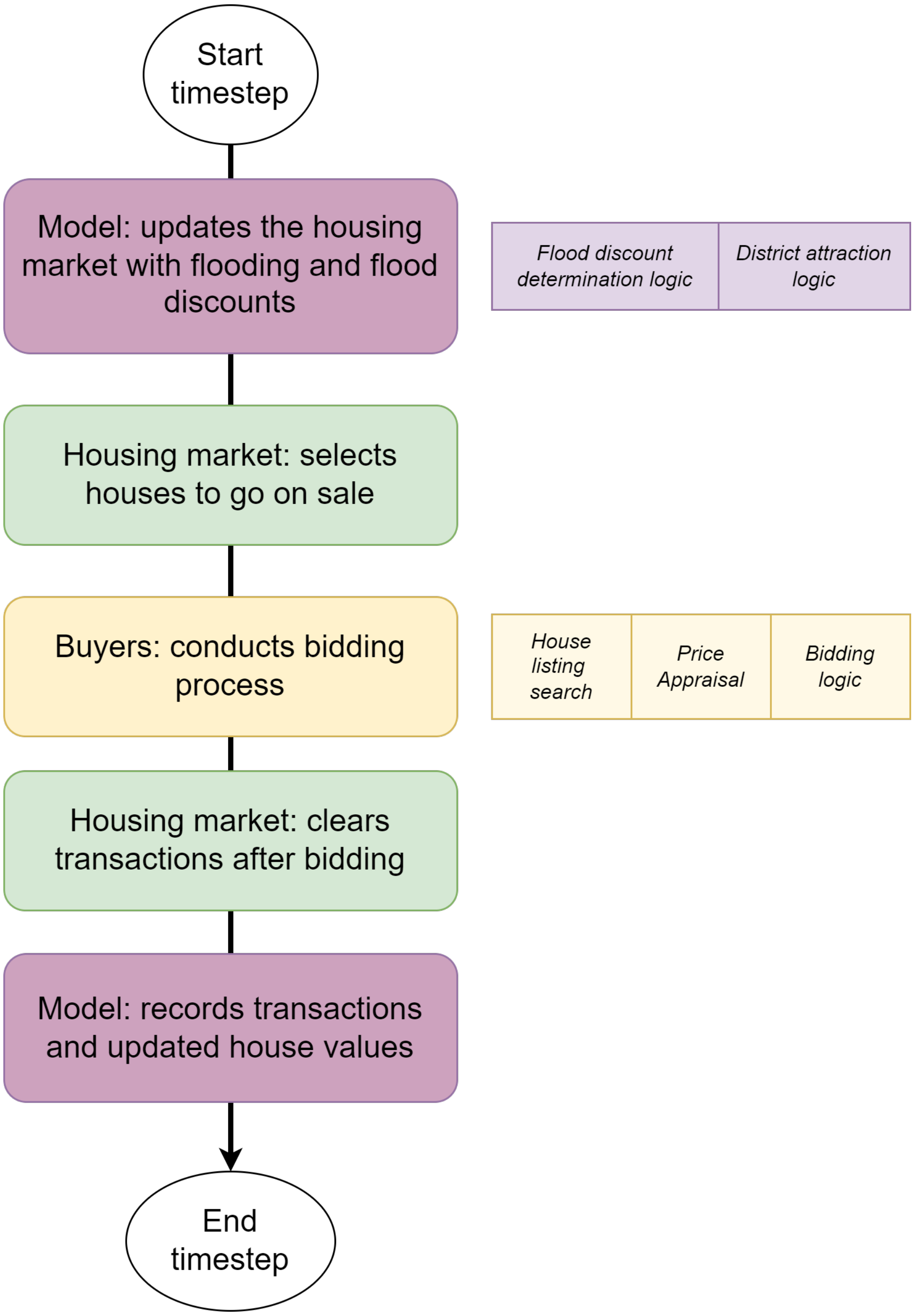


Figure 4.1: High level flow of the model processes conducted per time step. The boxes on the right refer to subprocesses in Figures 4.5.

and amnesiac behaviour respectively. This model aims to capture the amnesiac behaviour, by modelling the decisionmaking of homebuyer agents who are initially deterred by districts that experienced flood events, but eventually forget about the flood risk entirely within a decade.

This amnesiac behaviour is supported by the following model elements:

1. the “attractiveness” of the district the house is located in, based on their flood history.
2. the decaying of flood discounts at an individual house level.

In the model, the attractiveness per district is described as:

$$A_{district} = A_{normal}(1 - \frac{N_{discounted}}{N_{total}}) \tag{4.1}$$

where A_{normal} refers to the normal attractiveness of the district, $N_{discounted}$ refers to the number of discounted houses, and N_{total} refers to the total number of houses in the district. Here, a district that has experienced widespread flooding would be significantly unattractive to homebuyers, and thus more homebuyers would avoid these districts in favour of other unflooded districts.

However, after houses are flooded, they suffer a flood discount that reduces over time (see the later section on house price discount from damage, and decay over time). When the houses have recovered from their flood discount, this positively contributes to the attractiveness of the district, thus attracting more homebuyers.

When a district experiences another flood, a portion of the houses might be flooded again. The current model implementation does not add the newer flood discount on top of the current discount, but only replaces it with the higher value of the two. As a result, it has a tendency to underestimate the actual discount. Additionally, with the current implementation of district attraction, repeated flooding also leads to a reapplication of the same attraction penalty, even though intuitively homebuyers would avoid the district more.

4.3. Model Initialisation

The initialisation phase is the preparatory step, when the model sets up the necessary items before the housing market is simulated. As the model receives numerous forms of input, the initialisation phase is broken down into two main processes, namely placing houses in the model, and determining the generation of buyers and sellers for the housing market simulation.

4.3.1. Placement of houses, assignment of flood discounts

This process randomly generates the housing market stock for the simulation, by randomly placing houses in Rotterdam’s districts and assigns flood discounts for houses that are situated on flood-risky areas. The following processed data from the Model Data chapter are used:

- Population demographics data, describing the number of inhabited addresses per district (Model Data chapter, section 3.4)

- Input flood scenario(s) and their respective timings (Model Data chapter, section 3.2)
- Combined risk profile data, describing the districts affected by flood, and the distribution of flooded/unflooded locations (Model Data chapter, section 3.2). The combined risk profile data is filtered for only the flood scenarios apply for the simulation.
- Depth-damage functions (Model Data chapter, section 3.3) item Damage-discount ratio (Model Data chapter, section 3.5)

The key subprocesses are as follows (also depicted in Figure 4.2):

1. Based on the target number of houses to populate in the model (default 5000), the model calculates the distribution of house model entities per district, based on the population demographics data
2. Iterating through every district, the model generates the required number of houses per district
3. If the district is included in the set of flooded districts, the model uses the distribution of flooded/unflooded tiles in the combined risk profile data to assign a location to the houses[2]. Therefore, a subset of houses in this district may be flooded. Houses that will be flooded are categorised as Flooded, houses in flood-affected districts are categorised as Close Proximity, and the rest are categorised as Safe.
4. Houses on flood-risky locations are assigned the associated flood depth(s) from the combined risk profile.
5. Houses on flood-risky locations are further assigned flood damage(s) from the depth-damage function, and then the price discount(s) from the damage-discount ratio.

For steps 4 and 5, the derivation of flood discounts is described in the equation:

$$flood\_depth \xrightarrow{Damage(x)} flood\_damage \xrightarrow{Discount(x)} flood\_discount \tag{4.2}$$

where $Damage(x)$ refers to the depth-damage function, and $Discount(x)$ refers to the damage-discount function, which in this case is a constant.

4.3.2. Generation of seller listings and buyer agents

This process determines the required amount of seller entities and buyer agents for the model simulation. It accepts the following model inputs:

- Population demographics data, specifically the fraction of emigrating households per district per year (Model Data chapter, section 3.4)
- The ratio of buyer agents to seller entities. As the buyers participate in a bidding process, there are more buyers than sellers. In the model, this is set to 7 buyers agents per house listing.

[2]The assignment of ”location” is only required to get the flood discounts in the end, and the ”location” attribute is not required further in the current model

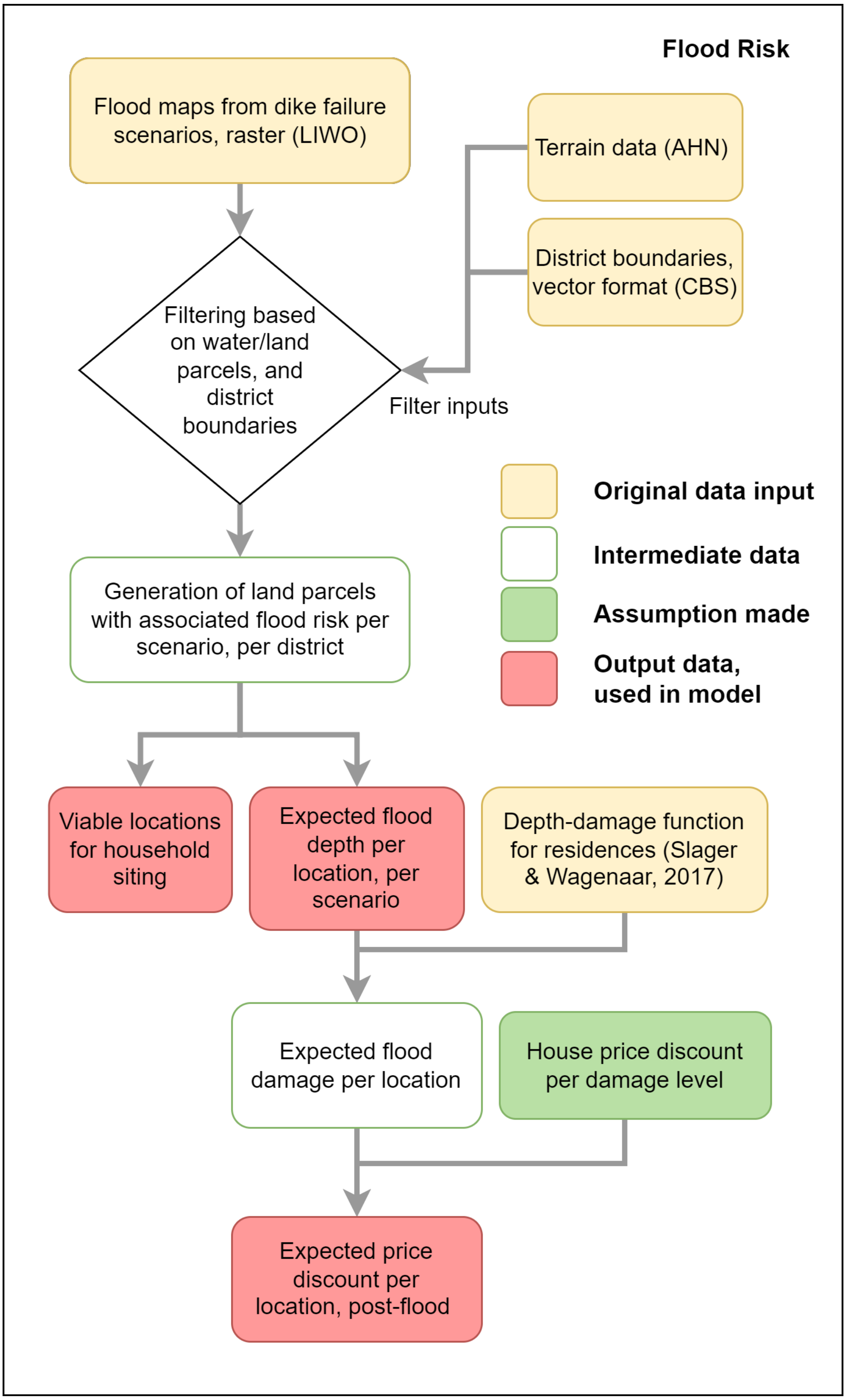


Figure 4.2: Flow diagram depicting the combined operations of the placement of houses and assignment of flood discounts at the initialisation phase, from data processing until its usage in the model.

The subprocesses are conducted as follows:

1. In step 1 of the previous process, the number of households per district are reduced to a smaller number for the simulation. This variable is used to derive the number of seller listings per time step, by multiplying it with the fraction of emigrating households per district per year. As the input data has a temporal scale of 1 year, the values are divided by the number of timesteps per year (in this case, by 4 quarters in a year).
2. The number of buyer agents to be generated per timestep is then derived from the number of sellers per time step, by totalling the number of buyers and multiplying them the ratio of buyer to seller agents.

The subprocess is illustrated in Figure 4.3.

However, a strong assumption was made that the number of sellers are constant per quarter. The total number of buyer agents to be generated are assumed to be proportional the number of seller listings:

$$N_{buyers} = R_{buyers} \cdot N_{sellers} \tag{4.3}$$

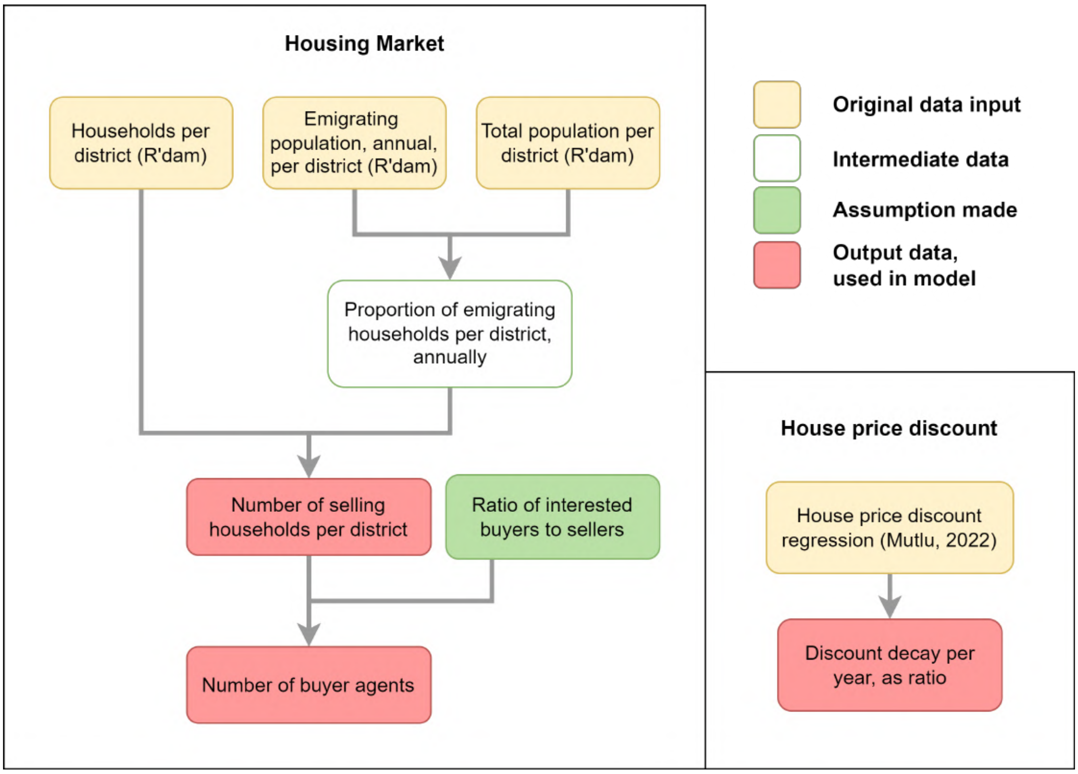


Figure 4.3: Flow diagram depicting the combined operations done for the generation of buyers and sellers at initialisation, from the data processing stage to its usage in the model

where R_{buyers} represent the buyer-seller ratio, and N represents number of entities.

Additionally, no mechanism was included such that recently purchased houses are restricted from going on sale in the next timestep.

4.4. Model Simulation

The stylised housing market is designed with simple heuristics governing agent-level behaviour, due to the current degree of uncertainty of agent-level behaviour in housing markets. It is described in two components: the buyer agents and the housing market model environment. A sequence diagram of actions conducted every timestep is shown in Figure 4.4, with detailed flow diagrams (Figure 4.5) describing key operations.

A simulated timestep is briefly described as follows:

1. The housing market environment randomly selects which houses would go on sale
2. Buyers choose a listing from the available sellers
3. Buyers appraise the price of the house, to see if the house is discounted from prior flood exposure
4. Buyers submit a bid, either at an advised price if they were first, or incrementing on the current bid
5. The housing market handles the transaction formalities, choosing the winning bid and updating the house prices

Buyer Behaviour

A prospective buyer's logic follows three main phases:

1. house listing search
2. house price appraisal
3. bidding

House listing search

Buyer agents are offered a random choice of all available sellers in the current timestep , weighted by attractiveness of the sellers' district location. If districts contain flood-damaged houses, the corresponding district suffers a penalty to its attraction coefficient, thus giving a relative advantage to unflooded districts; without flood-discounted houses, the attractiveness coefficient of all districts are equal. This abstraction aims to represent an intuitive preference for homebuyers: homebuyers at this point are aware that some districts were flooded, and would prefer to avoid searching there.

For simplicity, all properties are priced at a ratio of 1.0 (or 100%) and not in explicit prices. Subsequently, agents do not factor the price of the properties in their search.

House price appraisal

After selecting a house listing, the buyer checks if the property currently has a price discount from being flooded previously. If the property is discounted, the buyer will apply a price discount to its bid. Buyers do not have the possibility of balking on the house choice, and will always proceed with the bidding.

Bidding

Buyer agents then submit their bids to the listing. The bidding procedure is a simplistic design, with no negotiation, balking, or hedonic pricing:

1. If the buyer is first in the bidding queue, they will bid 96% of the list price. The list price is the current home value of the property, but if the property is flood-discounted the buyer will apply a discount on top of the list price. The initial value of 96% was taken as a rule-of-thumb from Filatova (2015), and can be modified in the model.
2. If the buyer is not the first in the bidding queue, they will submit a bid increased by 1%. Subsequent buyers would increment the bid higher by a consistent 1% per buyer. This value is an assumption made based on the bidding tendencies in Filatova (2015), and can be modified in the model.

The logic is described in the following equation:

$$P_{bid} = \begin{cases} P_0 \cdot \mu_{start}(1 - R_{discount}), & \text{if } N = 1 \\ P_{current} + \mu_{increment}, & \text{otherwise} \end{cases} \tag{4.4}$$

Where P_0 is the list price, $R_{discount}$ is the flood discount of the house (if applicable), and $P_{current}$ is the current winning bid of the queue; μ_{start} and $\mu_{increment}$ refer to the initial bid fraction (of the list price) and the bid increment per bidder respectively. The bidding procedure can be described as a "last-bidder wins" mechanism; there is no negotiation between the potential buyers and sellers, and the model assumes the seller always accepts the highest price in the bidding pool.

4.4.1. Housing market environment

This section describes the makeup of the housing market environment, the data inputs taken, and the operations done at the simulated timesteps. In ABM terms, the housing market environment has no overt decision-making capability; it only serves to generate sellers from the available stock of houses, records and updates the state of the model after the housing market transactions are complete.

The housing market conducts the following operations:

1. Generation of seller listings and buyer agents
2. House price discount from damage, and decay over time
3. District attraction determination
4. Price updating

Generation of seller listings and buyer agents

At initialisation (before the simulation), the housing market calculates the number of seller listings to be created per timestep, and subsequently the number of buyer agents to be generated per timestep, based on the total amount of sellers. At every timestep, the housing market would

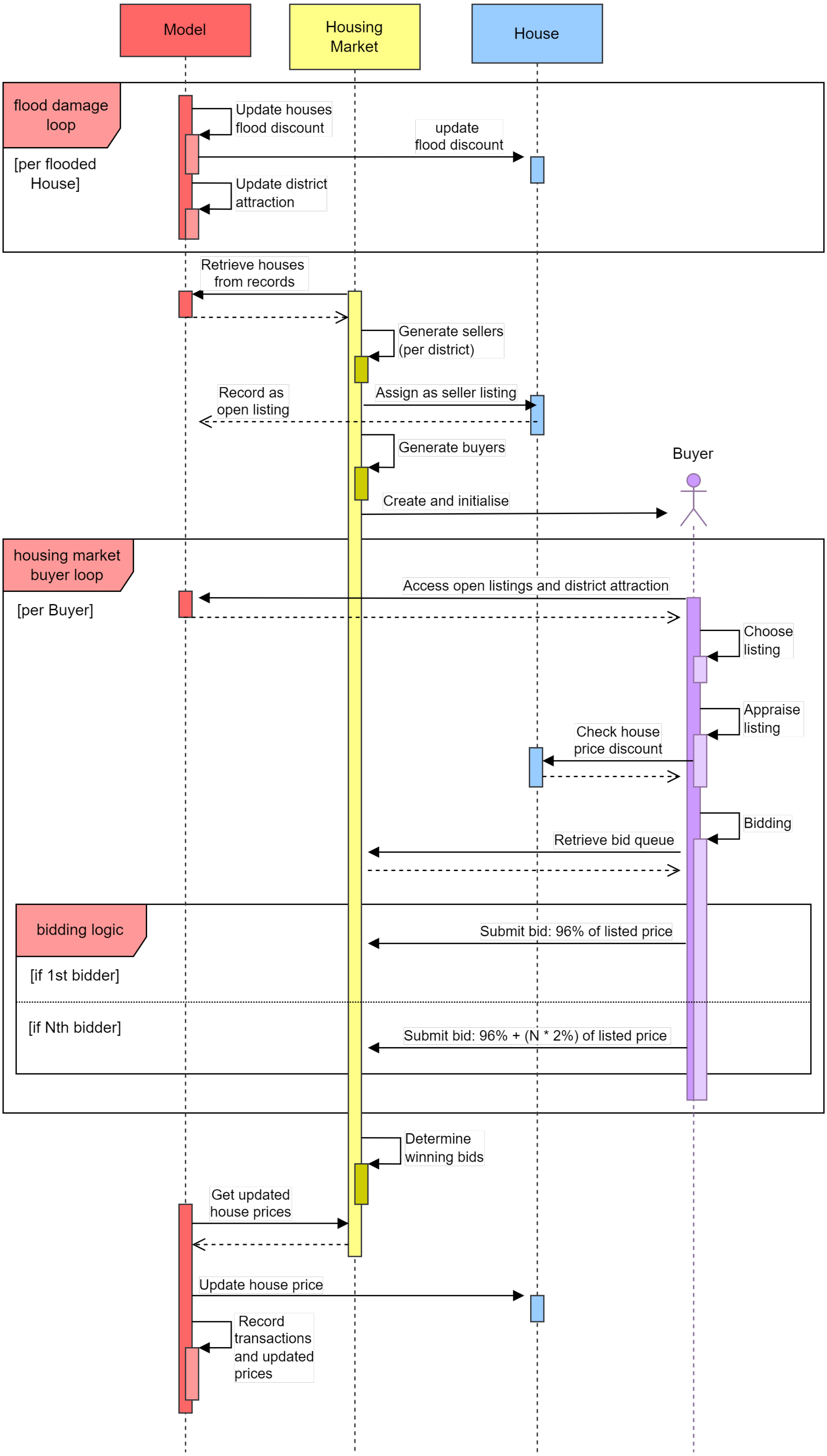


Figure 4.4: Sequence diagram of the actions conducted in a timestep in the ABM. The column of lines represent separate model entities, and the diagram describes the sequential interactions between these entities, read from top to bottom. First, in the *flood damage loop* block, the model updates the flood discounts for houses and the district attraction. Next, the housing market generates the housing market for that timestep, and creates all Buyer agents. Each Buyer agent undergo the *housing market buyer loop* by choosing a house, appraising its price, and bidding on the house. After the block, the housing market determines the winning bids and passes the transactions details to be recorded by the model.

randomly choose sellers entities, and create a pool of buyer agents. However, no mechanism was included such that recently purchased houses are restricted from going on sale in the next timestep, so it is possible that houses may be repeatedly brought on sale in short time.

House price discount from damage, and decay over time

When a flood event occurs, a portion of houses are damaged according to their location, as assigned in the model initialisation. These houses suffer a price discount, which causes buyer agents to submit lower bids. The housing market environment then calculates the associated starting price discount per damaged house. The price discounts $discount_{house}$ are applied as follows:

$$discount_{house} = D_{house} \cdot R_{damagediscount} \tag{4.5}$$

where D_{house} is the damage level per house from the flooding, and $R_{damagediscount}$ is the damage-discount ratio (set as 1%).

In subsequent timesteps after the flood, discounted houses start reducing their price discount, according to a modified regression curve derived from Mutlu et al. (2022). This represents the amnesiac aspect of the housing market, as the flood experience becomes forgotten. The discounts slowly reduce to 80% of the initial discount just before 5 years, and then reduce more aggressively, disappearing after 12 years or when the discount is lower than 0.1%, whichever comes first. A flow chart of the flood discount determination logic is shown in Figure 4.5, on the top right.

Price updating

In the model simulation, the housing market is responsible for collecting the bids for the timestep, and update the values of the houses from the transactions. The updating consists of two modes:

1. For normal bids, the new house value is multiplied with the old house value (default).
2. For bids with discounted houses, the new house value replaces the old house value, until the discount expires

The difference in updating methods was to ensure that the discounted houses were not continuously reduced in value until they become very low numbers. However, this creates a lag effect, as unflooded houses tend to increase in price over time, while discounted houses essentially start later after the discounts have ended.

District attraction determination

At every timestep, the housing market environment updates the district attraction, depending on the ratio of number of discounted houses over the number of total homes in the district:

$$A_{district} = 1 - \frac{N_{discounted,district}}{N_{total,district}} \tag{4.6}$$

When more discounted houses become undiscounted, the attraction coefficient of the district

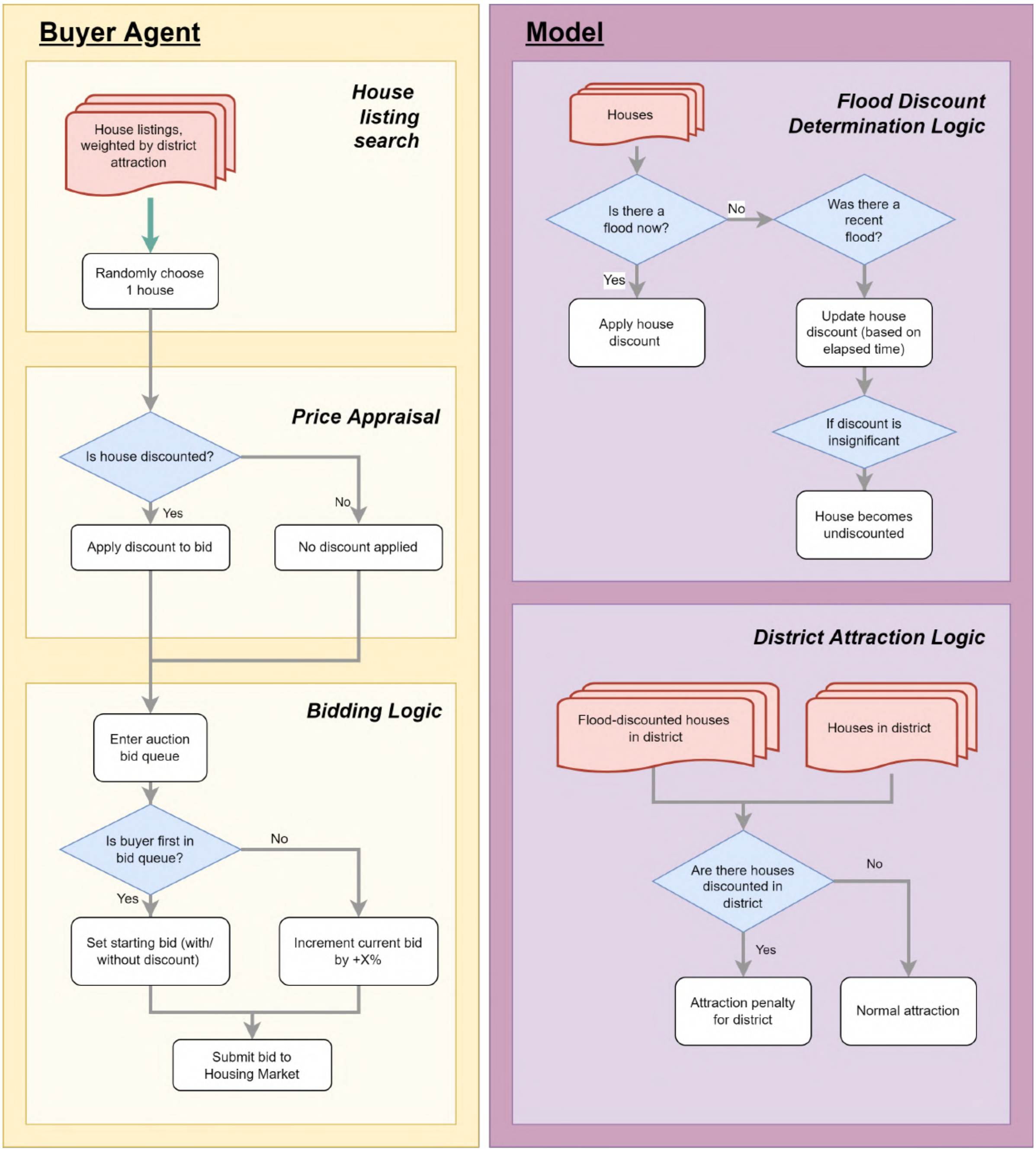


Figure 4.5: Detailed flow diagrams of operations done by buyer agents (left, yellow) within a timestep, and the model environment (right, yellow)

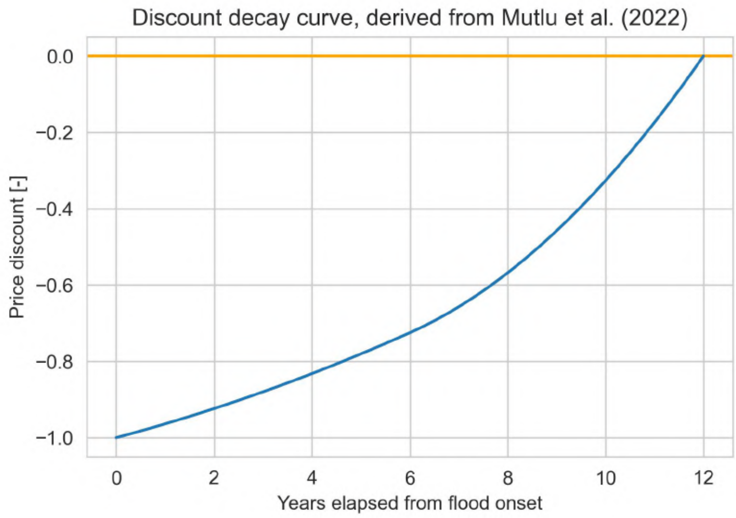


Figure 3.8: Discount decay curve, shown again. It describes the ratio of initial discount over time, with the discounted property reducing in discount until it reaches 0 at 12 years elapsed

increases, and thus all houses within that district become more attractive to potential buyer agents. The logical flowchart is depicted on the "District Attraction Logic" block in Figure 4.5.

4.5. Experiment design

In the model, the price is influenced by the number of bidders and the current discount of the house, if applicable. The research focus is to analyse the price trends in the Rotterdam housing market shocked by flooding. For the study, three categories of experiments are conducted:

1. Control scenario with no flooding. This serves as as comparison benchmark for the other scenarios.
2. Single flooding, with varied scenarios. This is primarily to investigate the effect of different flood scenarios on housing market dynamics.
3. Multiple flooding (2 flood events) , with varied scenarios and varied intervals between the first and second flood. This is to investigate the effect of different flood intervals on housing market dynamics, and to observe if any model artifacts emerge from this arrangement.

To distinguish the different categories of houses, they were sorted by the following rules:

- Houses in districts without floods are considered "flood-safe" (for that simulation)
- Houses that were flooded in the simulation are considered "flooded".
- Houses that were not flooded, but were located in flooded districts are considered "close proximity".

The experiment setups are summarised in Table 4.1, while the constant inputs are shown in Table 4.2.

Experimental setup of the model

Experiment	Varied parameters	Flood timing(s)	Iterations	Variants
Control	N.A.	N.A.	40	40
1 flood	flood scenarios (6)	t = 0	40	240
2 floods	permutations of flood scenarios (6x6), flood interval between flood events (6)	t1 = 0, t2 = [1,2,4,6,8,10]	1	216

Table 4.1: Summary of the experimental setup of the model, including the varied parameters and number of experiments.

Constants

Model inputs	Value(s)
Number of houses in model	5000
Ratio of buyer agents to seller agents	7: 1
Random seed	1
Attraction weight per district	100
Discount-damage rate	1 (1% per 1% damage)
Minimum bid	96 %
Bid increment	1%
Number of houses per district	2020 statistics (Section 3.4)
Depth-damage function	Structural damage curve, residences (Slager & Wagenaar, 2017)
Emigrating fraction per year	2020 statistics (Section 3.4)

Table 4.2: Table listing the constants into all experiments. The bottom 3 entries in yellow refer to empirical inputs.

For all expreriments, the models are simulated for a total of 26 years. This is because the largest flood interval is 10 years from the start of the simulation; an added 16 years is simulated to capture the effect of the discount decay, which has a theoretical maximum of 12 years.

The multiple flooding scenarios consist of a first flood at the start of the model (t=0), and a second flood after an interval; this interval is varied at 1, 2, 4, 6, 8, and 10 years. All experiments are run with a target population of 5000 households, corresponding to 500 agents per timestep/quarter, or 2000 agents per year.

4.5.1. Experiment metrics

From the model, the house transaction entries are recorded for plotting, which contains the following key information:

- transaction prices, the percentage the list price that won the bid
- experiment specifics (flood scenario(s), flood timing)
- house category (flood safe/ close proximity/flooded)

The experiments are sorted according to the categories listed in this section (single/multiple) and analysed with some exploratory data analysis methods. Chapter 5 shows the output of the results, for both experiment categories.

5

Results

This section presents the results from the model experiments, where the single flooding and multiple flooding experiments are compared against the control, in terms of the *transaction price trends* over time and the *price indices* of the houses. Here, the transaction price refers to the "percentage of the listed house price of the winning bid", while the price index refers to the "resultant house price after multiple transactions"[1].

The methodology used in this analysis relies on the difference-in-differences (DID) method, which finds the difference between the experiments and the control trends, and presents the deviation of the experiments' trends from the control.

1. Firstly, the control outputs are presented as a depiction of the baseline output from the ABM. Here, the DID method is also elaborated with more detail.
2. Next, the results for the single flooding experiments are shown across different flood scenarios and categories of houses (flooded, close proximity, and safe).
3. The results for the multiple flooding experiments are shown across different flood timing intervals and categories of houses.
4. Lastly, the model design is critiqued with respect to the presented results, specifically on the conceptual design of the model and also individual model elements.

The results are presented with respect to the model characterisation, describing how the output characteristics are affected by model components.

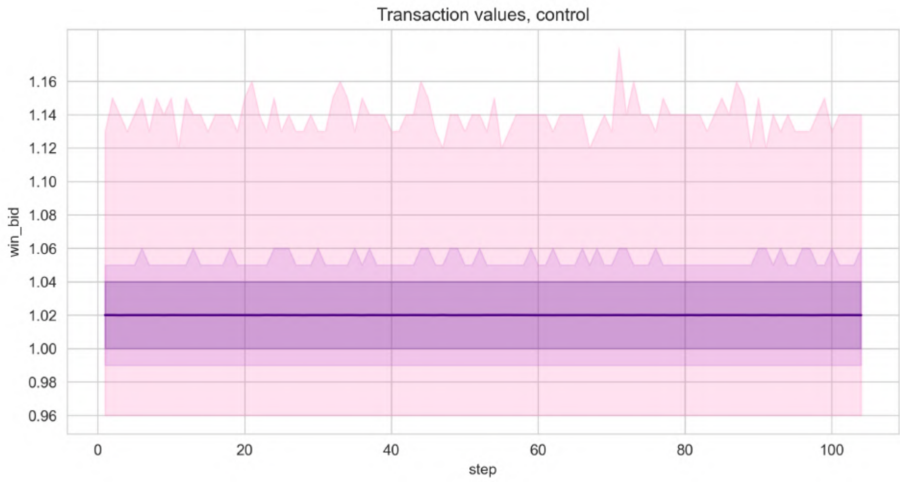


Figure 5.1: Transaction prices of the control dataset, with bands of the full range (0th-100th percentile), the interdecile range (10th-90th percentile), and the interquartile range (25th - 75th percentile)). Here, it can be seen that most winning bids fall around 102% of the list price. Therefore, 102% was used as a comparison baseline for comparing the transaction prices in the flooding scenarios.

5.1. Control outputs and DID method

The plotted outputs for the transaction prices are depicted in Figure 5.1. From the transaction price trends, the control output yields a consistent mean of 102% of the list price. This is due to the model not being perturbed by any flood events, thus not leading to a shift in attractiveness from flooded districts to flood-safe districts. However, the upper bound of the bids may occasionally reach up to 112% of the price and beyond. Given that the house search process is stochastic, where buyer agents choose any house from a weighted distribution instead of by hedonic utility; this means that agents might all choose to bid on a house, even though the bid queue for the house contains numerous other bidders.

As the transaction price mean is steady, the DID method is rudimentally done by subtracting the value of 102% from all the transaction data. As the units of measurement are in percentages, the deviations observed would be in percentage points from the expected mean.

As for the price indices, the results for the combined 40 iterations are plotted on a fitted regression line in Figure 5.2. The regression used was an linear ordinary least squares (OLS) method, which seeks to find a linear function describing the mean of the results. The given regression line is

$$y = 0.00364x + 1.01856 \tag{5.1}$$

where x is the number of years elapsed, and y is the expected price index for the year.

Mechanistically, the price index trend is based on the transaction prices, as the value of the house is multiplied with the transaction price per transaction. Given that on average most

[1]Transaction price can be understood as how much more/less a buyer paid for a listing, while the price index is the resultant appreciation/depreciation in value after multiple transactions. For the latter, if a house was consecutively bought at above the listed price, the price index of the house would increase gradually over consecutive transactions.

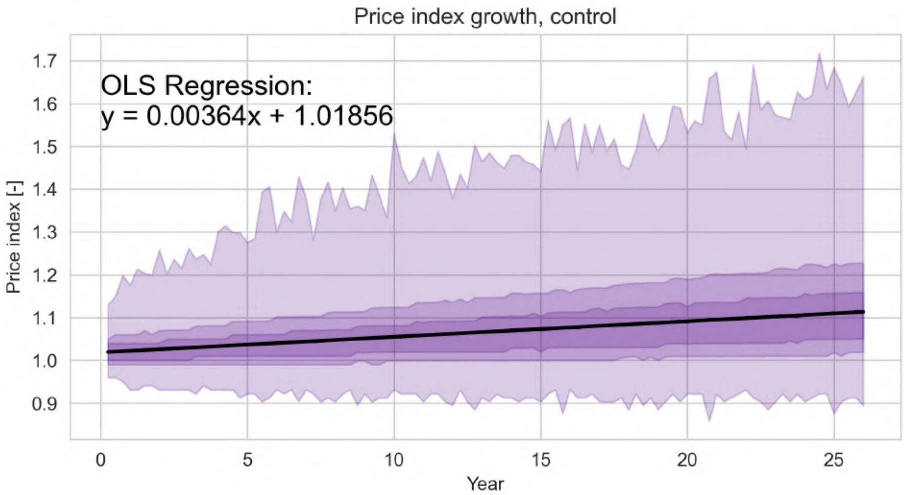


Figure 5.2: Price indices of the control dataset with fitted linear regression line, with bands of the full range, the interdecile range (10th-90th percentiles), and the interquartile range (25th - 75th percentiles)). The ordinary least squares regression suggests that on average the house prices grow at a rate of about 2% every 5-6 years, it is subsequently used as a comparison baseline for comparing the price indices in the flood scenarios.

transactions are conducted at 102% of the listed price (i.e. 2% above the listed price), the price index would increase gradually. However, given the wide distribution of transaction prices from stochasticity (ranging from 96% to up to 117%), the distribution of price indices enlarges over time, with some properties growing to 70% more than the original list price at the beginning.

In further sections, Equation 5.1 is used as the control line to compare the price indices of the single and multiple flooding scenarios. Again, the units will be in percentages, and observed deviations would be in percentage points from the expected value.

5.2. Single flooding

5.2.1. Transaction prices

Flood scenarios

Flood Scenario	Mean flood severity [m]	Flood coverage [ha]
maashaven34.6_4e5	0.226	367
boerengatsluis_1e6	0.563	584
maashaven36.1_4e5	0.584	2638
nieuwe_maas_4e5	1.043	3876
parksluizen_1e6	1.096	2459
capelle_1e6	1.338	1462

Table 5.1: A reiteration of the flood scenarios shown in the Model Data chapter, section 3.1. The subsequent figures, Figures 5.3 and 5.6 are sorted according to mean flood severity.

Figures 5.3 and 5.4 depict the same transaction price graphs sorted based on the mean flood severity (see Table 5.1), but at different zoom levels. In general, the transaction prices of the

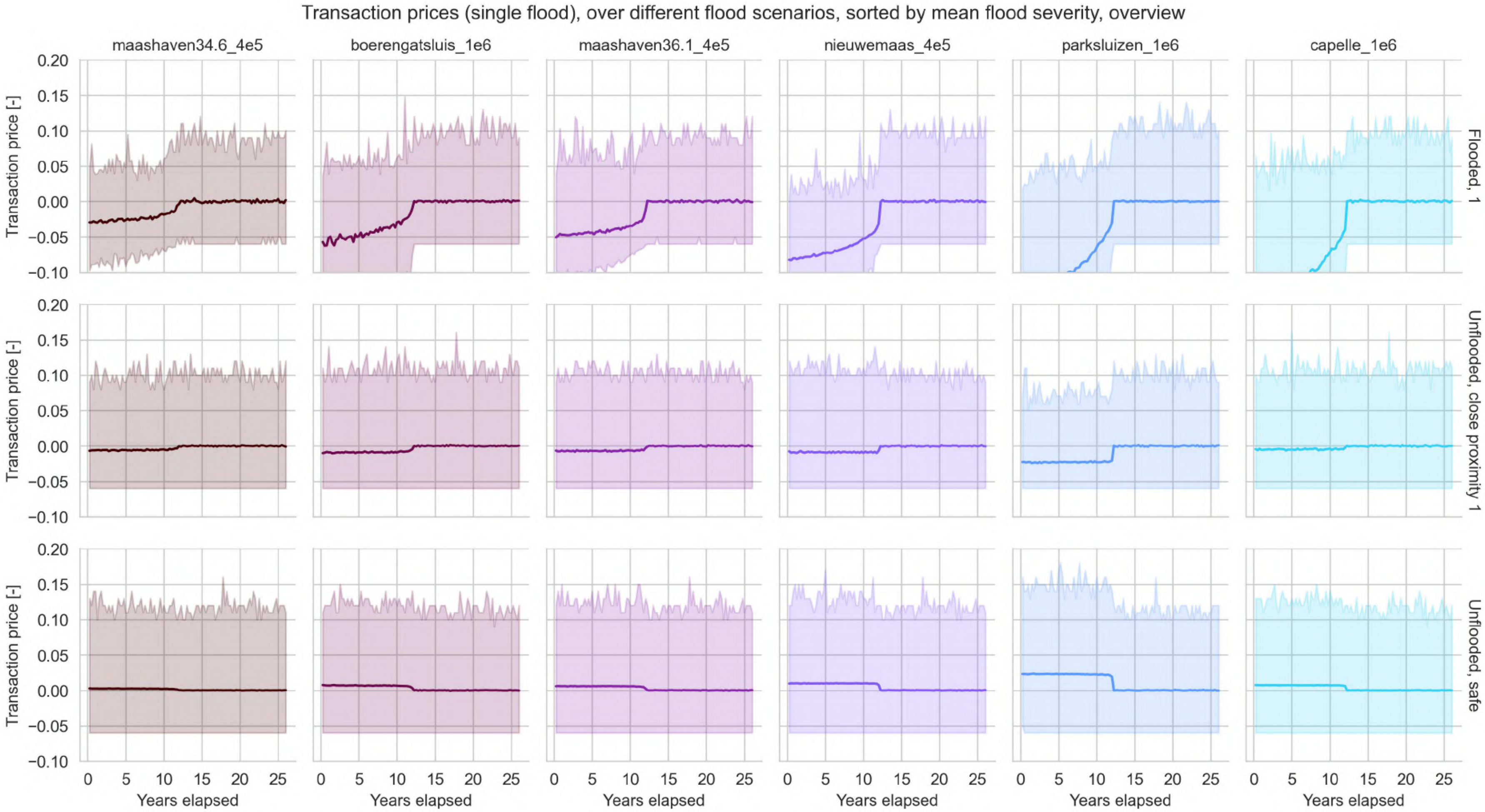


Figure 5.3: The price transaction trends for single flood experiments, where the columns refer to flood scenarios (rightwards = increasing mean severity) and the rows refer to the house category. A companion image, Figure 5.4 shows a zoomed-in view of the mean line. Here, the Flooded category (row 1) exhibits a consistent effect: increasing severity (mean flood depth) leads to more severe price discounts. However, increasing flooding severity cannot solely explain the increase in flood discounts/premiums seen in the close proximity and safe properties (2nd and 3rd rows respectively).

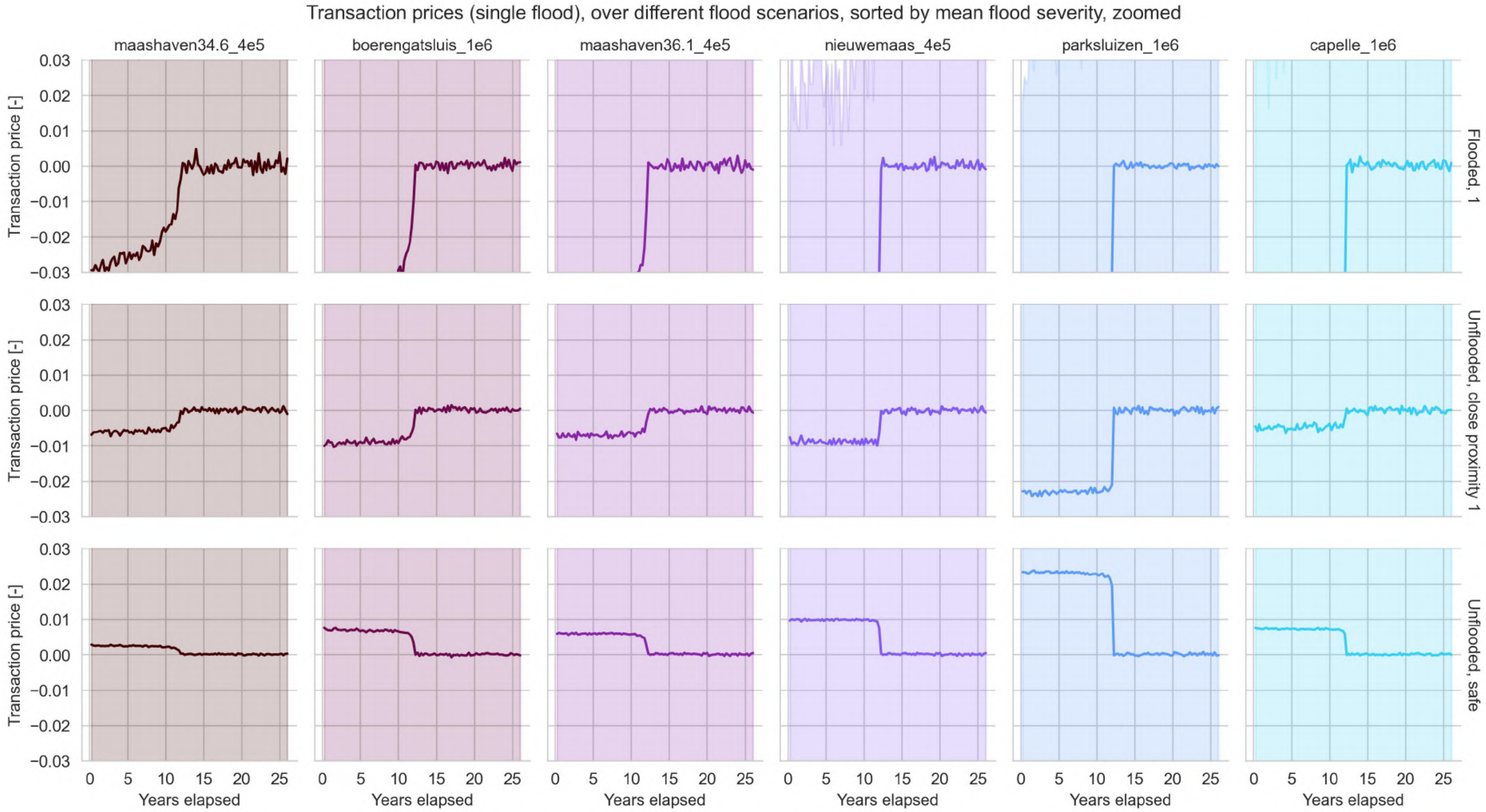


Figure 5.4: The price transaction trends for single flood experiments, where the columns refer to flood scenarios (rightwards = increasing mean severity) and the rows refer to the house category. This diagram focuses on the mean price line. It can be seen in the close proximity (2nd row) and unflooded (3rd row) categories that an increasing mean flood severity does not reliably lead to increasing flood discounts/premiums, even though it does increase the price discounts of flooded properties.

flooded properties (top row) are significantly lower than the control, and would only return to normal trading prices within about 12 years, which is according to the discount decay function.

In the overview figure (Figure 5.3), the discount decay for flooded houses (top row) follows the discount decay function, but the Close Proximity and Unflooded houses experience a step change in transaction price, where the transaction price abruptly returns to normal. This can be attributed to the model's district attraction mechanism, where a district's attraction is based on the ratio of discounted houses to total houses. The strict definition of discounted houses[2] means that most houses would only be undiscounted after 12 years.

Interestingly, the close proximity properties (middle row) suffer a price discount of up to 2% compared to the control, meaning that the mean is traded close to the list price (100%). This is because structurally, the district receives an attractiveness penalty, thus reducing the inflow of potential buyers, yet the prices were not guided by the flood discounts. Since the house search process is stochastic instead of hedonic, it likely underestimates the attraction penalty for flooded and unflooded houses in flooded districts, and thus underestimate the discount in close proximity homes because of the bounded minimum of 96% of the list price.

The prices of unflooded properties (bottom row) experience a minor price premium, with a mean of up to 2% (or 104% of the list price). This suggests a mild degree of flocking behaviour from flooded districts to unflooded districts, on average of two extra bidders in the bidding process (since one extra bidder contributes to +1% of the price). The relatively-modest price increase could also be attributed to the stochasticity of the house search process, where buyer agents simply choose any house from a weighted choice, instead of avoiding house listings with many bidders. Additionally, the model lacks some other aspects of bounded rationality, such as herding behaviour or panic buying. Therefore, it is likely that the price premium is underestimated in terms of short-term price peaks.

The two figures were arranged to identify whether flood severity or flood coverage better explains the price trends of the houses. The effect of the mean flood severity on the graph is more pronounced in the top row of Figure 5.3, where the increasing severity leads to increasing discounts. In both graphs, while an increase in flood severity or flood coverage reliably increases the discount of flooded houses, the effect on the transactions on the close proximity houses and unflooded houses is more inconsistent. With the current visual-based analysis, it is inconclusive whether mean flood severity or total flood coverage can reliably explain the price discounts or premiums.

5.2.2. Price indices

Figure 5.5 and 5.6 depict the same price indices trends graphs sorted based on mean flood severity, but at different zoom levels. The columns represent increasing mean flood severity moving rightwards, and the rows represent the house categories. As a guide to interpreting the

[2] Specifically, houses either are considered undiscounted when they've reached 12 years or their current discount is lower than 0.1%, whichever comes first.

Figure 5.5: The price indices trends for single flood experiments, where the columns refer to flood scenarios (rightwards = increasing mean severity) and the rows refer to the house category. This figure shows the mean house price index line and the distribution around the line (full range, 0th-100th percentiles), while a companion image, Figure 5.6 shows a zoomed-in view of the mean line. From left to right, it is observed that sorting the outputs via mean flood severity does not reliably explain the price premiums/discounts, for example in the scenario “parksluizen_1e6” (2nd column from right), the effect of the flooding is stronger than the “capelle_1e6” scenario (rightmost column).

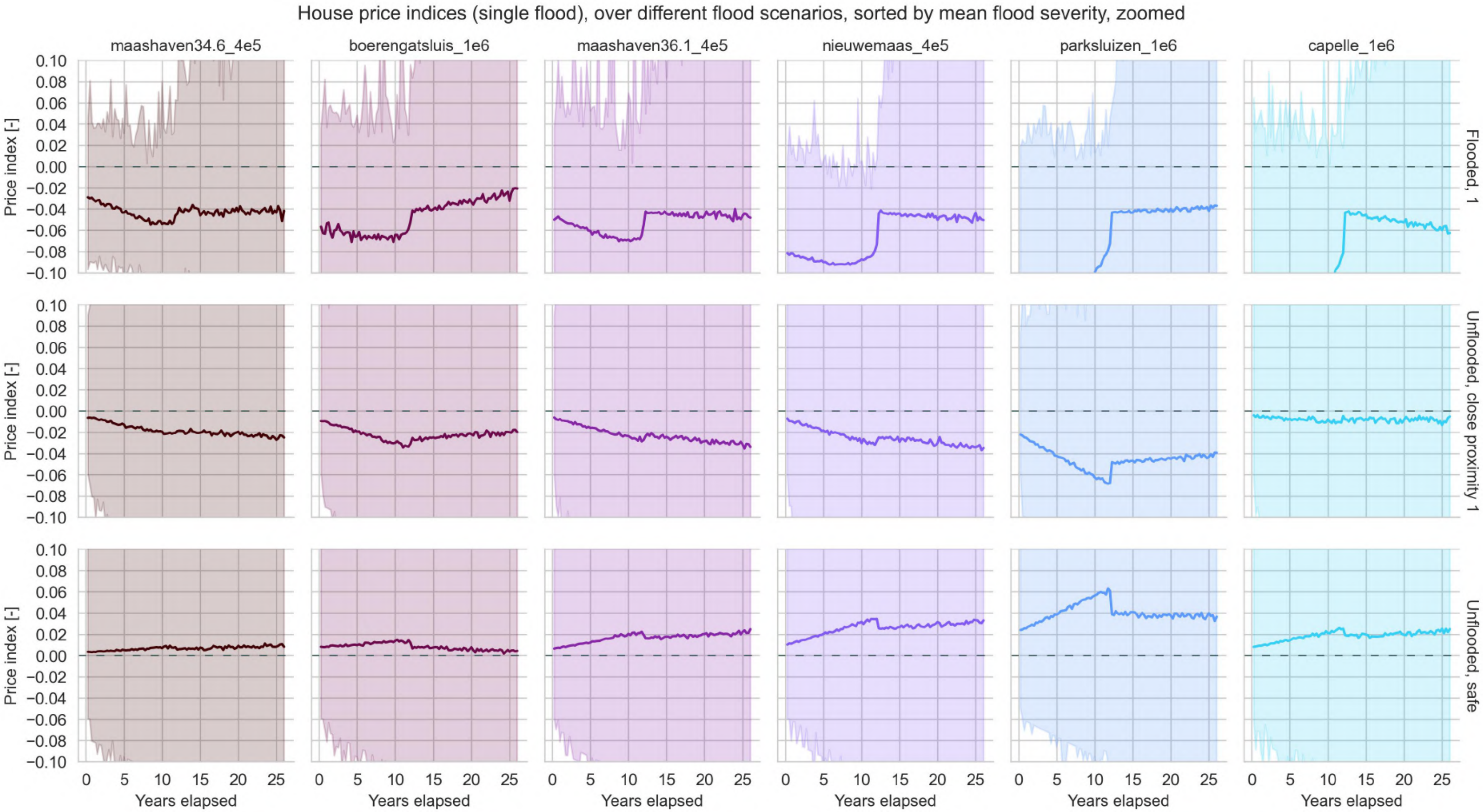


Figure 5.6: The price indices trends for single flood experiments, where the columns refer to flood scenarios (rightwards = increasing mean severity) and the rows refer to the house category. This diagram focuses on the mean price line. It can be seen in the close proximity (2nd row) and unflooded (3rd row) categories that an increasing mean flood severity does not reliably lead to increasing flood discounts/premiums. Additionally, the graph also shows the inconsistent price trajectories after the end of the flood discounts after 12 years, with some houses continuing to depreciate/appreciate instead of staying stagnant. This may be attributed to the innate rate of transactions in certain districts from the usage of empirical emigration statistics, elaborated in the subsequent section on spatial distribution.

price indices graphs, the transaction price graphs (Figure 5.3 and 5.4) represent the gradient of the mean price indices, and a transaction price DID of 0 leads to a constant gradient in the price indices graph. This section is divided per house category (flooded, close proximity and flood-safe), talking about general trends for each.

Flooded

This category describes houses that were flooded at the start of the simulations, and thus experience a flood damage price discount, similar to the transaction price graphs. In Figures 5.5 and 5.6, they are drawn on the first row.

Different flood scenarios lead to varying rates of price discounts, with generally the right side of the diagrams having more severe discounts (i.e. ”nieuwemaas_4e5”, ”parksluizen_1e6”, and ”capelle_1e6”). However, mean flood severity does not reliably explain the increasing discounts or premiums, especially for the close proximity and unflooded properties.

Notably, even though the worst of the flood discounts are seen at the start of the graphs in the transaction graphs (see Figure 5.5, 1st row), the worst of the price indices for flooded properties are close to the 10-year mark. This is a model artifact of the price discount mechanism’s interaction with the house price indices, that leads to a higher penalty for flood discounts that happen later in the simulation; a description of this behaviour is elaborated in the last section of this chapter (section 5.5.2, page 75), but can also be seen in figures in the Multiple Flooding section for price indices (Figure 5.14 on page 72).

After 12 years, the discounts abruptly reduce, and the house price indices may appreciate, depreciate or stagnate. This is also due to another model artifact as a result of using the empirical emigrating statistics per district. This is described in the subsequent line on ”Discontinuities after 12 years”, and explained in the Spatial Distribution section on page 56.

Close Proximity

This category describes houses that were situated in flooded districts, but were not flooded. Nonetheless, they experience a minor price discount due to their proximity to flooding, thus leading to a reduction in interest from potential homebuyers. In Figures 5.5 and 5.6, they are drawn on the 2nd row.

Generally, in the 12 years while the district is flood-discounted, their price index mean lines diverge away from 0, suggesting an underperformance of these properties compared to the control. The linear reduction of price indices can be attributed to the step-like nature of the flood transaction prices[3], which is in turn a product of the house price discount mechanism. In some cases, the price discounts can be steep and severe, such as in the scenario ”parksluizen_1e6” (2nd column from right), falling up to 6% off the expected trajectory.

After 12 years, the house price indices also may appreciate, depreciate or stagnate,

[3]The mean transaction price line indicates the gradient of the price indices line, if the mean transaction price line is constant, the price indices would have a constant gradient.

which is related to the model artifact from the usage of empirical emigrating statistics per district.

Safe
This category describes houses that were situated in flood-safe districts, and are not flooded. In Figures 5.5 and 5.6, they are drawn on the 3rd row.

The graphs are almost vertically-mirrored with their counterparts in the Close Proximity graphs, with their price trajectories better than the control trend. This is due to the perceived safety of these districts, leading to more potential buyers bidding on these properties; as a result, they experience a price premium over other properties in flooded districts. However, after 12 years, the price trajectory is abruptly reduced, and the price indices either appreciate, depreciate or stagnate from that point onwards; again, this is described in the next line on the discontinuities after 12 years.

Discontinuities after 12 years
In the focused graphs(Figure 5.6), after 12 years there's a sharp discontinuity, followed by varying trajectories of growth, stagnation or reduction, which does not match the transactions diagrams in Figure 5.4, as they stayed constant and in line with the control transaction price. Specifically speaking, if the transaction prices are in line with the control line after the flood, the price indices curve should be parallel to the control line, representing similar price growth.

The sharp discontinuities could be attributed to the design of the price growth mechanism, and this presentation of the output data. For the former, house prices in the model are updated only if they were sold on the housing markets, where their new prices are a product of the current list price and the transaction price; unsold houses are not updated until they themselves enter the housing market. Secondly, the graphed data is based on the transactional data, specifically only for properties sold in that timestep, and not the entire population of houses. The sudden change in discounts (seen in Figures 5.6) lead to a sudden boost in property prices for flooded and close-proximity properties being sold in that timestep, thus creating this spike in the price indices. This phenomenon is elaborated further with respect to model design elements in Section 5.5 on page 74.

After the discontinuity, the subsequent varying trajectories of price index growth could be explained by certain districts having a higher rate of emigration and thus a faster rate of price updating, leading to an intrinsic price index increase even while not under flood scenarios. This is further elaborated and illustrated in the subsequent section (Spatial distribution). A further critique on the design of price index growth is offered in the last section of the chapter, in Model Reflection from Results.

Spatial distribution

This subsection focuses on the effect of the flooding on the resultant house prices in different districts. The mean price indices of houses at the end of simulation (hereinafter: ”mean resultant prices”) in all districts are illustrated in maps, with an accompanying distribution plot showing the distribution of the datapoints around the mean price. First, the control outputs are presented as a visual illustration of the model outputs, and serves as a reference for the subsequent plots for different flood scenarios. The price trends of the control is presented in Figure 5.7:

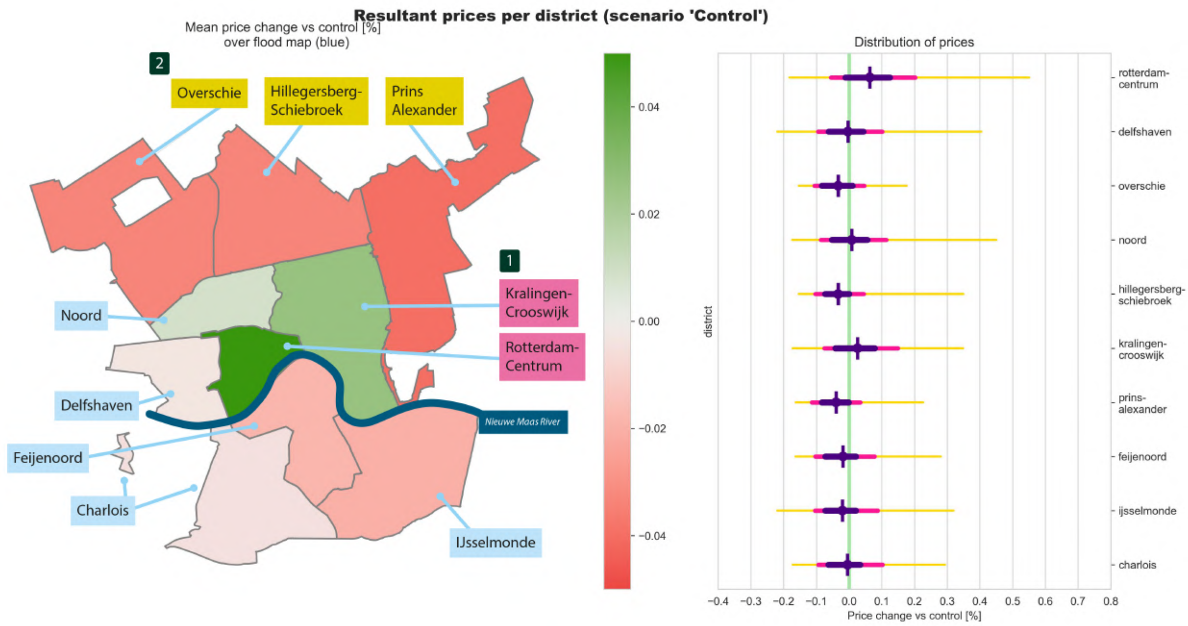


Figure 5.7: The resultant price indices for different districts in the control output, in DID form relative to the aggregated price index growth. The left subplot illustrates the mean price appreciation, while the right shows the distribution of price indices. Notice how districts such as Rotterdam Centrum and Kralingen-Crooswijk experience higher-than-expected price growth (annotation 1), while districts such as Overschie, Hillegersberg-Schiebroek and Prins Alexander experience lower price growth (annotation 2).

The control results show that different districts’ prices appreciate at different rates. This is due to the interaction of the following model elements:

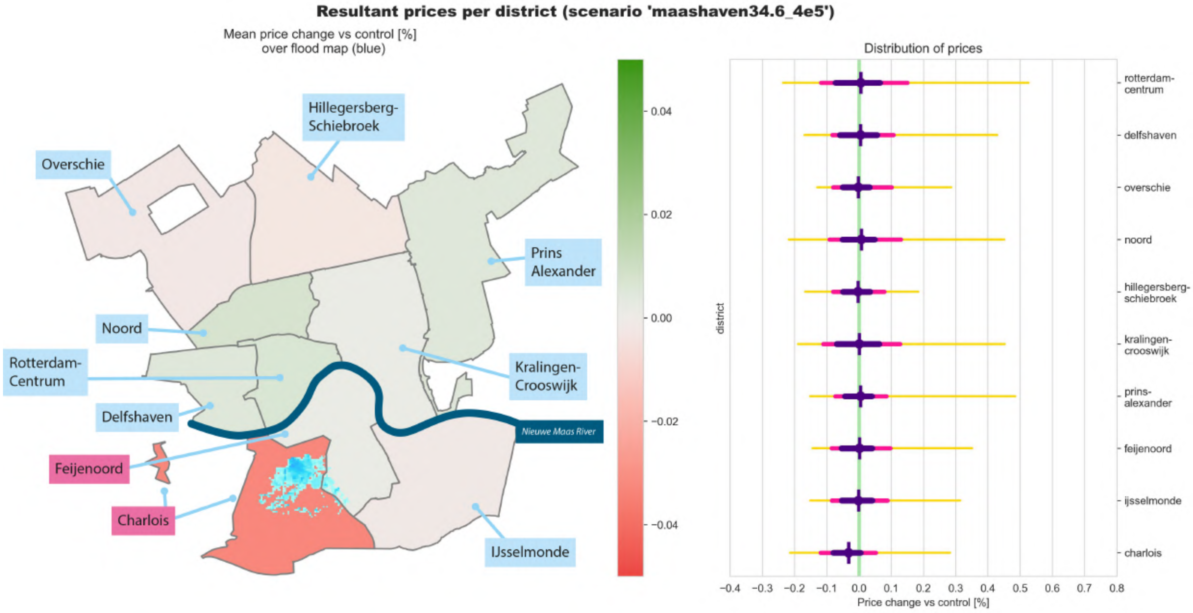
- heterogeneous fractions of emigrating households per district means that certain districts sell more houses per time step. For example, Rotterdam Centrum puts almost 12% of its houses on sale every year, while on the other hand Overschie puts only 4.5% of its houses on sale.
- house prices are updated by multiplying the transaction price, thus meaning a higher rate of transactions in a district leads to a higher price appreciation.

Comparing the ’percentage leaving’ column in Rotterdam Demographics table (Table 5.2) and the districts with the highest price appreciation in Figure 5.7 highlights this correlation. Districts such as Rotterdam Centrum and Kralingen-Crooswijk (annotation 1 in figure) experiences higher price appreciation while also having a higher emigrating fraction, and vice versa for districts such as Prins Alexander, Overschie and Hillegersberg-Schiebroek (annotation 2 in

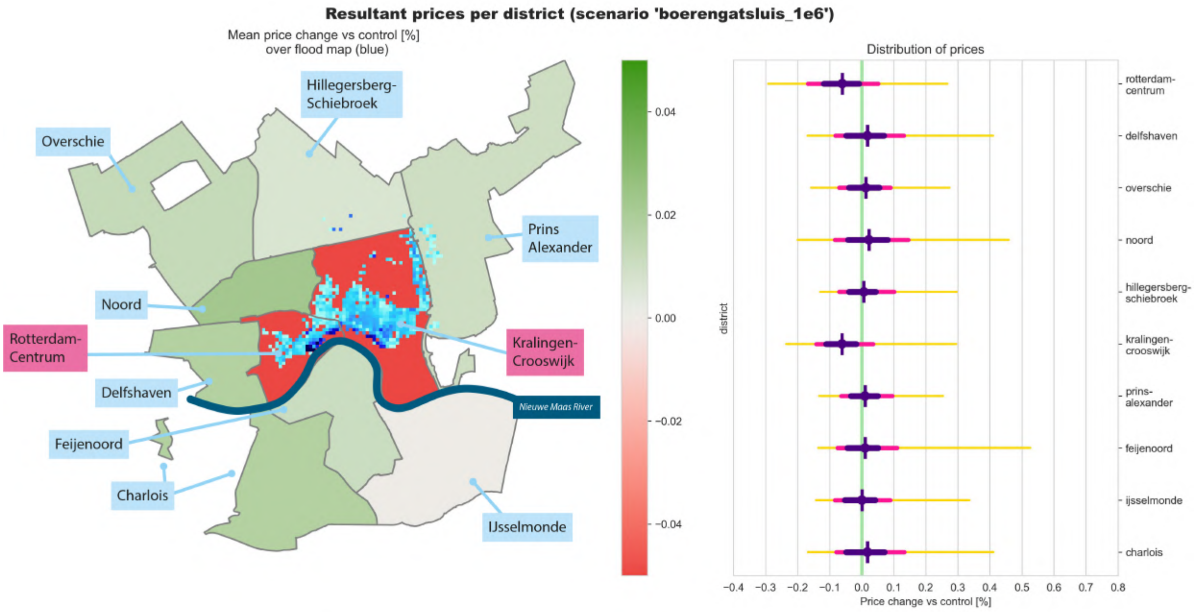
Rotterdam Demographics, per district

Districts	Number of inhabited addresses	Population size	Emigrants per year	Percentage leaving
Rotterdam Centrum	18445	36039	4288	11.9%
Delfshaven	33975	76774	5694	7.4%
Overschie	8276	19201	870	4.5%
Noord	26164	52479	4171	7.9%
Hillegersberg-Schiebroek	19833	44730	2136	4.8%
Kralingen-Crooswijk	26699	54466	5319	9.8%
Prins Alexander	44626	95926	4688	4.9%
Feijenoord	34134	76539	4298	5.6%
IJsselmonde	27615	61340	3966	6.5%
Charlois	32123	69377	5024	7.2%

Table 5.2: District demographics for the districts in Rotterdam, for 2020 (repeated)

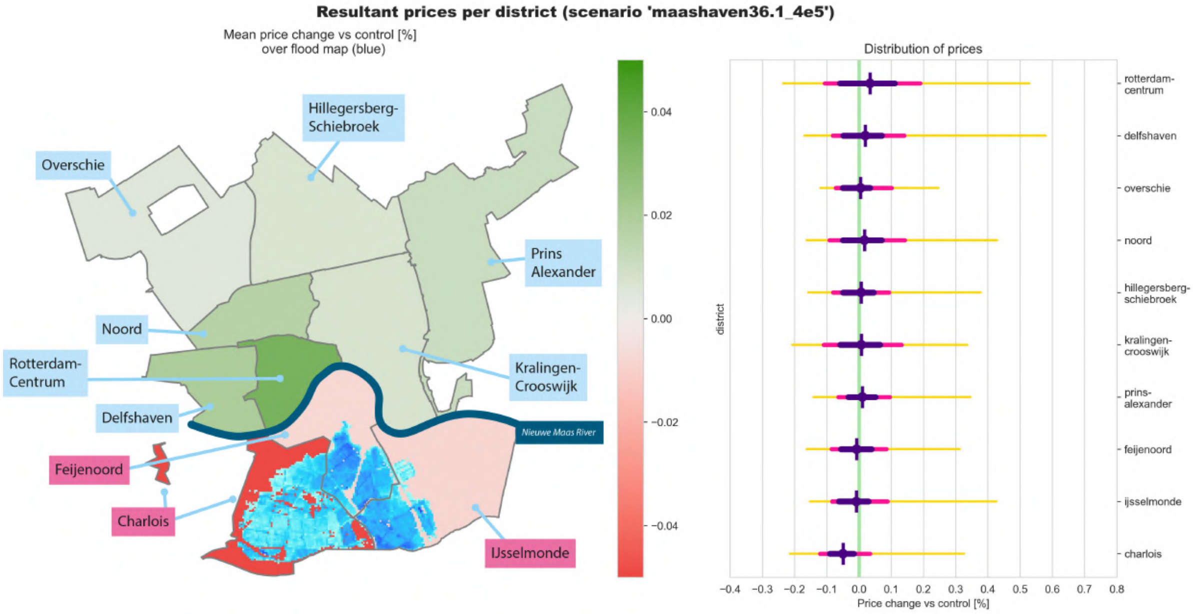


(a) "Maashaven34.6_4e5" scenario.

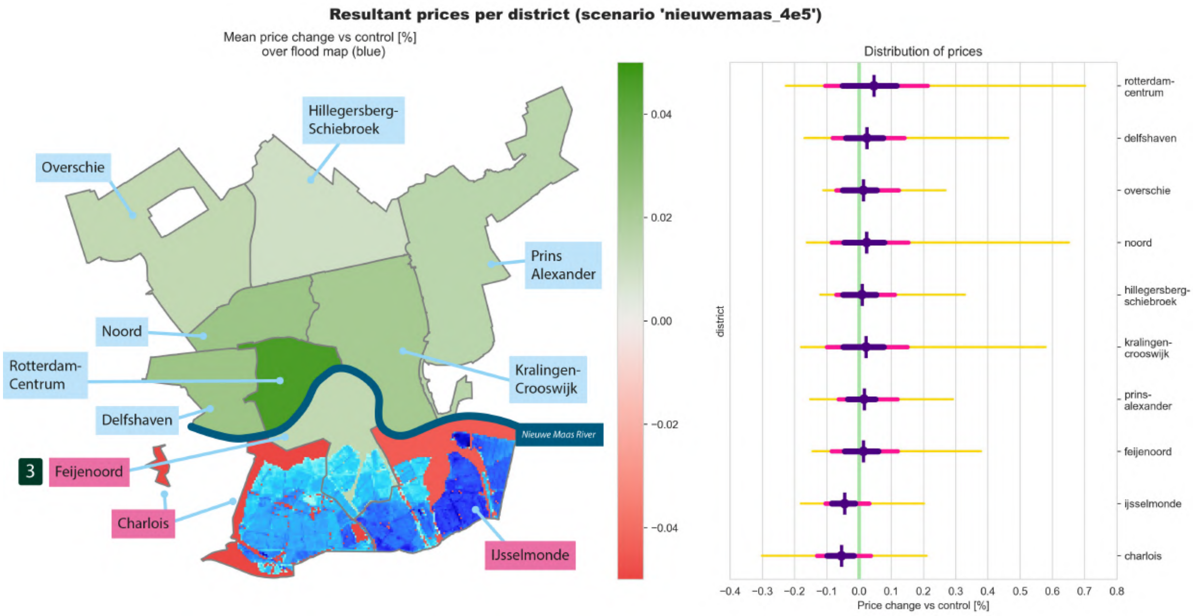


(b) "boerengatsluis_1e6" scenario.

Figure 5.8: Plots of resultant price indices, separated per district. The map on the left indicates the mean price indices per district, with flooded districts annotated in pink, while the right indicates the distribution of prices per district. The maps are ordered in terms of increasing mean flood severity.



(c) "maashaven36.1_4e5" scenario.



(d) "nieuwemaas_4e5" scenario. Note how Feijenoord district is affected by the flood but still has a mildly positive price index.

Figure 5.8: Plots of resultant price indices, separated per district. The map on the left indicates the mean price indices per district, with flooded districts annotated in pink, while the right indicates the distribution of prices per district. The maps are ordered in terms of increasing mean flood severity.

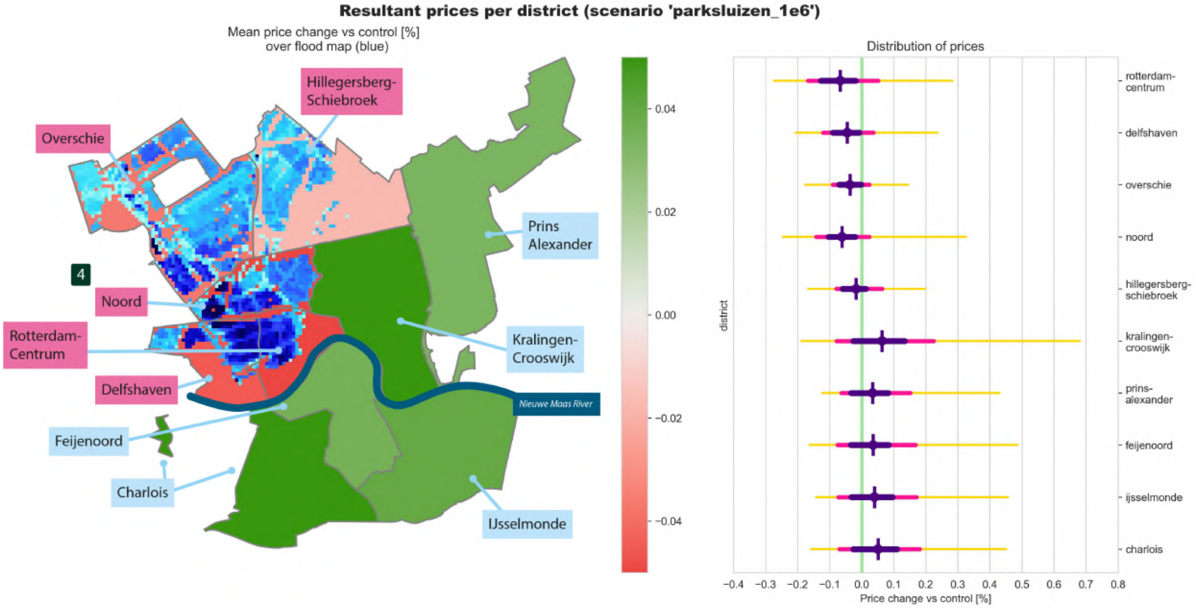
figure).

As a result, the inclusion of heterogeneous emigrating fractions per district leads to distortions in the model behaviour. Recall from Section 3.4 (page 20) that the emigrating fractions per district data is based on the emigrating population, and not the house purchase transaction statistics. Given the goal of comparing flood discounts/premiums across different scenarios, the usage of similar emigrating fractions per district would lead to more consistent results. Subsequently, the mean resultant prices here are used to correct the resultant prices of from flood scenarios. While this correction does not address the fundamental house sales rates across districts, it serves as a useful initial illustration.

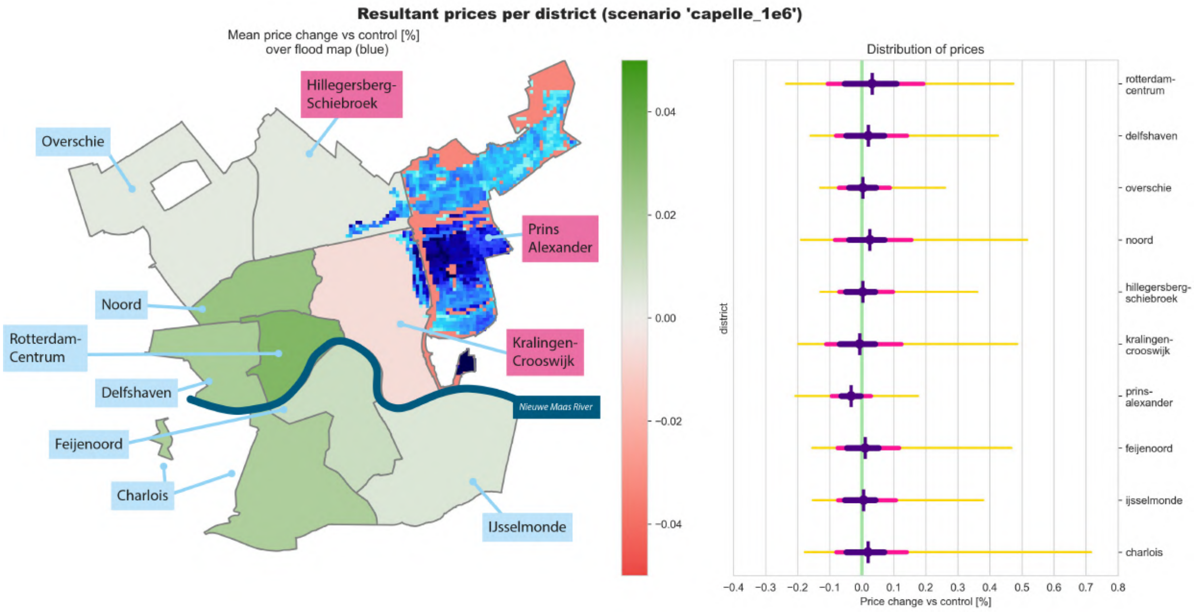
Next, the mean resultant price indices for the flood scenarios are shown in the following map and distribution figures, with extra overlaid flood maps. A general trend can be observed in the figures: a larger flood covering more districts further depresses price growth in flooded districts, but also further inflates price growth in unflooded districts. This is especially clear comparing the scenario “maashaven34.5_4e5”with the other severe flooding scenarios.

However, some interesting observations are present in the individual figures:

1. (Annotation 3 in Figure 5.8d) In the “nieuwemaas_4e5” scenario, the Feijenoord district was flooded but still had a small positive price index for its properties. The
2. (Annotation 4 in Figure 5.8e) In the “parksluizen_1e6” scenario, the severe flooding of more districts and districts with high sales rates (i.e. Rotterdam Centrum) leads to a strong positive premium for other districts in the area. This can be thought of as a large portion of the housing market stock being discounted, hence significantly increasing the attractiveness of houses in other districts. Especially compared to the “capelle_1e6” scenario with a more severe mean flood depth,
3. Across scenarios such as “maashaven36.1_4e5”, “nieuwemaas_4e5” and “capelle_1e6” (Figures 5.8c, 5.8d and 5.8f respectively), the Rotterdam Centrum district generally experiences more growth, even though the district is adjacent to the river. This is again due to the high sales rate of houses in this district, and the lack of agent-level logic in retreating from river-adjacent areas.



(e) ”parksluizen_1e6” scenario. Note that the large amount of flooded districts (especially Rotterdam Centrum) led to a significant price premium of other districts. This can be attributed to districts like Rotterdam Centrum holding an outsized portion of housing stock in the model housing market.



(f) ”capelle_1e6” scenario. Note that while this is the scenario with the deepest mean flood depth, the other districts do not receive as large a price premium as compared to the “parksluizen_1e6” scenario

Figure 5.8: Plots of resultant price indices, separated per district. The map on the left indicates the mean price indices per district, with flooded districts annotated in pink, while the right indicates the distribution of prices per district. The maps are ordered in terms of increasing mean flood severity.

5.3. Multiple flooding

This section focuses on the effect of the time intervals between floods on the housing markets. As two floods will impact the housing market, there are subsequently more house categories, and as such the graphs are split according to unflooded properties and flooded properties. The house categories are defined as follows:

- Flood safe homes.
- Close proximity: 1st flood only, 2nd flood only, or both. Recall that close proximity houses are houses that are situated in flooded districts, but were not flood-damaged.
- Flooded: 1st flood only, 2nd flood only, or both.

Due to the larger set of house categories, this section is split in two: unflooded houses (flood safe and close proximity) and flooded houses. For both subsections, the housing market is described in terms of transaction prices and their result on the house price indices, contrasted with the control outputs via the DID method. In the figures used, the colour scheme will be used consistently throughout the section: magenta for short flood intervals, and lime green for longer flood intervals.

5.3.1. Unflooded houses: close proximity and safe

Transaction price trends

Firstly, the transaction price trends for the unflooded houses are presented in Figure 5.9 on page 63, focusing on the mean transaction prices over time per category. A companion graph, Figure 5.20 is provided at the end of the chapter, as an overview version of this graph showing the distribution of transaction prices. The transaction price trends are sectioned by house category, in the following order from top to bottom:

Close Proximity 1

This category refers to houses that were in close proximity to the 1st flood, but were not affected by the 2nd flood. In Figure 5.9, they are shown on the 1st row.

Initially, houses experience an initial price discount due to the districts' lack of attraction, but after the 2nd flood in another district, their transaction prices immediately return to be on parity with the control (recall it is 102% of the list price). This may be because of the relative competitive disadvantage of the district being nullified by the disattraction of other districts[4]. In larger time intervals (right half of Figure 5.9), the transaction prices are slightly more positive, which can be due to the district being further along its price recovery trajectory, thus meaning the district is slightly more attractive than other flooded districts.

Close Proximity 1+2

This category refers to houses that were in close proximity to both floods (i.e. a flood that hits

[4]As relative weights determine whether buyer agents choose houses in those districts, if all districts are equally unattractive, all districts are hence equally attractive to potential buyers.

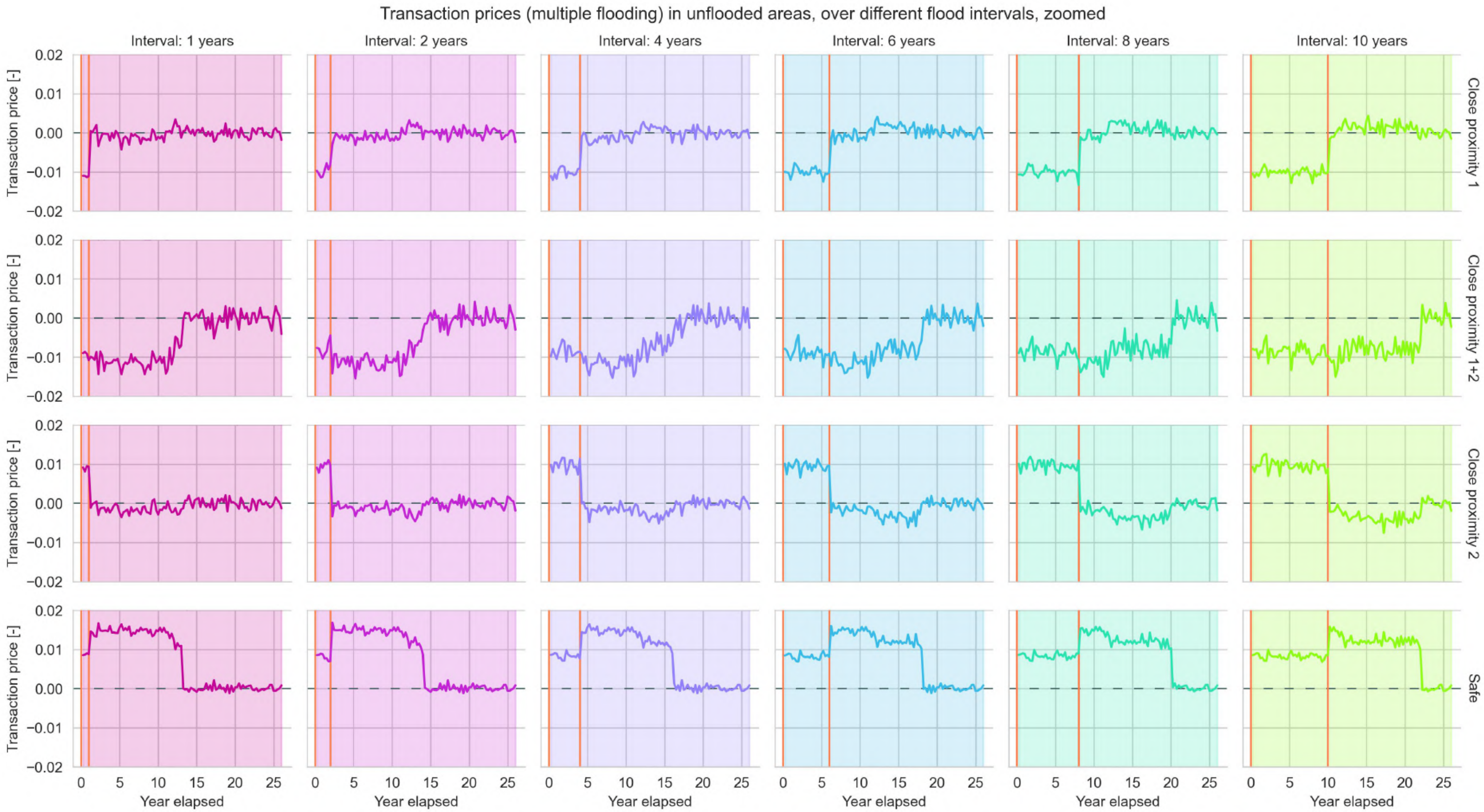


Figure 5.9: The transaction price trends for multiple flood experiments (unflooded properties), sorted according to flood interval (column, rightwards = increasing interval) and house category (row). The flood timings are indicated with orange vertical lines. Due to the wide distribution of results, the figure focuses on the mean line trends in detail, and an overview figure is provided at the end of this chapter as Figure 5.12.

the same district twice). In Figure 5.9, they are shown on the 2nd row. From the graph, the 2nd flood essentially further extends the flood discount recovery, but does not further increase the flood damage discount, nor affects the transaction price of houses after the flood discount period.

Additionally, the noisier nature of the mean line compared to the other rows also suggests that there is a low number of houses that are in close proximity to both floods in the set of flood scenarios.

Close Proximity 2

This category refers to houses that were in close proximity to the 2nd flood, but not affected by the 1st flood. In Figure 5.9, they are shown on the 3rd row. They experience a price premium after the first flood, but subsequently lose the price premium after the 2nd flood, thus cancelling out the price premium.

Additionally, the transaction prices tend to be slightly lower than the control transaction price of 102%, and seem to be more pronounced with increasing flood intervals (rightwards). This may be due to the other flooded districts being more attractive as their flood discounts are ending, thus making the houses in this category relatively less competitive; however, they are still sold at a marginally higher rate than the Close Proximity 1+2 category.

Safe

This category refers to houses that were in districts that were not affected by floods. They are shown on the bottom row of the Figure 5.13, experiencing a price premium as a result of both floods. The combined effect of the two floods have an additive effect on the price premium of these houses, especially when the floods events occur closely. This is because of the multiple floods rendering a larger portion of the housing market stock as unattractive, thus leading to a more significant flocking of potential buyers to these flood-safe properties.

House price indices

Next are the house price indices for the unflooded houses, which are shown in Figures 5.10, 5.10, and 5.11, showing the effect of the transaction prices on the house price indices. The first two are graphs of the mean price indices lines for different flood intervals, plotted together for easy comparison, while the latter is an overview plot showing the distribution of price indices for each flood interval and flood category. Again, the house price indices trends are sectioned by house category.

Close Proximity 1

This is represented in the 1st row of Figure 5.10. Prices initially depreciate at a linear rate, with the 2nd flood event arresting the depreciation. Shorter flood intervals lead to an earlier halt in depreciation, leading to a higher house price index. Here, even though the longer flood intervals have a marginally-higher mean transaction price, the resultant house price index at the end of simulation is about 1% lower than shorter flood intervals.

Close Proximity 1+2

This is represented in the 2nd row of Figure 5.10. Houses generally depreciate in a similar gradient for the discounted duration (<12 years), but stabilise about 3%-4% of the control trend. After that, the price indices tend to stagnate or reduce slightly. From the graphs, shorter flood intervals to lead to less price depreciation, but only a difference of around 1% compared to larger flood intervals. However, given the noisy price transaction graph, this cannot be taken as a significant result from the model.

Close Proximity 2

This is represented in the 1st row of Figure 5.10. Here, the house prices initial appreciate at a linear rate, until the impact of flood discounts from the 2nd flood event arrive, leading to the depreciation of prices. As correlated with the mean line in Figure 5.9, row 3, the longer flood intervals lead to a slightly steeper price depreciation, while the price depreciation for shorter flood intervals is more gradual. However, the resultant price indices are still higher for longer flood intervals, and still managed to be marginally higher than the control trend.

Safe

This is represented in the 2nd row of Figure 5.10. Here, shorter flood intervals lead to an earlier initial appreciation of prices. However, longer flood intervals experience a larger price index gain; this is because later in the model, the house prices would have appreciated more (as house prices are updated in a multiplicative manner), thus meaning the price premiums in housing market transactions in later stages have a more pronounced effect on the house price.

5.4. Flooded houses

5.4.1. Transaction price trends

The transaction price trends for flooded houses are presented in Figure 5.12 and 5.13. Both figures are the same graph, but with the former for a broad overview, and the latter for a focused look at the mean transaction price line around 0.

Flooded 1

This category refers to houses that are flooded only by the 1st flood and not the 2nd flood, and is depicted in Row 1 of Figure 5.12. All houses suffer the same degree of flood discounts at the start (as the flood scenarios are the same). However, houses can still suffer a price discount after 12 years, probably because of their proximity to the 2nd flood, similar to the close proximity graphs seen earlier in Figure 5.4. As a result, transaction prices for these houses would remain lower than expected until after the 2nd flood discount period is over. This graph highlights the inadequacy of this plotting method, specifically how it does not account for houses that are flooded once but may or may not be in close proximity to the 2nd flood.

Flooded 1+2

This category refers to houses that are flooded twice by both flood events, and is depicted in

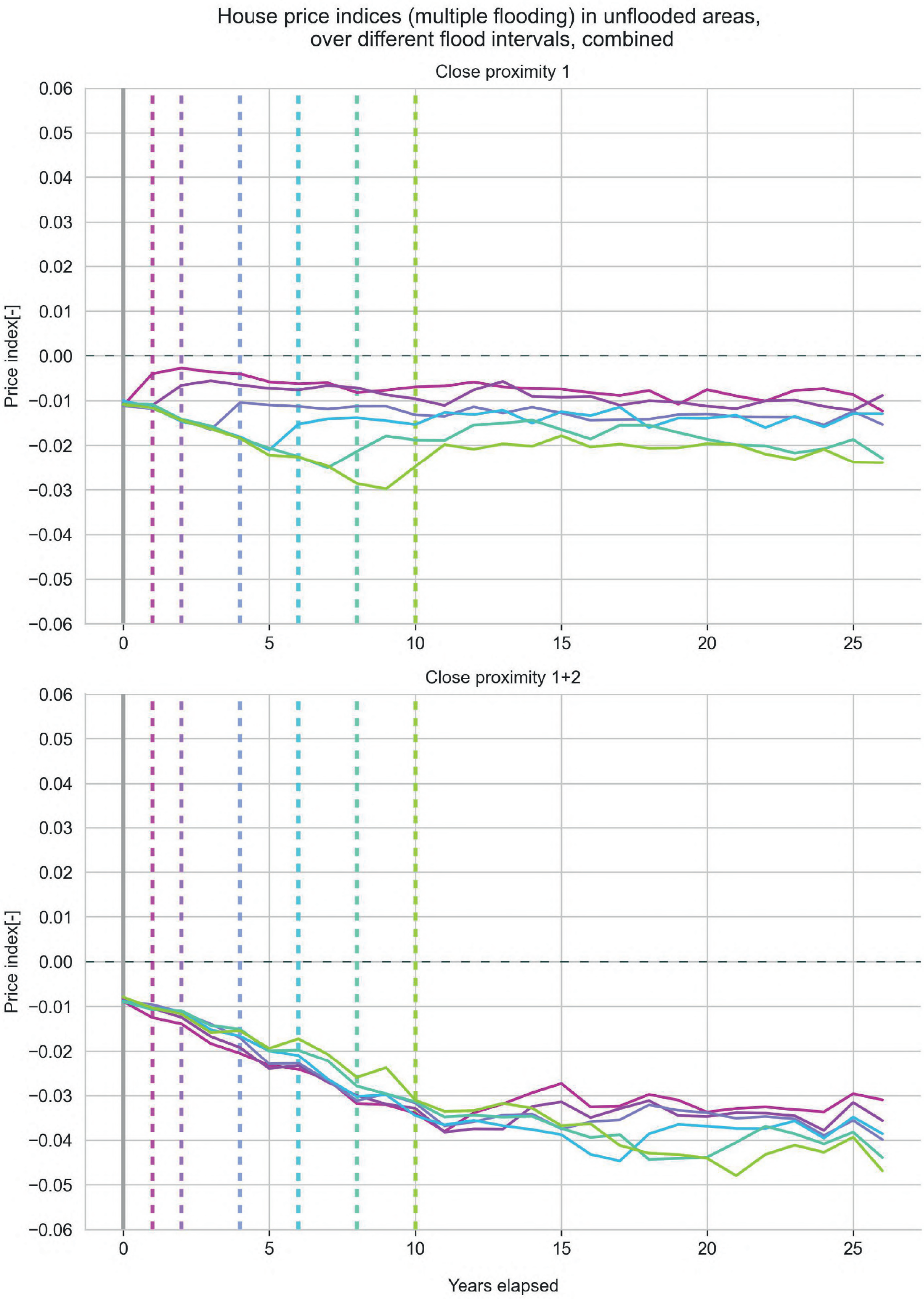


Figure 5.10: Part 1 of the house price indices trends for multiple flooding experiments, showing for houses with close proximity to the first flood only, and houses that are in close proximity to both floods. This graph focuses on comparing the temporal differences in the mean trends, another graph showing the distribution of points is provided subsequently in Figure 5.11 on page 68.

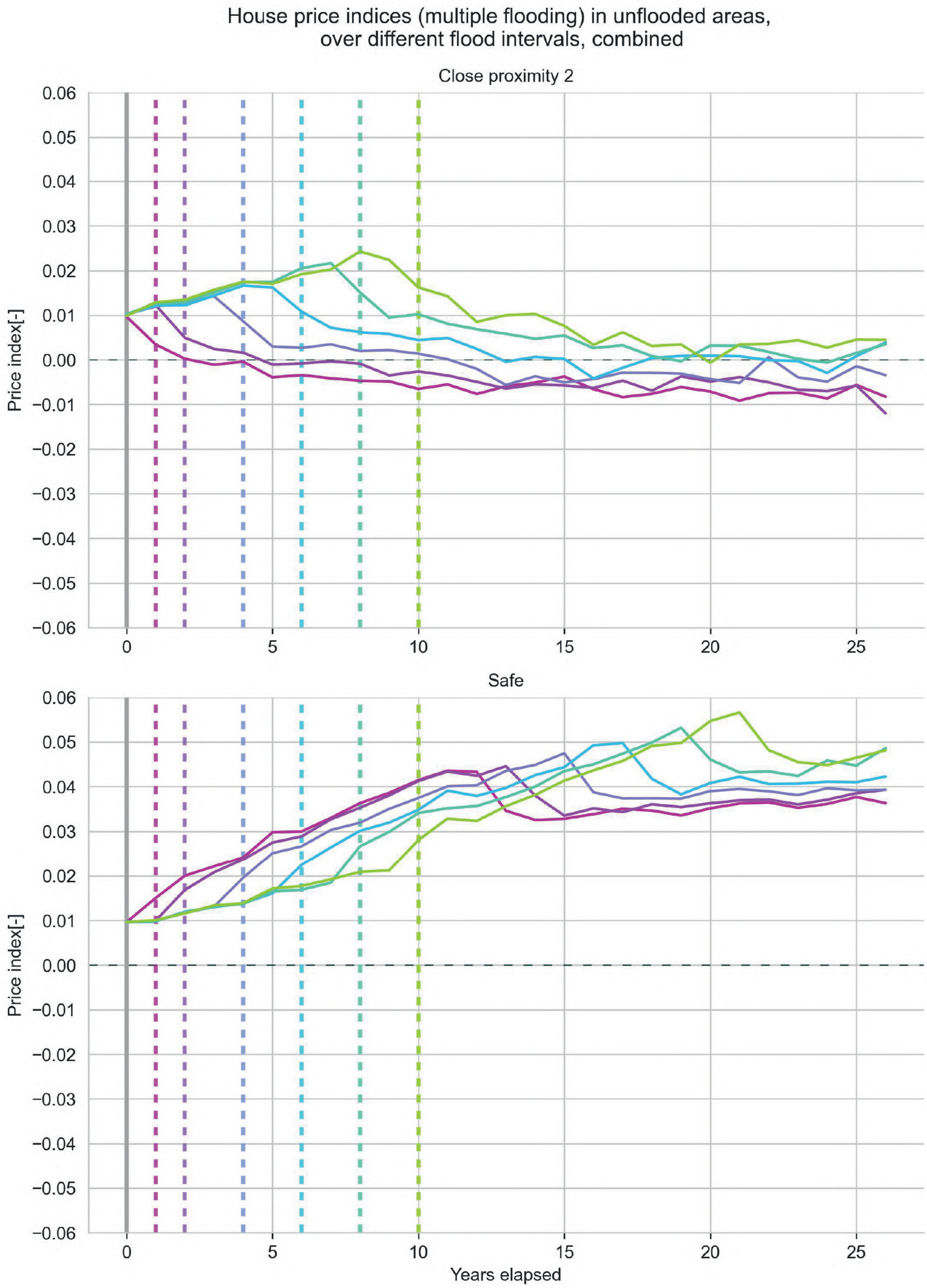


Figure 5.10: Part 2 of the house price indices trends for multiple flooding experiments, sorted according to categories of unflooded houses. This graph focuses on comparing the temporal differences in the mean trends, another graph showing the distribution of points is provided subsequently in Figure 5.11 on page 68.

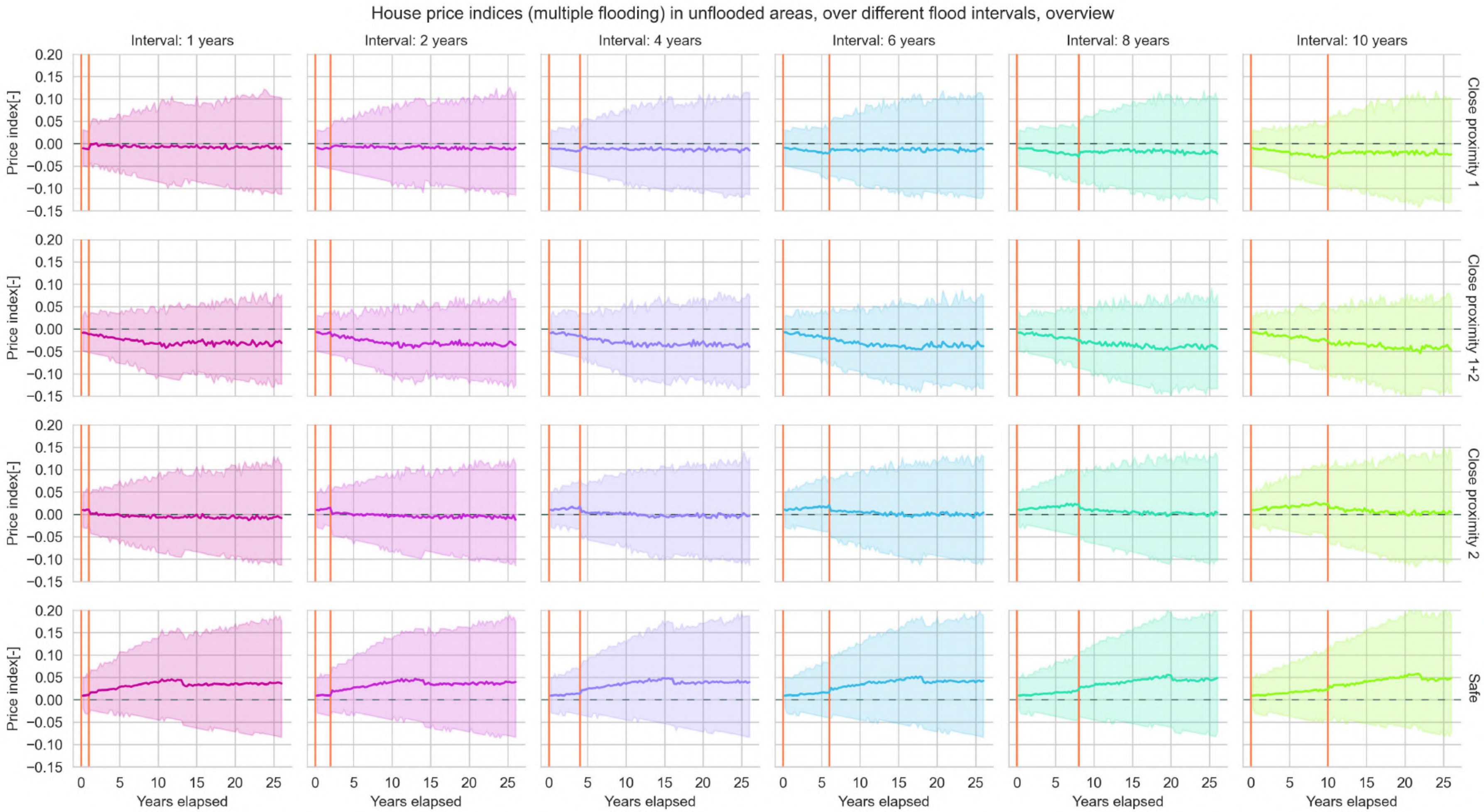


Figure 5.11: House price indices trends for multiple flooding experiments, sorted according to categories of unflooded houses (per row) and the flood interval (per column).

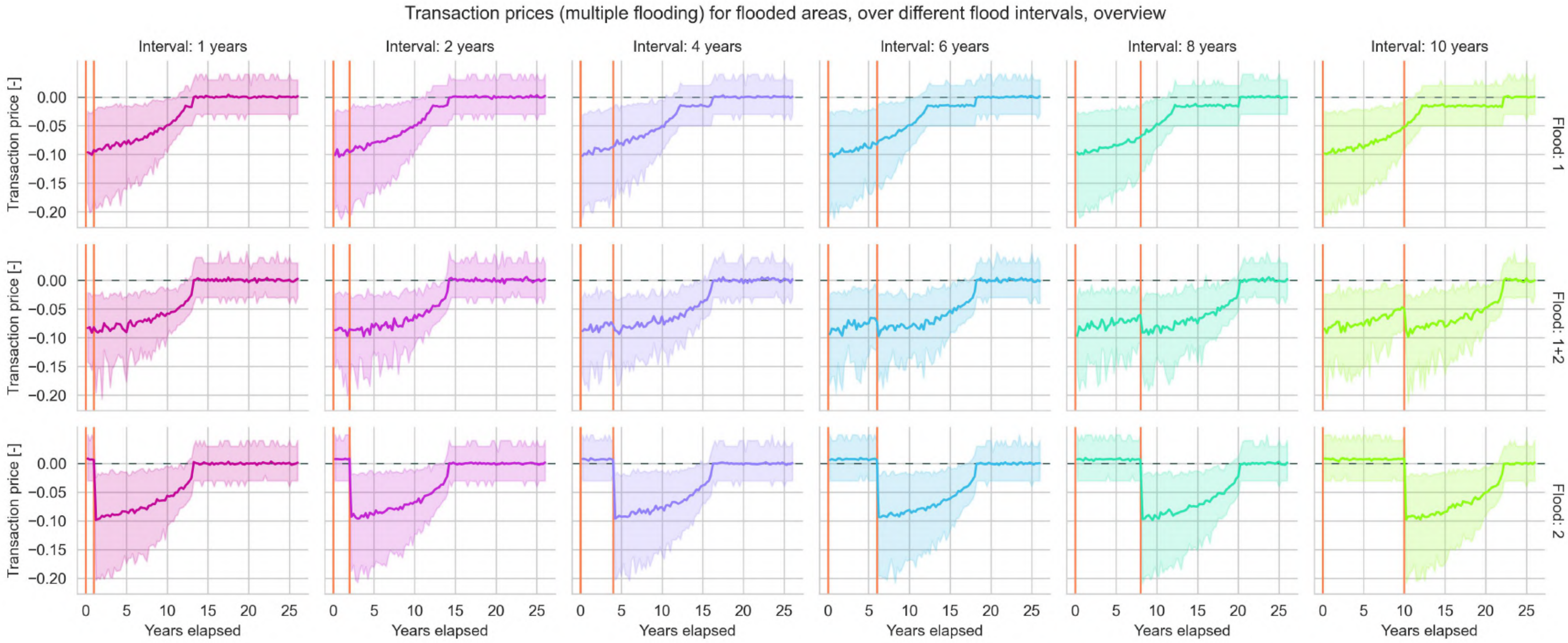


Figure 5.12: The price transaction trends for single flood experiments (flooded properties), sorted according to flood interval (per column, rightwards = increasing interval) and house category (per row). A companion graph focusing on the mean trend line is provided at Figure 5.13 at page 70

Figure 5.13: The price transaction trends for single flood experiments (flooded properties), sorted according to flood interval (column, rightwards = increasing interval) and house category (row). This graph focuses on the mean trend line, highlighting two things: 1) the Flood 1 row (1st row) on how the 2nd flood impact the flood discount of the houses in the district, and 2) the Flood 2 row (3rd row) on the price premium in the houses before the 2nd flood.

Row 2 of Figure 5.12. Here, it is seen that the 2nd flood essentially resets the flood discount decay back to its original value, thus extending the discount period of the houses. Additionally, the noisy mean line also suggests that a low proportion of houses in the housing market are flooded twice.

Flooded 2

This category refers to houses that are flooded only by the 2nd flood and not the 1st flood, and is depicted in Row 3 of Figure 5.12. There is a small price premium after the 1st flood event, similar to the Close Proximity 2 category for unflooded houses. However, after the 2nd flood, they experience flood discounts, and take the same time (12 years) to recover.

5.4.2. House price indices

The effect of the transaction prices lead to the house price indices graphs on Figures 5.14 and 5.15. The former focuses on the mean trend line for the price indices graph for easy comparison, while the latter focuses on the distribution of price indices.

Flooded 1

On the 1st row of Figure 5.14, the house prices follow the transaction price trends exactly until the end of the 1st flood discount period (12 years). Then, the house price indices may stabilise or depreciate linearly, depending on the duration of the 2nd discount period due to its close-proximity status. If the duration of the 2nd discount period is long, the house price index of the houses would be lower.

Flooded 1+2

On the 2nd row of Figure 5.14, the house prices start out already at a lower price index, but increasing flood intervals lead to a deepening depreciation of the house price indices. This is because of the DID methodology for the house price indices, as the graphs are plotted with respect to the baseline of the control price indices trend; a longer period of flood discounts would cause the house price index for this house category to further diverge, thus leading to a deeper house price index for larger flood intervals.

Flooded 2

On the 3rd row of Figure 5.14, the house prices start at a positive level due to the price premiums, but suffer a large and deep depreciation when the 2nd flood occurs. This highlights a crucial flaw in the flood discount abstraction, because the flood discounts are applied as if the house were still valued at 100% (similar to the start of the model, before any transactions), and not based on the current house price. This flaw is elaborated in the subsequent section, specifically Section 5.5.2 on page 75.

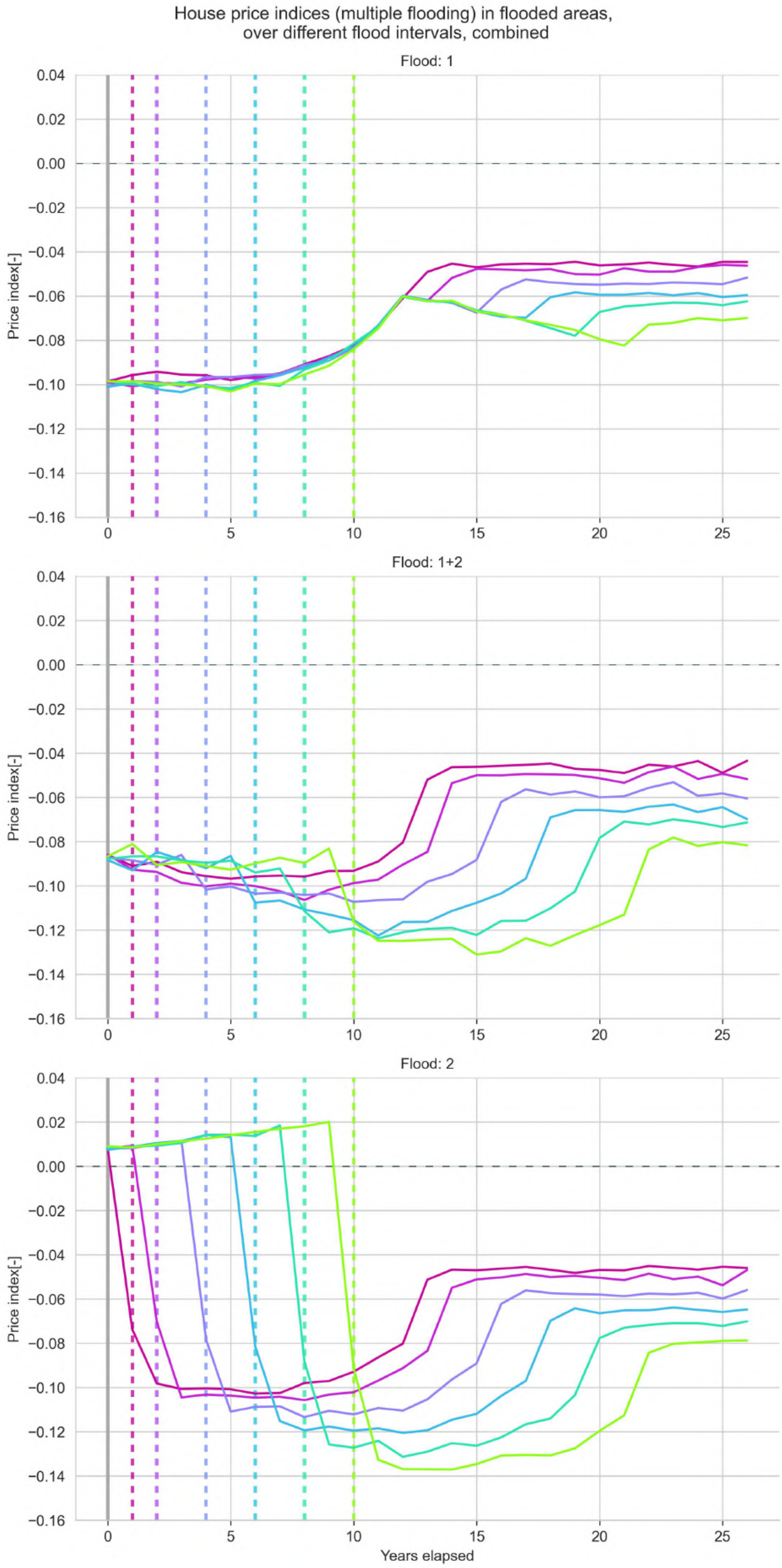


Figure 5.14: House price indices trends for multiple flooding experiments, sorted according to categories of flooded houses. This graph focuses on comparing the temporal differences in the mean trends, another graph showing the distribution of points is provided subsequently in Figure 5.15 on page 73. Note that the differing degrees of house price reduction is due to a model artifact, elaborated in text, with more details on Section 5.5.2 on page 75.

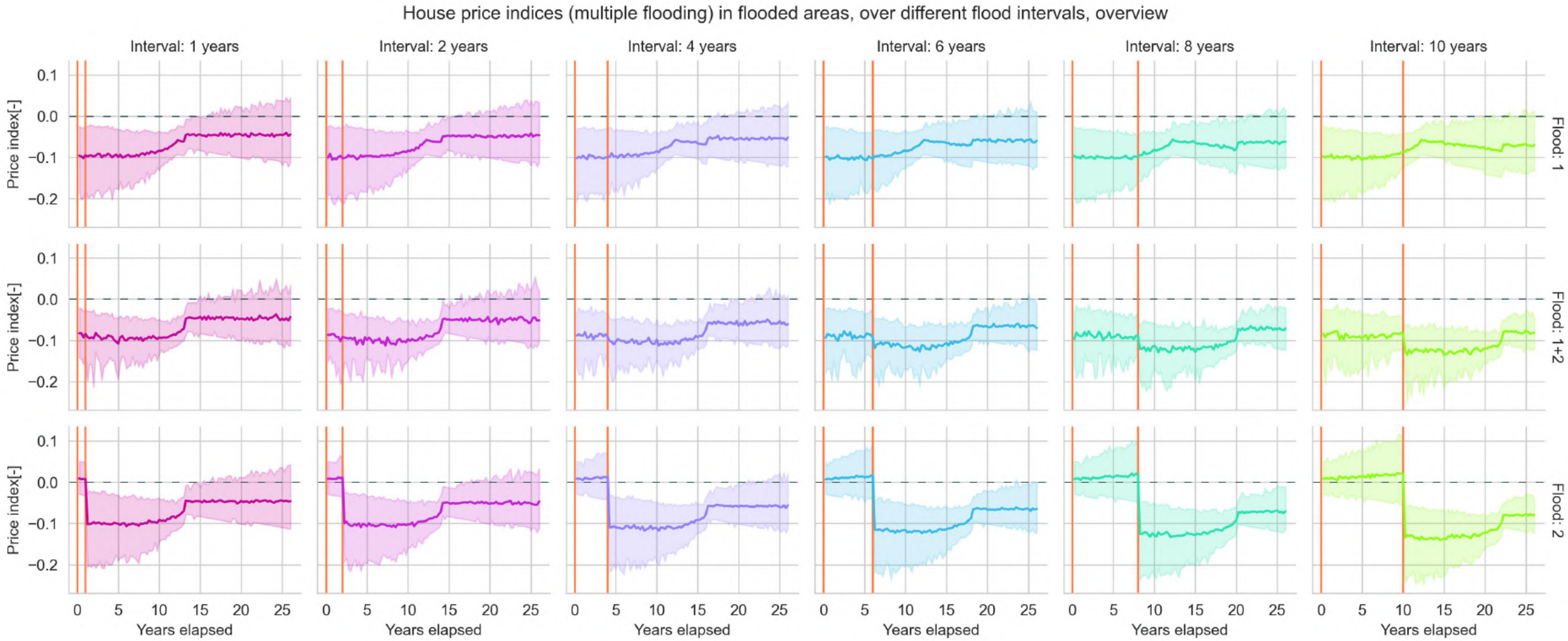


Figure 5.15: House price indices trends for multiple flooding experiments, sorted according to categories of unflooded houses. This graph focuses on showing the distribution of house price indices per category.

5.5. Model reflection from results

This section critically examines the model design choices and output analysis methods, based on the outputs from the results. Firstly, it should be mentioned that the results indicated several rigid and unrealistic aspects of the model, and thus limits its value as a policy decision support tool in its current state. However, as per the exploratory research direction, the results provide several critical insights into the modelling effort, and may be useful in highlighting future research directions. The subsections here first critiques the conceptual design of the model, and then the lower-level model elements.

5.5.1. Critiques on fundamental systems

From the results in this chapter, there are three general types of price regimes:

1. Flood-damaged houses, suffering a *severe price discount* based on their flood damage.
2. Houses in flood-discounted districts ("Close Proximity" category), suffering a *mild price discount* due to the lack of attraction of their respective district.
3. Flood-safe houses in unflooded districts, experiencing a *price premium* due to the increase in attraction of their respective districts.

The presence of two discrete price regimes for flood-damaged houses and close-proximity houses raises the question "whether experienced flood damage entails price discount for houses?". As price discounts are a social construct and thus governed by the bounded rationality of housing market actors, flood discounts may already arise as a result of a house's locational association with a flooded area. Therefore, a potential flaw in this study is equating flood discounts as a direct function of flood damage. While flood damage can be a core determinant of the severity and duration of flood discounts, translating quantitative flood damages to individualised per-house flood discount may already be too "empirical" for housing market actors, which may only consider the perceived severity and the rough location of floods[5]. As a suggestion, the flood discount mechanism should consider a general area around the flood as "flood-discounted", and aggregate the mean flood severity to better simulate the status quo homebuyer rationale.

Subsequently, the spatial classification of "close proximity" should come into question. In the model, this was assumed as "houses that are in flooded districts but were not damaged by floods". It is likely possible that instead of "close proximity" being at the district level, housing markets actors may base it on province, municipality, district, or neighbourhood spatial level. For example, severe flooding in the western part of the Netherlands may then motivate homebuyers to consider living outside of Rotterdam entirely, instead of the more inland districts of Rotterdam. As a result, studies into homebuying rationales with respect to flood risk could be undertaken, specifically studying at which spatial level would homebuyers consider as "risky" to areas that were previously flooded.

[5] After all, homebuyers are not likely concerned with measuring exact flood depths and calculating a discount based on it.

5.5.2. Impact of model design and assumptions

Housing market design

The results in the Multiple Flooding section highlight a weakness in the district attraction mechanism, specifically on houses that are only in close proximity with either 1 flood. Houses that are discounted from any one flood would then have a reduced discount for the other flood, even though the other flood event might remind housing markets of prior flooding, and thus refreshes or restarts the flood discounts. This phenomenon is due to the design of the district attraction mechanism; specifically, districts have an attractiveness weight that can be negatively impacted by floods, thus giving a relative competitive advantage to other unflooded districts and motivating homebuyer agents to prefer the unflooded districts. However, in edge cases such as when all districts in Rotterdam are flooded, all of the districts' attractiveness weights would be relatively similar, and thus leading to a negligible flood discount.

Flood discounts decay

Recall that this element is about how the flood discounts are forgotten over time. In the model, the flood discount decay of houses follows a modified regression curve by Mutlu et al. (2022) (see Section 3.5 on page 22). The ratio-based characterisation of the flood discount decay leads to a rigid outcome, where almost all houses are abruptly undiscounted after 12 years, leading to an unrealistic surge in attractiveness after 12 years. The transaction prices seen in the model would have been similar to the regression curve by Mutlu et al. (2022), with an initial discount that gradually reduces until it follows the norm. As a result, the current flood discount decay system is unfit for purpose. In reference to the critique of the flood discount mechanism earlier in this section, the flood discount decay system should focus on the perceived severity and the areas that were flooded, instead of a granular per-house calculation of damage.

Additionally, the modelling effort also highlights a knowledge gap that could be consolidated from empirical studies such as Mutlu et al. (2022), Atreya et al. (2013) and Bin and Landry (2013). It in still unclear how variables in flood events, such as effect of flood damage severity, number of houses affected, and the recovery rate of damage, affect the decay of flood discounts over time.

House price index

The house price index was a simple abstraction to simulate how house prices grow over time, and here several flaws exist in how house prices were updated in the model. Specifically, list prices of houses are not based on prior history of transactions, or price of houses in the same district. In the model, the house prices are only updated for houses that were sold, and the list prices of other houses in the district were not updated to reflect this growth. This led to the sharp discontinuities seen in Figure 5.6. As a result, this likely led to an underestimation of house price indices.

Additionally, the inclusion of the house price indices highlights a deficiency when interacting with the house price discounts subsystem. In graphs such as Figure 5.14, later-occurring floods have a larger effect on the price index than earlier floods, even though the flood scenarios themselves are the same. This is because the discount for flood-damaged houses uses a fixed price index of 1.0 (or 100%) as a baseline, and does not account for any further price index growth. As a result, when a house price has appreciated over time, a flood damage discount would have an unrealistic devastating effect on the house, and would then lead to another unrealistic recovery back to the initial price index of 1.0, instead of the expected price for the region.

5.6. Extra graphs

This section serves as an appendix for graphs that were not included in the main body. Specifically, they include:

1. Single flooding: transaction prices graphs, sorted according to flood coverage[6]. 2 graphs are provided: one for overview and another zoomed in.
2. Single flooding: price indices graphs, sorted according to flood coverage. 2 graphs are provided: one for overview and another zoomed in.
3. Multiple flooding: transaction prices for unflooded properties, with an overview scope.

[6] See Table 5.1 in the Flood Coverage column for the ordering

Figure 5.16: Transaction price trends for single flood experiments, sorted according to flood coverage. As with the sorting according to flood severity, flood coverage alone cannot explain the trends in price discounts or premiums.

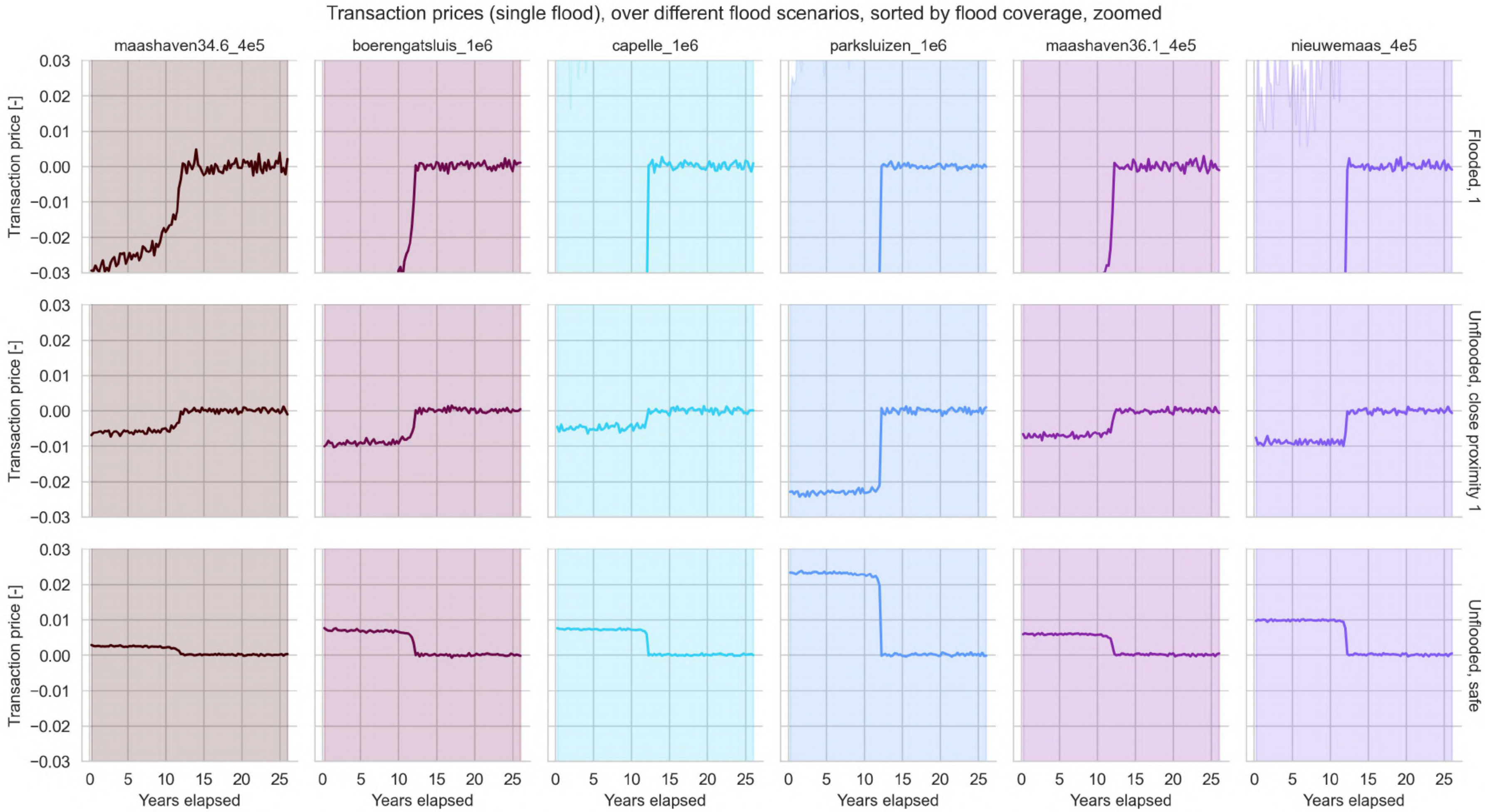


Figure 5.17: Transaction price trends for single flood experiments, sorted according to flood coverage.

Figure 5.18: Price indices trends for single flood experiments, sorted according to flood coverage.

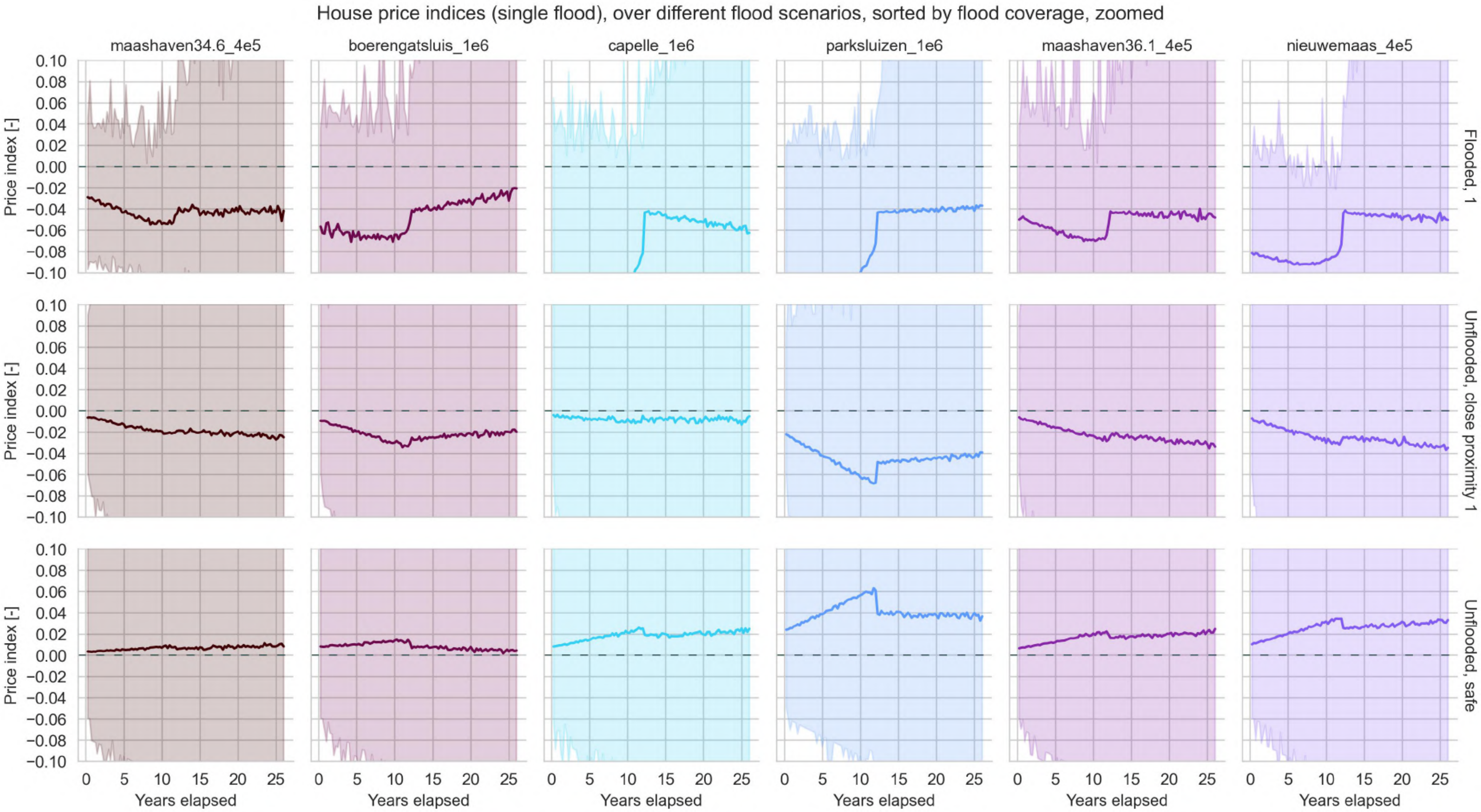


Figure 5.19: Price indices trends for single flood experiments, sorted according to flood coverage.

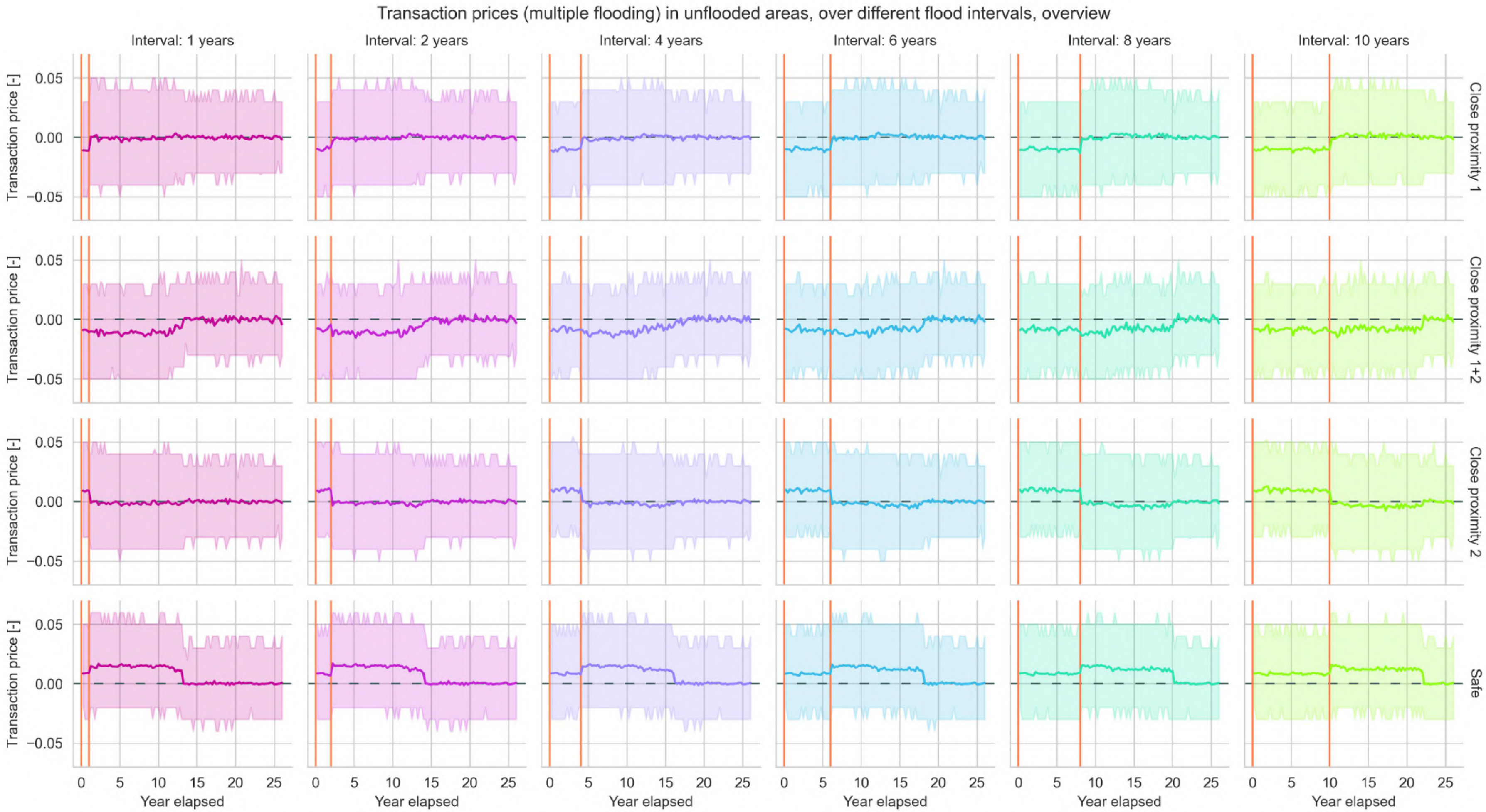


Figure 5.20: Transaction prices for unflooded properties in the case of multiple flooding, showing values that fall within the interdecile range (10th-90th percentile). The columns are sorted by increasing flood interval moving to the right, and different house categories on the rows.

6 Discussion

This chapter summarises the findings from Chapter 5, and critically reflects on the study in terms of the data exploration and model design. The main findings of the data exploration and modelling are summarised as follows, with respect to the key research questions:

6.0.1. Data exploration

1. There are rich datasets at the flooding and demographic level in Dutch open data that can empirically characterise the flood risk of areas in the Netherlands, and also characterise the population demographics.
2. There are still knowledge gaps towards understanding the endogenous mechanism for housing markets "forgetting the flood", notably on when the forgetting begins, whether the forgetting trend is affected by flood severity, and how would hysteretic behaviour be characterised. Additionally, at what point would housing markets stop forgetting about floods should be investigated, given recent studies have indicated a growing awareness in housing markets (Cheng et al., 2019; Fu & Nijman, 2021; Seo et al., 2021).
3. There are data gaps on the Dutch homebuyer decisionmaking in open data, specifically on how they choose satisficing mortgage terms, and how would flood risk or past flood experience factor into their considerations.
4. Ethical concerns may arise from the high spatial resolution of spatial datasets, such as flood maps and potentially land-use maps. It is likely that a hypothetical model may prescribe severe flooding and damage to specific houses, which when presented without context may create public discontent or depressed market sentiment. As a result, political sensitivity should be exercised when presenting outputs from such hypothetical models.

6.0.2. Agent-based Model Design

1. The study applies a modular framework to integrate empirical and spatially-consistent flood risk into a housing market model, for Dutch flood scenarios. The framework can be applied to different areas and different spatial scales, but requires the unification of spatial and temporal resolutions of inputs.
2. An abstracted version of an amnesiac housing market was constructed as an agent-based model, with homebuyer agents that are discouraged from buying homes in recently-flooded areas, but would eventually “forget” the flood history.
3. A series of computational experiments were conducted with various empirical flood scenarios and flood timing. The results demonstrate some degree of intuitive behaviour, such as price premiums in flood-safe properties, but showed unrealistic behaviour due to model artifacts.
4. As a result, the model is unfit for prediction purposes, but the modelling process itself offers several areas of further research, notably in terms of how flood discounts (its onset and subsequent decay) are affected by flooding and housing market actors.

In the following sections, the research impact of the study is discussed with respect to the current state-of-the art as presented in the Problem Context chapter. Afterwards the limitations within the study are described, along with future improvements to address these limitations,

6.1. Research Impact

6.1.1. Employment of empirical flood scenario data

The cornerstone of this thesis study lies with the usage of empirical flood scenarios instead of broad flood risks. In the study, various flood scenarios impacting Rotterdam are combined into a “combined risk profile” that spatially links the distributions of flood-safe/flood-risky locations across different flood scenarios. Firstly, the “spatial consistency” of the method is useful for accurately representing the vulnerability of any location to more than one flood event is correctly represented. Secondly, the employment of flood scenarios instead of uniform flooding (such as in Caloia and Jansen (2021)) offers the possibility to examine shocks to local housing markets. The method can be applied for different flood scenarios and different spatial levels, but some adaptation is needed to unify different spatial resolutions.

6.1.2. Foundation for exploring potential housing market configurations

While the model is an unvalidated “toy” model with stylised relationships, it is a starting point for testing the impacts of various empirical flood scenarios on housing market configurations. Using a stylised analog of status quo, amnesiac, household decision-making behaviour, the model was able to show flocking behaviour, as homebuyers avoided flood-risky districts and competed with each other in flood-safe districts.

The exploratory modelling effort highlights the scientific insights from “failing”, by critically reflecting on model mechanisms and identifying areas of research interest. For example, the rigid behaviour observed in the model outputs suggest a need for more organic decisionmaking at the homebuyer level, for example the inclusion of herding behaviour and modelling willingness to pay. Additionally, the modelling of flood discounts also raised some further research questions towards characterising and parametrising flood discounts.

The modelling process in this study also highlights the need for incremental development and testing, by stress-testing different submodels and characterise the effect of the submodel on the overall model, and identify their limitations.

6.2. Policy Implications

While the model designed in this thesis study cannot be recommended for predicting flood discounts directly, the data and modelling exploration conducted in this study shows that there is still a substantial amount of work needed to understand house price discounts from increasing flood risk. From a Dutch-centric perspective, there are data gaps that hinder the empirical representation of a Dutch housing market. Additionally, while several studies have empirically studied the quantitative effects of house prices from flooding, a systemic framework of flood discounts is still lacking.

Concerningly, from a broader perspective, housing market collapses from climate risk in general may be interconnected with other social systems, such as the regional economy; while this study cannot prescribe any advice on how flood discounts affect the broader economy, this statement serves as a reminder of the potential connected effects between housing markets and other social systems, where a perturbation in either can trigger a change in another.

6.2.1. Identification of data gaps

The data exploration effort with Dutch open data showed several aspects of high data quality as well as areas that are currently insufficient for key interactions in the flooding/housing market complex system. With datasets such as the proportion of low-income/high-income citizens per district, the national income statistics, and household consumption data, it is possible to model an empirical spatial distribution of citizens with representative income values and consumption behaviours, which can be useful for modelling, for example, the effect of flood damage on changing consumption behaviours, and its effect on a regional economy.

However, there are some missing information while trying to model the flood discounts and home purchasing decision-making. In terms of flood discounts, flood discounts are currently characterised at a per-case level, and cannot be parametrised with respect to the housing market actors or the severity of the flood. In terms of home purchasing decision-making, open data currently lacks crucial fine-resolution data at the individual mortgage financing level, such as the preferred mortgage debt repayment duration, and preferred loan-to-value values across different socio-economic brackets.

6.2.2. Knowledge gaps in housing markets under flooding

The current body of research provides some broad findings on the general housing market themselves, such as how severe flooding in western Netherlands can lead to capital depletions in banks (Caloia & Jansen, 2021), or how discounts are being observed in climate-risky areas (Taylor & Aalbers, 2022). However, there are still knowledge gaps in terms of micro-level social mechanisms, such as the parametrisation of flood discounts and the decisionmaking of housing market actors with respect to flood risk.

While it is possible to estimate flood damage levels from Dutch flood data, the estimation of flood discounts becomes difficult due to the lack of representative flood discount data for housing markets similar to Rotterdam, and a systemic understanding of how housing market actors affect flood discounts. As flood discounts are driven by a social mechanism, it is likely that the amnesiac/myopic behaviour in social systems would lead to cases of underestimation and overestimation of flood discounts, possibly with drastic fluctuations (Axtell et al., 2014; de Koning et al., 2018; Pryce et al., 2011). Crucially, it is also important to characterise the effect of the decay or preservation of flood discounts over time, and possibly accounting for other effects such as the “safe development paradox” (Haer et al., 2020), risk disclosure (Cheng et al., 2019; Filippova et al., 2020), and housing market memory or learning (Fu & Nijman, 2021; Seo et al., 2021).

6.3. Limitations and Future Improvements

A quote from George Box says that “All models are wrong, but some are useful”, and it is crucial to critically identify limitations in the modelling research, because models are incomplete representations of reality. This section discusses these limitations, and raises future research possibilities alongside. It is split along two themes, the conceptual limitations on the problem framing, and the limitations in the methodological aspect.

6.3.1. Conceptual limitations

Flood scenarios

Firstly, in terms of flood scenarios, the study only focuses on individual failures in the flood protection structures. It is likely that severe flood scenarios may cause multiple failures, or originate from other sources such as increased rainfall. As a result, future research may include modelled or expert opinion on future flood scenarios, for both riverine or coastal flooding scenarios.

Spatial boundaries

Secondly, the study is conducted under the assumption that under flood conditions, homebuyers would prefer flood-safe locations. However, it is possible that severe flooding in Rotterdam may reduce the attractiveness of that housing market, thus leading to net outmigration and reduced prices. As a result, prospective homebuyers may consider moving out of Rotterdam instead of migrating to a safer district. For future research, the migration balance within the housing market could be included endogenously, such that it drives the housing market demand in the region.

Another caveat that applies especially to the Netherlands is the lack of inclusion of land use information. While the flood map is filtered of water bodies, the Netherlands have areas of unprotected land such as outer dike areas. Houses placed on these land parcels would then experience significant flooding, and are then recorded to experience significant damage. As a result, the usage of land parcel information would reduce this error, especially for less-urban areas.

Recovery and Adaptation

Thirdly, the study also ignores the effect of post-flood recovery and adaptation. Property prices may rise after recovery, as homes are rebuilt to modern standards, or when flood mitigation construction are in place (Haer et al., 2020; Mutlu et al., 2022). However, the slow pace of recovery may negatively impact the recovery of prices, which may also affect the temporal trends of price discounts (Hamideh et al., 2021; Rezakhani, 2022).

In terms of future research, these may be included as scenarios, and integrated in decision-making metrics for homebuyers to enter the housing market. For example, homebuyer agents may be reminded of recent floods from slow recovery, thus leading to a longer period of discounts. Conversely, the presence of newer flood mitigation measures may cause homebuyers to perceive that that area is flood-safe (Haer et al., 2020; Pryce et al., 2011).

6.3.2. Modelling limitations

Data usage

The data exploration aspect is conducted only for open data in the Netherlands. This leads to several caveats on the validity of this study.

Firstly, there is a possibility that private data sources might hold the necessary information to answer the aforementioned data gap questions. Secondly, there is also the language barrier affecting the data search process. A majority of data is presented in Dutch, which means that useful data can be misunderstood or missed entirely. Thirdly, the study is conducted on the housing market and flooding domains, in which the author is not a subject matter expert in. The latter two caveats mean that there is a possibility of a mismatch in meaning, where the terminology used may be misunderstood.

While caveat 1 can be remedied by the exploration of private data sets, this may have a negative impact on the transparency and reproducibility of the data processing aspect. Caveats 2 and 3 can be mitigated via expert consultation and thorough communication on what terms mean within the domain.

Modelling price discounts

The district attraction mechanism as implemented led to more agents preferring flood-safe areas, thus leading to price premiums in those areas. However, as elaborated in section 5.5, there are several critical flaws in the model design, such as the characterisation of how flood discounts arise and decay, and in the pricing of houses.

In terms of future research, these observations further motivate the study and experimentation of other mechanisms for modelling the attraction or rejection for flood-risky properties. The results highlight that price discounts are a social phenomenon, and thus motivates the inclusion of bounded-rational behaviour, with imperfect information in homebuying, and peer-based decision-making. From here, future research may explore heterogeneity in risk acceptance and finances, and social networks. Additionally, another interesting direction is the homebuyer's willingness to discount risk or tendency to forget about risk could be explored as an extension to this, which may be useful in modelling climate gentrification.

Experiments and Model analysis

The study only uses a small, hand-selected subset of the available flood data, where there are numerous other flood scenarios in the LIWO database (Rijkswaterstaat, n.d.). As a result, there is a selection bias in the inputs towards severe flood scenarios. A recommendation here would be to systematically include a larger set of flood data, and conduct an exploration of the effects of different flood scenarios on the system. The large input space can be further refined via input/output space exploration, to narrow down the input space from interesting outputs (Lee et al., 2015).

As seen in the multiple flooding experiments, there's also the limitation of too much aggregation, especially when considering that there are milder flood scenarios and more severe flood scenarios. The current method cannot characterise flooding at an empirical level from the different flood inputs, thus motivating the need for added sensitivity analysis across the input space (Lee et al., 2015; O'Sullivan et al., 2016). Additionally, the sensitivity analysis would also be a key aspect in validating the model, by describing the magnitude of effect of input parameters on the model.

6.4. Conclusion

The state of the changing climate necessitates adaptation measures to survive. However, currently housing markets are only beginning to consider the effects of increasing flood risk on the housing markets' actors' decisionmaking, after decades of discounting past and future flood risk. As a result, current literature cannot describe future potential dynamics when housing markets are shocked by floods.

Therefore, this study aims to model the effect of empirical flood scenarios on the housing market in Rotterdam. This framework aims to 1) explore the available data that can be used to empirically-describe the system, 2) consolidate the knowledge into an agent-based model, and 3) gain insights on the effects of stylised housing market dynamics, based on status quo agent-level behaviours, to identify their effects on house price trends.

The study is broken into two parts, the data exploration phase, and the modelling phase.

The data exploration phase identifies relevant data sources from Dutch open data and processes them into usable data for modelling purposes. Notably, it found rich datasets that can describe a city-level population in terms of income distribution. Additionally, it also found several data gaps in the characterising mortgage financing decisions at an individual level, and also the characterisation of flood discount mechanisms with respect to flood parameters and housing market configurations.

The modelling phase links the flood scenario inputs to a stylised housing market system of Rotterdam, based on the amnesiac behaviour seen in the current housing market literature. Computational experiments were run with various empirical flooding scenarios for Rotterdam, firstly with single floods and then with various permutations of repeated flooding. The results show the stylised housing market was capable of showing a differentiative effect on house prices for flood-risky and flood-safe areas, but to an underestimated degree. The results also show some limitations of the model due to the inaccurate characterisation of system relations, thus meaning the model itself cannot be used for policymaking purposes. Instead, the modelling effort highlights the knowledge deficiencies in the understanding of flood discount mechanisms, which may be useful for future research.

To conclude, this study highlights a framework for integrating empirical flood scenarios into agent-based models, allowing modellers to compare different plausible flood scenarios on the same housing market system. It provides a building block for further research on city-level climate resilience, in which the housing market is only a component in a city ecosystem. Additionally, the data and model exploration also raised several research questions on the characterisation of flood discounts and individual mortgage financing decisions. For future research, a more endogenous and validated characterisation of flood discounts, the inclusion of other flood scenarios, and improved methods for analysing flood discounts are some key areas for improvement.

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A

Appendix A: Model code

A.1. Model Availability

The code is made available at https://github.com/FishOuttaWotah/epa-rdam-housing-under-floods/tree/master. It contains all the necessary code used in the model. However, most of the data is not included due to file size restrictions. Appendix B describes acquiring the data for the terrain data (as DSM maps from Actuelehoogtebestand Nederland).

A.2. Model code structure

The code consists of three core phases:

1. the data preparation phase before simulation
2. the simulation phase of multiple scenarios (termed “experiments”)
3. the post-simulation output data prep phase

Here is an overview of the file structure:

1. (root) The core *“.py”* dependencies are here, with the different aspects of the code sorted, albeit not very neatly. There are 4 classes of files:
   (a) the @experiments.py file, which initiates the experiments setup and runs the model under various scenarios
   (b) ”agent” prefix, which mostly contain functions or classes that involve agents and/or the creation of agents. (*agent_household* is a misnomer, households were agents in this model. Additionally, *env_housing_market* is technically an agent, but the current version of Pycharm is very unreliable with renaming.)
   (c) ”env” prefix, which contains functions/classes that form the model environment (not the code environment), i.e. the flooding mechanisms, flood damage and housing market.

(d) ”model” prefix, which contains functions/classes that are necessary for the simulation part, i.e. the ABM scheduler and data updating schemes. *model_init* is the script containing the MESA Model definition, *model_scheduler* for the MESA scheduler, and *model_ledger* for functions updating the state of the model per step.

2. The data directory, which contains the raw data from Dutch open data. Not all data is included due to file size restrictionsThese are specifically the terrain data (DSM maps), the wijk and buurt (district and neighbourhood) vector data, and the flood data themselves. I may look to include some instructions how to download them yourself, for now I'll assume the data is there.
3. The *data_exploration* directory, which contains Jupyter notebooks that handle the data prep and the post-simulation data analysis.
4. The *data_model_inputs* directory, which hold intermediate data (cleaned from the Data Prep phase) and are used for the model simulation itself.
5. The *data_model_outputs* directory, which hold output data generated from the Simulation phase, but still need to be processed for further statistical work or graphical plotting. The raw output data are also not included (about 300MB) due to file size limitations.

A.2.1. Data Preparation

This study uses various raw data from Dutch open data sources, and these data sources need to be modified somewhat to be used in the model. The raw data is stored in the data directory, the Jupyter notebooks used to process these data is in the *data_exploration* directory, and the output of these raw data is in the *data_model_inputs* directory.

To generate the model input data, several Jupyter notebooks need to run:

- *map_dtm_merge* to merge the terrain DSM maps (they come in tiles).
- *pre-flooding-specific* to generate the necessary flood submaps per district
- *pre-rdam-city-only* to filter out districts that were not used

Further details are elaborated in Appendix B

A.2.2. ABM simulation

Next is the actual simulation run itself. The main file is @experiments.py. The model runs in 2 parts: first the control scenarios and single flood scenarios (with 40 replications) and the multiple flood scenarios (with 1 replication each). You'd need to change the variable *run_pt* from 1 to 2 to ensure the entire experiment is run. Total time takes about 30 mins on the author's 2017 PC, with 24GB RAM and i7-7700HQ processor. Note the simulation is mostly RAM-limited. By default, the script runs on 7 logical cores.

A.2.3. Post-simulation

Most of the post simulation data output is generated in the *plotting_aggregation.ipynb* Jupyter notebook in the *data_exploration* directory. This takes the raw output data (which is not provided here in Github due to its large filesize of about 300MB) and converts them into nice graphs and statistics. This also does a data prep operation for the plotting of price indices per district, which is done in the *pre-flooding-specific-plotting.ipynb* notebook in the *data_exploration* directory.

A.3. Model design assumptions

This section outlines the key assumptions underpinning the model. Due to practical limitations of the thesis study and expertise of the author, these assumptions simplify the model design process.

A.3.1. Flood scenarios

A1 The flood discount decay trend is similar to the flood discount trends seen in the Limburg floods on 1993 and 1995, based on Mutlu et al. (2022).

A2 Flood discounts are assumed to be forgotten completely, with no hysteretic behaviour.

A3 The effect of post-flood price appreciation due to flood mitigation effects (perceived or otherwise) is not applied.

A4 The flood discount-damage ratio is assumed to be 1% of home value per 1% of flood damage.

A5 Flooding scenarios are individual dike or sluice gate failures, without considering compound events or pluvial flooding scenarios.

A6 Flooded homes do not undertake flood mitigation, prevention or adaptation measures

A7 The government does not undertake flood mitigation, prevention or adaptation policies.

A.3.2. Housing market

B1 Buyers do not negotiate prices with sellers, and sellers will always accept the highest bid price.

B2 Buyers are price-agnostic and have no budget constraints.

B3 Buyers don't follow local herding behaviour.

B4 All buyers will bid 96% of the list price if they are the initial bidder.

B5 All buyers will increment their bid price by +1% of the current bid.

B6 All houses in the housing market are single-family, ground-floor homes. (As the main study objective is flood discounts, which are assumed to apply to apartments in a similar fashion)

B7 All houses are owned and inhabited houses, thus excluding rental properties.

B8 Home abandonment is not a possibility for homeowners. Therefore, households that are flooded cannot decide to sell their houses.

B9 Houses can be sited on any land tile, not according to any empirical land-use categorisation.

B10 The number of sellers are equal to the number of emigrating population of Rotterdam.

B11 The number of sellers generated is always constant per time step.

B12 The number of buyers are always proportional to number of sellers.

B13 The number of buyers generated are independent of flood events or other exogenous events perturbing the housing market.

B14 Internal migration across districts is not considered in the model, assuming to be represented in the emigrating population.

B15 The attractiveness of a district is a ratio of the number of houses discounted over the total number of houses within the district.

B16 All house prices are not affected by hedonic property-/neighbourhood-/district-level amenities

A.4. Model Verification

Verification refers to ensuring that the model was built correctly as intended. The model development process relies on two key verification methods, namely unit testing and debugging. Unit testing refers to the verification of small components, such as checking if a mathematical function produces the expected output. To minimise unexpected outputs, functions are checked with their respective documentation to 1) ensure that the provided inputs are correct, and 2) to establish the expected output format from said function.

Given the complicatedness of the model, errors may arise from the interaction of multiple components. The model was debugged using the Pycharm IDE's inbuilt debugging toolbox, which allows for the modeller to peer into the system states at deeper levels of model operation. This is especially important for establishing whether informational links between connected components are correct.

B

Appendix B: Data acquisition

B.1. Terrain data from AHN

The Digital Surface Model (DSM) terrain data is used to filter out water terrain, especially for inland water bodies such as ponds, lakes and canals. However, the data is provided in a user-unfriendly way at the time of writing, and some degree of manual work is needed to prepare the model. Specifically, the map is provided in individual tiles, and need to be combined together for the model.

The map tiles are available here at https://ahn.maps.arcgis.com/apps/mapviewer/index.html?layers=77da2e9eeea8427aab2ac83b79097b1a. Zoom into the map (by scrolling) towards Rotterdam, and seek out the following tiles as indicated in Figure B.1. Click on an individual tile and download the DSM map with the link *AHN4 DSM 5m*, and repeat for each tile indicated in Figure B.1. The maps will be downloaded as a zipped *.tiff* file.

Unzip the files into a folder called *DSM* in the *data* folder of the model. In the *data_exploration* folder, run the Jupyter Notebook script *map_dtm_merge.ipynb* to merge the tiles together into a singular image.

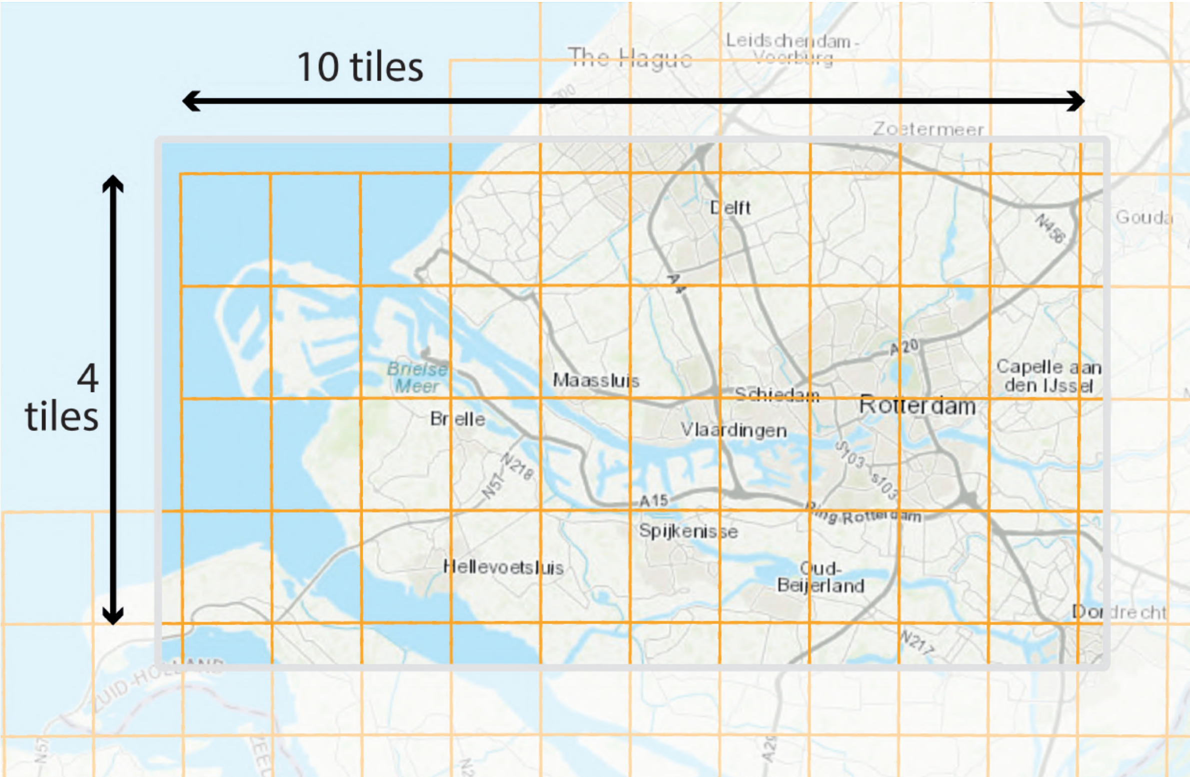

Figure B.1: Visual reference for downloading the required terrain map tiles from AHN.

B.2. Border Vector data for provinces, districts, and neighbourhoods (*provincie, wijken, en buurten*)

This section explains the data acquisition for the border vector data for provinces, districts and neighbourhoods. The version used in this study is https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/wijk-en-buurtkaart-2020, and the download link is available at the bottom of the page at https://www.cbs.nl/-/media/cbs/dossiers/nederland-regionaal/wijk-en-buurtstatistieken/wijkbuurtkaart_2020_v3.zip.

This provides the vector shapefiles as a zipped folder, which should be extracted into a separate folder in the *data* directory. This will then be pre-processed by running the Jupyter notebook *pre-rdam-city-only.ipynb*. By default, the script looks for the shapefiles in *data/WijkBuurtkaart_2020_v3*.

B.3. Flood scenario data from LIWO

This section explains the data acquisition procedure for the LIWO data (Rijkswaterstaat, n.d.), specifically detailing the steps to find and download the data for the LIWO flood maps used in this thesis study. This is because the specific flood scenarios do not have a direct URL, and the download procedure is tedious as of writing. The LIWO site contains various maps, for example composite water depth maps, flood scenarios maps, and flood risk maps to name a few. This thesis study specifically uses the flood scenario maps, termed *Bekijken overstromingsscenario's*, which are available at https://basisinformatie-overstromingen.nl/#/scenarios/6

Within the map, the flood scenarios would appear as individual pins or aggregated points (a circle with a number)[1]. The aggregated points would separate into individual pins when zoomed in.

Zoom into the area of Rotterdam, and look for the following pin labels, which would show when the cursor is over the pin. A visual guide is provided below to help identify the points, with an exaggerated pin in yellow for easier location.

1. Rotterdam_Boerengatsluis
2. Rotterdam_Parksluizen
3. Maashaven (dkr_17 km34.6)
4. Maashaven (dkr_17 km36.1)
5. Capelle-West_Nijverheidstraat (Hmp. 51)
6. Nieuwe Maas km995 (dkr17 km41.2)

Click on the pins to load the flood scenario. After the scenario has loaded, there will be a dropdown menu on the left of the screen (under "Waterdiepte"), denoting the return period of the flood. For this study, the more severe return periods are used per scenario, specifically:

[1] The map may take a while to load, if the site seems unresponsive, try reloading it, turn off any ad-blockers and/or check if the site is given relevant permissions.

1. Rotterdam_Boerengatsluis: 1/1,000,000
2. Rotterdam_Parksluizen: 1/1,000,000 and 1/10,000
3. Maashaven (dkr_17 km34.6): 1/40,000
4. Maashaven (dkr_17 km36.1): 1/40,000
5. Capelle-West_Nijverheidstraat (Hmp. 51): 1/1,000,000
6. Nieuwe Maas km995 (dkr17 km41.2): 1/40,000

When the correct flood scenario and flood return rate are selected, the map can be exported by clicking on "Scenario exporteren" on the bottom left to download the flood scenario file as a zipped .tiff file. These scenario files should then be extracted into separate folders (with with each flood scenario per folder), and placed into the *data/flood_breaks* folder, and it would be used by the Jupyter notebook script *pre-flooding-specific.ipynb*. Note that this notebook also uses the pre-processed outputs from the prior 2 sections, so complete those pre-processing operations before running this script.

Figure B.2: Rotterdam_Boerengatsluis

Figure B.3: Rotterdam_Parksluizen

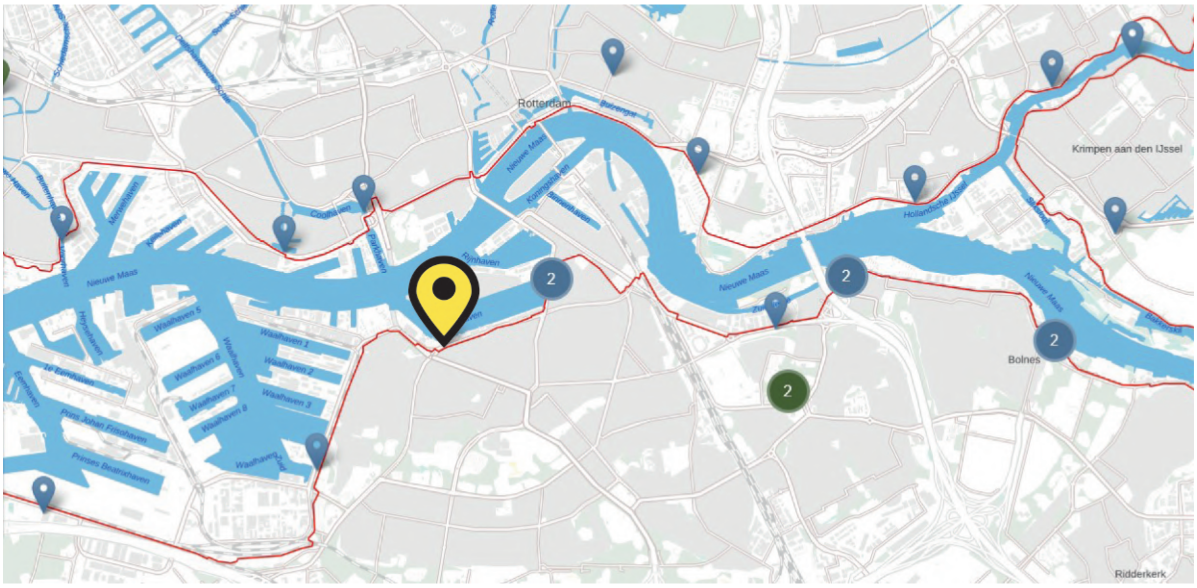

Figure B.4: Maashaven (dkr_17 km34.6)

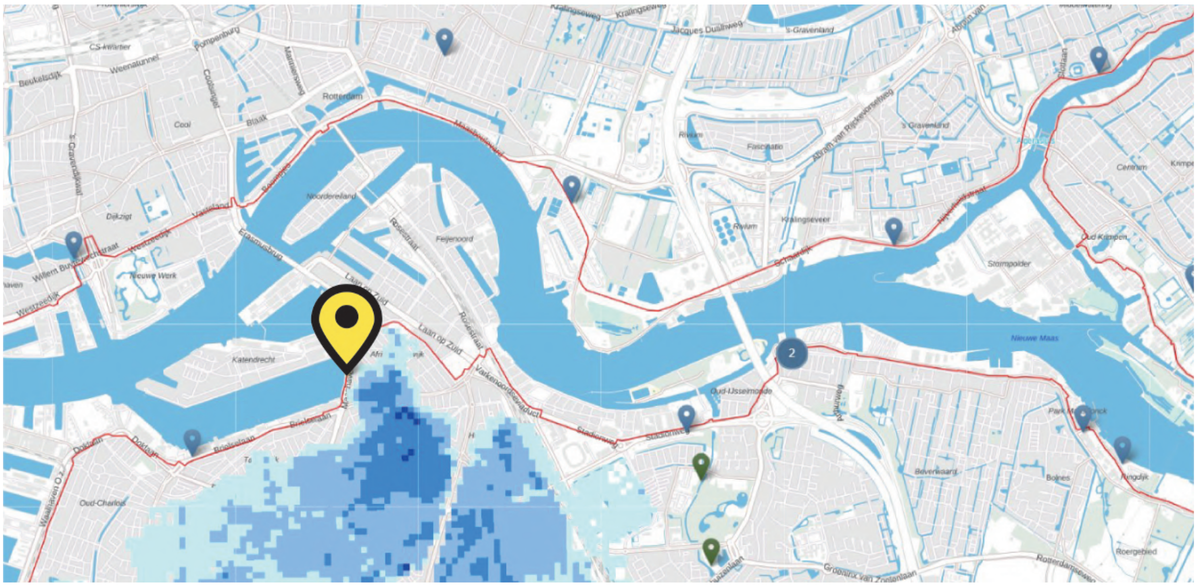

Figure B.5: Maashaven (dkr_17 km36.1)

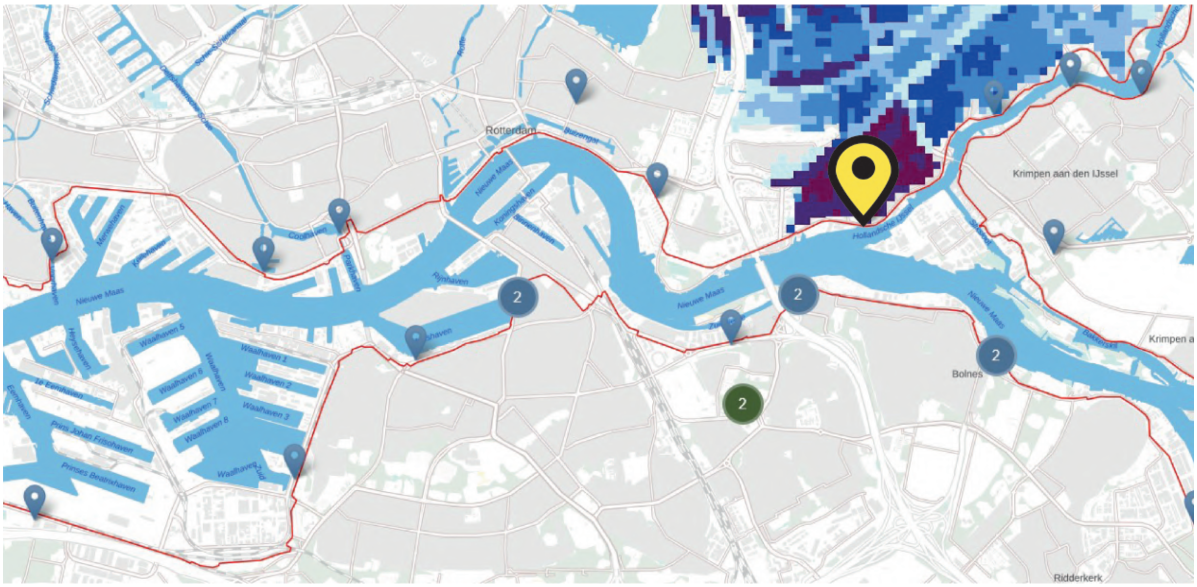

Figure B.6: Capelle-West_Nijverheidstraat (Hmp. 51)

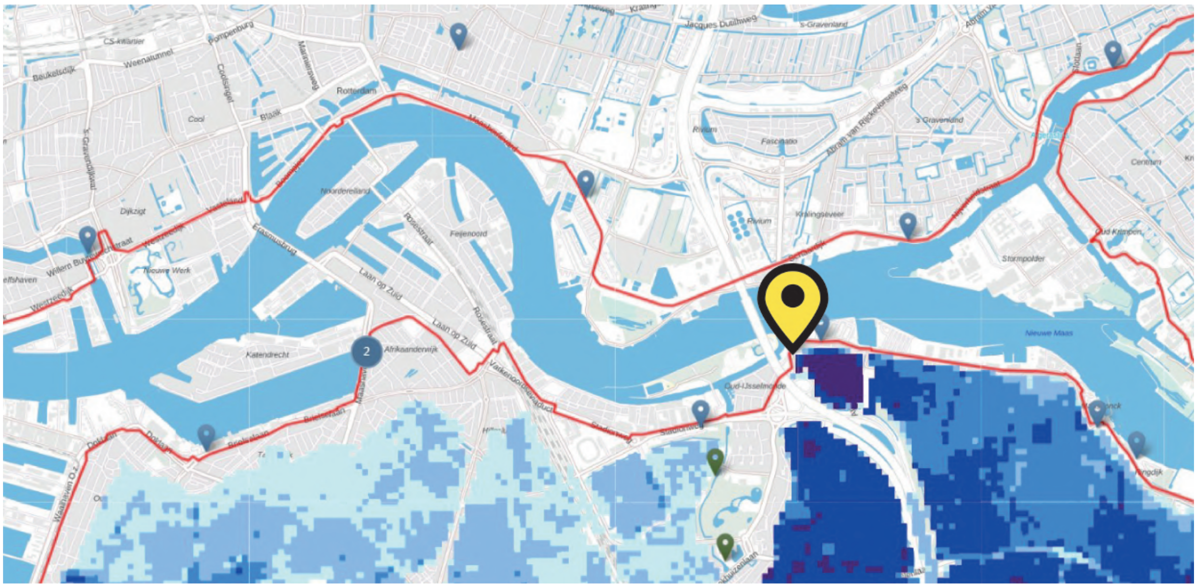

Figure B.7: Nieuwe Maas km995 (dkr17 km41.2)