When do we leave? Modelling coastal cliff erosion, human behaviour and the property market

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i Abstract

Environmental hazards should be explored alongside the social processes that they influence. As climate change leads to unprecedentedly frequent and severe coastal hazards, large populations of individuals living along the global coastline may behave in unexpected ways. The development of effective, proactive coastal management policies requires improvements in our currently limited understanding of these potential changes in human behaviour. This gap in understanding was highlighted during Cyclone Gabrielle in early 2023 in Tāmaki Makaurau/Auckland, Aotearoa/New Zealand, which led to flooding and land failures, including in coastal, clifftop areas. Property destruction led to the development of reactive policy which caused significant social tension and economic loss. This study examines the relationship between coastal cliff erosion, individual decision-making and socioeconomic conditions within a community in north Auckland. We aimed to improve understanding of this poorly understood socioenvironmental system. To achieve this we developed a simplified agent-based model, treating physical and social phenomena as components of a complex system. A heterogeneous population of homeowners were the main agents, making property decisions based on their personal tolerance for risk. The model was run under various cliff erosion scenarios to explore their potential socioeconomic consequences. We found that increased erosion led to a reduction in market value and increase in the population's tolerance for risk. The two main mechanisms of cliff erosion, gradual and storm-driven, had different impacts on the system as a whole. Gradual erosion allowed more time for risk to be perceived and acted upon, resulting in more home sales to buyers with progressively lower incomes and higher risk tolerances. Storm erosion led to sudden changes in risk that could not be perceived in advance, leading to unexpected destruction of assets for homeowners with relatively low tolerances for risk. Our modelling suggests that in the absence of risk offsetting measures other than avoidance, coastal cliff erosion leads to a population of homeowners who are both highly tolerant and highly vulnerable to risk. Such socioeconomic demographic changes have significant implications for coastal management, and raise questions of risk accountability.

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From the operating system I ran the model on to the markup I wrote this dissertation in, this project was entirely completed using free and open-source software. As always I am extremely grateful to the developers and maintainers of these tools for providing their expertise, passion and time. Of particular note for this project are the Debian operating system, i3 window manager, NumPy and Shapely Python libraries, QGIS and OpenStreetMap GIS projects, and LaTeX - although there are many more. All of these tools were invaluable in completing my research and inspire me to continue working on open-source projects.

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Chapter 1: Introduction

Climate change will result in more frequent and severe coastal hazards, introducing high levels of risk to human and natural environments (Pörtner et al., 2022). Human behaviour is important to understand alongside the physical impacts of these hazards due to their interactions with each other (Lazarus et al., 2016), especially in the face of uncertain climate change (McNamara et al., 2011). Individual-level human behaviour is often ignored in research, despite its importance in effective coastal management (Heymann, 2019). Management will be vital to mitigate harm to coastal settlements, which can be more vulnerable to hazards due to factors such as urban intensification (Bevacqua et al., 2018). Vulnerability to climate hazards varies spatially even at a national scale, and despite adaptation policy often being enacted at a local scale (Dawson et al., 2009), studies of coastal adaptation often focus on large areas (Rouse et al., 2017). There is therefore a need for local-scale research that combines the physical impacts of climate change with individual human behaviour in a coastal environment.

Residential market dynamics can be important signals for changes in coastal management (Anderson et al., 2019). Humans make decisions within a property market, choosing to buy and sell homes based on a variety of factors, including hazard risk (Buchanan et al., 2019). Homes are also often the highest source of wealth for individuals (Symes, 2022), and so are a good socioeconomic indicator to assess when exploring population-wide impacts of coastal hazards. Residential property markets, and the homeowners within, can therefore be representative of both individual decision-making and emerging socioeconomic conditions.

Social, market and hazard interactions within coastal clifftop environments are poorly understood because most socioenvironmental research focuses on low-lying sandy beaches and sea-level rise (SLR) (Del Rıéo & Gracia, 2009). This was highlighted in Aotearoa/New Zealand (A/NZ) when Cyclone Gabrielle caused sudden cliff erosion events (Harrington et al., 2023), the socioeconomic consequences of which were not understood or planned around. Computational models can improve our understanding of such interactions and their consequences by simulating uncertain future hazard scenarios and the potential impacts on social processes (Aven & Renn, 2015).

Overall, the aim of this study was to address the following questions:

- What socioenvironmental interactions take place within a local-scale, coastal, clifftop property environment under increasing levels of erosion?
- Are there socioeconomic deprivation and/or vulnerability implications to increasing cliff erosion?
- In a coastal, clifftop setting, how does individual decision-making impact the property market as a whole?

Consequently, our approach encompassed four key research objectives:

1. **Develop a computational model that represents physical and social processes in a local-scale coastal, clifftop environment.** Cliff erosion will increase risk to individuals and therefore social systems. The model will be simplified through discrimination of what phenomena are included, as well as what interactions occur between model components.

2. **Explore the relationships between individual human behaviour, housing market dynamics and coastal cliff erosion.** Coastal cliff erosion may influence individual behaviour, potentially interacting with residential property markets.

3. **Assess how different scenarios of coastal cliff erosion impact social systems.** Modifying erosion rates can represent different climate scenarios. The physical impacts of this are often researched, but the socioeconomic consequences are not.

4. **Improve understanding of how the interactions between system components lead to emergent behaviour.** Emergent behaviour can be explored through aggregated variables that change on an individual scale over the course of the model run, and/or drastic shifts or tipping points in system behaviour.

Chapter 2: Background

2.1 Residential property and coastal hazards

2.1.1 Coastal clifftop property

Coastal, clifftop property markets are a poorly understood environment that will be exposed to increasing risk due to climate change. Young and Carilli (2019) found that cliffs make up over half of the global coastline, and that erosion, exacerbated by SLR, and subsequent retreat is occurring in one-third of coastal states. Populations and property in clifftop areas have grown along with general coastal intensification, yet most climate hazard research focuses on beaches and sandy coasts (Del Rıéo & Gracia, 2009). Where cliffed areas are studied, impacts of erosion are typically a simple quantification of newly inaccessible home values (Burgess et al., 2007; Pearson et al., 2005) rather than exploring the underlying physical, social and market dynamics. As contemporary coastal adaptation issues often revolve around private property (Gibbs, 2016), understanding local-scale property dynamics could result in more effective management of the clifftop environment. Anderson et al. (2019) argued that these market dynamics can play a critical role in climate adaptation, signalling policymakers to take proactive risk-prevention actions. Thus, with climate change set to greatly increase the impact of coastal hazards, there is a need to understand how the property market, and therefore individual homeowner behaviour, reacts so that effective adaptation can take place.

2.1.2 Aotearoa/New Zealand context

Figure 2.1: Coastal cliff erosion in Stanley Bay, Devonport after Cyclone Gabrielle (Craig, 2023)

In A/NZ, coastal climate adaptation and property markets are strongly linked, where Manning et al. (2015) argued that perception of changing house prices is a primary factor in adopting adaptation measures. Climate risk currently has a low influence on house prices both globally (Gibbs, 2015) and in A/NZ (Filippova et al., 2020). Climate hazards are mostly seen as a distant threat, a perception that is also reflected in a lack of comprehensive adaptation policies in A/NZ (Manning et al., 2015; Rouse et al., 2017). This policy deficit became apparent when Cyclone Gabrielle caused significant flooding and storm surge events in early 2023 (Harrington et al., 2023). Many homes were destroyed, partly due to land failure/slip events particularly in coastal, clifftop environments such as the Devonport Peninsula of Tāmaki Makaurau/Auckland (Figure 2.1). In the aftermath of the cyclone there was significant legislative uncertainty regarding responsibility for the management of damaged/destroyed homes. Reactive policy was quickly developed to buy out homeowners (Cyclone Recovery Unit, 2023), an approach that has been shown to cause emotional and financial stress (Shi et al., 2022). A greater understanding of socioenvironmental interactions with events like Gabrielle in A/NZ could lead to development of proactive policy that reduces future tension.

2.2 Approaches to understanding socioenvironmental interactions

2.2.1 Complex systems

Behaviour within the property market and its interaction with environmental hazards can be studied through the application of complex systems science (CSS). CSS studies phenomena by exploring individual components that contribute to their existence and function (Ladyman et al., 2013). Siegenfeld and Bar-Yam (2020) argued that it is a unifying framework of scientific analysis, favouring the study of interactions between components rather than the traditional disciplinary approach of focusing on components in isolation. One aspect of a complex system is the emergence of system behaviour resulting from interactions between individual components, behaviour that may not be deduced by examining system components in isolation (Epstein, 1999). This bottom-up approach can generate greater understanding of the system as a whole when compared to studying the phenomena in isolation. Werner and Mcnamara (2007) explored flood protection developments in New Orleans as coupled complex systems through economic and landscape models. They found that economic incentives for humans to build levees for smaller floods came at the expense of catastrophic damage during disasters. By exploring the processes surrounding flooding from a bottom-up, CSS perspective they were able to understand what can lead to increased vulnerability, rather than simply analysing the impact of that vulnerability. Their approach was transdisciplinary, including social science, economic, and geomorphic components - CSS facilitated a broad view of the problem. When reviewing flood risk models with human components, Taberna et al. (2020) concluded that taking a CSS approach can lead to a better understanding of social adaptation to climate hazards. Interactions between individuals, market behaviour and cliff erosion can benefit from CSS because the systems consist of many interacting components that may cause emergent behaviour, and they exhibit processes from across disciplines (Dearing et al., 2006; Limburg et al., 2002; Macmillan et al., 2016).

2.2.2 Computational modelling for understanding systems

Computational modelling is a vital tool for understanding how climate hazards and social systems interact. A model is an abstraction of a process/system that can represent its behaviour. They can be used both to predict potential conditions and to understand the processes behind a system (Held, 2005). Models, developed with algorithms that can be executed computationally, are highly involved in climate hazard management (Pörtner et al., 2022). They can estimate how a system reacts to uncertain climate scenarios, and can include human processes (Aven & Renn, 2015). For example, Dawson et al. (2009) estimated the impacts on socioeconomic and property market conditions from coastal cliff erosion under future climate scenarios using a computational model, finding that economic risk was expected to greatly increase with future flooding. Damage from this hazard could be preemptively managed with such an estimation before the consequences are realised. Models that promote understanding over prediction can focus on the complex components of a system and their interactions, facilitating management strategies that can account for dynamic interactions within an environment over time rather than solely managing the potential future outcome (Bevacqua et al., 2018). Both of these modelling goals are useful, and not mutually exclusive as Calder et al. (2018) argued that computational models that promote understanding often lead to greater predictive ability in future research. Accurately predicting how property markets will change in response to increasing hazards is difficult due to the unprecedented nature of climate change. Current market behaviour regarding coastal hazards is mostly based on a static climate (Filippova et al., 2020), which is likely to change as traditional homeowner assistance like insurance becomes less viable due to climate change (Storey et al., 2022). This change in behaviour may vary throughout the population, as different individuals have different values and beliefs towards property and climate hazards. There is therefore a need to better understand how a heterogeneous population of homeowners, and therefore the property market, may react to different hazard scenarios (Filatova et al., 2011), rather than making uncertain predictions based on existing dynamics. Computational models are vital towards achieving this by simulating potential hazard scenarios and social dynamics.

2.2.2.1 Computational modelling techniques

Various computational modelling methods are used to study the interactions between human behaviour and the property market, including in the context of environmental hazards. Empirical modelling utilises observations of market dynamics under hazard events. This can then be compared to the market under normal conditions to evaluate the relative influence of the hazard. Filippova et al. (2020) compared empirical home transaction data before and after homeowners were made aware of SLR risk, and revealed little behavioural change. While buyers' behaviour after a climate hazard/change in perception can be derived with this method, it fails to provide an understanding of the processes underlying their decision-making. It also can only be used retroactively, so potential climate scenarios and their interactions with the property market cannot be directly understood through empirical analysis as the data are based on climate conditions at the time of observation (Gibbs, 2015). Mathematical models represent phenomena with formulae and other mathematical concepts, and do not have to rely on empirical data. Bakkensen and Barrage (2017) developed a mathematical model to analyse coastal flood risk perception and its interaction with property market dynamics. They concluded that existing risk perceptions result in an overvaluation of property. The heterogeneity of individual risk perception is accounted for in their work, but only through binary categorisation of individual perceptions. Their model also has a high level of complexity and thus low level of communicability. Esmaeili et al. (2010) modelled housing dynamics with human behaviour by combining mathematical modelling with other techniques, resulting in a more approachable model that makes less behavioural assumptions. A common technique in property market analysis is hedonic modelling. Hedonic models assume that individual attributes for a house, which could include climate risk, discretely contribute to its overall value, combined through regression analysis to result in a valuation (Nicholls, 2019). These models are used mostly for static valuations, but can also be coupled with other techniques like geographic information science (GIS) and process-based modelling to incorporate hazard risk and individual behaviour (Filatova, 2015; Kuminoff et al., 2010). Hedonic modelling is useful in assessing the impact of a hazard on property valuation, but the linear assumptions and top-down approach cannot determine the mechanisms, such as human behaviour, that lead to these valuations (De Koning and Filatova, 2020). Empirical, mathematical and hedonic modelling are all useful but a different technique is needed to account for heterogeneous behaviour among homeowners, their potentially nonlinear interactions with climate hazards and property markets, and general uncertainty, all with an approachable level of complexity.

2.2.2.2 Agent-based modelling

Agent-based models (ABMs) are computational models that can be applied to the interacting systems of human behaviour, property markets and environmental hazards. ABMs comprise distinct, autonomous objects that have sets of rules and behaviours. Agents can interact with each other within an environment, where both the interactions and the environment can impact their behaviour. Agent interaction can lead to overall system behaviour while accounting for variation within agents and/or processes that compose it (Macal & North, 2010). In the case of human behaviour, agents can represent individuals with heterogeneous decision-making traits. ABMs were originally developed to explore human populations in the Schelling (1971) segregation model, which began a field that was formalised as generative social science by Epstein (1999). In an ABM, individuals can make decisions and interact, resulting in emergent behaviour at a population level that can not always be predicted even with perfect knowledge of individuals, complementing traditional behavioural science (Epstein, 1999). Kennedy (2011) argued that modelling human behaviour is challenging due to a short history of empirical observation, with even less observation of behaviour under climate hazards due to their previously unseen severity and frequency (Pörtner et al., 2022). Human behavioural rules can be modified in an ABM, and therefore can test different theories of individual behaviour under different climate scenarios. They can later be calibrated with empirical evidence (Heckbert et al., 2010), allowing future managers to more accurately predict how the system will react to real-world scenarios. ABMs can include physical drivers, such as climate hazards, alongside agent behaviour (Werner & Mcnamara, 2007), and have been employed in a wide range of socioenvironmental research. Dubbelboer et al. (2017) coupled environmental drivers with bank, insurance, government and human agents. Their ABM estimated that human behaviour driven by economic incentives intensifies surface water flooding, results which allowed the authors to evaluate current insurance schemes under future climate conditions. While effective in this use case, their model is not applicable in other areas due to the geographically-specific rules used. Using an ABM to estimate the impact of climate risk on coastal homeowners, McNamara and Keeler (2013) found that homes are abandoned when risk is too high for the homeowner. Their inclusion of heterogeneous risk perceptions for individuals through the ABM led to nonlinear interactions and an effective representation of subjective climate risk expectations. They modelled several generic structural drivers like economic incentives which makes it more applicable to other geographies, but the model is complicated and difficult to understand through rules and assumptions surrounding the construction of defence structures. De Koning and Filatova (2020) developed a GIS-enabled ABM with a heterogeneous homeowner population alongside a coastal flooding model. They found that increased flooding triggered different human behaviour and resulted in higher vulnerability. Modelling coastal flooding and human behaviour with ABMs is common practice (Taberna et al., 2020), but flooding and cliff erosion may result in different behaviour. Fontaine and Rounsevell (2009) developed an ABM to study cliff erosion alongside coastal flooding. They discussed how GIS-enabled ABMs are vital for understanding residential dynamics. Risk zones for flooding and cliff erosion were not categorised separately in their research, and so individual dynamics of clifftop behaviour could not be determined. Overall, ABMs are an effective CSS approach for socioenvironmental research, accounting for heterogeneous populations, nonlinear behaviour, individual decision-making and more by coupling with other modelling techniques. GIS-enabled ABMs are particularly suited for the property market, allowing spatial variability in market dynamics/decision-making based on hazard proximity. Overall, there is a need for an ABM that includes isolated interactions between coastal cliff erosion and human/market behaviour.

2.2.2.3 Model complexity

The level of complexity, or scale at which abstractions are made, when developing a model is an important research consideration. Pindyck (2017) argued that simplified and all-encompassing environmental models both rely on the same biases, yet simple models are easier to access and understand. Complex systems can be represented with simple models as CSS involves finding simple rules that underpin emergent complex behaviour. Aggregated, emergent behaviour resulting from simple interactions between heterogeneous individuals can better represent a population than creating complex behavioural models (Gallegati & Kirman, 2012). Simplified representations of processes are therefore well-suited for complex systems.

2.3 Conclusion

In summary, there is a need for socioenvironmental research focussing on the coastal, clifftop property market, and the associated individual decision-making. Such research can further the understanding of how these systems interact, enabling effective management in areas that need it, such as the Devonport Peninsula. To focus on the spatial variation in the housing market, the model should be GIS-enabled. To reduce location-specific bias, top-down structural impacts could be reduced, but behaviour can still be influenced by simple market forces. Given the complex nature of these interacting components, an ABM will be an effective method to achieve the goals of this research. The model should include a heterogeneous population of individuals who vary in their behaviour towards risk to effectively represent real-world subjectivity. The ABM should be simplified, facilitating understanding and communication of the results while still representing the system(s) effectively.

Chapter 3: Methods

3.1 Model development

An agent-based computational model was identified as the best way to explore socioenvironmental systems. The following sections describe the development of each model component used for our research, as well as how these components couple and interact, to meet research objective 1.

Input: Array of homeowner agents, cliff and land geometry

Erode cliff edges ▷ *Section 3.1.3*
Detect if any homes are inaccessible ▷ *Section 3.1.4.1*
Remove inaccessible homes from neighbourhoods and apply value reductions to neighbours ▷ *Section 3.1.4.2*
Calculate distance of homes in cliff zone to the cliff edge
Categorise homes based on distance ▷ *Section 3.1.4.1*
Apply value reduction to homes that change risk categorisation ▷ *Section 3.1.4.1*
Detect and apply neighbourhood trend effects to each home ▷ *Section 3.1.4.2*
Calculate risk of each home ▷ *Section 3.1.4.3*
Perform home sales where risk can no longer be tolerated ▷ *Section 3.1.4.4*

Output: Array of homeowner agents, cliff and land geometry

Figure 3.1: Pseudocode representation of each ABM step

Our ABM calls each model component in sequence at each model step, as detailed in Figure 3.1. Running the ABM for a number of steps allows a time series to be produced, where the output of each given step is used as starting conditions for the next step. After the ABM run is complete, geophysical and housing data from each step are saved for analysis. Each step represents 1 month in real time as weekly increments would be computationally difficult and yearly increments would provide insufficient granularity for individual decision-making.

3.1.1 Platform

We used the Python programming language to develop the model, utilising the NumPy package for an array-based agent structure. As Abar et al. (2017) discussed, many bespoke software platforms exist for developing ABMs. Most are object-based, whereby agents are represented as individual instantiated objects in the software environment. Each agent must therefore exist in memory separately, which can be computationally inefficient as each agent must be iterated over when calculations are required. An alternative to this is an array-based approach, where agents are represented as vectors within an array. This can be more efficient as the entire array can be manipulated at once rather than in individual iterations. The array-based approach for ABMs can greatly speed up performance relative to the traditional object-based approach (Kerr et al., 2021).

We anticipated the model to be computationally intensive due to the many interactions between physical and social components, particularly with regard to geospatial operations. The model also required the development of individual components such as the cliff erosion model, which may be difficult to couple with software packages. We therefore developed the model in code in an array-based structure, without using existing ABM packages to maximise performance. Python was selected for this due to familiarity and its high usage in the scientific community (Harris et al., 2020), thus maximising reproducibility.

Model components were developed in modules that were referenced by a main class. All model code will be made open-source and freely available, which allows research to be independently assessed and/or built upon, enabling further understanding of the system being modelled (Sarofim et al., 2021).

3.1.2 Data

We aimed to explore potential future system dynamics for research objectives 2, 3 and 4. Data on current physical and social conditions were therefore required to establish the starting conditions of the model.

Table 3.1: Summary of model input data (LINZ=Land Information New Zealand)

Model component	Data required	Data source	License
Erosion	Coastline position	LINZ	CC BY 4.0 DEED
Erosion	Digital elevation model (DEM)	LINZ	CC BY 4.0 DEED
Housing market	Residential property locations	LINZ	CC BY 4.0 DEED
Housing market	Residential property valuations	Auckland Council	Proprietary
Housing market	Potential buyer wealth	Inland Revenue Department	CC BY 4.0 DEED

The data we used are described in Table 3.1. Most data providers use the Creative Commons attribution license (CC BY 4.0 DEED) which allows free use provided the data is attributed to the provider, as in this study. Valuation data provided by Auckland Council are proprietary but can be visualised under the conditions that the data are not shared and that areas other than that of this study are not presented. To reduce potential licensing conflicts, data will not be included when sharing the methodology/code for this project. All spatial data and operations in this project used the New Zealand Transverse Mercator (EPSG:2193) map projection due to its high accuracy in the study area and the unit of metres making distance calculations straightforward.

3.1.2.1 Study area

Our researched focused on the Devonport Peninsula of Tāmaki Makaurau/Auckland, A/NZ, due to its contemporary relevance for cliff erosion events. The specific geometry of the study area was created to discretise the processing (i.e. have a set area where the model is defined to run). The polygon that defined the study area allowed processing to be constrained, and provides geometry for other data to be clipped to. We ended the peninsula extent where the cliffed environment stops to create the polygon.

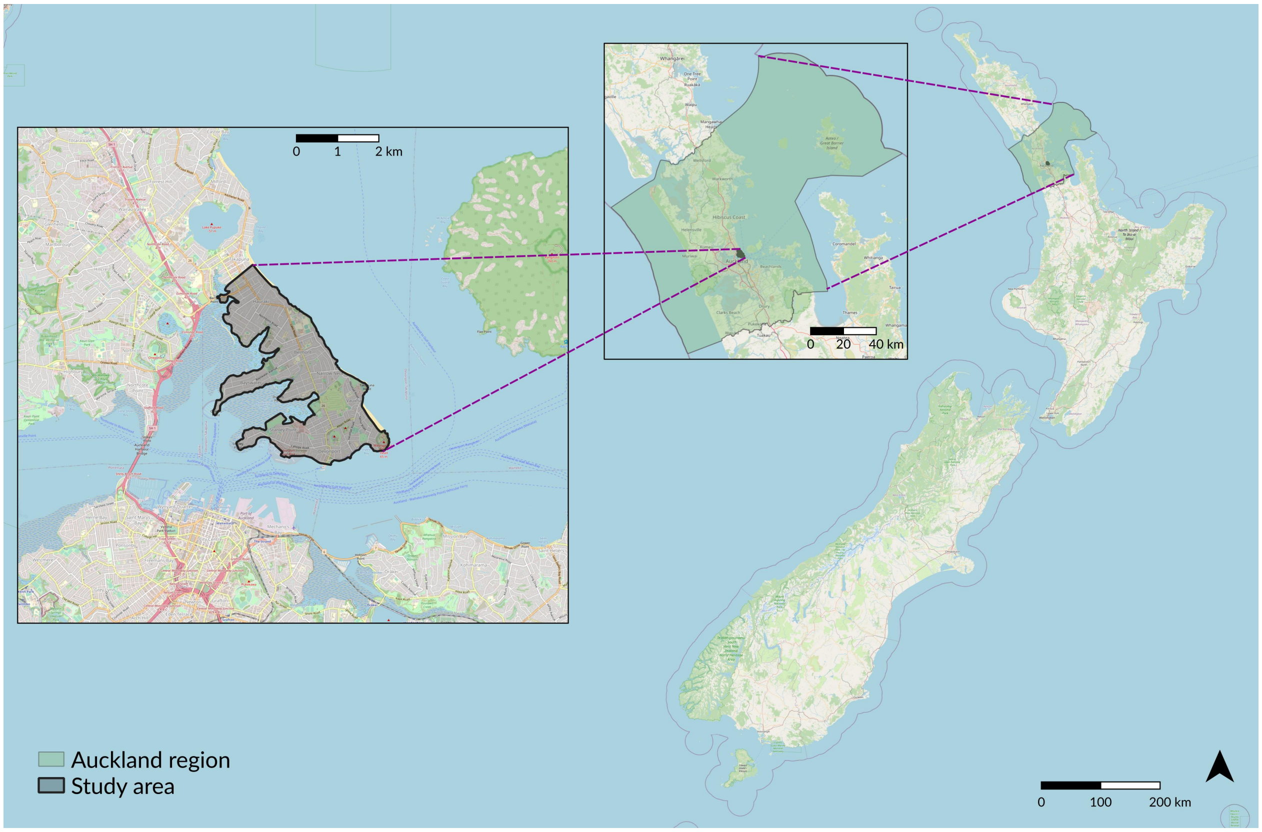

Figure 3.2: Study area in relation to A/NZ and Auckland region

The study area geometry (Figure 3.2) follows the peninsula, ending at a set line halfway along Takapuna Beach. The geometry is based on land parcel boundaries, and therefore excludes features that protrude beyond the peninsula's landmass, such as marinas.

3.1.2.2 Home values and positions

Homes needed to have an initial value so that the effect of erosion and other model dynamics could impact the residential market. Auckland Council provided land parcel valuation data for use in this project. Parcels that were not within residential zones were excluded. There are often multiple homes within a given land parcel, so individual building data were required. Operating on the assumption that homes within the same parcels will have similar values, we used building position data to transfer parcel-based valuations to individual residences. Buildings under 40 m^2 (see Section 3.2.1) were assumed to be sub-structures of a home and were removed. We then spatially joined the remaining building geometries to the parcel data, resulting in a dataset of spatially referenced homes with associated values.

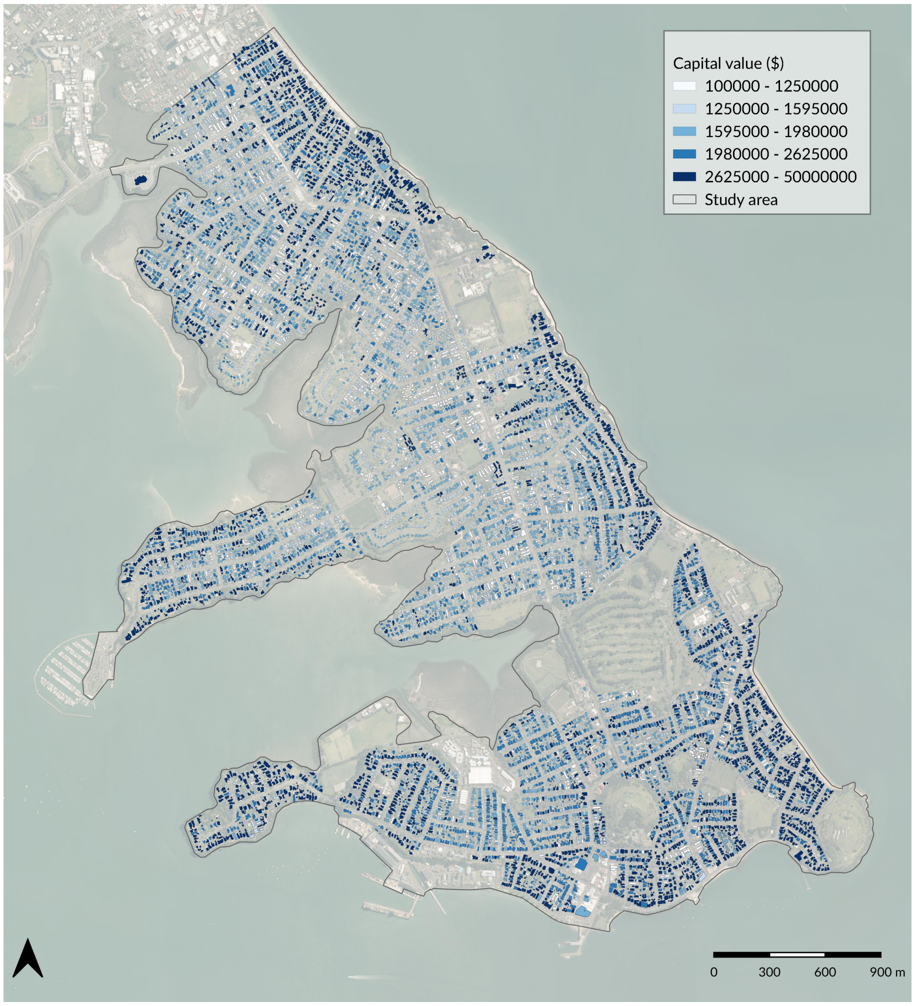

Figure 3.3: Position and capital valuation of homes within Devonport. Basemap provided by LINZ

The resulting dataset of baseline market conditions, mapped in Figure 3.3, contains 21,394 homes with a median capital valuation (CV) of $1,750,000. The CV metric is used as Auckland Council states it is the most likely selling price, therefore representing market value.

3.1.2.3 Cliff positions and erosion zones

Current geospatial cliff positions were required as a basis for future erosion. LINZ provides a dataset for cliff edge locations (Land Information New Zealand, 2012), but the inclusion criteria are vague, and many cliffs that had slip events during Cyclone Gabrielle are not included. We therefore developed an algorithm to detect and define cliff geometry to ensure complete coverage of significant cliffed areas in Devonport.

For the purposes of this study, a cliff is defined as a sudden and significant increase in elevation from sea level to the built environment. The rate of increase, or slope of the cliff face, should be high enough such that the land can be subject to sudden failure/slip events, alongside gradual erosion from wave action and other coastal processes. Slope is a major factor influencing cliff instability, and can be used as the sole variable to define cliffs (Del Rıéo & Gracia, 2009). We developed the algorithm following the slope-based cliff identification method.

The algorithm creates perpendicular transects on the centroid of each line that comprises the coastline dataset. Elevation values from a digital elevation model (DEM) are taken at set points along each transect, excluding values below mean high water. We took DEM values at the end points of 20 m transects. The difference between these values divided by the transect length defined the slope. Following Del Rıéo and Gracia (2009), a conservative slope value of 60° is used. If the slope between the end points of a given transect is larger than this value, the coastline segment it lies on is saved as a cliff edge. After this initial extraction, cliff lines that had an alongshore length lower than 50 m were considered outliers and removed.

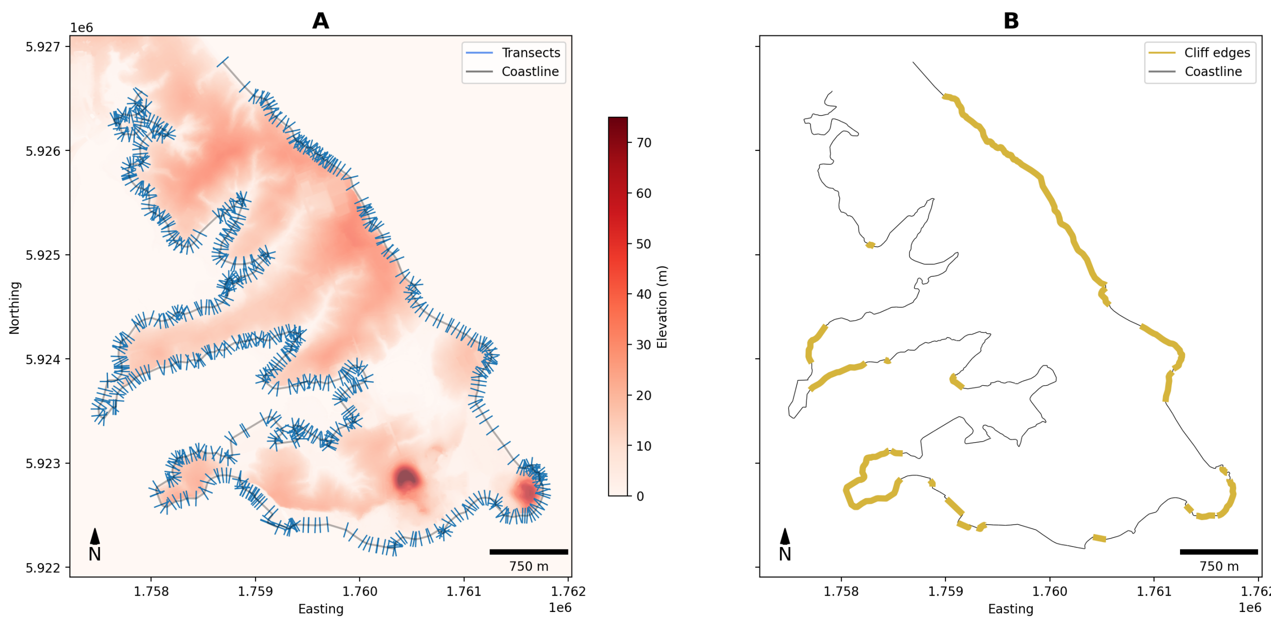

Figure 3.4: Example of cliff definition transects and DEM (A) and output cliff edges (B). Transect lengths are exaggerated

Running the algorithm in the study area (see Figure 3.4) resulted in the identification of 8.1 km of cliff edges along the 26.8 km of total coastline (data source mapped at 1:50000 scale). A limitation of this process is the 1 m vertical resolution of the DEM which, while the highest resolution that can be obtained publicly, creates a significant margin of error in elevation difference calculations.

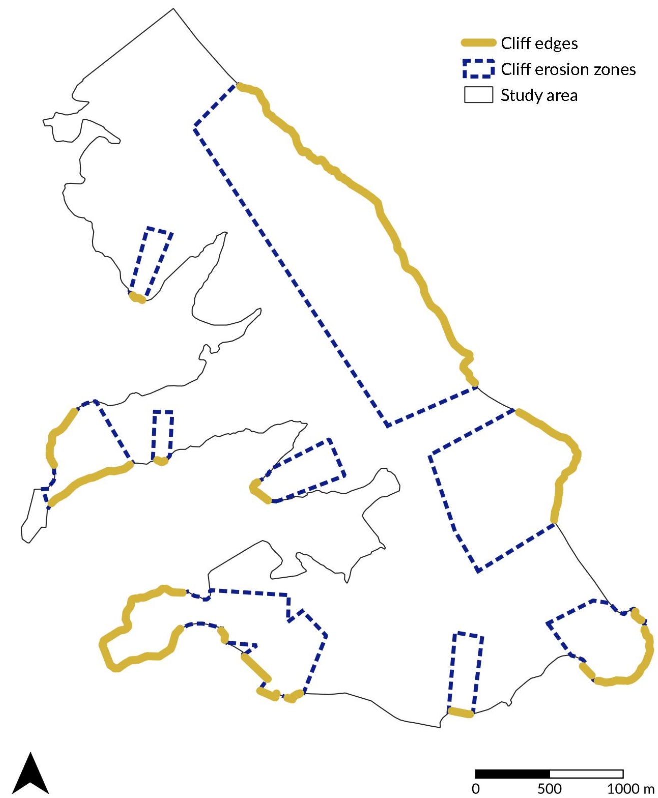

Figure 3.5: Cliff locations and erosion zones

We made the assumption that cliffs would only retreat perpendicularly to their current position, and therefore cliff edges would not extend laterally. A dataset was therefore required to restrict cliff erosion to this rule. We manually created polygons of erosion zones to achieve this, as shown in Figure 3.5.

3.1.2.4 Potential buyers

A market of potential buyers was required to purchase homes. The buyers needed risk tolerance and purchasing power attributes, so they could be tested for ability to tolerate risk that a previous homeowner could not, and for the financial means to purchase a property. Risk tolerance of potential buyers was assumed to have the same distribution as current homeowners (see Section 3.1.4.3).

Murphy (2014) explained that housing affordability can be a function of income, often expressed as the median multiple, where a market's affordability is determined based on the multiple of median income needed to reach median home value. As our model gauges affordability on an individual/household basis, we extrapolated the income multiplier theory such that each potential homeowner's income was multiplied to define purchasing power. Purchasing power of potential owners was derived from recent yearly income data in A/NZ.

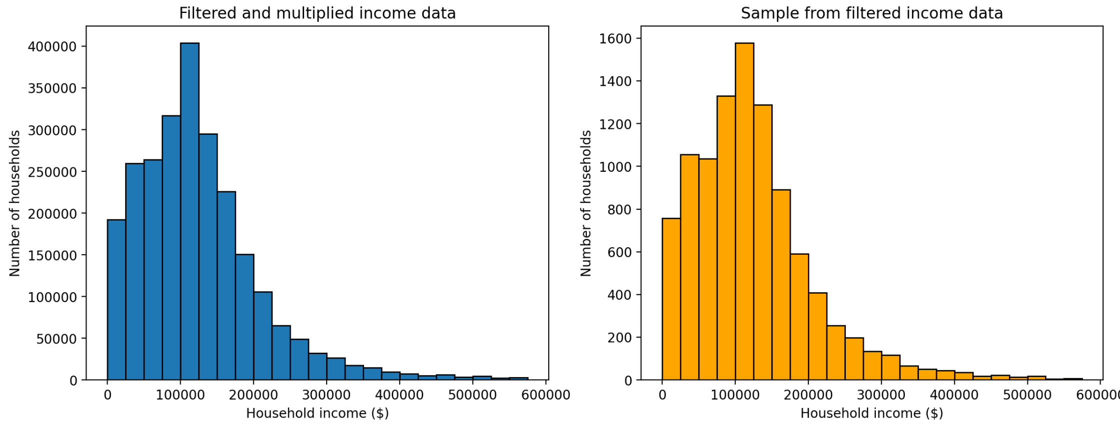

Figure 3.6: Filtered income data (left) and example of taking a sample of 10000 households from this distribution (right)

Income data were filtered to a minimum income of $10000 and maximum of $300000, to exclude the skew towards extreme earners that would bias sampling. Individual income was doubled to represent household income, assuming that each household comprises at least two earners, as evidence in Auckland shows that couples are significantly more likely to purchase property (Law & Meehan, 2013). A random sample from the income data was then taken to produce a representative selection of the population. This sample, combined with a randomised risk tolerance (see Section 3.1.4.3), represents a population of potential buyers. Figure 3.6 shows the filtered data and an example sampling.

3.1.3 Cliff erosion model

Coastal cliff edges erode through gradual erosion and sudden land failures. Both erosion types are exacerbated by a variety of phenomena, including lithology, cliff slope and exposure to wave energy (Dickson & Perry, 2016). Gradual erosion describes regression of the cliff edge at a set rate, in a way that is reasonably consistent along the length of the cliff edge. Sudden land failures describe larger and localised erosion events, often the result of storms increasing wave energy and land instability in a specific location. Our cliff erosion model therefore needed to account for both of these erosion mechanisms.

3.1.3.1 Gradual erosion

Gradual erosion was represented by a linear retreat of the cliff edge, with the rate of retreat constant across all cliff edges. This simplification ensured assumptions were not made about spatially variable exacerbating factors, as collecting data on such factors was outside of the scope of this study. Semi-randomisation of retreat rates along a given cliff edge was considered, but this assumes that the susceptibility of cliffs to gradual erosion is subject to change, which could not be proven. Instead, the gradual erosion rate was semi-randomised (parameterised with a random sample from a margin of acceptable values) across all cliffs equally to represent temporal environmental stochasticity without making assumptions on specific exacerbating factors.

We developed an algorithm to alter cliff geometry as a result of gradual erosion processes. After cliffs erode, new cliff edge geometry is required so that distances to homes can be re-calculated. A new land shape is also required for a spatial reference to detect if homes have collapsed over the cliff edge. Therefore spatial operations were developed that move cliff geometry in the direction of erosion by the erosion rate ($\pm$ margin of error), resulting in new cliff positions and land shape. If storm erosion is present, cliff and land geometries need to be altered by slip events, so the algorithm is discussed together with storm erosion in Section 3.1.3.3.

3.1.3.2 Storm erosion

Slip/storm erosion was represented by semicircular removals of land at the cliff edge, whereby the new cliff edge follows the outline of the semicircle. These concave slips were positioned randomly along all cliff edges, and the number and size of slips were semi-randomised to represent environmental stochasticity. A consistent shape of land failure was a required simplification to maintain the assumption that all cliff edges are treated as equally susceptible to erosion processes. The semicircle shape was chosen due to its simplicity of implementation through spatial buffering, which also allows geometric complexity to be parameterised by the number of points that shape the circle, facilitating optimisation.

Simplification of geometry is necessary as slips increase the number of lines comprising a given cliff's geometry. Increasing the geometric complexity this way makes spatial operations involving the cliff edge difficult as there are more points composing the edge that must be examined by the algorithm. During geometric simplification, geometries are recursively split and removed where straight-line distances between split points are shorter than a specified tolerance parameter (Douglas & Peucker, 1973). This is performed on cliff lines after storm erosion occurs. The simplification is within a parameterised tolerance, which is less than the magnitude of gradual erosion (e.g. 6 mm of gradual erosion = $\leq$1 mm simplification tolerance) so that the granular effects of gradual erosion are not removed from the cliff edge geometry.

3.1.3.3 Erosion model implementation

We implemented the erosion model with a module, where all modules are called when the model progresses forward in time. Both gradual and storm erosion alter the geometry of the cliff, so they were developed in conjunction. If a storm has not occurred, the subroutine that creates slip events causes no change.

The erosion model operates by buffering existing cliff geometry, then taking the landward boundary of this buffer which will represent the new, eroded cliff edge. During this process, if there is a storm event, further buffers representing slip events will be created at randomised point(s) on the new cliff edge. Storms are initiated based on a parameterised probability. A random number between 0 and 100 is generated, and if the storm parameter is higher than this number a storm will occur. Gradual erosion distance, slip event count and slip event size are all semi-randomised with a margin of error.

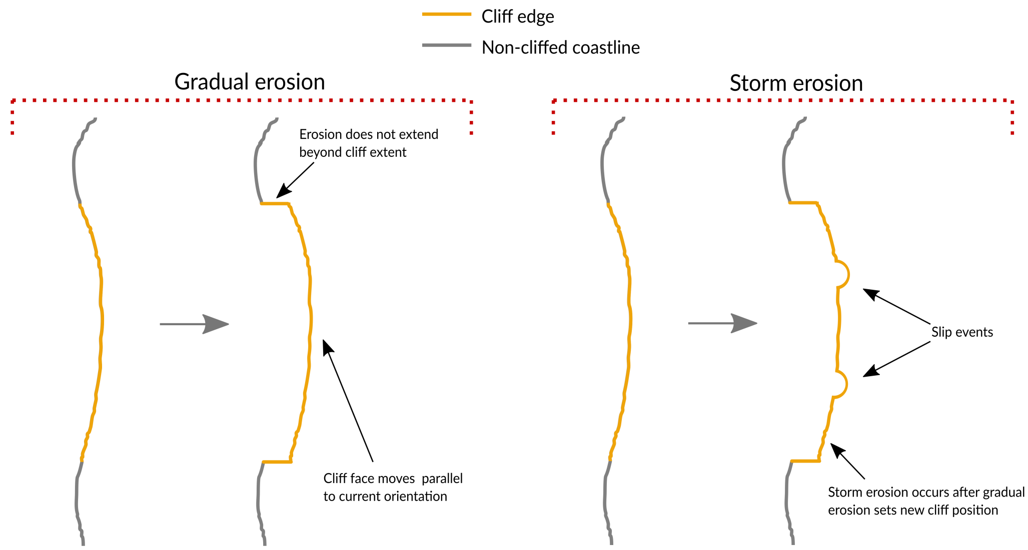

Figure 3.7: Comparison of gradual and storm erosion model mechanisms

The two methods of erosion modify cliff geometry in distinct ways, as visualised in Figure 3.7. A scenario with solely gradual erosion (left) retreats the cliff edge while retaining the original shape. When storms are introduced (right), slip events cause the cliff geometry to change shape.

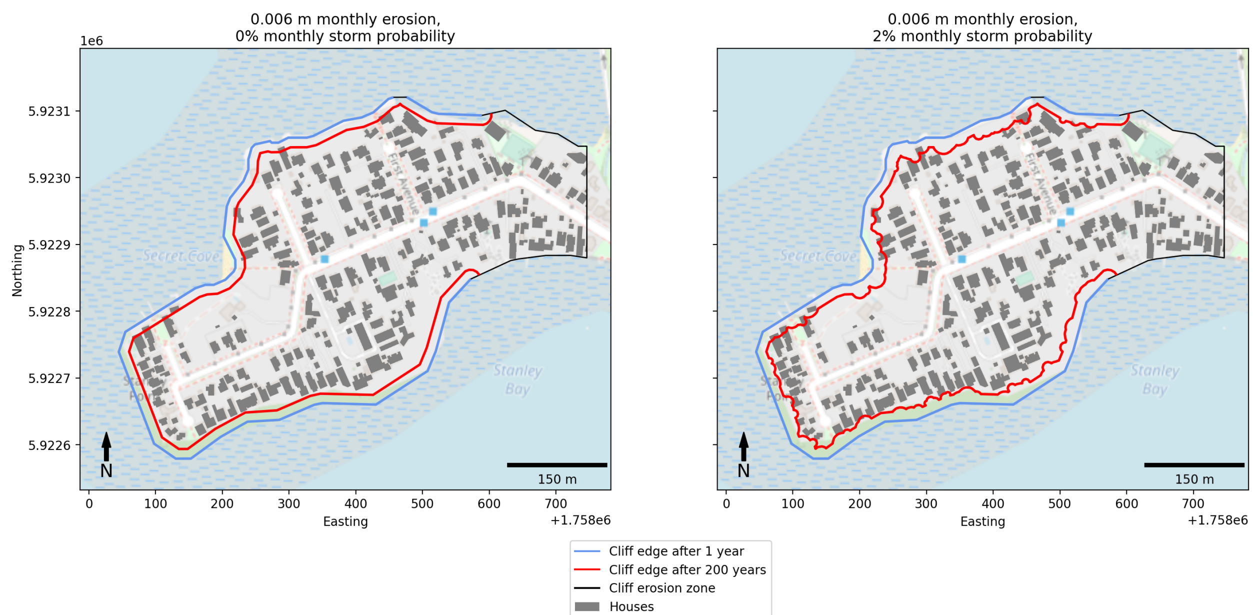

Figure 3.8: Example of the erosion model's impact on land and cliff geometry. Stanley Point is plotted with cliff edges after running model for 200 years, both without (left) and with (right) storm erosion

Figure 3.8 maps selected output of the cliff erosion model. It shows how the implemented algorithm can alter geometry over the course of a model run as expected from Figure 3.7. While highly simplified, the model includes the main mechanisms of cliff retreat, environmental stochasticity and the ability to alter cliff and land geometries.

3.1.4 Coupling and interactions

The ABM comprises many interacting components. These interactions allowed us to meet research objectives 2 and 4, enabling exploration of relationships and emergent behaviour to build understanding.

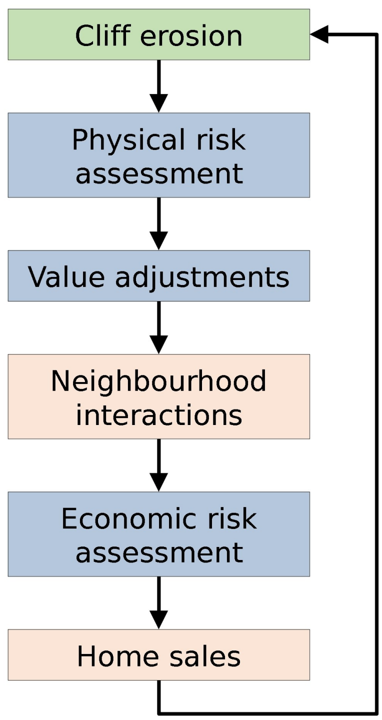

Figure 3.9: Coupling of components in the ABM. Shows physical driver (green), market dynamics (blue), and human behaviour (orange)

The order in which processes interact in the ABM is presented in Figure 3.9. Cliff erosion leads to the physical risk categorisation of homes, which impacts their values, affecting the value of the neighbouring properties. The difference in current home value from the purchase price is used to calculate a risk metric (thereby incorporating both physical and economic risks). The risk of the home is evaluated against the homeowner's risk tolerance, and if they cannot tolerate the risk they will attempt to sell the home. If there is a suitable buyer who is willing to tolerate that risk, the home will be sold. If the home does not sell, it will remain on the market and gradually reduce in asking price. The model then progresses in time, moving back to cliff erosion. The following sections describe these processes in more detail.

3.1.4.1 Cliff position, risk and value

Cliff erosion interacts with home values by penalising them based on risk. We made the assumption that increased risk will result in reduced property values - a rational market response to an increasing probability of complete asset loss (Eaves et al., 2023). This accounts for physical (and subsequent economic) risk perceived by potential buyers. Storey and Noy (2017) anticipated that climate hazards will lead to decreasing home values, although the mechanisms that lead to this market behaviour are highly uncertain (Storey et al., 2022). Because of this uncertainty, and as a method of simplification, we represent the financial consequences of risk from cliff erosion through fixed proportional value reductions.

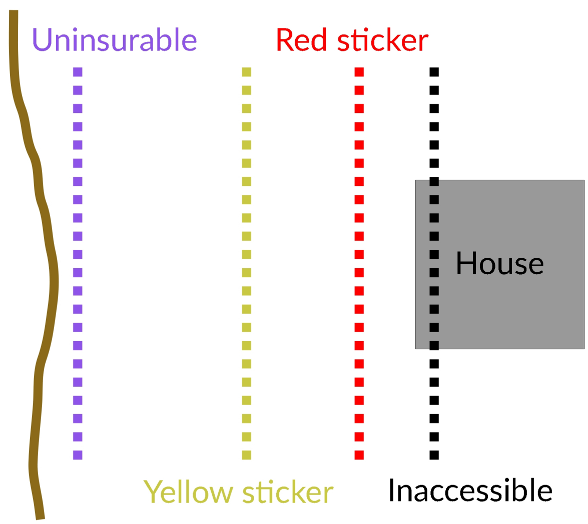

Figure 3.10: Abstract example of risk category distance cut-offs

After cliff erosion occurs, the distance of each home within the cliff zones to the cliff edge is calculated. If this distance is within a parameterised physical risk category cutoff (Figure 3.10), the home will move into this risk category and receive a value penalisation. Risk categories are labelled (uninsurable, yellow sticker and red sticker) and have an associated proportional reduction, which increases inversely with distance. This assumes a constant reduction in price temporally and spatially, and that physical risk is a function of proximity to a cliff edge. In reality, the physical risk of a property to the effects of any environmental hazard is based on many factors, such as building design and materials (Lindell, 2013). The distance-based physical risk measure is a simplification that allows physical risk categorisation in the absence of data on these factors.

3.1.4.2 Neighbourhood effects

Risk-categorisation changes, and consequent value penalisations, impact the value of neighbouring homes. Residential valuations are highly spatially dependent. This is often discussed through the concept of submarkets, where prices of homes within a submarket are similar because they have similar attributes and are thus substitutable (Bourassa et al., 2007). Submarkets are typically defined by shared geographical areas, property characteristics or census units. However, Bourassa et al. (2007) discussed how submarkets can be dynamic, where neighbourhood interactions vary on a property-by-property basis rather than being static across an area. Since we aimed to explore potentially novel relationships within the property market, using predefined submarkets based on current perceptions was not appropriate. Instead, we defined a fixed area around each home. The price trends of other homes within this neighbouring area was used to influence the value of a given home, thereby assuming a level of substitutibility. The fixed-radius approach has been used effectively in other property-market studies, such as that of Biswas (2012), who explored the influence of nearby foreclosures on a given property's value by creating buffers around each property.

To implement this approach for neighbourhood influences, a spatial distance matrix was created between all homes in the study area. For each home, other homes that were within a parameterised distance were added to another array, resulting in a final array of neighbours for each home. The average value of homes within a given home's neighbourhood array was calculated at each step after physical risk deductions. We then calculated the difference between this average and that calculated at the previous step. A random value between 0 and that difference was then added to/deducted from the homes value. As this component is purely altering values based on neighbourhood trends, there will be no change if the neighbours' values also do not change. If a home becomes inaccessible/completely destroyed, all neighbours receive a static proportional value reduction to represent the perception of significant risk. The inaccessible home is then removed from the matrix for all homes it neighbours.

3.1.4.3 Risk and risk tolerance

Risk categorisations and neighbourhood trend adjustments impact a given home's risk level. Risk needs to be quantified so that it can be compared to the risk tolerance of homeowners. There are many dimensions to risk, but in the context of climate hazards the main contributors to risk are geophysical environment and socioeconomic conditions (Park & Vedlitz, 2013). The trend in an individual home's value in the ABM represents both of these contributors, as home value is modified both by physical hazard proximity and neighbourhood perceptions.

$$\text{home risk} = 1 - (\text{current home value} - \text{home purchase value}) \tag{3.1}$$

Therefore, risk is quantified as the difference between a home's purchase price and it's current value, as shown in Equation 3.1. Assuming current value will be lower than purchase value, this results in a numeric representation between 0 and 1 that can be directly compared to a homeowner's risk tolerance. The economic risk will be set to 0 if current value is above purchase value.

Risk tolerance is notably different to risk perception, as a risk can be perceived yet not acted upon if an individual is willing to tolerate the consequences of that risk (Anderson et al., 2023). Tolerance for risk is therefore chosen as the key determinant of individual decision-making in this research. This assumes that perception of risk is constant across homeowners, although risk impacts are bounded by the neighbourhood distance. Risk perception is based on a variety of complex interacting factors (Lujala et al., 2015), so this simplification was necessary to fit within the scope of the study. Anderson et al. (2023) summarised existing risk tolerance studies, arguing that it is an emerging field and therefore there is little empirical evidence to base model parameters on. Therefore, to avoid making assumptions, and as a method of model simplification, in the ABM risk tolerance is defined as a random value between 0 and 1 for each homeowner.

3.1.4.4 Property market

Risk level and tolerance interact with the property market by defining a threshold at which a home is offered for sale. If a homeowner can no longer tolerate the risk associated with their property, they will attempt to sell it to remove their personal exposure to this risk. In the ABM, if the calculated risk value is greater than the homeowner's risk tolerance value, the home will automatically be put on the market in a stimulus-response behavioural model (Mustapha et al., 2013). The response that homeowner agents make to the stimulus of market forces on their home exhibits bounded rationality (Epstein, 1999). While homeowners act in a static and rational fashion as risk exceeds their threshold, the threshold itself removes them from perfect rationality as it represents behavioural variation. They are also bounded by their stimulus (risk-based value) being impacted only by local information through the constraint of neighbourhood distance.

In the model, if a home is put up for sale, eligible buyers are found (see Section 3.1.2.4). A semi-randomised sample is then taken from these eligible buyers to create a list of 'interested' buyers. The interested buyer with the highest purchase power (representing a highest-bid scenario) takes over the property. If a home is put on the market but there are no eligible and/or interested buyers, the value is reduced slightly to increase the probability of a future sale.

In reality, the decision to purchase a home is not solely based on economic/risk eligibility, but also many other social processes (Levy et al., 2013) that are difficult to quantify and include in a simple model. Randomness was therefore incorporated into the algorithm, to ensure that a property purchase is not purely a result of eligibility. The assumption that sale price cannot exceed 20% higher than the value is in place to restrict sales, otherwise potential buyers with high purchasing power would always be available to purchase homes.

3.2 Sensitivity analysis

In order to critically explore the relationships within the socioenvironmental system, we ran the ABM many times at different parameter values. This allowed us to explore of sensitivity that the system has to changes in key components. Gradual erosion rate and storm probability were the model parameters tested in this study, as per research objective 3. Sensitivity analysis of parameters that control cliff erosion will result in scenarios of behaviour that can build on understanding of the socioeconomic environment's response to climate change. All other parameters were kept constant, but there are many randomised elements in the model as discussed in Section 3.1. The ABM was run for 200 years, or 2400 months/steps, to represent two periods of planning timeframes used by local authorities in A/NZ.

3.2.1 Parameterisation

The model was built to improve understanding in an area with few empirical examples and limited research, so assumptions were inevitable. Many assumptions are reflected through parameter values that control model behaviour.

Table 3.2: ABM parameter descriptions and values

Component	Parameter	Definition	Value	Reference
Geophysical	gr_{base}	Baseline gradual cliff erosion rate	0.006 m	Roberts et al. (2020)
Geophysical	sr_{base}	Baseline storm probability	1%	Basher et al. (2013); Glade (1998)
Geophysical	s_n	Number of slips during storm event	10 m ± 5 m	
Geophysical	s_d	Size of slip events	5 m ± 2 m	Jongens et al. (2007)
Housing	a_{home}	Minimum building footprint size for home definition	40 m^2	Fernandez et al. (2021)
Housing	$m_{purchase}$	Purchasing power multiplier	8	Squires and White (2019)
Housing	p_n	Number of potential home buyers	500000	
Housing	v_{access}	Maximum proportional value deduction to homes neighbouring a newly inaccessible home	0% to 20%	
Housing	$d_{neighbour}$	Neighbourhood distance/distance at which nearby properties interact	250 m	
Risk	d_{cats}	Risk category distances	(3 m, 1 m, 0.5 m)	
Risk	v_{cats}	Risk category proportional value penalisations	(10%, 30%, 100%)	

Parameters and model dynamics were defined using peer-reviewed research where possible. As these assumptions are parameterised, they can be updated with future research. Key parameters are described in Table 3.2.

Defining a baseline probability of storm erosion (sr_{base}) was not straightforward. In the context of this research, the definition for a storm is an event where cliff land failure occurs, thereby potentially impacting residential development on the clifftop. In the Devonport study area, cliff failure events are controlled by both rainfall and wave action. Monitoring of storm events is poor in A/NZ, whereby storms are mostly recorded when a sea level threshold is exceeded, rather than recording cliff failures (Basher et al., 2013). When solely looking at rainfall, Glade (1998) found the Auckland region to have an average of 1-in-5 year cliff-failure storm return, but they did not include the severity of failure events in their analyses. Due to this lack of data, a 1% storm probability was chosen as a higher-end estimate from the Basher et al. (2013) discussion on storms. The lack of storm data also meant assumptions had to be made for the severity of a storm event, represented by the number (s_n) and size (s_d) of landslip events. Jongens et al. (2007) found that landslip events of up to 10 m can occur along cliffs in the study area, but such events have a frequency of >1-in-100 years. They also note that the underlying geology of cliff faces are a large determinant of slip size, with slips on all cliffs ranging between 2 m and 15 m. Following the simplification of assuming all cliff edges are equally susceptible to erosion processes, a conservative slip size of 5 m, with a margin of randomisation of $\pm$ 2 m, was used to mitigate the likelihood of land failure based on extremely rare events. The number of slips during a storm event was based on the assumption that the Auckland region has a high spatial variability of storm impacts (Chappel, 2013).

Regarding housing, the minimum floor size of a home (a_{home}) was derived from a recent Auckland Housing assessment, whereby 40 m^2 is around the minimum size of dwellings found in the region (Fernandez et al., 2021). The number of potential buyers (p_n) was created by halving the earning population of 2.5 million to 1.25 million (as the income data was previously doubled to represent household income), then reducing it to 500000 on the assumption that only a subset of the population would be interested in purchasing property. We used an income multiplier of 8 to define purchasing power ($m_{purchase}$), based on an affordability assessment of Auckland by Squires and White (2019). This assumes that housing affordability is static.

Another key parameter is the value penalisations that occur when a home is recategorised (v_{cats}). For the uninsurable category, Storey et al. (2022) associated an immediate drop in home value as insurance becomes unavailable, but this is not quantified due to a lack of empirical examples. For the yellow sticker category, development is needed for habitability and so a larger deduction is applied. For the red sticker category, a home is no longer able to be sold as it cannot be entered without structural fixes. Therefore the chosen deductions of 10%, 30% and 100% for the uninsurable, yellow sticker and red sticker categorisations, respectively, are reasonable values that although likely incorrect in detail, represent the anticipated effect. This will require further investigation in future research. The static deductions assumes homes cannot be repaired/strengthened to decrease their risk. A similar assumption is made for the value deduction associated with a neighbouring home becoming inaccessible (v_{access}), although this was semi-randomised to account for variations in market perception.

Monthly erosion rates of gr_{base}, 0.01, 0.016, 0.041 and 0.083 m were used when testing gradual erosion sensitivity (with sr_{base} storm probability). Monthly storm probabilities of 0, sr_{base}, 2, 5, 10, 50 and 100% were used when testing storm sensitivity (with gr_{base} gradual erosion rate). Baseline conditions of one variable were used when performing sensitivity analysis on another to establish the sole influence of the variable being tested.

3.2.2 Response

After model runs were complete, household data were aggregated to produce time series trends. Aggregation of key variables can represent emergent behaviour from the processes and interactions that occurred and altered these variables at an individual level (Cederman, 2005; Epstein, 1999; Gallegati and Kirman, 2012). Spatial aggregation was also conducted, whereby individual home data were binned into geospatial hexagons created within the study area with areas of 2.2 km^2. The main dynamics explored were that of value and risk tolerance, as representatives of market and social conditions, respectively.

Chapter 4: Results and Discussion

The following sections visualise, interpret and discuss key dynamics and final states of the system over different model runs. A discussion is built alongside interpretation throughout the sections since the many interacting components make it difficult to assess one phenomenon in isolation.

4.1 Risk and behaviour

Physical and economic risks are the stimulus behind individual decision-making in the model. The following section explores how changing erosion rates affect the decisions individual homeowners make, and how these generate social system conditions.

4.1.1 Risk tolerance dynamics

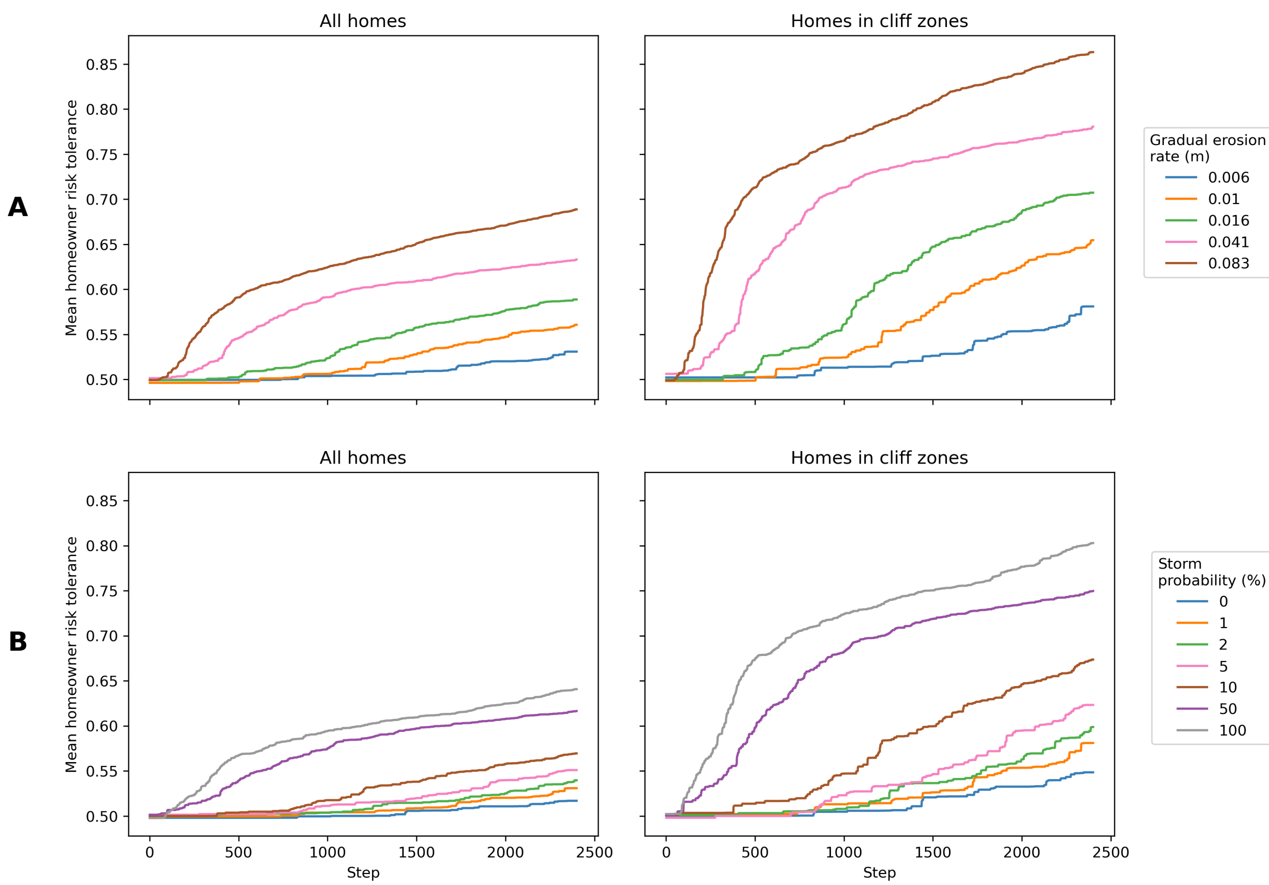

Figure 4.1: Mean homeowner risk tolerance over time under changes of gradual erosion (A) and storm erosion (B)

Average risk tolerance of homeowners increased over time, as shown in Figure 4.1. The extent of this increase was positively linked to both gradual erosion and storm probability, and varied according to the spatial location of homes. Homeowners in cliffed areas exhibited significantly higher increases in risk tolerance when compared to the entire group of homeowners. Risk increased as the cliff edge eroded, and Figure 4.1 shows that tolerance for this risk increased alongside, resulting in a population of homeowners more willing to tolerate the risk of cliff erosion. There was a notable change in trend concavity at the highest gradual erosion rates and storm probabilities after roughly 500 steps, where the steepness of the trend reduced. This represents an increase of inaccessible homes with high erosion, removing homes from the market and therefore removing the ability for their risk to be transferred to a buyer.

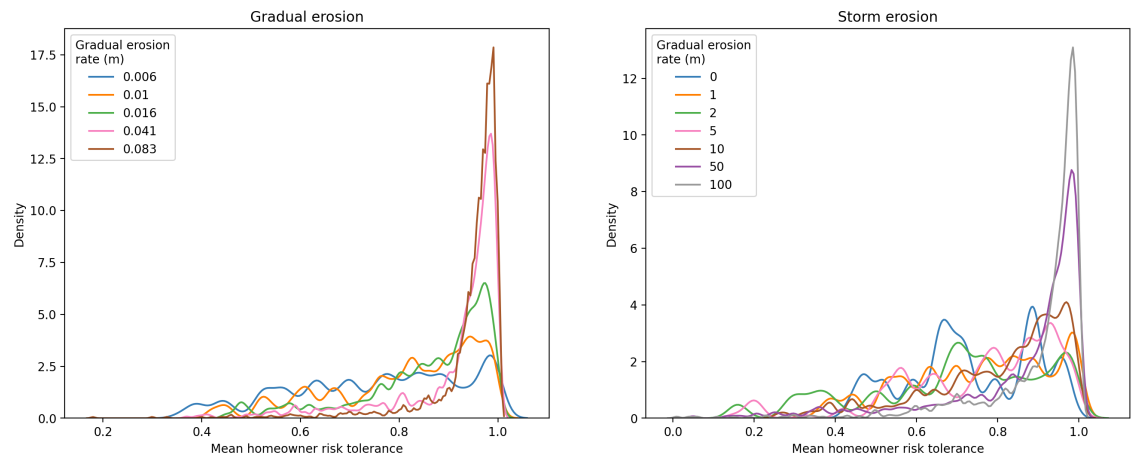

Figure 4.2: Kernel density estimates of risk tolerance of homeowners whose homes became inaccessible during model run, under changes of gradual erosion and storm probability

Figure 4.2 shows that risk tolerance was likely to be higher for those whose homes become inaccessible, although this varied based on gradual erosion and storm probability. This links to real-world opposition to the management approach of managed retreat, whereby homeowners may want to continue to occupy their home in spite of extreme risk due to a high tolerance for it (Harker, 2016). The left skew of most distributions show that there was a population of homeowners with low risk tolerance who are left with an inaccessible home. This skew is more variable under storm erosion, indicating that gradual erosion more readily allows for risk to be perceived and transferred to new, more risk-tolerant homeowners in advance of complete home loss. As per Harker (2016), such homeowners may be less willing to support managed retreat even as the risk becomes uncontrollable. The large slip events of storm erosion can supersede any prior risk categorisation, making the homeowner subject to the consequences of a risk for which they are unprepared. Storm erosion can affect populations with low risk tolerance and therefore more willing to support any form of management. Gradual erosion leads to increasing risk tolerances, potentially reducing support for certain management techniques as the homeowners are willing to tolerate the risk themselves.

4.1.2 Behavioural responses to risk

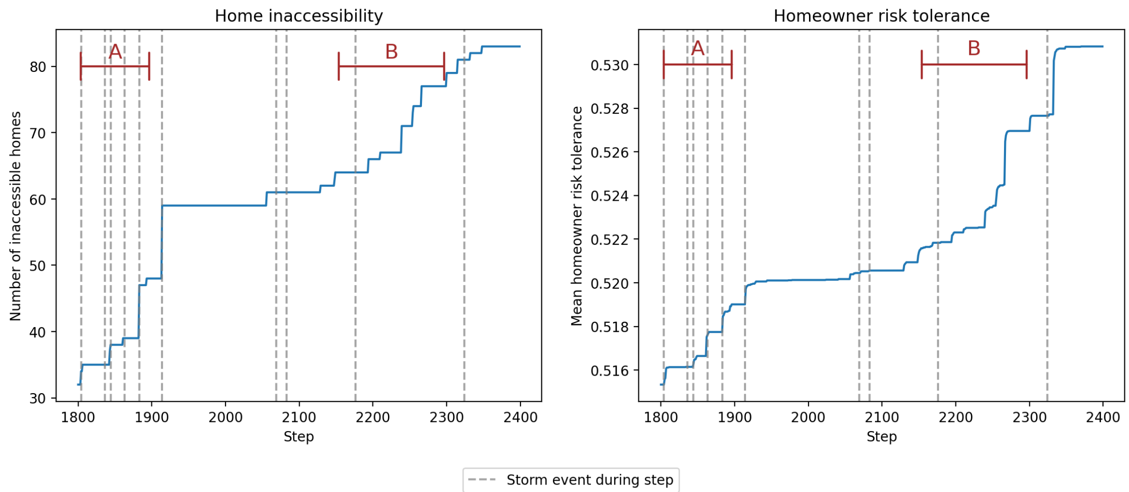

Figure 4.3: Number of inaccessible homes (left) and mean risk tolerance (right) over a 50 year/600 step subset of time, under baseline physical conditions, with highlighted time intervals (A and B)

Focusing on the final 50 years of the baseline conditions model run, Figure 4.3 shows that home inaccessibility and risk tolerance followed a similar trend. This was the result of inaccessible homes causing a drop in value of neighbouring properties, increasing risk which leads to homes potentially being sold to buyers with higher risk tolerances. The relationship here shows that under low levels of erosion, behavioural responses to risk were highly predictable through the monitoring of neighbouring inaccessible homes, even when accounting for uncertainty in many processes that lead to homeowner decision-making.

Figure 4.3 also shows how home loss, and subsequent changes in risk tolerance, did not linearly follow a certain type of erosion. For example, at time interval A there was a series of storms that resulted in sequential increases of inaccessible homes, as might be expected through slip events. However, at time interval B there were fewer storms but a similarly sequential increase in inaccessible homes. The similarity of these trends show that under the right conditions, gradual erosion and storm erosion can impact physical risk, and consequently drive homeowner behaviour, in similar ways. The latter trend may have been the result of a group of homes built at similar distances from the cliff edge, therefore becoming inaccessible at similar times under a gradual rate of erosion. This results in behaviour similar to that seen after storms, but in a way that is more predictable due to the known distance to the cliff edge.

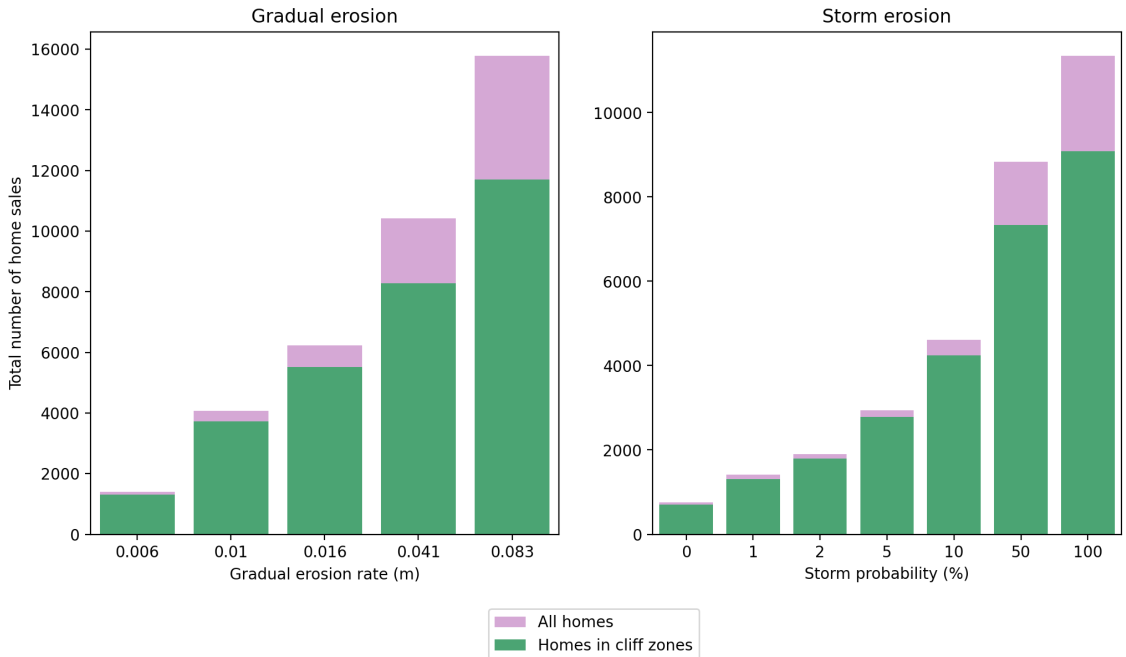

Figure 4.4: Total number of home sales by erosion type and rate after 200 year model runs

Risk exceeding tolerance causes individuals to interact with the property market, and Figure 4.4 shows that such behaviour increases in frequency with erosion. Most sales occurred in the cliff zone, representing more risk-based individual decision-making in this area, but a significant proportion of sales were also made throughout the rest of the study area. Many homes were sold more than once, as is seen in real-world coastal hazard environments such as in New York City after Hurricane Sandy (Ortega & Taşpınar, 2018). The proportion of sales outside of the cliff zone is lower with storm erosion, even at very high probabilities, indicating storms result in more localised behavioural trends compared to gradual erosion.

4.2 Market dynamics

Our model assumes rational market responses to risk, imposed on homes through value penalisation. This couples with human behaviour, as risk exceeding tolerance causes an attempt to sell homes, potentially altering values further. As such, the following sections explore the dynamics of the residential market.

4.2.1 Home values

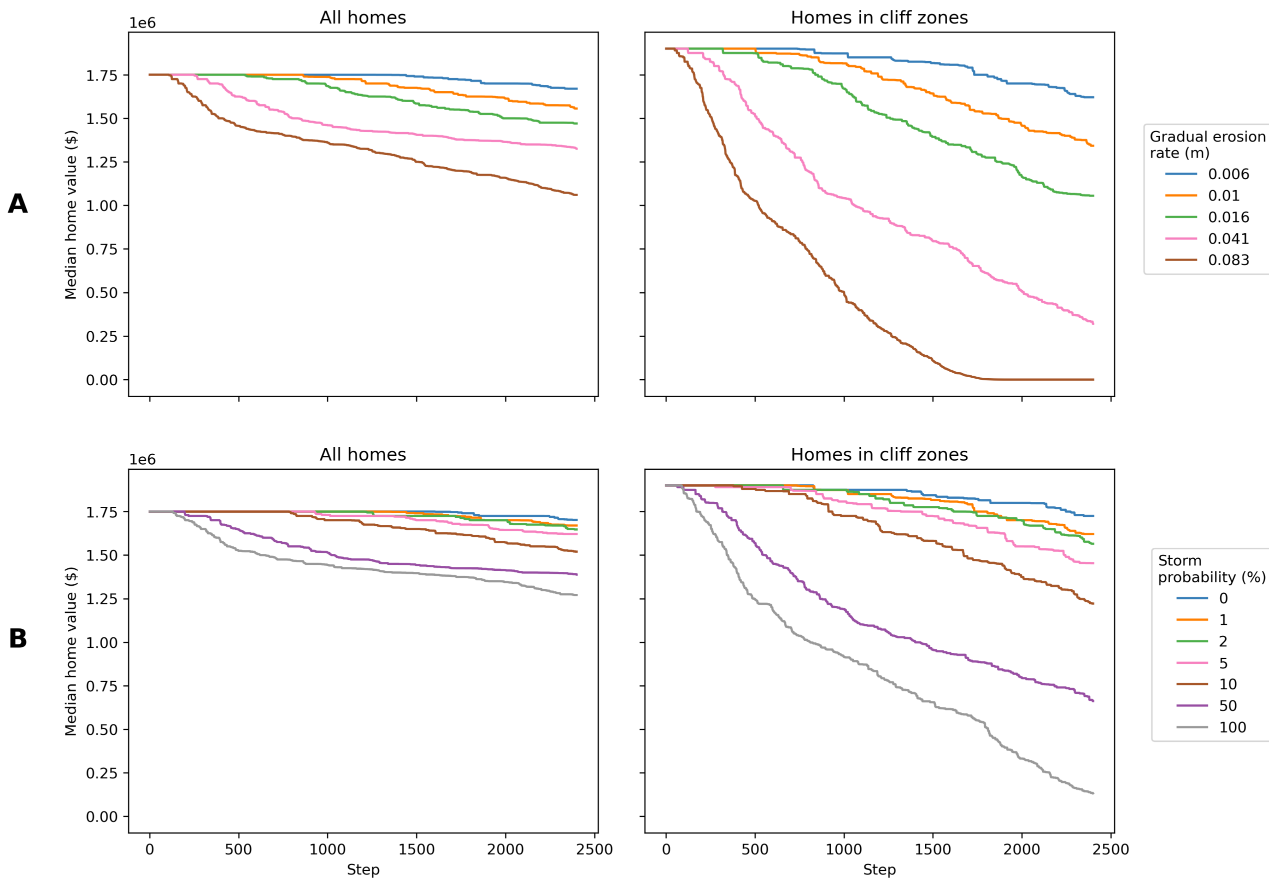

Figure 4.5: Median home value over time under gradual erosion (A) and storm erosion (B)

Figure 4.5 shows that home value decreased over time. This decrease was inversely linked to both gradual erosion and storm probability, and varied based on the spatial location of homes. Homes in cliffed areas began with a notably higher median value compared to all homes, but were subject to significantly larger and faster decreases in value as erosion increased, ending in much lower median values. Gradual erosion (Figure 4.5.A) and storm erosion (Figure 4.5.B) had similar trends. Decreasing market values due to climate-related risk like this are becoming evident in contemporary empirical studies (Clayton et al., 2021; Lamas Rodrıéguez et al., 2023).

The median home value (Figure 4.5) was inversely related to average risk tolerance (Figure 4.1). Homes are priced based on risk and sold based on tolerance exceedance, and therefore when sales take place the risk tolerance must increase and the value is likely to decrease. As risk increases, homeowners sell their homes to avoid tolerating it. The buyers have knowledge of and tolerance for this risk, and are able to purchase the home for a lower value as a result. This process could be inferred as high-wealth homeowners moving away to avoid risk, selling to lower-wealth buyers who are forced to tolerate higher levels of risk in order to be able to afford home ownership. This places the burden of the coastal hazard risk on poorer homeowners - who, while having a higher tolerance for risk, are arguably less able to mobilise if the risk becomes destructive (Prowse & Scott, 2008). Regardless of personal risk tolerance, the consequences of complete home loss are therefore more dire for low-wealth homeowners than for high-wealth homeowners.

While each step change, or each set of home sales, represents only a minor change in risk tolerance and value, over time this could accumulate into a significant change in socioeconomic conditions in the study area. The population of homeowners gradually became more accepting of hazard risk but are arguably less able to adapt to its effects (Grothmann & Patt, 2005) - a highly precarious socioeconomic environment.

4.2.2 Market loss

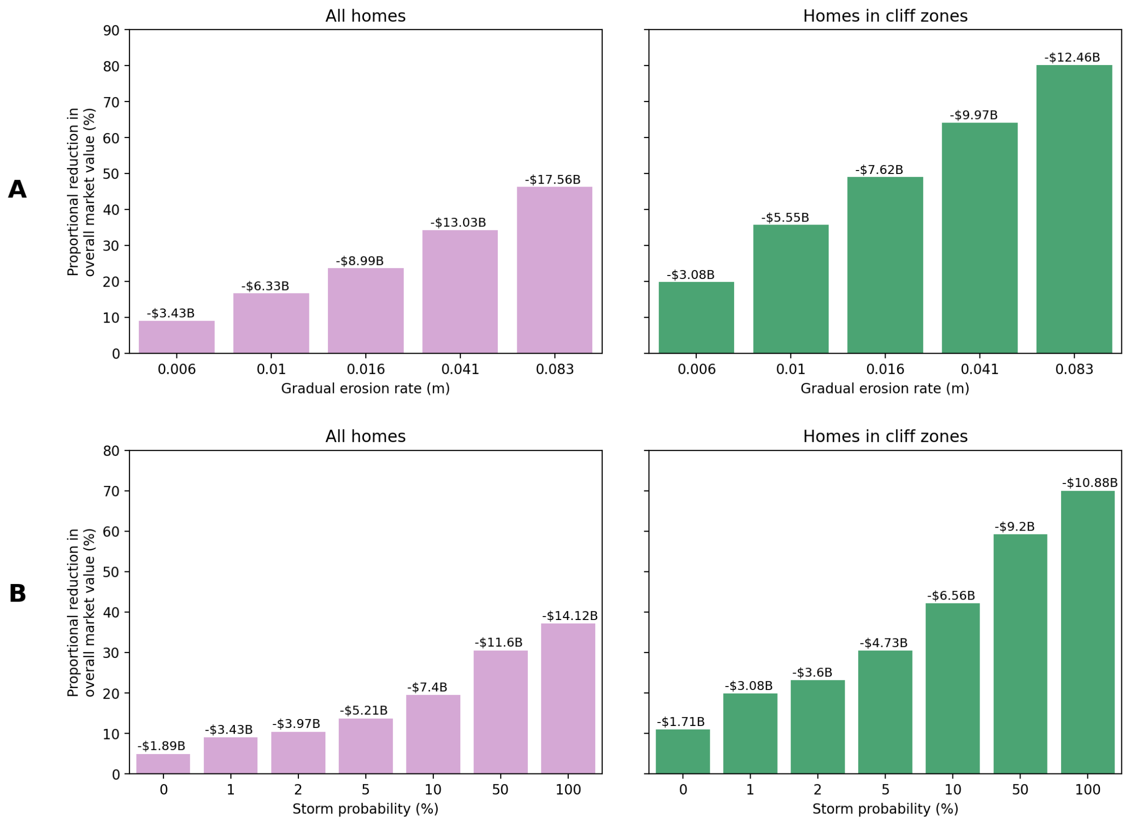

Figure 4.6: Proportional economic loss from original home values over model run, under gradual erosion (A) and storm erosion (B). Split by all homes and homes in cliff zones, where proportions are based on original value in respective areas. Bars are annotated with total value lost (where 'B'=billion)

Trends of decreasing median home value explored in Figure 4.5 indicate significant financial loss, increasing with erosion rates, as shown on Figure 4.6. These results align with Burgess et al. (2007), who found a semi-linear relationship with cliff erosion rates and costs associated with total property damage. As expected from Pearson et al. (2005), total financial loss is greatly impacted when land failure makes buildings inaccessible, but this spreads through the market with risk-based pricing. Higher proportions of the cliff-zoned market value were lost with increasing erosion compared to the overall market. Large proportions of value for the overall market were still lost, mainly due to clifftop properties initially being priced much higher (on average) than the rest of the market, therefore significantly influencing the market as a whole. Even under baseline conditions, $3.43 billion was completely lost through value reductions, representing a large financial loss for individuals as well as the national economy. Figure 4.6 shows that in the absence of risk transfer methods other than selling, there is a potential for massive economic loss under even minor cliff erosion. This loss, much like risk and behaviour as explored in Section 4.1, will also spread to those not only in immediate physical risk of coastal cliff erosion.

4.2.3 Spatial variation

To further explore the variation seen between homes inside and outside of cliffed areas, we mapped changes in risk tolerance and value over selected model runs.

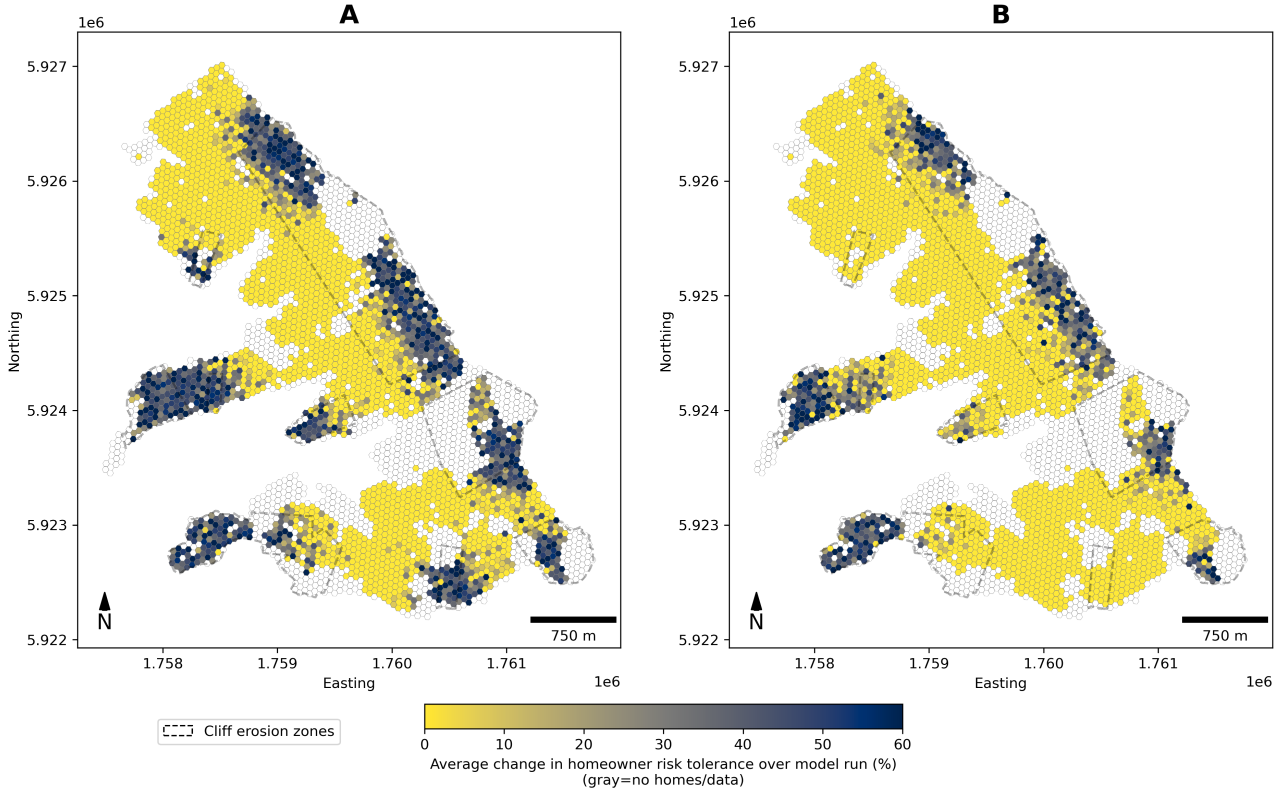

Figure 4.7: Change in mean homeowner risk tolerance over model run by hex-grid, at baseline conditions with gradual erosion rate of 0.041 m (A) and storm probability of 10% (B)

Figure 4.7 shows that changes in homeowner risk tolerance are more spatially extensive under high levels of gradual erosion (Figure 4.7.A) compared to high levels of storm erosion (Figure 4.7.B). Some grids in high-risk locations showed little to no change, indicating an initially high risk tolerance and consequently few changes in homeowner. For example, gradual erosion led to changes in the population of every cliff zone, whereas storm erosion had no impact in the southernmost cliff zone. This was because storms did not cause slips in that area due to random variability, therefore not increasing risk to some properties. Dickson and Perry (2016) described how cliff failure events are highly spatially dependent, and Figure 4.7 shows that this is also the case for their social impacts. Despite both maps presenting a high-risk coastal hazard scenario, gradual erosion impacted the entire clifftop environment whereas storm erosion only impacted subsets of it.

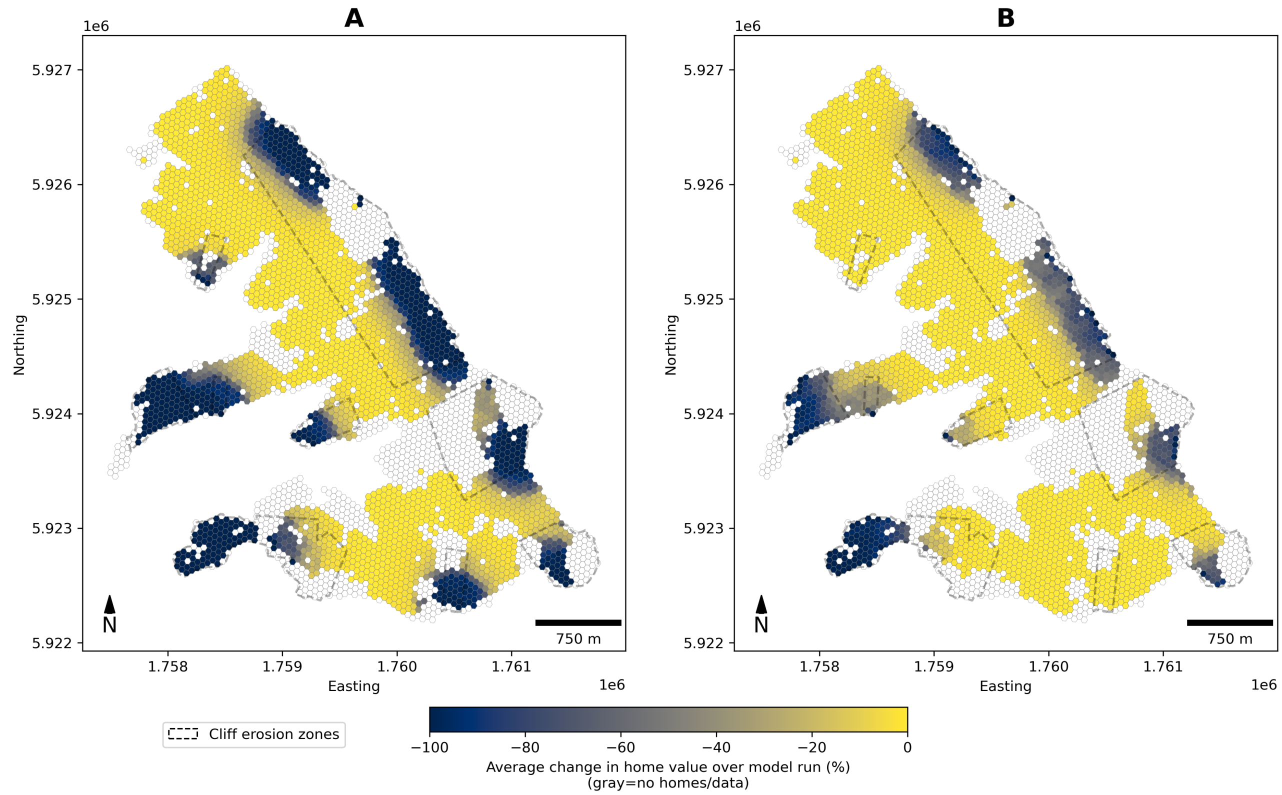

Figure 4.8: Change in median home value over model run by hex-grid, at baseline conditions with gradual erosion rate of 0.041 m (A) and storm probability of 10% (B)

Changes in median home value also exhibited significant spatial variation, as shown in Figure 4.8. Changes are clustered around the cliff zones, with significantly more uniformity in values compared to risk tolerance (Figure 4.7) - risk tolerance remains heterogeneous while median values become more homogeneous. These clusters of change are present under both gradual (Figure 4.8.A) and storm erosion (Figure 4.8.B), with the latter showing less uniformity.

These maps (Figures 4.7 and 4.8) show how the impacts of cliff erosion, on both economic and social systems, are highly spatially dependent. This spatial variability has major implications for managing the impacts of cliff erosion. For example, Lawrence et al. (2020) found that opposition to managed retreat was high for homeowners where neighbouring homes would be retreated, partly because the homeowners were worried about their value reducing. We have shown that in the absence of such management interventions, homes not at risk of erosion can reduce in value significantly as perception of risk spreads. Managed retreat of a home's neighbours may actually decrease their net loss of value by providing a precedent for future support should they become at risk.

The differences in the proportion of homeowners affected by each erosion type are also significant. Often management initiatives are community-driven, something that will be more difficult to achieve if a lower proportion of the community is at risk (Keys et al., 2016; Shi et al., 2022). Under gradual erosion, key social and economic indicators will be noticed by far more homeowners in the community, potentially leading to more community-led initiatives and/or support of authoritative management plans when compared to the fewer homeowners impacted by more destructive yet less spatially extensive slip events.

4.3 Tipping points

We found in Figure 4.5 that home values were initially higher in cliff zones, then reduced as risk increased, an indication of a change in perceptions of clifftop property. This behaviour is further explored in the following plots.

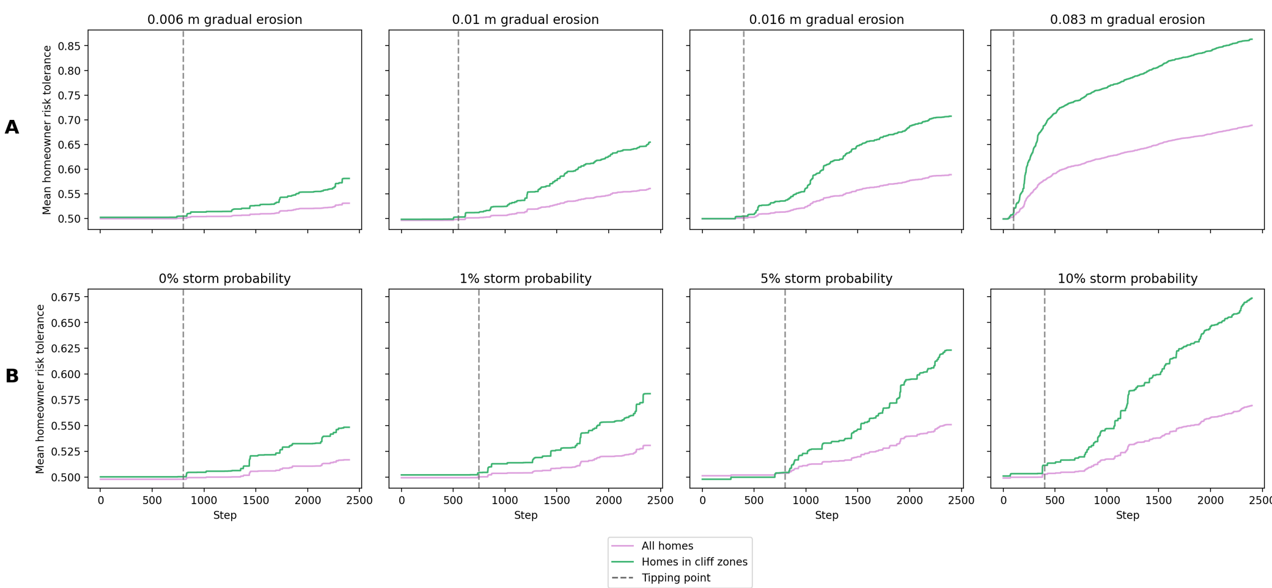

Figure 4.9: Mean risk tolerance over time under selected rates of gradual erosion (A) and storm erosion (B) with highlighted tipping points

Initially, the average homeowner risk tolerance in and outside of the cliff zone was similar, although slightly different, due to their uniformly random generation. We found that across every model run there was a tipping point at which homeowners in cliff zones began to have notably higher risk tolerances than average, with Figure 4.9 highlighting this in selected runs. The step at which this tipping point is reached varied with the erosion rate, with higher gradual erosion (Figure 4.9.A) and storm erosion (Figure 4.9.B) leading to an earlier tipping point. Risk tolerance did increase for all homes, but the anomaly between cliff zone homes and the entire market increased over time under both erosion types.

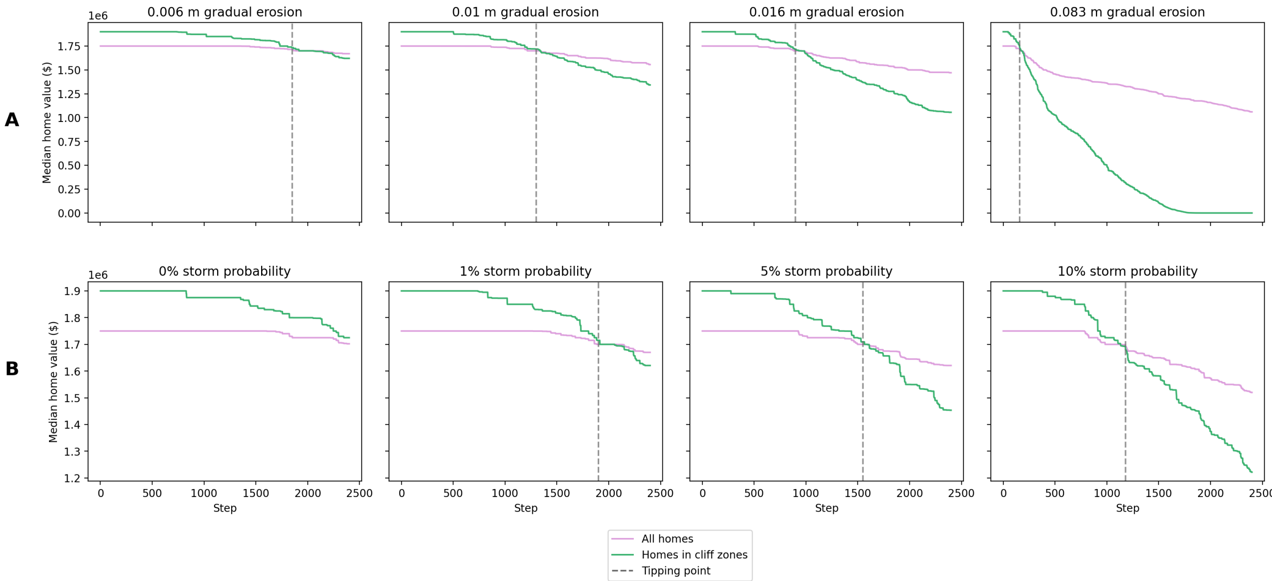

Figure 4.10: Median home value over time under selected rates of gradual erosion (A) and storm erosion (B) with highlighted tipping points

We found another tipping point in home values based on location. Figure 4.10 shows that there was a point at which homes in cliff zones are no longer priced at a premium, and continued to decline in median value at a higher rate than the market as a whole. As with Figure 4.10, the time it took to reach this tipping point was inversely related to gradual erosion (Figure 4.10.A) and storm erosion (Figure 4.9) rates. For each run, the tipping point for value occurred after the tipping point of risk tolerance.

Figures 4.9 and 4.10 highlight significant shifts in human and market behaviour as a result of cliff erosion. The value premium of clifftop property was removed in response to increased risk, while simultaneously altering the social demographic of homeowners to those with higher tolerances for risk, therefore affecting social and economic components of the system. The tipping point of risk tolerance preceding that of market value means that increased tolerances for risk can act as a signal for future market changes. Currently, properties in hazardous zones are often priced at a premium due to amenity, such as the water view typical of coastal clifftop properties (Filippova, 2009). Our results show that this premium may be removed if risk is incorporated into value, with the market instead favouring homes outside of hazardous areas. Erosion and risk-based market behaviour could therefore lead to tipping points in socioeconomic conditions, reducing asset values and increasing tolerances for risk. Such tipping points are seen in other socioenvironmental systems as a result of climate change, which are important to understand as effective management could mitigate or prevent their impacts (Barnard et al., 2021; van Ginkel et al., 2022). Our results show that without any mechanisms to increase adaptive capacity in preparation for increasing risk, tipping points towards decreasing socioeconomic conditions in coastal clifftop environments may be reached under gradual and/or storm erosion. There is no recovery after these tipping points are reached as cliff erosion is unidirectional.

4.4 Summary

Our model showed that increasing the severity and magnitude of coastal cliff erosion led to large shifts in the socioenvironmental system's state towards lower home values and higher individual tolerance for risk. Greater risk from cliff erosion resulted in value reductions, which led to more individual decision-making and consequent market activity. This market activity often resulted in a decrease in home value, now owned by a homeowner with a higher tolerance for risk. Over the entire population, this led to a market-wide reduction in home values and community-wide increase in risk tolerance, where both of these trends were linked to increasing gradual erosion rates and storm probabilities.

In regards to socioeconomic conditions, the model showed that cliff erosion, combined with risk-based pricing without intervention, will lead to a population of homeowners who are simultaneously highly tolerant of and highly vulnerable to risk. The overall reduction in asset values reduces homeowners' economic mobility and therefore increases vulnerability to risk, yet their tolerances for risk are very high. This is a significant change from current socioeconomic conditions in the study area, which has high wealth and low socioeconomic deprivation. Governments are incentivised to protect wealthy households to preserve their own wealth via taxation, and therefore households with higher wealth have more influence in developing management plans (Siders and Keenan, 2020; Wilson, 2010). These wealthier homeowners could therefore put pressure on government to implement adaptation plans and remain in their home. In the absence of such interventions, wealthy homeowners have the economic mobility to avoid the risk, transferring it to a new homeowner with a higher tolerance. As risk is transferred continually to more tolerant homeowners at lower values, we ended up with a highly vulnerable population (a process that could be signalled from tipping points). Since such a population may be more likely to support management plans like retreat (Gibbs, 2016), there could be another incentive for government to wait to intervene until the shift in socioeconomic conditions has occurred - therefore both having less opposition to retreat and lower costs due to reduced market values. This incentive contrasts with that to protect wealthier homes to retain tax revenue. Regardless of the management plan taken, current wealthy homeowners are subject to the lowest loss compared to with other group.

Gradual and storm erosion often impacted socioeconomic conditions in different ways. The impacts of gradual erosion were felt by a far larger proportion of the community than for spatially localised slips from storm erosion. Smaller groups being subject to more physically damaging slip events may cause tension between those homeowners and the rest of the community as management approaches are suggested. Given the critical mass of community support required to effectively implement management approaches (Keys et al., 2016; Lawrence et al., 2020, Shi et al., 2022), storm erosion may lead to less long-term planning compared to gradual erosion, which personally impacts larger groups of the community.

We also found that an absence of risk transfer mechanisms and/or management plans led to massive financial loss for the economy as a whole and for individual homeowners, particularly for those who are most economically vulnerable. Given there is currently little understanding of the most effective placement of responsibility for such a loss (Noy, 2020), and local and national authorities are unsure about setting precedents for buyouts that cannot be maintained as climate change worsens (Gibbs, 2016; Lawrence et al., 2020), the situation where the loss is completely absorbed by the homeowner, as represented in our model, could be a reality without intervention.

Chapter 5: Conclusion

5.1 Modelling and objectives

We developed a simple model that represents a complex set of interacting socioeconomic components in response to changing physical drivers in the coastal clifftop environment (research objective 1). Despite many assumptions and simplifications, the model produced dynamics and final system states that improve our understanding of how these components interact and the potential consequences of such interactions (research objectives 2 and 4). We conclude that simplified models are effective at improving our understanding of poorly understood environments and interactions.

The model has helped us understand the relative differences in socioeconomic impacts induced by gradual and/or storm-driven cliff erosion (research objective 3), in the presence of risk-based pricing but the absence of risk-offsetting measures other than avoidance. The model also exhibited a consistent signal for impending socioeconomic deprivation through risk tolerance and/or value tipping points. We now understand that effective means to offset risk may be crucial in managing coastal clifftop environments, as well as effective public consultation that incorporates the views of all agents regardless of wealth.

5.2 Limitations

The simplified nature of our model potentially limits the validity of the conclusions that can be drawn. Simplifications, many of which were discussed in previous sections, were involved in model component selection, model development and interpretation of model outputs. In terms of component selection, we chose only to focus on risk-based and neighbourhood pricing, for example. Even aside from economic inflation, in A/NZ the housing market is highly speculative and prices vary independently of hazard risks (Fraser et al., 2008). An example of simplification in model development was our choice to base homeowner decision-making purely on risk tolerance. In reality, this is based on a variety of factors such as entrenched sense of place or nearby sales activity (Buchanan et al., 2019). When interpreting the model output, an example of a simplification was to assume that homeowner wealth was based purely on home value. While in A/NZ housing is generally the most significant source of wealth for individuals (Symes, 2022), a home may not be the homeowner's only asset, or the home may be partially owned by banks through mortgages. These are just a few examples of assumptions and simplifications made in the methodology and interpretation of this research.

There is a high reliance on the precision of coastline data for the erosion model. Given that gradual erosion rates must be precise to millimetre level, the coastline data upon which this erosion works should be equally precise. In our source data this was not the case, with the smallest segments of coastline extending 10 m. This is a limitation of the analysis as the model bases all future erosion on a potentially imprecise dataset. The geometry of a coastline is based on the scale at which measurements are made, which is limited by measurement technologies and mathematical constraints (McNamara & Da Silva, 2023). Researchers and planners who rely on low gradual erosion rates for their models should consider this uncertainty of scale and precision in the source data.

5.3 Future work

We designed the model such that it can be easily modified for use in further explorations. Future research could build on the model to modify the assumptions made in its formulation. An example of this is the cliff erosion model, which could be developed further with more accurate erosion controls like lithology or slope. Other agents and social influences could also be included, such as insurers, mortgage brokers and top-down governance. The model could also be updated with empirical examples that may disprove or change the assumptions we made in our research. The structured model design also enables increases in complexity and/or the specific response of interest, further improving our understanding of the system.

Further sensitivity analysis could improve our understanding of the relative influences of other components in the system aside from physical drivers, such as risk tolerance. Risk tolerance was defined randomly, and was static throughout model runs. In reality, risk tolerance is based on many interacting factors (Lujala et al., 2015), and can change over time (Lawrence et al., 2020). Future researchers could perform sensitivity analysis on the distribution from which risk tolerance is sampled, as well as incorporating socioeconomic factors that may adjust a given homeowner's tolerance over a model run. This is only one example of a key parameter that could influence model dynamics and output. Further sensitivity analyses of other parameters could improve our understanding beyond that achieved from this research project. The model could also be run several times for each scenario, which we did not, to account for outliers in the stochastic/random parameters/processes.

Chapter 6: References

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