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### Abstract

Recent floods in America, Europe, Asia and Africa reminded societies across the world of the need to revisit their climate adaptation strategies. Rapid urbanization coinciding with a growing frequency and intensity of floods requires transformative actions in cities worldwide. While abandoning flood prone areas is sometimes discussed as a public climate adaptation option, little attention is paid to studying cumulative impacts of outmigration as an individual choice. To explore the aggregated consequences of households' outmigration decisions in response to increasing flood hazards, we employ a computational agent-based model grounded in empirical heuristics of buyers' and sellers' behaviour in a flood-prone housing market. Our results suggest that pure market-driven processes can cause shifts in demographics in climate-sensitive hotspots placing low-income households further at risk. They get trapped in hazard zones, even when individual risk perceptions and behavioural location preferences are independent of income, suggesting increasing climate gentrification as an outcome of market sorting.

## 1. Introduction

Climate change is not a matter of the far distant future. High-impact storms are already increasing in frequency, with the 2017 hurricanes Harvey, Irma and Maria ranking among the 5 costliest hurricanes in US history [1]. The impact of climate change on flood damage is expected to be even worse in the future when sea level rise increases, and severe storms become more common [2]. In the US in particular, both historically-expected floods increase in frequency as well as unprecedented floods are expected to amplify with climate change [3]. Moreover, current population and assets exposure is argued to be underestimated, with 41 mln people living in 1:100 year flood zone instead of 13 falling under the official Federal Emergency Management Agency (FEMA) flood maps [4]. Rapid population growth and urbanization in coastal and wetland areas, driven by

economic, cultural and environmental amenities that the coast and waterways offer [5], lead to further increase of assets and the number of people exposed to intensified flood hazards [6, 7]. Adaptation to climate change that aligns both public and private actions requires an understanding of how people behave in response to increasing flood risks, how they are incentivised to adapt and what implications this has for the resilience of various groups of society. This is supported by theory and rich empirical literature on risk perception and its dynamics in response to floods [8, 9], and on people's willingness to take climate adaptation measures such as insuring against flood risk or flood proofing their homes [10–12].

Despite a strong empirical focus on households' adaptation measures, individually-driven outmigration as an adaptation option is still under-explored [13, 14]. Outmigration may increasingly gain popularity in the long run when risks become too high and incremental

adaptation measures too expensive [15]. Transformational changes—such as to move away from hazard zones [16]—could become a viable option. Households may voluntarily choose to do so at the point where risk is unacceptably high, and people switch to abandoning hazard areas [17]. This puts high-income households in a favourable position over low-income households, who may find themselves trapped due to the lack of resources to move [18]. It goes in line with the concept of ‘trapped population’ [19], that distinguishes between individuals who decide not to relocate versus those who are forced to stay in hazard-prone areas, possibly exposing themselves to progressively severe adversities. Moreover, floods can lead to climate gentrification [20] as high-income households push up demand and prices for safe locations, further forcing socio-demographic shifts in urban areas. While flooding has immediate economic consequences for all affected, the longer-term impacts are more detrimental for those who are economically vulnerable. The consequences of floods are therefore also characterized by environmental injustice [21] and disproportionately undermine socio-economic resilience of low-income households [22].

Yet, an open question remains: what is the risk threshold for people to decide to switch to out-migration? What would be cumulative socio-demographic impacts of these behavioural traits if we wait for floods to happen? A theoretical model suggests that as floods intensify and risk information diffuses, flood-prone areas become gradually unattractive creating economic stimuli for outmigration [23]. Yet, empirical exploration of these socio-economic process are scarce, with little knowledge on possible thresholds and distributional impacts of this process across populations and places [24]. In particular, a quantitative study bringing these aspects together is missing. To address this gap, we study how people’s risk perceptions change dynamically with the occurrence of major floods, exploring whether and when people switch to outmigration as an adaptation option and what implications it has on a city. In an empirical agent-based simulation parametrized using unique survey data from 8 US flood-prone states we show how individual choices, institutionalized in property markets, involuntarily lead to demographic shifts in response to natural hazards. We show that this process can gradually sort out high and low income households, amplifying inequalities and placing vulnerable households further at risk. By comparing socio-economic dynamics in two coastal cities with different proportion of houses in hazard-prone locations and under different scenarios of flood frequency we demonstrate, under which circumstances massive outmigration is triggered. Irrespectively of the scale of impacted households, we find that floods launch socio-economic feedbacks that create favourable conditions for climate gentrification.

## 2. Methods

### 2.1. Evolving climate-driven flood risks in artificial societies

Comprehensive surveys [25, 26], hedonic analysis [27, 28], and flood modelling [29] deliver a variety of empirical evidence for the relationships between climate-driven floods and adaptation choices, property values and socio-demographics in hazard zones. Although surveys are a useful method to measure flood risk perceptions of individuals, they provide just a snapshot in time and omit interactions among socio-economic actors. Hence, it is difficult to quantify from surveys how this dynamics would impact socio-demographics in hazard zones over time. Hedonic analysis on the other hand can be used to assess the aggregated marginal impact of flood risk on property values, but it is difficult to trace back the behaviour and perceptions that underlie these price effects [30]. Combining behavioural evidence on risk perceptions and factors affecting them with the dynamics of market institutions permits one to explore how urban socio-economic patterns are shaped in flood-prone areas and how they evolve over time.

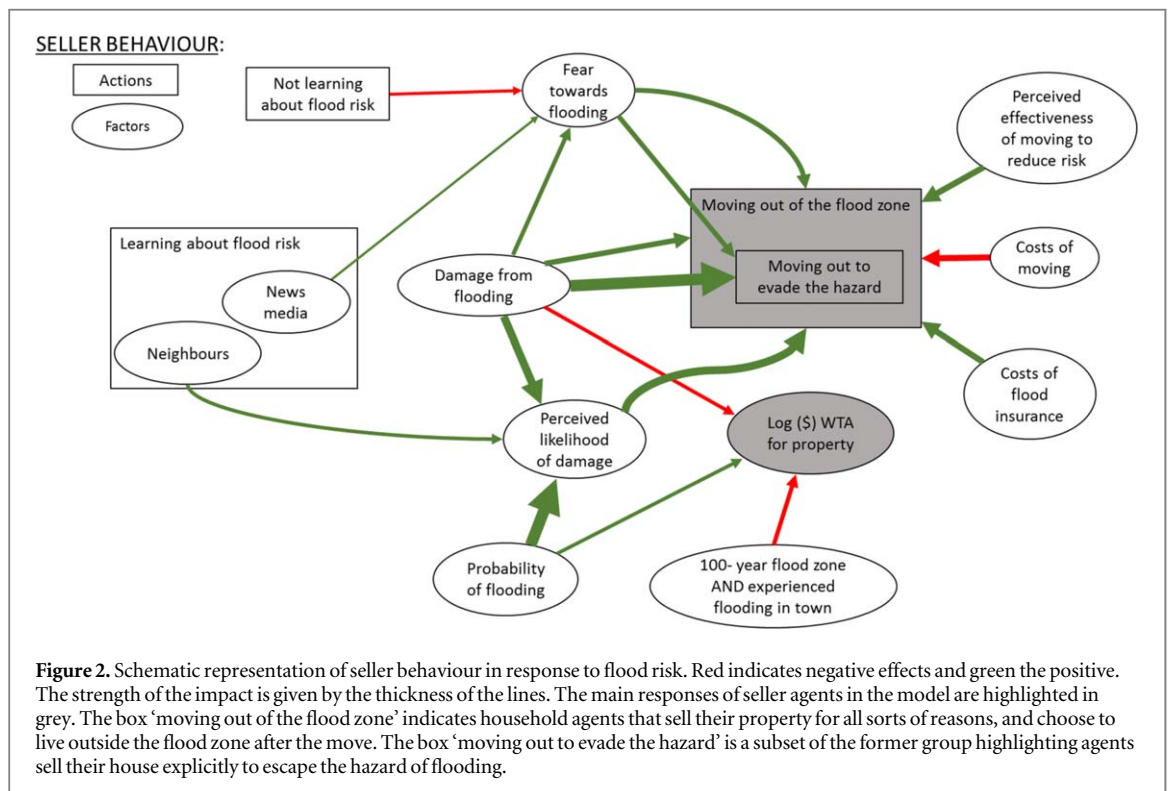
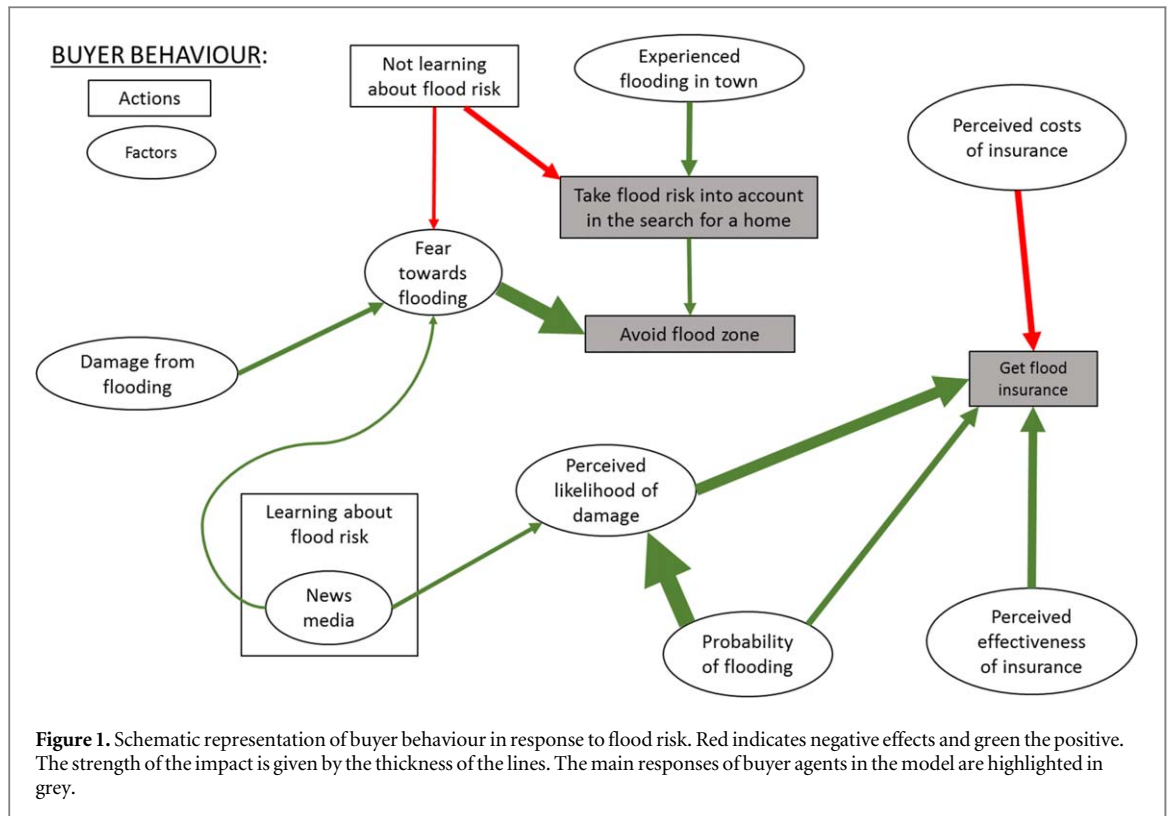
Agent-based modelling (ABM) is the key method to trace the emergence of system behaviour modelled from the bottom up through the explicit coding of behavioural rules guiding individual decisions and interactions [31, 32]. Various theories [33] and data sources are employed to validate behavioural rules and resulting macro patterns in these artificial societies [34]. The main advantages of ABM are its capabilities to study the aggregated effects of adaptive behaviour of many interacting heterogeneous agents with bounded rationality who learn from their experiences and adjust decisions [35]. Notably, ABM can be used to model systems out-of-equilibrium [36], which allows the exploration of non-marginal changes and regime shifts [37]. ABM is increasingly becoming the mainstream method to merge a variety of data on behavioural traits, with adaptive learning, dynamics of institutions and spatial or environmental changes essential to study socio-economic impacts of climate change [38, 39]. In the flood domain, ABM has been used to study feedbacks between land use and inundation [40], evolution of housing markets in flood-prone areas [41, 42], and uptake of flood insurance [29].

### 2.2. Modelling behavioural responses to climate-driven flood risks and housing markets

To explore the impacts of potential bottom-up out-migration from flood zones on the socio-demographic structure of cities in face of repetitive floods, we employ a spatial ABM of a housing market where buyers and sellers with heterogeneous risk perceptions and incomes interact [30, 43]. Table 1 describes the main model inputs and the data sources used for validation of these inputs. We use GIS data on

**Table 1.** Inputs, description and data sources of the RHEA model.

Model input	Description	Data source
<i>Residential property</i>	<p>Houses with georeferenced location and a set of structural characteristics: age, square footage of the house, size of the lot (acres), number of bedrooms, a dummy variable indicating whether the house is in a special flood hazard area (SFHA), and a variable indicating the annual probability of a flood affecting the property</p> <p>At initialization the value of the properties is estimated based on real estate transactions from 2000 to 2004 (Beaufort), and from 1992 to 2008 (Greenville)</p>	The GIS parcels with structural characteristics were supplied by the authors of Bin <i>et al</i> [46] (Beaufort), and Bin and Landry [28] (Greenville)
<i>Households' incomes and housing budgets</i>	<p>When households enter the market as a buyer, they decide on their housing budget that is partly random (drawn from a normal distribution with mean = 0 and sd = 0.77), and partly based on their income by the equation:</p> $e^{4.96 + 0.63 * \ln(\text{income}) + \text{random}[\sigma = 0.77]}$	<p>The income distribution of the households in the model is based on US national statistics [47]</p> <p>The percentages of income that households allocate to housing is validated with survey data [45] and US national statistics [47]</p>
<i>Household's risk perceptions and risky behaviour</i>	<p>Households have heterogeneous attitudes towards flood risk. Some households are highly risk-averse and would never buy a house in the flood zone while others do not even think about flood risk when they buy a house. This depends on their personality and the information that they gather about the risk (e.g. personal experience or talking to neighbours). The information about flood risk that homeowners receive changes during the simulation due to simulated floods and interaction among others agents</p>	The heuristic rules of how our modelled agents update their risk perception and behaviour are derived from a detailed survey among 1040 households along the south and east coast of the USA [45]. The survey was designed to provide input for the modelling of our agents
<i>Behavioural rules for buyers and sellers</i>	<p>The behavioural rules of buyers and sellers form the core dynamics of our housing market model. Buyers look for a home within their budget constraints and preferences for housing attributes and home location. Sellers offer their homes at the highest possible price. Buyers and sellers negotiate over prices. The housing market is the aggregated consequence of all these behaviours, trade attempts and successful transactions. Which is why we used various sources of expert knowledge and survey data to help us formulate the behavioural rules for the agents in our model</p>	<p>2 × 2 h in-depth interviews with real estate agents to specify the main architecture of the market (how ask and bid prices are formed, how agents negotiate prices, how they adjust prices, how learning on price expectations is happening)</p> <p>19 × half-hour to one hour interviews with real estate agents in North Carolina on the things that households are looking for in a home.</p> <p>surveys among 519 buyers and 521 sellers along the south and east coast of the USA [45]</p>
Algorithm for updating the seller's price expectations	<p>Sellers formulate their ask price according to current market conditions. All transactions in the simulation are stored at each time step and are used as input for the price expectations in the next time step. We run hedonic regression on these transactions to capture the marginal price of property characteristics, and we use spatial interpolation of the residuals (kriging) to assess the value of neighbourhood location. The price is also corrected for demand for similar properties in the same neighbourhood in previous time step, even when the properties are not sold yet. High demand results in a higher price and low demand in a lower price than estimated with hedonic analysis</p>	<p>The choice of the pricing algorithm with hedonci analysis and kriging is based on rigorous cross-validation of actual property transactions [48]</p> <p>The correction for demand was implemented in the model after consulting with real estate agents in North Carolina in 19 × half-hour to one hour interviews</p>



structural characteristics of properties (e.g. age, sq. feet, number of bedrooms, etc [28]) to initialize the spatial environment in two case-study coastal towns. The GIS data offer us exact latitude and longitude locations of the properties. The datasets also contain 1:100 and 1:500 flood zones, as designated by the FEMA that offers flood maps based on location and

elevation of the property [44]. To instantiate agents behavioural rules we use the household survey conducted separately among buyers and sellers (total  $N = 1040$ ) in January–February 2017 in eight coastal states in the USA, of which some have recently experienced major flooding [45]. At the core we model location choices of individual households and their



perceptions towards flood risk, which may affect their behaviour in the housing market, as illustrated in figures 1 and 2. Agents<sup>4</sup> vary in incomes, preferences for location and attitudes towards flood risks that adapt over time.

*Buyers* choose a dwelling affordable for their income based on its price and giving them high utility based on individual preferences and house characteristics. We tested both Expected Utility and Prospect Theory specification of individual choices under risk and found that Expected Utility explains better the empirical macro phenomena [30], such flood risk discount elicited from the housing transaction data over 11 years [28]. However, when experiencing a hazard event behavioural biases alter individual choices. Namely, households' attitude towards flood risk may inhibit them from buying a property in a flood zone (figure 1), as elicited from the survey data [45].

Households may choose to put their house on sale and look for a home in another location. *Sellers* form an efficient ask price based on hedonic analysis of the actual house sales in the region [28]. We further model *adaptive price expectations* in this ABM market using hedonic analysis and kriging of recent simulated supply, demand and transactions (analogous to appraisals of real estate agents in the real housing market). Seller always choose the highest bidder, hence houses that are much in demand likely sell above original asking price. If house receive no bids, a seller would gradually reduce the ask price. Those sellers who used to reside within a flood zone will more likely search for a new house in a safe location when they have experienced a flood (figure 2) [45].

Further, we simulate how people *update their risk perceptions* and their preferences for living in a flood zone after the occurrence of a major flood, which is grounded in theory and empirical observations of household-level preferences and behaviour in response to floods [45]. This is modelled by altering the posterior probability that buyers will avoid properties in the flood zone, or that households abandon the flood zone, conditional on their level of fear towards flooding, their experience with flooding and whether their property got damaged from floods. Individual changes in behaviour cumulatively affect the aggregate supply, demand, and value of properties in hazard versus safe areas. Driven by adaptive households' preferences, the effects of floods propagate through market interactions, affecting the socio-demographic structure of climate-sensitive urban areas.

To account for increasing frequency and the extent of flooding expected with climate change, we run the

model under different flood occurrence scenarios and apply it to two cases in North Carolina, USA: beaufort and Greenville. Both cities are in an area where hurricanes caused major flood damage to properties in the past. The cities differ in the nature of the flooding (coastal storm surge versus inland river flooding) as well as in the extent of the flood zone—Beaufort has a larger share of hazard-prone properties (29.9% and 21.5% are in the 1:100 and 1:500 flood zone, compared to 6.4% and 0% respectively in Greenville), and hence the impact of flooding is more widespread. We simulate 15 years of property transactions in the period 2015–2030. We assess the impact of floods by comparing three scenarios: a benchmark scenario with no floods, a scenario with a single flood in 2020 and a scenario with repetitive floods in 2020 and 2024. The likelihood of the second scenario may seem unrealistic from the first glance for flood zones of 1:100 frequency. However, Greenville has already had two major floods happen shortly after each other in 1996 (hurricane Fran) and in 1999 (hurricane Floyd) [28], even without climate change effects pronounced back then in the area. Hurricane Harvey was the third 1:500 year flood in three years [49]. Hence, we use the repetitive floods in two coastal towns with different shares of houses in flood zones to explore a bottom-up response to increasing flood probability and severity of floods with climate change. Considering downscaled climate change scenarios and their impact on flood occurrences in the area would be an important direction for future work. Given the stochastic nature of ABMs, we compare the three scenarios across 663 Monte Carlo runs (221 runs for each scenario).

### 3. Results: transitioning from affluent neighbourhoods to poverty traps

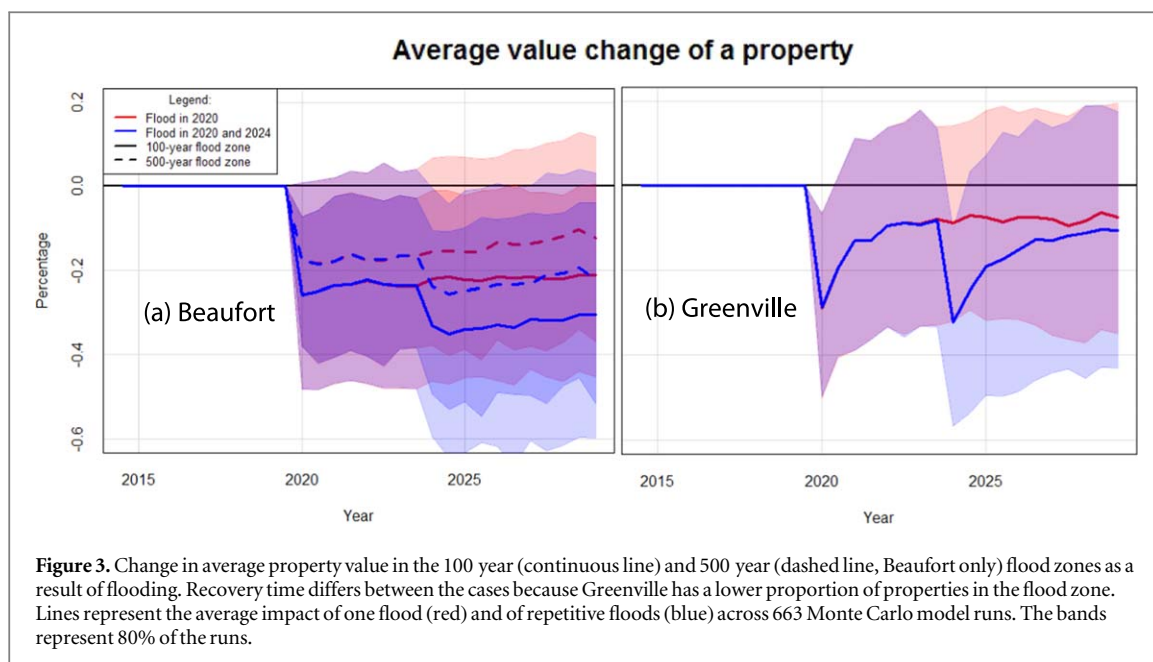
Affluent locations in a coastal town may become unattractive for living as floods become repetitive and signal the extent of risk when affecting a large share of local properties [23]. Housing markets drift into a new regime when damages lead to a drop in the aggregate demand, when market recovery does not occur smoothly, and when some people rush to relocate into safe zones while others remain trapped in the hazard zones [50].

#### 3.1. Damages and drop in demand

Under a variety of behavioural heuristics elicited from the survey, our spatial agent-based coastal housing market model indicates that a major flooding initially stagnates the market. Properties suffer damages and demand for properties in the flood zone declines rapidly as household agents avoid risk-prone properties. It causes a significant drop in property values in the hazard zones (figure 3).

In both towns the simulated peak price drop occurs immediately after the first flood, after which

<sup>4</sup> For the sake of readability of this paper we decided to keep our description of our ABM very general. For more details please have a look at our supplementary methods, or at the online version of our model at the online ABM sharing platform CoMSES, which includes the model code, ODD + D description and input data. <https://comses.net/codebases/8e6c8883-d618-4286-808f-8632adf4f1e0/releases/1.0.0/>.



values slowly start to recover. The price recovery is a result of newcomers entering the market from outside who have not yet experienced local floods. These people are generally less risk-aware than those who have experience with flooding and damage to property [45] and see an investment opportunity in the temporarily low-valued properties in the hazard zones. As a result of market sorting, this group of risk-unaware buyers generally have a lower income than households who lived there before the flood. Due to path dependence over time, the effect is amplified by the fact that demand for safe properties increases followed by prices, forcing low-income households into hazard zones. Consequently, our model shows that the first flooding results in a price drop of 26% (29% for Greenville) on average in the 100 year flood zone and 20% in the 500 year flood zone for Beaufort (figures 3(a) and (b)). The second flood leads to a 35% drop (32% for Greenville) in property values on this simulated market in the 100 year flood zone and 25% in the 500 year flood zone.

### 3.2. Market recovery

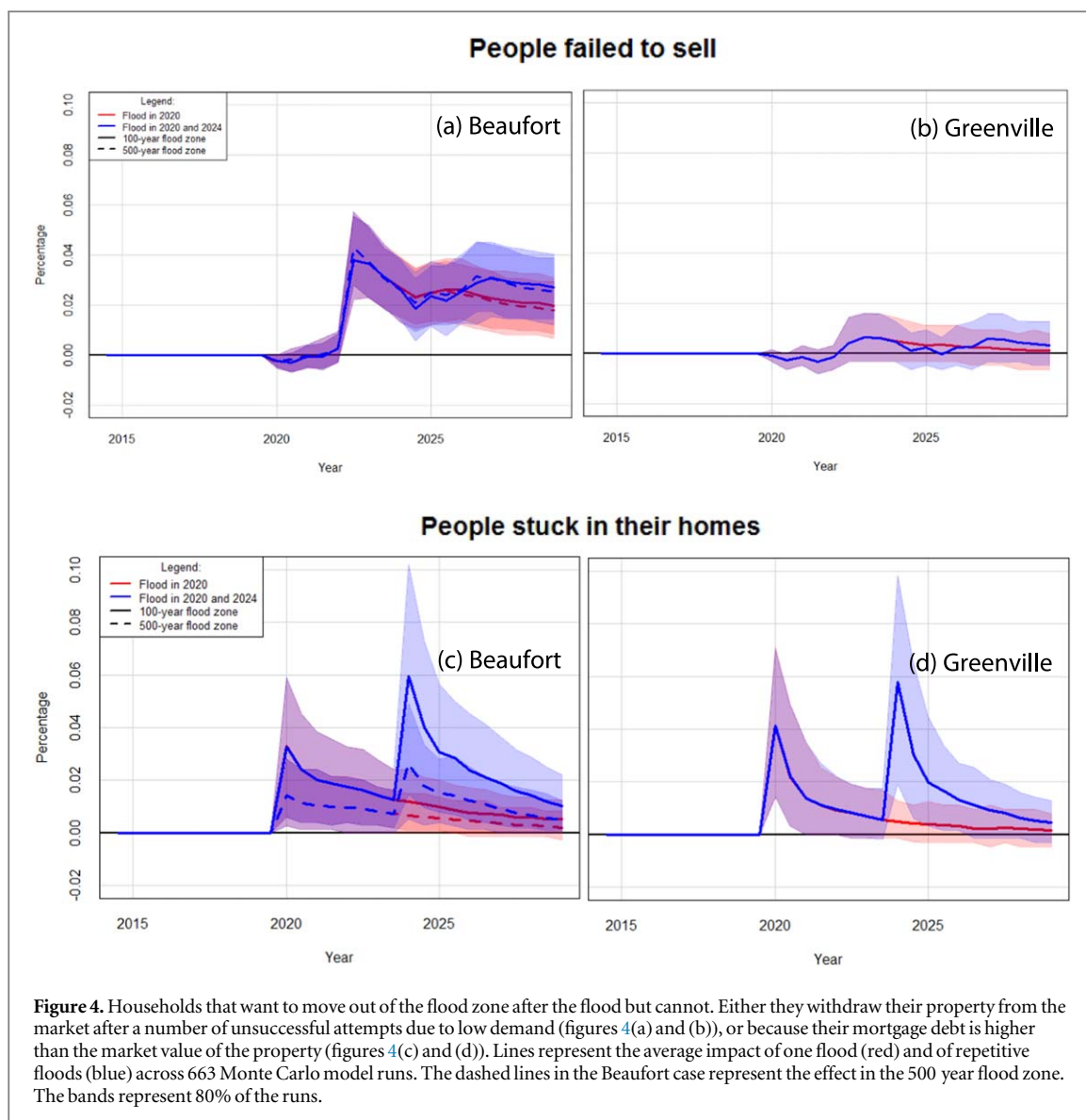
Recovery time of property values strongly depends on the number of properties in the flood zone and the number of households affected by the flood. Our model illustrates that markets with only few properties in hazard zones (Greenville, figure 3(b)) quickly recover, as the city population forgets about few local flood occurrences in the large pool of unaffected properties. Hence, there is sufficient demand from risk-unaware households moving into flood zones, and it does not create a lasting market effect. In contrast, markets with a large share of flood-prone properties (Beaufort, figure 3(a)) witness a troublesome shift in the market trend. When many people have experienced flooding or property damage the

price drop is significant and lasting. Moreover, there is a surplus of properties for sale in the flood zone compared to the relatively few risk-seeking households that buy them, resulting in a large share of unsuccessful sale attempts in Beaufort after the flood (figure 4(a)).

### 3.3. Outmigration from flood-prone areas

In the model, empirical behavioural traits prescribe some affected households to relocate from hazard areas after a flood. It results in a significant outmigration of households away from the flood zone, particularly when the number of affected households is relatively small. The fraction of households moving out is a lot smaller when there are more properties affected, limited by market demand for flood-prone properties. Namely, while a great number of household agents desire to move out, the relocation is limited by the number of people that are willing to buy these properties. Initially the sales increase slightly due to risk-unaware buyers that are attracted by the low prices, but in the long run people risk getting locked in the hazard zones because few people want to buy their houses (figures 4(a) and (b)). This is particularly the case in Beaufort that has a large share of affected households and relatively few risk-unaware buyers (figure 4(a)). Moreover, when prices drop sharply following a flood it impedes some household agents from selling at a price lower than their mortgage<sup>5</sup> (figures 4(c) and (d)). Hence, households with a low down-payment become locked into living in hazard areas. Households that invested more personal capital in the property (and have lower mortgages) have better

<sup>5</sup> This immediate effect of people getting stuck does fade away relatively quickly when prices recover and people have paid off more of their debts. The pattern is independent of the study area, which indicates that paying off the mortgage is more important as prices do not recover very well in Beaufort after the flood.



**Figure 4.** Households that want to move out of the flood zone after the flood but cannot. Either they withdraw their property from the market after a number of unsuccessful attempts due to low demand (figures 4(a) and (b)), or because their mortgage debt is higher than the market value of the property (figures 4(c) and (d)). Lines represent the average impact of one flood (red) and of repetitive floods (blue) across 663 Monte Carlo model runs. The dashed lines in the Beaufort case represent the effect in the 500 year flood zone. The bands represent 80% of the runs.

opportunities to migrate out of the hazard zones, since they can afford accepting a lower price for their house.

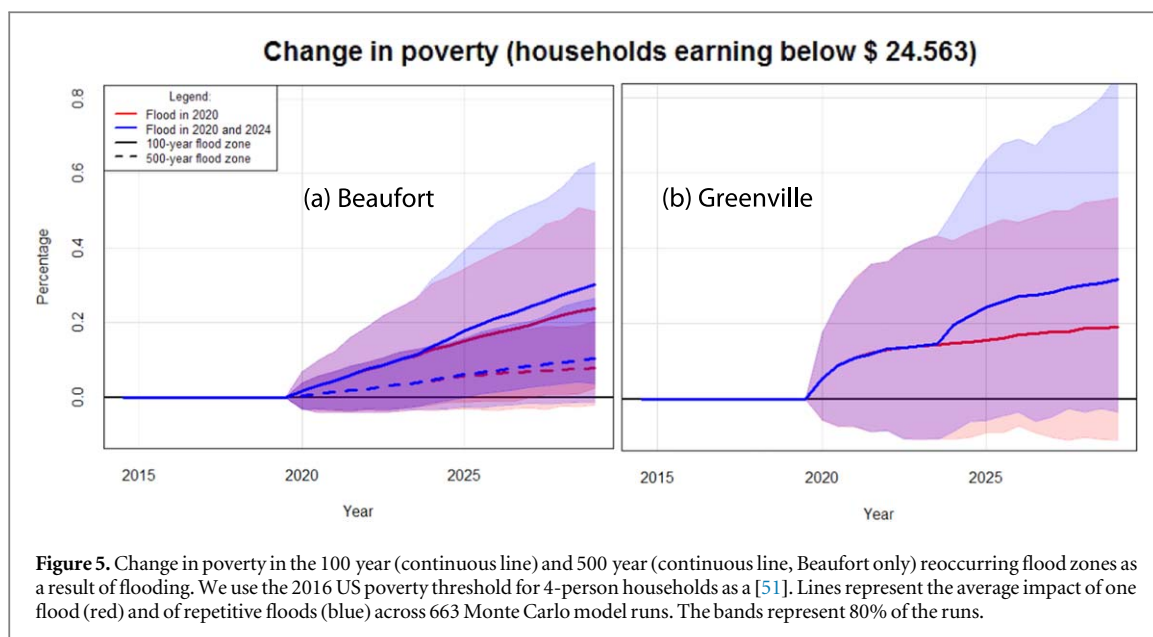
### 3.4. Climate gentrification

The two above-mentioned processes—a drop in demand and prices after the flood, and new low-income risk seekers moving in—together cause a gradual increase in poverty in the years following major flooding events. Our results demonstrate that flood damages and the drop in property values results in a gradual decrease in incomes of households residing in the flood zone, with the lower income cohorts affected stronger. Across all Monte Carlo runs the median income of households in the 100 year flood zone decreases by 2%–3% after a single flood and 4%–6% in ten years with two major floods, while in that same period the lowest income quintile decreases by 4% up to 7%–9% respectively. As such, the poor people get poorer, increasing social vulnerability in flood-prone areas. Consequently, the percentage of

households earning beneath the poverty threshold increases steadily in both modelled towns in the years following a flood (figure 5), which happens already after a single flood. In the repetitive floods scenario we see that the first flood has the strongest impact, showing that the impact of a flood on poverty is more pronounced after a long period without floods.

Although we see that prices and selling conditions recover somewhat in a span of 5–10 years after the flood, in particular in Greenville, the increase in poverty seems to be more permanent in both study areas. Even when prices have a tendency to return to their old level, poverty still increases by over 30% compared to the control scenario (no floods) ten years after the first flood. The processes gradually change the centre of gravitation on a market pushing high-income households towards safe zones, while attracting increasing numbers of vulnerable households to riskier locations. This goes hand-in-hand with climate gentrification based on speculative investments in





**Figure 5.** Change in poverty in the 100 year (continuous line) and 500 year (continuous line, Beaufort only) reoccurring flood zones as a result of flooding. We use the 2016 US poverty threshold for 4-person households as a [51]. Lines represent the average impact of one flood (red) and of repetitive floods (blue) across 663 Monte Carlo model runs. The bands represent 80% of the runs.

low-hazard properties [20], which further reinforces the trends of high-hazard neighbourhoods falling into decline.

#### 4. Discussion and conclusions

This paper contributes to the climate adaptation literature by studying the consequences of household-level outmigration decisions on socio-demographics and urban resilience, mediated through housing market responses. Our coastal housing market ABM shows that household behaviour in response to floods triggers market sorting, which enhances the risk of climate gentrification. Low-income households get trapped in hazard zones, even when households' risk perceptions and behavioural preferences are independent of income. The behavioural rules in our simulations are validated with empirical survey findings on outmigration triggered by floods that are already happening in our current climate, including the floods caused by Harvey [45].

We use the spatial ABM to study urban sorting triggered by consecutive floods, which could be expected as floods intensify in frequency and volatility with climate change. The comparison between the two coastal towns—with 6.4% of houses in the 100 year flood zone (Greenville) versus 29.9% of houses in the 100 year flood zone and another 21.5% in the 500 year flood zone (Beaufort)—provides an intuition on how markets with boundedly-rational agents with heterogeneous risk attitudes react when floods intensify in severity. Hence, we can already find some empirical parallels of our model's scenarios such as the outmigration that happened after hurricane Katrina<sup>6</sup> [52].

<sup>6</sup> In the model we did not simulate a complete abandoning of properties. All properties in the model had to be re-occupied. We are uncertain how this affects the results, but the model allows possibilities to further explore this.

The results of this paper highlight that a bottom-up 'Laissez-Faire' approach to climate adaptation could locally result in increased social vulnerability to flood risk, the extent of which will likely expand rapidly given the climate and population trends along the coast [6]. We stress that a timely and coordinated approach of well-structured institutional action is necessary in order to increase urban resilience against climate-change-driven floods. An artificial society, such as in the presented ABM, can be instrumental in exploring adaptation pathways where costs and benefits are shared by public and private actors, permitting to explore cross-scale adaptation [14] policies.

While our model shows important market-driven effects of floods on urban resilience, the interaction with other institutions and socio-demographic processes might amplify or attenuate the effects. Our model can be extended by including other relevant drivers of socio-economic vulnerability to floods, and ways to channel smooth urban transformations in climate-sensitive areas. Future research may focus on: (1) connecting to labour markets—storms put businesses out of operation or cause major interruptions, and job (un)availability inhibits people's options to outmigrate, (2) integrating of sociodemographic push and pull effects—the impacts are amplified by urban blight when critical poverty thresholds are reached in the hazard area, and (3) modelling of institutional responses—insurance companies, (federal) risk-management agencies and policy interventions can play a major role in the recovery trajectory after a flood, and in damage prevention before the flood. Institutions in particular can be instrumental in improving social resilience against future flooding and assuring the benefits of cross-scale adaptation [53]. The model is explicitly designed to explore bottom-up drivers of resilience against flooding. Given that it projects an emerging increase in social vulnerability, it is

worthwhile to investigate what role institutions can have in alleviating the impacts of future floods.

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## Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. An online version of our model is available at the online ABM sharing platform CoMSES, which includes the model code, ODD+D description and input data (<https://www.comses.net/codebases/8e6c8883-d618-4286-808f-8632adf4f1e0/releases/1.0.0/>)

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