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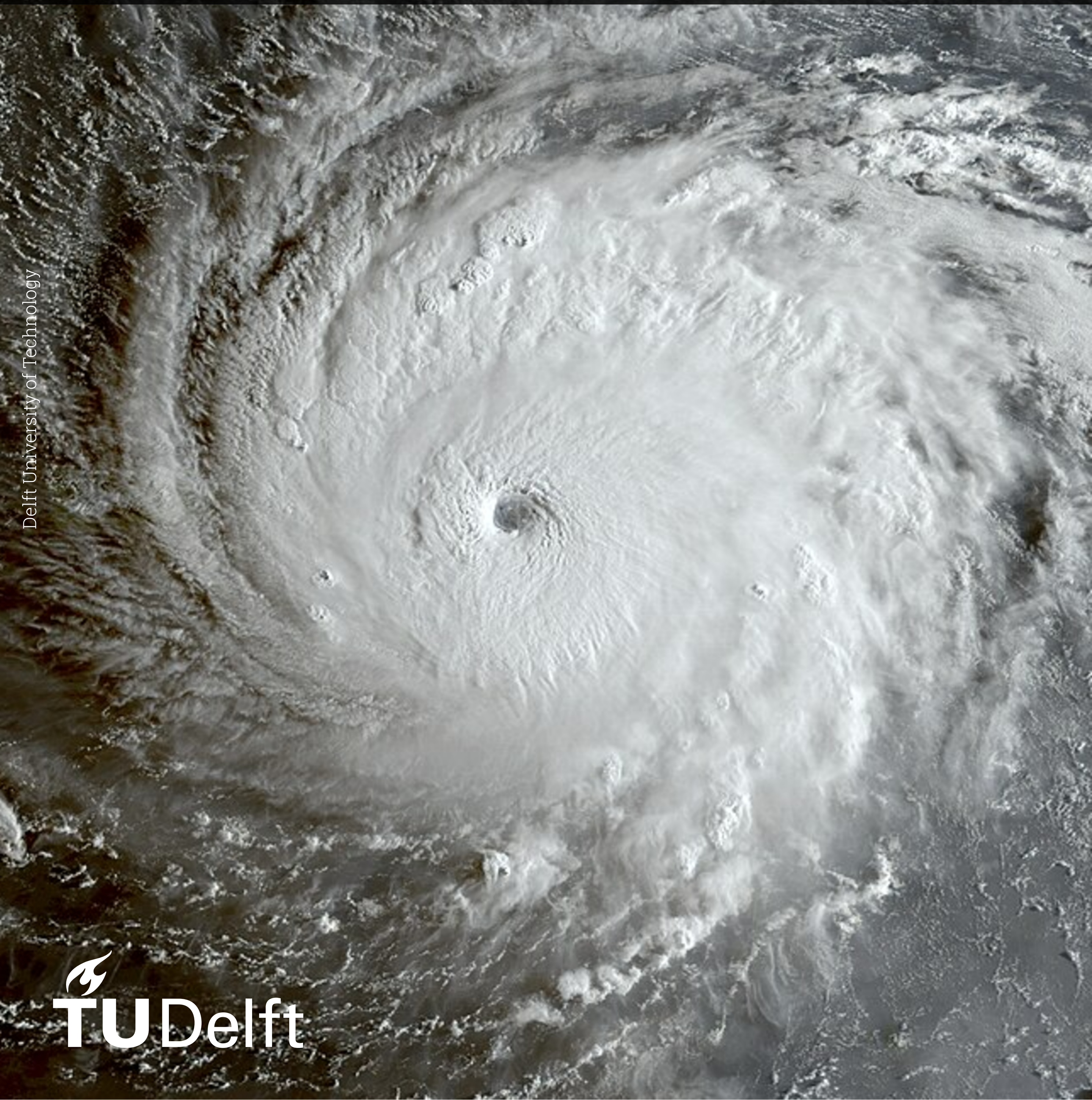
An Agent-Based Analysis of Hurricane Evacuation decision-making behaviour



Delft University of Technology

TU Delft

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An Agent-Based Analysis of Hurricane Evacuation decision-making behaviour

by

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Cover: Geostationary image of 2017's Hurricane Irma , captured by Naval Research Laboratory (Modified)
Style: TU Delft Report Style, with modifications by Daan Zwaneveld

All used code is accessible on GitHub: https://github.com/roesel1/EvacDecModel

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Preface

Although the focus of my thesis was on hurricanes, writing it felt like a hurricane itself. One week I'd be happy because I had written a great introduction, built a first working ABM model, or gotten some nice survey results. The next week I'd be in despair because the introduction had to be rewritten, the once-promising ABM model turned out to be flawed or my laptop and my Qualtrics license failed me at a somewhat crucial time. Still, I can honestly say that, on average and with a p-value of less than 0.001, it was an enjoyable experience.

A big part of what made it enjoyable were the amazing people involved. Starting with my first supervisor, Natalie van der Wal, whom I want to thank for all the help during my thesis and during my time as a student assistant. The guidance was always incredibly insightful, and I appreciated that the focus wasn't just on delivering impressive thesis results but also on enjoying the process as much as possible and having fun.

I would also like to thank Tatiana Filatova and Silvia Ariccio. Tatiana for the helpful meetings and feedback, and Silvia for the project topic and all the support with setting up the survey and getting familiar with place attachment.

Besides my thesis supervisors, I'd also like to thank my family, especially my mom and dad. Without their support, I never would have been able to do all this. In particular, I want to thank them for the total of one month I spent working from home. That was really great and I'm very grateful for it.

And this doesn't only apply to the past year. Like any good researcher would generalize, this gratitude extends to all the years before as well. One of the best tips I ever got from my mom was to embrace my work. Back then it was pen and paper, now it's a laptop, and I must say I think I've done a pretty good job embracing it. You can judge that for yourself now by reading through it all!

Finally, I want to thank everyone who's reading this. If you've made it here and are reading this, you must have some meaningful connection to this thesis and me. Good on you!

Roelof kooijman
Delft, August 2025

Executive Summary

Hurricanes and floods accounted for 71% of natural disasters between 1995 and 2015 and are closely linked. In 2017, Hurricane Harvey caused 68 deaths, 36 of which occurred in Harris County, Houston, while Hurricane Irma led to 92 deaths, primarily due to storm surges. The intensity of such events is expected to increase due to climate change. To address these rising risks, both mitigation and adaptation are essential, with evacuation being one of the most widely used adaptation strategies. However, evacuation decisions are complex and influenced by a wide range of factors. Understanding how these factors interact, both among themselves and with interventions such as evacuation warnings, is crucial.

The purpose of this thesis is to provide insight into how key factors relevant to evacuation decision-making influence each other and how evacuation warnings impact evacuation behaviour. Prior research has identified nine relevant factors being (1) Response efficacy; (2) Self-efficacy; (3) Risk perception; (4) Social cues; (5) Environmental cues; (6) Evacuation experience; (7) Socioeconomic status; (8) Socio-demographics; and (9) Place attachment. While the role of place attachment to home and neighbourhood has been studied, the influence of attachment to evacuation destinations during hurricanes remains unclear.

The interaction of these factors in shaping evacuation behaviour has been theorized through several frameworks. For this thesis, the Theory of Planned Behaviour (TPB), Protection Motivation Theory (PMT), and the Protective Action Decision Model (PADM) were compared. PADM was found to offer the best fit, as it overlaps most with the identified factors and has a temporal structure ideal for modelling evacuation decisions.

Evacuating large populations safely is complex and difficult to study in real life. Simulation models, particularly Agent-Based Modelling (ABM), allow for nuanced analysis of individual behaviour, social interaction, and spatial context. Although some existing ABMs use the PADM framework, they are limited in realism, holistic integration, dynamic decision-making, and validation. This thesis uses PADM to model nine relevant factors, aiming to shed light on evacuation behaviour and policy effectiveness. The study's survey and model are based on Miami-Dade County, Florida, using data from Hurricane Irma (2017), a Category 5 storm.

The research combined survey analysis and agent-based simulation. The survey included questions to capture all key factors, which were analysed using confirmatory and exploratory factor analysis. The resulting factors, consistent with literature, were used for the multinomial logistic regression model predicting destination choice, and for correlation analysis of evacuation intention. The ABM was used to simulate the dynamic interplay of these factors over time and examine the impact of different evacuation warning strategies.

Factor analysis largely confirmed expected relationships. Notably, self-efficacy was found not to be destination-specific, and social influence did not differ between communication with acquaintances and observing neighbours' behaviour. Respondents perceived hurricane and storm surge risks similarly.

Correlation analysis of evacuation intention confirmed literature findings, with all factors significant. A new result was the significant effect of destination place attachment on intentions to evacuate to family/friends, hotels, and public shelters. This suggests that attachment to a destination increases the likelihood of evacuation. Further, place attachment, response efficacy, and self-efficacy were significant for specific destinations, and several factors influenced the decision to shelter in place. The multinomial logistic model based on these factors achieved an F1 score of 0.573, which indicates an overall weak predictive performance.

The agent-based simulation reported an average evacuation decision time of 113 hours (from September 3 at 00:00 onward), with a favourable distribution of decisions over time. Most agents left the risk identification phase nearly simultaneously, but left risk assessment more gradually, resulting in some indecisive agents. Exiting the protective action assessment phase began slowly, but accelerated as landfall neared. Family or friends were the most popular destinations, followed by hotels, then public shelters. Social interactions in the model made popular destinations even more attractive, as compared to survey data.

Two scenarios were explored in addition to the base case. In the media distrust scenario, reduced influence of media cues slowed the accumulation of risk perception, delaying risk identification and assessment. The low risk assessment scenario raised the perception threshold needed to move to the action phase, prolonging the risk assessment period. In both scenarios, hurricane watch and warning communications became more effective, as more agents remained undecided when warnings were issued. The number of indecisive agents increased in both scenarios, with the largest increase (330 agents) in the low risk assessment scenario, compared to just 50 in the base case.

Policy interventions examined the effects of advancing or delaying hurricane and storm surge watches and warnings, and of adjusting the gap between them. Effectiveness was measured by average decision time, the temporal spread of decisions, and the number of indecisive agents. Advancing both warnings and maximizing the interval produced the fastest average evacuation times and the widest spread of decisions, but did not reduce indecisiveness.

It should be noted that while advancing warnings is effective in the model, these interventions did not consider economic impacts or the risk of unnecessary evacuations, which could reduce future compliance. Thus, the results do not present a complete picture of the practical effectiveness of advancing warnings. Nevertheless, the model remains a valuable tool for policy analysis and offers insights into individual decision formation. Furthermore, evacuation timings from this model could inform travel-phase simulations for more realistic predictions of traffic and congestion.

This thesis advances the field by dynamically modelling evacuation decision-making through clearly defined behavioural phases, as opposed to static decision rules typically found in literature. It also highlights the importance of accounting for destination place attachment, moving beyond the traditional focus solely on home or neighbourhood attachment.

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1 Introduction

Hurricanes and floods account for 71% of all natural disasters between 1995 and 2015. These two natural disasters are closely interconnected. In 2017, Storm Harvey resulted in 68 direct deaths, 36 of which occurred in Harris County in the Houston metro area (Blake & Zelinsky, 2018). Another hurricane that demonstrates the destructive nature of such hurricane was Irma in 2017, which caused 92 deaths. Of these deaths, the majority were caused by storm surges (Blake & Zelinsky, 2018). It is expected that the intensity of storms will increase due to the effects of climate change (Alhamid et al., 2022; European Environment Agency., 2017; Yavuz et al., 2020).

To prevent the impact of climate change from worsening, mitigation, adaptation, and other measures must be taken (IPCC, 2022). According to the IPCC (2015) report, the goal of mitigation is to reduce the amount of greenhouse gases emitted or to increase the capacity of sinks to absorb them. However, it can not be expected that climate change effects can be mitigated, stressing the need for adoption measures to increase the resilience of coastal communities. The most effective adoption measure during hurricanes is to provide information about the risks and what individuals should, which is evacuating the area. These types of measures can be seen as transformational adaptation, focusing on informing individuals and promoting behavioural change (IPCC, 2015). Knowledge providing insight in the relevant factors which lead to the decision to evacuate is crucial.

The meta-analyses of Huang et al. (2016) and Van Valkengoed and Steg (2019) identified disaster experience, self-efficacy, outcome-efficacy, risk perception, descriptive social norms, and place attachment as relevant factors for evacuation decision-making. Flood experience influences how seriously individuals take warnings based on their past encounters with floods (Girons Lopez et al., 2017). Self-efficacy refers to a person's confidence in their ability to take effective action (Floyd et al., 2000), such as evacuating. Outcome-efficacy is the belief that evacuation will actually help reduce danger or harm (Floyd et al., 2000). Risk perception affects how individuals judge the likelihood and severity of the flood threat, shaping their motivation to act Lindell and Perry (2012). Descriptive social norms involve the influence of observing others' actions, where seeing neighbours evacuate can prompt similar behaviour Lindell and Perry (2012). Place attachment reflects the emotional connection to one's home or community, which can create hesitation or resistance to evacuate even when at risk (Bonaiuto et al., 2016).

The focus of the study will be on evacuation decision-making during hurricanes. Theories and models exits which bundle the relevant factors together to create an complete overview of this evacuation decision-making. The Theory of Planned Behaviour (TPB) views evacuation as driven by behavioural intentions, shaped by attitudes, social norms, and perceived control (Ajzen, 1991; McLennan et al., 2014; Thakur et al., 2022). However, it downplays the role of risk perception. In contrast, the Protection Motivation Theory (PMT) centers on how people assess threats (severity and vulnerability) and their coping ability (response and self-efficacy), making it more suited to understanding risk-driven behaviour (Floyd et al., 2000; Rogers, 1975). The protection action decision model (PADM) is a more extensive model with a less strict focus on specific factors. It outlines the different phases individuals go through before implementing an protective action like evacuating Lindell and Perry (2012). The inclusion of phases gives PADM a temporal character compared to TPB and PMT. PADM stands out for its temporal structure and broader coverage of factors influencing evacuation and adaptation decisions compared to PMT and TPB Dillenardt et al. (2022).

The application of PADM in studies is found in statistical analyses, qualitative survey reviews, and in combination with other theories, such as PMT. These studies represent psychological processes that occur on an individual level at a collective level. This approach misses valuable insights into the differences in behaviour between individuals. Second, when results are examined homogeneously, only a utilitarian perspective can be applied for policymaking. The result is policies that maximize collective resilience while neglecting vulnerable sub-groups. A heterogeneous approach would allow for an egalitarian perspective, thus enabling policies that ensure the most vulnerable groups are safeguarded as well. Additionally, these studies consider evacuation behaviour statically, they define a behaviour rules which do not change over time, while this does not align with the decision-making process seen in reality (Lindell & Perry, 2012). Also, the development over time of social and environmental cues is no taking into account.

To address the above limitation ABM could be developed based on PADM. The ABM can tackle the disadvantaged of homogeneous and static studies. An ABM can provide insights into: 1) how psychological and social-physical factors influence evacuation decision-making behaviour, 2) how changes in decision-making impact the evacuation process., 3) how evacuation orders influence the evacuation behaviour. The model can leverage existing literature of psychological and environmental factors. This contribution would improve the understanding of how individual decision-making processes influence the evacuation efficiency of a large area. It also presents a research approach that demonstrates how to implement PADM in an ABM. Furthermore, it can examine what the most effective timings are for issuing official evacuation orders.

The goal of this research is to provide insight into: (1) the evacuation decision-making behaviour for an upcoming hurricane, and (2) examine the effectiveness of evacuation warning communication. The corresponding research question is:

What is the effect of psychosocial factors, environmental factors and evacuation warning communication on evacuation decision making in the case of a hurricane?

The corresponding sub-questions are:

- SQ1: Which psychosocial factors and environmental factors are required for modelling evacuation behaviour in a hurricane scenario?
- SQ2: How can these psychosocial factors, environmental factors be integrated into an Agent-based model?
- SQ3: How do different timings of evacuation warning communication influence evacuation behaviour?

The question will be answered using two approaches. First a statistical analyses of the environmental and psychosocial factors will be executed to provide insight in the influence of relevant factors on evacuation intention and destination choice. The statistical analyses will answer the first sub-question (SQ1). The second approach is agent-based modelling. The model will be used to answer the two other sub-questions (SQ2 and SQ3).

The structure of this thesis is as follows. First, the relevant literature is reviewed in detail. Next, the methodologies for both approaches are presented, beginning with the statistical analysis followed by the ABM formulation. The results are then reported separately for each approach. Finally, the discussion section synthesizes the findings from both methods to provide the overall conclusions and recommendations of the thesis. Appendix A gives a more elaborated overview of the thesis structure.

2
State of the art

This section will start exploring the various relevant factors for evacuation decision-making. Then it will discuss various theories and models which combine factors for describing evacuation behaviour. Lastly, integration of these factors and theories/models in Agent-Based Models (ABM) is examined.

2.1. Environmental and psychological factors

The factors that influence evacuation decision-making have been researched extensively. Van Valkengoed and Steg (2019) examined factors relevant to adaptation behaviour in response to climate change effects. The study found that disaster experience, risk perception, and descriptive norms have been investigated in the context of hurricane evacuation. These factors do have an effect on adaptation behaviour. Unfortunately, the focus here was not evacuation itself. Huang et al. (2016) conducted a meta-analysis of studies examining variables that influence evacuation decision-making, specifically for hurricanes. Thirty-eight studies analysed individuals' behaviour after a hurricane, while eleven used hypothetical hurricane scenarios. The study found that social cues, official warnings, mobile home ownership, risk area, storm surge risk, and environmental risk were the most influential variables. Socio-demographic characteristics appeared to be less effective in influencing evacuation behaviour. Additionally, the study concluded that results from hypothetical hurricane scenarios are generally consistent with those from actual hurricane events. Wang et al. (2021) examined all variables relevant to emergency evacuation and categorized them according to the evacuation phase in which they were studied. It distinguished between a pre-travel phase and a travel phase. This study focuses on the pre-travel phase and therefore ignores all factors focusing on the travel phase.

In addition to reviewing overview studies, other individual studies were also examined. Rather than discussing these studies separately, Table 2.1 presents all identified factors, which will be explained further in the following sections. It must be noted that the specific variables will be named since they belong to a certain factor. For example, Huang et al. (2016) identified mobile home ownership, which belongs to the socio-demographic factor.

Factor	Description	Source
Response efficacy	Belief that evacuation will effectively reduce risk or harm.	(Morss et al, 2024) (Qing et al, 2022) (Van Valkengoed en Steg, 2019)
Self efficacy	Confidence in one's ability to evacuate safely and effectively.	(Lindell and Perry, 2012) (Steward, 2022) (Van Valkengoed en Steg, 2019)
Risk perception	Individual's assessment of the threat and severity of the hurricane.	(Baker, 1991) (Lindell and Perry, 2012) (Van Valkengoed en Steg, 2019)
Social cues	Influence of others' actions or behaviors on the decision to evacuate.	(Bian et al, 2019) (Huang et al, 2012) (Huang et al, 2016) (Van Valkengoed en Steg, 2019)
Environmental cues	Physical signs of danger (e.g., rain, strong winds) prompting evacuation.	(Huang et al, 2012) (Huang et al, 2016) (Huang et al, 2017) (Lazo et al, 2015)
Evacuation experience	Prior experience with evacuating in past disasters.	(Richard, 2017) (Morss et al, 2024) (Van Valkengoed en Steg, 2019)
Socioeconomic	Economic status factors like income, job type, and financial resources.	(Huang et al, 2016) (Whitehead et al, 2000) (Lindell et al, 2011)
Social demographic	Personal characteristics such as age, gender, education, and household size.	(Huang et al, 2016) (Morss et al, 2024) (Whitehead et al, 2000)
Media usage	The extent and sources of media used to gather information before or during the event to decide to evacuate or not.	(Jiang et al, 2019) (Du et al, 2017)
Place attachment	Emotional connection to a specific location, shaped by personal, cultural, or social meanings.	(Ariccio et al, 2020) (Bonaiuto et al, 2011) (Bonaiuto et al, 2016) (Stancu et al, 2020)

Table 2.1: Factors relevant for evacuation

Response efficacy refers to an individual's belief that evacuating is effective in reducing or avoiding the threat. Morss, Prestley, et al. (2024) created linear regressions for evacuation prediction. Response efficacy proved to be the most influential. Similar findings were made by Quinn et al. (2018), which examined if the response and self-efficacy following the protection motivation theory where effective for explaining evacuation intention. It must be noted that Van Valkengoed and Steg (2019) reports on the importance of outcome efficacy. While not exactly the same as response efficacy, it indicates the importance of response efficacy.

Self-efficacy refers to an individual's confidence in their own ability to perform a specific action or behaviour, such as successfully evacuating during a hurricane. Stewart (2015) found that individuals with high self-efficacy are more likely to comply with evacuation recommendations. Similar, Qing et al. (2022) states that self-efficacy positively influence the intention to evacuate, although it has less influence then response efficacy. Lindell and Perry (2012) describes self-efficacy as an effective predictor when individuals have only a few protective actions to undertake. They also notes that contextual facilitators must be considered. Instead of looking at somebodies perception it can be examined if the individual has the required resources for implementing action. For example, for evacuation a vehicle is needed. Without a car evacuation becomes harder. The results of self-efficacy for evacuation are in line with the general influence of self-efficacy on adoption behaviour (Van Valkengoed & Steg, 2019).

Risk perception refers to an individual's assessment of the likelihood and potential severity of a threat, influencing how they respond to danger. As the definition suggests, risk perception is a latent factor typically measured through perceived intensity and likelihood. Baker (1991) found that living in an area at risk increases the intention to evacuate. Huang et al. (2017) confirms the importance of living in risk areas. Furthermore, it found that higher expected wind impacts leads to higher evacuation intention. Morss, Cuite, and Demuth (2024) found that the expected likelihood influences evacuation intention. It also concluded that expected hurricane impacts evacuation intension, where personal harm is seen as more important then property damage. Lindell and Perry (2012) indicates that risk perception is important by becoming aware of the hurricane threat and convincing protective action is required.

Social cues refer to signals from other people, such as friends, neighbours, or community leaders, that influence one's decision to take protective actions like evacuation. Here, it is important to differentiate between evacuation managers and evacuees (Wang et al., 2021). The main intervention for evacuation managers, in the United States, is issuing evacuation warnings and orders (National Hurricane Center, n.d.). Official evacuation warnings are seen as the best predictor for evacuation (Huang et al., 2016, 2017). For evacuees the bonds with peers and visual behaviour of people in neighbourhood influences there own evacuation behaviour (Lindell & Perry, 2012; Wang et al., 2021). Huang et al. (2016) concludes that the evacuation of peers has big influence on evacuation behaviour, , it also finds a consistent influence of business closing. Similar results where found in an earlier study of Huang et al. (2012). The influence of media can be seen as social influence through the access and use media sources (e.g., TV, radio, social media) to obtain information before, during, and after a disaster. Lee et al. (2021) found that media leads to more perceived consistency in information which influence evacuation decisions. Of the media channels, television broadcast are consulted most often Sherman-Morris et al. (2020). The media forms one of the first points of access for hurricane related information (Demuth et al., 2012).

Environmental cues refer to observable physical signs in the environment, such as winds speeds and rain, that indicate an imminent threat. Huang et al. (2012) found that perceived storm characteristics influence evacuation intention. Huang et al. (2016) showed that environment cues have an indirect effect on evacuation intention through expected storm threat, expected wind impacts and expected evacuation impediments. Environmental cues play an role in shaping the risk perception of the individual which influence the intention to evacuate Baker (1991) and Lindell and Perry (2012).

Evacuation experience refers to an individual's previous encounters with evacuation situations. Experience can both have negative and positive effect on evacuation intention Huang et al. (2012). People who experienced hurricanes are expected to have better idea what to do and therefore evacuate faster Lindell and Perry (2012). If people who evacuated form a storm and, in hindsight, think it was unnecessary will less likely to evacuate the next hurricane Huang et al. (2012). While these studies indicate significant relations, Huang et al. (2016) analysed all studies for experience and concluded that both are not significant. This aligns with similar findings for Baker (1991). Since, no clear indication can be given for the real relevance hurricane experience is still deemed important.

Socioeconomic refers to the economic and social conditions of an individual, including income and employment, which affect their capacity to prepare for and respond to emergencies. Individuals income is not a predictor for evacuation intention (Huang et al., 2012). Huang et al. (2016) found that it is relevant for expected evacuation impediments, which does have an influence on evacuation intention.

Social demographic refers to characteristics such as age, gender, ethnicity, and family structure that influence an individual's vulnerability and response strategies during emergencies. These characteristics vary widely. In general it can be said that social demographics have small impact on evacuation intention (Huang et al., 2016). Morss, Prestley, et al. (2024) reports small, but significant impact of gender and education on evacuation intent. Huang et al. (2012) found a significant impact for gender, but not for education. Ethnicity and race are less relevant when considering evacuation intent (Huang et al., 2012, 2016; Morss, Prestley, et al., 2024). It however does influence other factors like risk perception and self-efficacy Morss, Prestley, et al. (2024). Additionally, the destination choice when evacuating is influenced by ethnicity and race (Whitehead et al., 2000).

Place attachment refers to the emotional and psychological bond individuals feel toward their home or community, which can affect their willingness to evacuate in the face of danger. Place attachment is one of the factors which influence general adaptation behaviour against natural disasters (Van Valkengoed & Steg, 2019). Qing et al. (2022) did not found a significant relation between evacuation intention and place identity or place dependence. Instead, it influenced response efficacy. Risk perception is another relevant factor influenced by place attachment (Bird et al., 2011; Bonaiuto et al., 2016). Interesting is that the majority of work of focuses on place attachment towards home or the neighbourhood of home. A small number of studies examined evacuation sites for tsunamis (Ariccio et al., 2020; Villagra et al., 2021). Ariccio et al. (2020) and Villagra et al. (2021) that PA to an evacuation site can significantly influence the decision to evacuate to that location (Ariccio et al., 2020).

Stancu et al. (2020) expands on the findings related to evacuation site PA by examining the role of PA styles and risk coping strategies. Using the attachment styles conceptualized by Lewicka (2011) and Quinn et al. (2018), the study found that different attachment styles result in the use of different risk coping strategies. Additionally, Stancu et al. (2020) examined the importance of PA intensity, or the strength of the bond between person and place Williams and Roggenbuck (1989). It was found that PA intensity has a significant effect on perceptions of risk and distress.

The current research examined home, neighbourhood and evacuation site place attachment. This raises the question if destination place attachment, towards family/friends, hotel or public shelter, also has influence on evacuation intention during hurricanes. For example, in tourism it is found that people go to destinations with high place attachment (Prayag et al., 2013). During hurricane evacuation the majority evacuates towards family/friends, hotels/motels or public shelters (Bian et al., 2019; Whitehead et al., 2000). Unknown is how place attachment towards these type of destinations influence evacuation intention during an incoming hurricane.

2.2. Evacuation timeline

Multiple researchers have created theories which combine the relevant factors to create a holistic view of evacuation behaviour. Before examining specific theories, it is important to consider the entire timeline in which adaptation measures take place. Zhuo and Han (2020) identified three categories for adoption measures: real-time emergency management, long-term adaptation planning, and hydrological modelling. It must be noted that although the study itself focused specifically on flooding, it can also provide a clear overview for hurricanes. Moreover, the accompanying storm surges result in severe flooding, which aligns with the focus of Zhuo and Han (2020). The equivalent of hydrological modelling for hurricanes is atmospheric modelling (Chen et al., 2007). Atmospheric modelling will not be discussed further here, as these models focus heavily on realistically simulating hurricanes, which is beyond the scope of studying evacuation behaviour.

2.2.1. Long-term adaptation planning

Long-term adaptation planning focuses on policy interventions aimed at increasing the resilience of coastal communities. It typically addresses the living spaces of households or buildings in general, or seeks to improve knowledge and awareness. The goal of such studies is to assess the effectiveness of policies over extended periods. In the context of evacuation, this may involve improving the understanding of evacuation planning and increasing preparedness for hurricanes Adhikari et al. (2021) and Dunning (2020). One specific measure is the development of resilient planning pathways for natural disaster preparedness Villagra et al. (2024). However, this category is less relevant when the threat is imminent. Therefore, no further focus will be placed on long-term adaptation.

2.2.2. Real-time emergency management

Real-time flood emergency management focuses on the behaviour of individuals during emergency and how policies can improve emergency outcomes. These policies either focus on the decision to evacuate or the decision regarding where to evacuate. These two questions are central to evacuation models (An, 2012).

Wang et al. (2021) analysed multiple evacuation models incorporating human behaviour. Based on this analysis, a general timeline was created that provides an overview of the different phases of evacuation, from the occurrence of a hurricane to the re-entry of evacuees to their home area. The timeline presented in the study is shown in Figure 2.1. It divides the evacuation process into different phases for two types of agents: evacuees and evacuation coordinators. For both agents, the evacuation is divided into the pre-travel and travel phases. The transition to the travel phase occurs when the evacuee turns their decision to evacuate into the action of evacuating. Based on Figure 2.1, the scope of this thesis can be defined. First, the role of evacuation coordinators will not be considered. Although they have a significant impact on the process, realistically incorporating coordinators would shift the focus too far away from the evacuation behaviour of the evacuees themselves.

During a hurricane evacuation, the experiences of evacuees differ significantly between the pre-travel and travel phases. In the pre-travel phase, evacuees focus on becoming aware of the risk, assessing the risk, making the decision to leave, and preparing for departure Lindell and Perry (2012). Once the travel phase begins, evacuees face the challenges of physically relocating, which includes navigating traffic congestion, using designated evacuation routes, and accessing fuel, rest stops, and shelters. Throughout both phases, the goal is to ensure evacuees can leave safely, efficiently, and with access to the support they need.

However, the behaviour and process differ drastically between phases, as evacuees shift from preparation to action. In the pre-travel phase, behaviour is more deliberative people monitor news updates, weigh risks, consult with family, and gradually gather supplies Lindell and Perry (2012) and Wang et al. (2021). There is often uncertainty or hesitation. In contrast, the travel phase demands immediate decision-making and physical movement, often under stress and time pressure. Due to the lack of behavioural overlap between the pre-travel and travel phases, it is overly complex to define behaviour in a way that meaningfully describes both. So, during this thesis, the focus will be on the pre-travel phase. Hurricanes in general have long warning periods, but studies show that people still wait until the last moment to evacuate Lindell and Perry (2012) and Roy and Hasan (2021). This leads to congestion of the road infrastructure. Feng and Lin (2022) indicates that ordering earlier evacuation orders for some regions would make overall evacuations for hurricanes more efficient. However, earlier evacuation orders will not guarantee earlier evacuations, since other factors are crucial Huang et al. (2016), Lindell and Perry (2012), and Lindell et al. (2005), see section 2.1. Insight in how behaviour leads to the decision to evacuate could provide insights for policy interventions which could release the road congestion seen in the travel phase by improving the situation during the pre-travel phase. So the focus, in this thesis, will be the pre-travel phase.

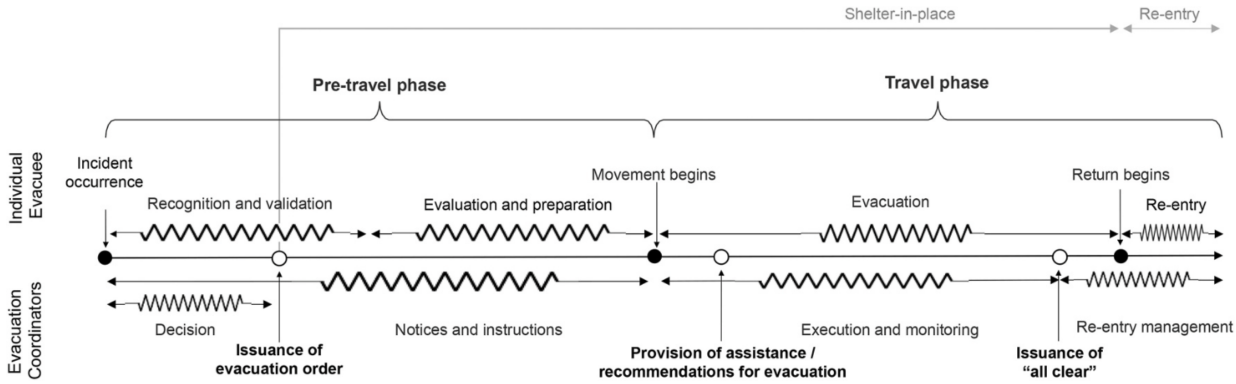

Figure 2.1: Evacuation timeline derived from Wang et al. (2021)

2.3. Theories for evacuation decision-making

Many theories are created to combine the relevant factors for pre-travel behaviour. Here, the Theory of Planned Behaviour (TPM), Protection Motivation Theory (PMT)and Protection Action Decision Model (PADM) will be discussed. While other theories exists, TPB, PMT and PADM are are extensively acknowledged and utilized across disaster risk reduction, as well as social and behavioural science disciplines (Tan et al., 2024). The theories will be explained and then the application in disaster behaviour prediction will be given. At the end, it will be reasoned which theory has the best fit for evacuation modelling. The explanation of the theories are already applied to evacuation behaviour

2.3.1. Theory of Planned Behaviour

The Theory of Planned Behaviour, which exists out of three key components which can can predict an individual's likelihood of engaging in a specific behaviour. These factors are: attitudes toward the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991). Figure 2.2 shows an overview of the factors of TPB.

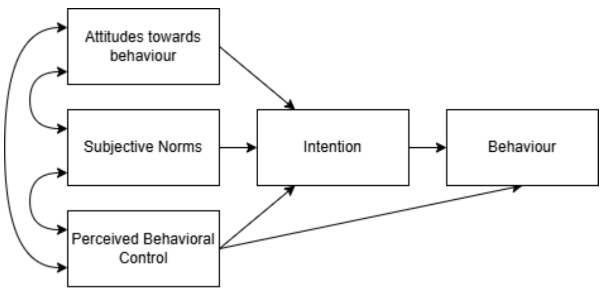

Figure 2.2: Overview of theory of planned behaviour

The first component, attitudes toward the behaviour, refers to a person's overall evaluation of evacuating whether they view it as beneficial or burdensome. This evaluation is shaped by beliefs about the outcomes of evacuating. For example, if an individual believes that evacuating will protect their life and property, reduce stress, and provide access to emergency services, they are more likely to hold a positive attitude toward evacuation. On the other hand, if they believe evacuation is unnecessary, overly disruptive, or costly perhaps because previous storm warnings didn't result in actual damage they may view it as an overreaction. Such negative attitudes can significantly decrease the likelihood of compliance with evacuation orders. Here, one could argue that the factors identified important: response efficacy aligns with attitudes toward the behaviour.

The second component, subjective norms, captures the perceived social pressure to perform or avoid the evacuation behaviour. People often look to their social environment family, friends, neighbours, or even media networks for cues on what they should do. If a person perceives that important others expect them to evacuate. Conversely, if their immediate community tends to ignore evacuation warning then this can discourage evacuation, even if official advice urges otherwise. The role of subjective norms has overlap with the earlier identified of social cues which also focus on the pressure from neighbours and peers on behaviour.

The third component, perceived behavioural control, refers to the individual's belief about their ability to successfully carry out an evacuation. To implement evacuation behaviour resources are required like a travel mode, financial means and availability of shelters. Ajzen (1991) explains that even if an individual has the resources it needs to perceives its own capabilities great enough to evacuate. The framing perceived behavioural control is similar to the one of self-efficacyAjzen (1991). Perceived behavioural control and intention can predict behaviour. A high perceived behavioural control can be seen as a high confidence in own capabilities to close the intention and action gap. TPB clearly describes that a difference between the intention to implement an action and actually implementing exits by having different components for intention and behaviour.

TPM is made for a wide variation of behaviour as long as it is involved in active decision-making. It has applications in long-term adaptations for disasters. Ng (2022) examined disaster preparedness for typhoons and found that attitudes toward the behaviour and perceived behavioural control were not significant in influencing disaster preparedness. Another study for typhoon did also not find a significant effect for perceived behavioural control on disaster preparedness (Zaremohzzabieh et al., 2021). For pre-travel decision-making,Thakur et al. (2022) applied TPM on evacuation from volcanic risk and found that using TPB is favourable for predicting evacuation intention. McLennan et al. (2014) applied the theory on wildfire evacuation and also found significant predictive power for evacuation intention. No studies exists applying TPM for evacuation in the context of hurricane evacuation.

2.3.2. Protection Motivation Theory

The Protection Motivation Theory was created by Rogers (1975) to examine health-related risks and behaviour. Then it was applied widely varying cases of which one is adaptation behaviour Li et al. (2024) and McLennan et al. (2014). It involves two key processes: threat appraisal and coping appraisal (Floyd et al., 2000; Rogers, 1975). Both key process can be divided in smaller components. A overview of these key processes and subcomponents is given in Figure 2.3.

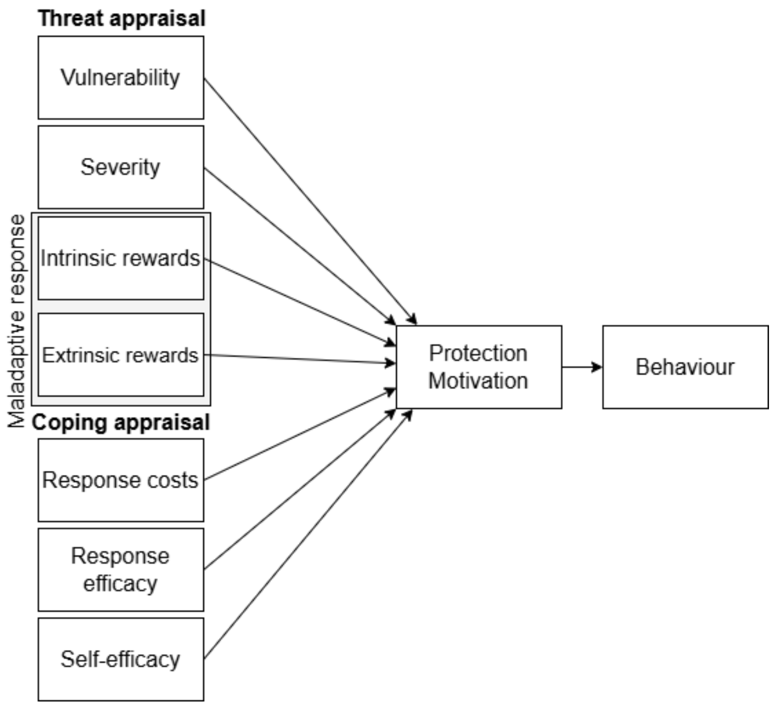

Figure 2.3: Overview of the protection motivation theory

The first two components of threat appraisal are severity and vulnerability. Severity refers to how serious an individual perceives the threat of the hurricane to be. This expressed in the perceived severity of injury, property damages and number of deaths. Vulnerability reflects the perceived likelihood of being affected by the hurricane. The severity and vulnerability are both partly based on prior experiences with threats (Kurata et al., 2023). The factor of risk perception is the same as the description of PMT, a combination of perceived impact and likelihood.

The other component of threat appraisal is the maladaptive response reward. This is the reward the individual gets when choosing not to adapt, so not to evacuate. This can be split into intrinsic and extrinsic rewards. Intrinsic rewards refer to the psychological or emotional benefits. An example could be the sense of security and comfortability of staying home. Extrinsic rewards are the reward experienced trough others. Here, the factor of social clues play an important role. Together with severity and vulnerability it form the threat appraisal.

Coping appraisal has three components which describe how the individual appraises protective actions, in this case evacuation. Response costs describe any required resources to implement the action. like time, effort money. The self-efficacy is ones own perceived capability of evacuating to a safer place. Response costs and self-efficacy are rather similar, but response cost is a objective depiction of the available resource while self-efficacy is the judgement of the individual thinks it can apply the resources to successfully implement the action. Response efficacy is the perceived effectiveness of the protective action. if the individual thinks evacuation will not result in more safety then it will be reluctant to evacuate.

Threat appraisal becomes an trade-off of the benefits of being exposed to the threat and the potential harm of the threat. Coping appraisal is the trade-off between the afford it takes to implement an action and the benefits gained from implementing it. A higher maladaptive response reward will lower threat appraisal while higher vulnerability or severity would increase it. Coping appraisal gets higher with lower response cost and higher with high self-efficacy and higher with high response efficacy.

PMT has been successfully implemented to examine protective response for long-term adaptation planning for flooding scenarios Flores et al. (2024) and Haer et al. (2016). It also has seen implementation in real-time emergency management. Kakimoto and Yoshida (2022) researched evacuation intention for torrential rain and using PMT. Liu et al. (2024) applied PMT in a case where evacuation intention was studied for a flooding scenario. Only one case exists where PMT is applied to hurricane evacuation (McEligot et al., 2019). This study made an agent-based model**??** for evacuation decision-making modelling for the Miami Beach are. It defined its agents behaviours using PMT with elements of the protective action decision model.

2.3.3. Protective action decision model

The protection action decision model (PADM) is a model which explains the pre-evacuation behaviour for natural disaster through the use of multiple phases (Lindell & Perry, 2012). It explains how predecisional processes, core perceptions and protective action decision making leads to protective actions. Additionally, it contains situational facilitators and impediments. The presents of impediments or lack of facilitators describe how individuals can go from intention to behaviour. Below the three predecisional processes, core perceptions and protective action decision making explained. A overview of the model is given in figure 2.4 and is derived from Lindell and Perry (2012).

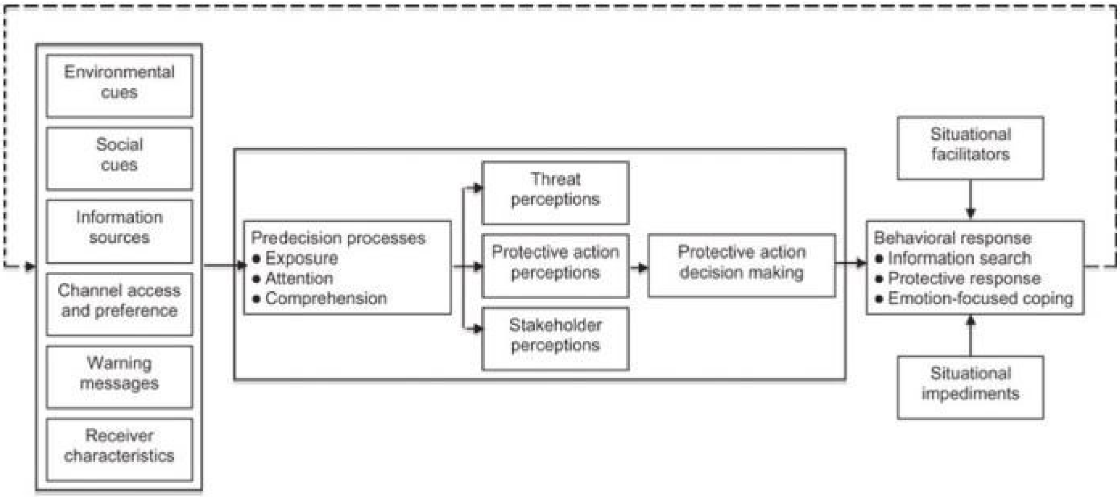

Figure 2.4: Overview of the protection motivation theory

The predecisional processes describe how individuals perceive environmental and social cues. First, the cue must be exposed to the individual; it cannot process something which it cannot sense. Second, it needs to heed attention to it. A cue can reach an individual, but if they are not paying attention to it, they will still not process its existence. For example, everybody has their nose in their vision. However, nobody is actively paying attention to it and therefore does not notice that it is there. Last, when an individual is exposed to and heeds the cue, they still must understand the cue. A radio message in Spanish is not understood by most Dutch citizens. The three processes are relevant for all the cues that the individual receives.

The core perceptions of an individual concern environmental threats, hazard adjustments, and social stakeholders Lindell and Perry (2012). The core perceptions describe how people process and assign value to the exposed cues that they heed and understand. Environmental threat perception explains how individuals process cues to perceive risk. Risk is divided into impact and likelihood. The threat perception describes how cues influence the impact and likelihood of a threat. Hazard adjustments refer to the perception of actions that reduce the impact and/or likelihood of a threat. Additionally, it considers the individual's perceived efficacy and resources to implement the action. Last is the perception of stakeholders; it describes the attitude toward the stakeholder and the perceived role and responsibilities of the stakeholder. If an individual feels that another stakeholder, like the government, holds responsibility to take action against a threat, they are less likely to implement action themselves. Additionally, following advice from a stakeholder who is not trusted is less likely Arlikatti et al. (2007) and Lindell and Whitney (2000).

Eight different phases make up the protective action decision-making process. They are given in Table 2.2; the table is derived from Lindell and Perry (2012). It must be noted that both the predecisional processes and core perceptions are intertwined throughout the different phases. Furthermore, the phases are presented as sequential in Table 2.2, but in reality, they are not. Every phase will be explained shortly. The explanation is fully based on Lindell and Perry (2012) and Lindell et al. (2006).

Number	Phase	Question	Outcome
1	Risk identification	Is there a real threat that I need to pay attention to?	Threat belief
2	Risk assessment	Do I need to take protective action?	Protection motivation
3	Protective action search	What can be done to achieve protection?	Decision set (alternative actions)
4	Protective action assessment and selection	What is the best method of protection?	Adaptive plan
5	Protective action implementation	Does protective action need to be taken now?	Threat response
6	Information needs assessment	What information do I need to answer my question?	Identified information need
7	Communication action assessment and selection	Where and how can I obtain this information?	Information search plan
8	Communication action implementation	Do I need the information now?	Decision information

Table 2.2: PADM phases with their central question and outcome.

Risk identification. The first step during disasters is realizing that a disaster is imminent or happening. This recognition can be triggered by environmental cues, but more often it comes from social cues like authority warnings, media, or peers. In both immediate disaster response and long-term hazard planning, individuals must determine whether a real threat exists. People often try to view their surroundings as normal, even when faced with evidence to the contrary. However, the stronger someone believes a threat is real, the more likely they are to take action regardless of the type of disaster. When the individual is convinced that a threat is imminent or happening, they will proceed to the next phase.

Risk assessment. Once a threat is identified, people evaluate how it might affect them personally. If they believe the risk is real and immediate, they are more likely to act. However, more time before impact can lead to delays as people seek information or protect property. Risk perception is influenced by how likely and severe the threat seems, how close it is, and how long its effects may last. Simple threats are easier to understand, while complex ones, like toxic exposure, can confuse people and reduce action. People often underestimate personal risk, and concerns vary from immediate danger to long-term health and life disruptions.

Protective action search. When people believe a threat is real and see potential negative impact as plausible, they start looking for ways to reduce the impact. Here, individuals must rely on their own knowledge or choose protective measures, such as sheltering or evacuating. People often recall past actions or learn from others by observing neighbours, hearing stories, or watching the news. Official warnings also suggest protective actions.

Protective action assessment. After identifying possible protective actions, people evaluate which action(s) is best. They weigh these choices against continuing normal activities, aiming to find the action(s) that provide the most protection. This decision involves trade-offs. For instance, evacuating protects lives but leaves property behind, while staying to protect property exposes individuals to danger. When time allows, people may combine actions, such as securing belongings before evacuating. People assess options based on their effectiveness, safety, and time required. A protective action must be seen as effective in reducing harm. Safety concerns, such as fear of accidents during evacuation, may influence decisions even if those risks are low. Time is another factor; some actions, like sheltering in place, are quick, while evacuation can be complex and time-consuming.

Protective action implementation This step occurs when people decide that action is necessary, a protective option is effective, and it's possible to carry out. However, many delay action until they feel the threat is urgent enough to justify the disruption to daily life. This results in that majority of individuals evacuate last minute creating problems like road congestion in potential dangerous weather.

Information needs assessment. During all the above phases individuals act in uncertainty, since they do not have complete overview all information. If individual perceives it needs more information before making a decision it will go to the information needs assessment phase. Here, the individual reasons which kind of information is needed. This can be for assessing the threat, actions or stakeholders.

Communication action assessment. When it is clear what information is wanted it must be determined where to obtain it. This leads to selecting sources and channels of information. People tend to turn to news media or officials when uncertain about the risk, while they often rely on peers when uncertain about protective actions or how to implement them.

Communication action implementation. Simaliry to the protective action implementation, individuals asses if it required to gather the information now or it has time to wait for a later time. If the threat timing and location is ambiguous individuals tend to be more active in information seeking then when it is not. There a three possible outcomes for this phase: (1) the information need is met; (2) no new or useful information is found; (3) the source is unavailable. Depending on the satisfaction of the individual it can decide to search for more information.

PADM already is implemented in various studies for disaster evacuation including hurricane evacuation. Zhang and Borden (2024) researched how risk perception and response to evacuation orders differ between communities in different states. Li et al. (2024) focused on evacuation behaviour for low-income communities in New York. Greer et al. (2023) and Wu et al. (2024) did not focus on the effect of specific communities but the evacuation behaviour in the dual-threat environment of a hurricane and COVID-19. Huang et al. (2017) used PADM to create a statistical model to see which factors are relevant for predicting evacuations. Besides statistical analyses PADM is partly implemented in computational model for policy testing Hatzis et al. (2024), McEligot et al. (2019), and Yeates et al. (2023).

2.3.4. Comparison theories

All three theories contain overlap with the identified factors in section 2.1. Table 2.3 shows which components correspond to which factors. The factors and components of theories are seen as similar if the description of the largely corresponds to the factor. It must be noted that these theories often get expanded or combined to suit specific needs of studies. For example, Kurata et al. (2023) who added the experience factor of experience and combined TPB and PMT or McEligot et al. (2019) combining PADM and PMT for behaviour rules of an model simulating evacuation behaviour. For the Table 2.3 no extend variants were considered.

It is visible that TPM has the least overlap with the factors. This is not surprising. The theory was made to predict general behaviour and not specific behaviour against threats. It also does not provide insight into how environmental, media cues influence perception or behaviour. PMT has better overlap with factors, since it incorporation the notion of risk perception. It also considers socioeconomics through response costs. Last, is PADM which has the best overlap. This due the inclusion of the predecisional processes which explain how individuals become aware of cues of their environment and evaluates this cues through the core perceptions. Notable is that all three do not specifically mention experience, social demographics and place attachment. Kurata et al. (2023) shows that experience influence the risk perception. For TPB, experience can influence attitude toward behaviour and behavioural control. The exclusion of place attachment is logical, since the theories examine behaviour which is not place depended. Integrating Place attachment would limited the application possibilities of the theory.

Besides the higher overlap with existing factors, PADM also has a temporal character which the other two does not have. The protective action decision-making phases, see Table 2.2, give a structured overview of the whole pre-travel as defined by Wang et al. (2021). TPB and PMT do not provide insight in how the decision-making process evolves over time. This makes them suitable for statistical analysis based on one time surveys, but less suitable for temporal studies.

Factor	TPB	PMT	PADM
Response efficacy	Attitudes towards behaviour	Intrinsic rewards, Response costs, Response efficacy	Hazard adjustment perception
Self efficacy	Perceived Behavioral Control	Self-efficacy	Situational facilitators, Situational impediments
Risk perception		Vulnerability, Severity	Environmental threat perception
Social cues	Subjective Norms	Extrinsic rewards	Stakeholder perception, Predecision processes
Environmental cues			Predecision processes
Evacuation experience			
Socioeconomic		Response costs	Situational facilitators, Situational impediments
Social demographic			
Media usage			Predecision processes
Place Attachment			

Table 2.3: Comparison of the relevant factors for evacuation decision-making and the three examined behavioural theories.

2.4. Modelling and Simulation of Pre-Travel Behaviour

Evacuating large communities in anticipation of hurricanes is a costly and complex undertaking. During Hurricane Irma in 2017, for example, approximately 6.5 million people were forced to evacuate in Florida (The Associated Press, 2017). The coordination required between evacuees and emergency management forms a complex adaptive system Wang et al. (2021). Improving evacuation outcomes within such a system presents significant challenges. These include the large geographical scale (Hentenryck, 2013), the large number of people affected (Hentenryck, 2013), a lack of empirical data (Wang et al., 2021), and the difficulty of determining the most effective ways to communicate evacuation orders (Morss & Hayden, 2010).

Currently, statistical analyses, such as those by Ariccio et al. (2020), Huang et al. (2012, 2016, 2017), Morss, Prestley, et al. (2024), Qing et al. (2022), Van Valkengoed and Steg (2019), and Whitehead et al. (2000), offer valuable insights by examining survey data. While these studies shed light on the effectiveness of evacuation orders, they do not fully explain why certain strategies work or how they can be improved. Besides statistical analyses, laboratory studies are also unable to sufficiently address human behaviour (Wang et al., 2021). Setting up real experimental setups for hurricane scenarios is not feasible. Replicating hurricane conditions is too expensive. An alternative is waiting for the next hurricane; however, this is extremely time-consuming and provides only a very short window for setting up experiments. Lastly, it requires test subjects to be exposed to dangerous circumstances, which is unethical. This aligns with the general disadvantages of experiments named by (Birta & Arbez, 2019).

An alternative solution to address these issues is the use of simulation models. A simulation model is a computerized representation of a real-world system or process used to study its behaviour over time under various conditions. These models can create fictitious scenarios that reflect real-world situations. They allow for policy comparison, testing the effectiveness of evacuation warning timings, and concept evaluation, assessing whether conceptual models of human behaviour are accurate. They also support safety assessments by evaluating how different evacuation timings influence behaviour and contribute to safer conditions (Birta & Arbez, 2019).

There are three main simulation paradigms: System Dynamics (SD), Discrete-Event Simulation (DES), and Agent-Based Modelling (ABM) (Maidstone, 2012). The most suitable paradigm depends on the purpose of the model and the field of application. System Dynamics models behaviour using feedback loops, stocks, flows, and time delays. Instead of focusing on individuals, it examines their aggregation. SD models provide insight into the dynamics between relevant factors at a higher aggregated level (Brito et al., 2011). Discrete-Event Simulation allows for a more detailed examination of behaviour by modelling individuals (Brito et al., 2011). It models behaviours as events, which have a starting and ending point. During the event, the individual is occupied. New events can be triggered by the end of other events or by changes in the model's state. ABMs also model individuals but treat time differently. While DES specifies start and end points, ABMs check the state and update at every time step. Since DES allows individuals to be occupied for longer intervals without requiring action, it is computationally faster than ABMs. Simaliry to ABM, SD allows for continuous adjustment of cue values over time since it uses a very small time step mimicking continuous time.

For modelling evacuation behaviour, it is important to consider social interactions, which take place at a disaggregated level. This makes the SD paradigm unfavourable, as it only models at the aggregated level. Additionally, realistic evacuation modelling requires spatial context, which SD cannot provide. Both DES and ABM support spatial modelling. However, DES's event-scheduling approach is less suitable when continuous updates are needed for multiple information cues. Environmental, social, and media cues change constantly. In DES, individuals cannot process cue changes while occupied by an event, requiring them to wait until the event ends to update their state. ABMs allow for constant updates of cue values, enabling not only information updates but also continuous consideration of social interactions and decision-making on whether to evacuate.

Agent-Based Modelling has been widely applied to scenarios where examining human behaviour is relevant Zhuo and Han (2020). It also enables the integration of individuals with different characteristics and behaviours, supporting an egalitarian approach (An et al., 2021). Additionally, it allows for the integration of spatial data from the physical environment (An et al., 2021), which is valuable for modelling areas with varying degrees of flood risk. Lastly, socio-demographic attributes differ between neighbourhoods in cities (U.S. Census Bureau, 2023b), which can be leveraged by ABMs. This allows models to account for both individual characteristics and neighbourhood-level differences. Thus, ABMs can model spatial heterogeneity and support the analysis of spatial injustices, where simply living in certain locations disadvantages individuals. Table 2.4 presents the advantages and disadvantages of the different paradigms. Modelling behaviour requires frequent updates of cues and internal state values, which becomes challenging with event-based steps, making Discrete Event Simulation (DES) less suitable. The aggregated modelling level of System Dynamics (SD) and its incompatibility with spatial data render it ineffective for simulating evacuation behaviour. Therefore, Agent-Based Modelling (ABM) is the most compatible approach, at the cost of computational efficiency.

Characteristics	SD	DES	ABM
Time	Continious approximation	Event-based	Fixed steps
Modeling level	Aggregated	Individual level	Individual level
Inclusion spatial data	No	Yes	Yes
Computational efficiency	Fast	Fast	Slow

Table 2.4: Comparison of the three paradigms based on four characteristics relevant when modelling evacuation decision-making behaviour.

Studies already exist that implement behavioural theories into ABMs for evacuation decision-making. Specifically, for the combination of PADM and hurricane evacuation, three models have been developed. The first ABM, from study McEligot et al. (2019), combined PMT and PADM to define agent behaviour, examining how agents chose to repair their homes, relocate, or elevate their homes after Hurricane Sandy. It also reported the percentage of houses damaged after the storm and how this damage related to the implemented actions. The model incorporated only socio-economic factors and flood experience, which are highlighted as important by PADM, and integrated them into the PMT framework, thereby extending PMT with PADM elements. However, it did not include social cues, media usage, or place attachment. Additionally, none of the decision-making phases were implemented, leaving behaviour rules static over time. Nor did it test any policies to improve the situation.

Yeates et al. (2023) created an extensive ABM following PADM to examine how official warning information spreads through communities. The model reported on evacuation acceptance and warning reception. Notably, the agents in the model were not capable of any specific decision-making, which is central to PADM. In addition to the lack of decision-making, it had other limitations. First, it was based on limited input from realistic data, which made the results unreliable. The model also did not include any sensitivity or uncertainty analysis to address the uncertainties stemming from the limited input. Furthermore, it provided no insight into the experimental setup behind the results, and no validation was performed. These issues suggest that it serves more as a proof of concept for integrating PADM into an ABM.

Hatzis et al. (2024) used PADM to simulate protective action responses to a tornado, such as monitoring the situation, seeking refuge, taking shelter, or fleeing the area. In addition to decision-making, it also modelled the travel phase corresponding to the chosen response and the fatality rate during travel. Like the other ABMs, this model did not account for the different phases of decision-making. It represented the conceptual ideas of predecisional processes and protective action assessment but did not include social cues, media usage, or place attachment. However, this study did examine the influence of tornado warnings, which qualifies as policy testing.

Table 2.5 provides an overview of the three studies. It becomes clear that none of the studies used PADM to model the decision-making process surrounding hurricane evacuation. Nor did any of the studies examine evacuation decision timing over a longer period as a model metric. Notably, all three studies lacked the implementation of social networks to model social cues, which is a strength of ABMs. From the PADM perspective, the absence of media usage is also important, since media forms a primary information source and is central to PADM. Finally, policy testing was not conducted by McEligot et al. (2019) or Yeates et al. (2023), and was only minimally addressed by Hatzis et al. (2024). This further underscores the need for a more comprehensive implementation of PADM in modelling hurricane evacuation decision-making behaviour.

Characteristic	Threat	Decisions	Model metrics	Missing Factors	Policy testing
McEligot et al. (2019)	Storm surge	Repair home Relocate from home Elevate home	Protective action distribution Percentage of houses damaged	Social cues Media usage Place attachment	No
Yeates et al. (2023)	Hurricane	None	Evacution acceptance Warning reception	Unknown	No
Hatzis et al. (2024)	Tornadoes	No action Sought refuge Sought shelter Flee the area	Protective action distribution Fatality rate ACtion completion time	Social cues Media usage Place attachment	Yes

Table 2.5: Comparison of the three studies implementing PADM in an ABM

2.5. Conclusion of State of Art

This chapter answered the first sub-question: *"Which psychosocial factors, environmental factors are required for modelling Evacuation behaviour in a hurricane scenario?"*. Current studies proved that the following factors are relevant for predicting evacuation behaviour for Hurricanes:Response efficacy, Self efficacy, Risk perception, Social cues, Environmental cues, Evacuation, Experience, Socioeconomics, Social demographics and Place Attachment. Not all these factors has similar size of impact, for example Social demographics in general are less impactful then social cues. However all are found significant. For the factor Place Attachment a gap is found for its focus. All existing work examine the attachment towards home, neighbourhood or evacuation shelter. None examined the role of Place attachment to destination locations such as family/friends homes or hotels/motels, while these are the main destination choice during hurricane evacuations. To investigate the role of destination place attachment further a fourth sub-question is created: *"How does destination place attachment relate to evacuation intention."*.

Section 2.2 places the evacuation behaviour within the general timeline of the whole evacuation process. The identified factors correspond to the pre-travel phase of real-time evacuation planning. The pre-travel phase behaviour can be modelled using three theories/models: TPB, PMT, PADM. PADM has the biggest overlapped with all the relevant factors. Additionally it provides a sound foundation to examine evacuation behaviour in a temporal manner. All the three theories/models do not have a direct notion of the role of experience, socio-demographics, socioeconomics or place attachment. For place attachment, this is expected since it requires spatial specification, which would limit the application of the theories in non-spatially relevant situations. Statistical analyses and experiments are not suitable for policy comparison, behaviour evaluation, and extended safety assessment. To address these issues, a computational model can be created. The SD, DES, and ABM approaches are considered, and ABM is deemed the most suitable for modelling evacuation behaviour. Currently, three studies have partly implemented PADM, but none have applied it extensively using the phases of protective action decision-making.

3

Survey development and data-analysis methods

In this chapter, the design of the survey and the methodology for its analysis are presented. The survey was developed with four primary objectives: (1) gain insights into how the nine relevant factors identified in Section 2.1 influence evacuation intention, with particular emphasis on the role of destination place attachment; (2) to utilize these factors in a multinomial logistic model to examine their relationship with destination choice; (3) to analyse the association between the nine factors relevant for evacuation decision-making and evacuation intention; and (4) to provide essential input data for the Agent-Based Model (ABM) described in Chapter 4.

3.1. Survey Construction

The relevant factors have been extensively studied in previous research, so the majority of the survey questions were adapted from existing studies. For place attachment to evacuation destinations, questions from Ariccio et al. (2020) were tailored to fit the context of hotels, friends' or family residences, and public shelters. Similarly, questions regarding self-efficacy and response-efficacy which are action-specific constructs were adapted from Lindell and Perry (2012). Additionally, specific questions were developed for the Agent-based model that are not directly based on prior studies. Most risk perception questions were asked twice, once concerning hurricanes and once for storm surges.

Figure 3.1 provides an overview of the survey questions. Items with similar phrasing but minor variations are combined using brackets [ ]. Socio-demographic and economic questions are excluded from the figure for brevity, as they are straightforward. The demographic variables measured include age, education, race and ethnicity, car ownership, and income. The complete survey is included in Appendix D.

The survey was distributed in the metropolitan area of Miami by the survey-distribution company Dynata. Although it would have been preferable to focus solely on Miami-Dade County, Dynata's survey panel in the county was not large enough to provide a sufficient number of respondents within the expected timeframe. Data collection took place from June 12 to June 27, 2025. The total number of respondents was 744. After removing incomplete responses, 454 valid responses remained.

To ensure that the survey responses were representative of the actual population, quotas were set for ethnicity, income, education, and age. These quotas were based on data from the American Community Survey (ACS) (U.S. Census Bureau, 2023b). The quotas were enforced during the first two weeks of data collection. However, they were relaxed in the final days to ensure that the target of 454 completed responses could be reached within the available time and budget. Figure 3.1 compares the population distributions from U.S. Census Bureau (2023b), which are used to define the quotas, with the actual distribution of the survey sample. Regarding ethnicity, the survey results do not align with the expected population. The White non-Hispanic population is significantly over-represented, while the Black Hispanic population is extremely under-represented. Although to a lesser extent, the Black non-Hispanic group is also overrepresented, and the White Hispanic population is under-represented. These discrepancies indicate that the survey sample does not accurately reflect the ethnic distribution of the general

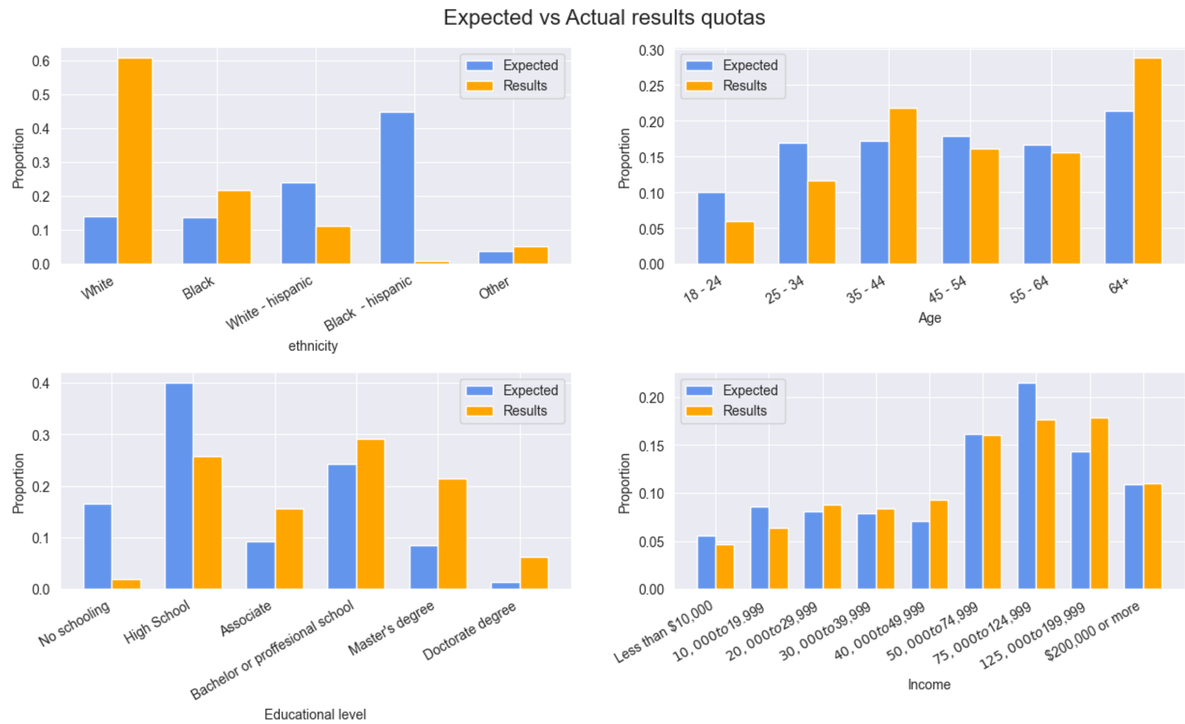

Figure 3.1: Bar plots for every used quota. The expected data is retrieved from U.S. Census Bureau (2023b) and indicates the real Miami population, while the results data represent the survey sample.

population.

In terms of age, the survey performs better. Most age intervals are reasonably well represented. However, the 64+ age group is over-represented, which leads to an under-representation of the two youngest age groups.

The distribution for educational levels also deviates from the population. The survey fails to capture the large proportion of people without any schooling. Additionally, individuals with only a high school education are under-represented. Conversely, all higher educational levels are over-represented, particularly those with a master's or PhD degree. Overall, the survey reflects a population with a higher level of education than is realistic.

The final quota considered was income. In this case, the income groups are fairly well represented. Only the 75,000–124,999 dollar and 125,000–199,999 dollar intervals are slightly misrepresented, but this difference is only minor.

In general, the survey sample offers a reasonably fair representation in terms of income and age, but it falls short in representing ethnicity and education, with Hispanic and less-educated populations being under-represented.

Table 3.1: Survey questions, some questions are merged using [] to make the table more compact. The social demo-graphics questions are not included since they are trivial.

Coding	Factor	Question	Source
ECB1	Enviromental cues	To what extent do you pay attention to weather conditions such as wind in your daily life?	(Huang, 2012)
ECB2	Enviromental cues	To what extent do you pay attention to weather conditions, such as wave strength or water turbulence, in your daily life?	(Huang, 2012)
ECB3	Enviromental cues	To what extent do you pay attention to the likelihood or intensity of rain in your daily life?	(Huang, 2012)
EI1	Evacuation intention	Faced with the threat of a hurricane, without considering other people, if I am allowed to evacuate voluntarily, I am willing to evacuate	(Qing, 2022)

EI2	Evacuation intention	Faced with the threat of a hurricane, if the people close to me have evacuated, I am willing to evacuate	(Qing, 2022)
EI3	Evacuation intention	Faced with the threat of a hurricane, if the government forces me to evacuate, I am willing to evacuate	(Qing, 2022)
EI4	Evacuation intention	Facing with the threat of a hurricane, if the government gives a certain subsidy, I am willing to evacuate	(Qing, 2022)
EI5	Evacuation intention	Faced with the threat of a hurricane, I will not evacuate	Own construct
NPA1	Neighbourhood place attachment	I believe that residents in my neighborhood can be trusted	(Filatova et al., 2022)
NPA2	Neighbourhood PA	I feel that I am a member of my neighborhood community	(Filatova et al., 2022)
NPA3	Neighbourhood PA	Being in this neighborhood gives me a lot of pleasure.	(Filatova et al., 2022)
NPA4	Neighbourhood PA	My neighborhood is my favorite place to be	(Filatova et al., 2022)
NPA5	Neighbourhood PA	My neighborhood reflects the type of person I am	(Filatova et al., 2022)
[F, H,P]PA1	Destination PA	My [families/friends home, hotel, public shelter] are well-informed that I will seek shelter at their location when a hurricane occurs	Own construct
[F, H,P]PA2	Destination PA	My family/friends will expect me to seek refuge when a hurricane occurs	(Ariccio et al., 2020)
[F, H,P]PA3	Destination PA	The home of my families/friends home is part of me.	(Ariccio et al., 2020)
[F, H,P]PA4	Destination PA	I do not feel integrated in the neighborhood of my [families/friends home, hotel, public shelter] .	(Ariccio et al., 2020)
[F, H,P]PA5	Destination PA	My [families/friends home, hotel, public shelter] is the ideal evacuation place for me.	(Ariccio et al., 2020)
REF1	Response efficacy - family/friends	How likely is it that evacuating towards the[families/friends home, hotel, public shelter] would be effective to reduce harm to yourself and your family?	(Morss et al, 2024)
SEF1	Self-efficacy	Do you have the ability to evacuate to [families/friends home, hotel, public shelter] by yourself?	(Lazo, 2014)
SEF2	Self-efficacy	Do you have the ability to help someone else evacuate to [families/friends home, hotel, public shelter]?	(Lazo, 2014)
EV1	Destination lcoation	To which state will you evacuate? If you are not sure, choose the option that is the most likely location.	Own construct
DC	Destination type	What is the most likely location that you would evacuate towards?	Own construct
DC	Destination type	To which type of location will you prefer to evacuate?	Own construct
EV2	Destination location	What is the number of the square which contains your evacuation destination?	Own construct
L1	Likelihood	How likely is it that your home would be affected by this storm?	(Morss et al, 2024)
L2	Likelihood	Imagine you stay in your home during this storm. How likely do you think it is that you could get hurt by the storm?	(Morss et al, 2024)

LS1	Likelihood_s	How likely is it that your home would be affected by the storm surge?	(Morss et al, 2024)
LS2	Likelihood	Imagine you stay in your home during this storm. How likely do you think it is that you could get hurt by the storm surge?	(Morss et al, 2024)
SEV1	Severity	How severe would the storm damage your home?	(Morss et al, 2024)
SEVS1	Severity	How severe would the storm surge damage your home?	(Morss et al, 2024)
RA1	Risk assesement	I think being careful about a hurricane is important. However, as long as it does not seem likely to hit my neighborhood, I will not take any action.	(Huang, 2012)
RA2	Risk assesement	I think being careful about a hurricane is important. However, as long as the impact is not severe when it reaches my neighborhood, I will not take any action.	(Huang, 2012)
RA3	Risk assesement	I think being careful about a storm surge is important. However, as long as it does not seem likely to hit my neighborhood, I will not take any action.	(Huang, 2012)
RA4	Risk assesement	I think being careful about a storm surge is important. However, as long as the impact is not severe when it reaches my neighborhood, I will not take any action.	(Huang, 2012)
RA5	Risk assesement	When friends, relatives, neighbors, or coworkers evacuate, it does not mean my neighborhood is in danger and I will not take action.	(Huang, 2012)
AR1	Risk assesement	Seeing businesses in the area close does not mean my neighborhood is in danger and I will not take action.	(Huang, 2012)
AR2	Responsibility	The people who remained in an evacuation zone after the evacuation order acted irresponsibly.	(Rickard, 2017)
AR3	Responsibility	People who do not heed the evacuation orders are responsible for what happens to them.	(Rickard, 2017)
AR4	Responsibility	People are responsible for seeking information about the risks posed to them and their property.	(Rickard, 2017)
ECA1	Enviromental cues	Sensing weather conditions, such as winds	(Huang, 2012)
ECA2	Enviromental cues	Sensing weather, such as wave strength or water turbulence	(Huang, 2012)
ECA3	Enviromental cues	Sensing weather conditions such as increased rain	(Huang, 2012)
ECA4	Enviromental cues	Seeing businesses in the area close	(Huang, 2012)
SC1	Social clue	Seeing friends, relatives, neighbors, or coworkers evacuating in your surroundings	(Huang, 2012)
SC2	Social clue	Hearing of friends, relatives, neighbors, or coworkers evacuating on different media	(Huang, 2012)
MD1-5	Media cue	How frequently would you consult the following media channels for hurricane information? - [Social media, Radio, Internet, Television, Newspapers]	Own construct
MD6-10	Media cue	How much do you trust the following media channels for hurricane information? - [Social media, Radio, Internet, Television, Newspapers]	Own construct

C1-5	Communication	Indicate to what extent you would communicate about the following aspects with people in person or over the telephone. - [Severity of the hurricane, What I will do during the storm, Severity of storm surges, Where I plan to stay, When I plan to leave]	Own construct
I1	Impediment	Are you responsible for a relative or friend with major medical needs?	(Lazo, 2014)
HE1	Experience	Have you ever evacuated from a hurricane in your past?	Own construct
HE2	Experience	Have you evacuated from storm Harvey in 2017?	Own construct
HE3	Experience	Have you ever evacuated your home during a hurricane in the past when it was not necessary?	Own construct
SN	Social Network	With how many friends or family members will you stay in constant contact before the hurricane hits?	Own construct

3.1.1. Factor analysis plan

Some factors are measured using multiple survey items. To derive singular values for each factor, a factor analysis was conducted, which also ensures that the associated survey questions indeed measure the same underlying concept. The coding of items in Table 3.1 indicates which items are expected to correspond to the same factors. Since there is a hypothesized relationship between observed variables and latent factors, Confirmatory Factor Analysis (CFA) will be used first, followed by Exploratory Factor Analysis (EFA).

CFA is preferred because it can verify whether the expected variables load on the predicted factors (Greene et al., 2023). However, a limitation of CFA is that it tests only preconceived relations and does not reveal unexpected patterns, such as variables intended to measure multiple factors loading onto a single factor or cross-loadings. Therefore, EFA is performed subsequently to identify any such patterns. Based on the combined results of CFA and EFA, variables can be removed and factor loadings recalculated to improve validity.

Factor loadings are then classified according to the variables that load on each factor and used to calculate factor scores. Scores are computed as weighted sums, applying a cut-off threshold of 0.5 (Distefano et al., 2009). Loadings below 0.5 are set to zero.

3.1.2. Assessment plan for Factor Analysis

The following metrics are examined to assess the appropriateness of the factor analysis and the quality of its results:

- Kaiser-Meyer-Olkin (KMO) Measure: Assesses sampling adequacy by verifying that partial correlations among variables are sufficiently small, indicating suitability for factor analysis.
- Bartlett's Test of Sphericity: Tests whether the correlation matrix significantly differs from an identity matrix, confirming that there are enough correlations among variables to perform meaningful factor analysis.
- Variance Inflation Factor (VIF): Evaluates multicollinearity among variables; high VIF values suggest strong correlations that may compromise the stability of factor solutions.
- Communalities: Indicate the proportion of variance in each variable explained by the extracted common factors; higher communalities imply that the variables are well represented by the factor model.
- Scree Plot of Eigenvalues: Provides a visual representation of the eigenvalues for each factor and helps determine the optimal number of factors to retain by identifying the "elbow" point where adding more factors yields diminishing returns.

3.2. Correlation analysis plan

To examine the association between evacuation intention and the relevant factors, a correlation analysis was conducted using the results of the factor analysis and the variables which did not require factor analysis. The relation between the factors is then analysed using the pairwise relationships among these variables through Pearson's correlation coefficient, thereby quantifying the strength of linear associations. The statistical significance of each correlation was evaluated. The resulting matrix will verify the important factors and examine the significance of destination place attachment.

In addition to evacuation intention, the correlations between all relevant factors and the evacuation destination choices were analysed. The data were divided into four subsets, each corresponding to a specific destination choice. For each subset, Pearson's correlation coefficients and their corresponding p-values were calculated. It should be noted that the dataset for the public shelter destination included only 29 samples; therefore, the results of the correlation analysis for this group should be interpreted with caution.

3.3. Regression analysis plan for Evacuation Destination Choices

To identify key factors predicting the intention to evacuate towards distinct destination types, like family or friends, hotels, public shelters, and sheltering in place, a multinomial logistic regression model was developed. It must be noted that the multinomial logistic regression models are less effective compared to algorithms like random forests and support vector machines. However, they deliver robust results and provide easy-to-interpret outputs (Couronné et al., 2018; Musa, 2013). The ease of interpretation facilitates integration into the ABM model, explained in Section 4, making logistic regression favourable for this application.

For sheltering in place, self-efficacy, response efficacy, and destination place attachment are not considered since no items were included for this option in the survey. However, neighbourhood place attachment can be seen as destination place attachment as well.

The majority of respondents chose to evacuate to family or friends. Specifically, 239, 95, 28, and 76 individuals chose to evacuate to family/friends, a hotel, a public shelter, or to stay at home, respectively. This distribution introduces two challenges. First, the dominance of the family/friends category can cause the multinomial logistic regression model to become biased toward this choice. This issue can be mitigated by penalizing classification errors during model training through the use of class weights in the fitness score calculation (Pedregosa et al., 2011). The weights are computed using Equation 0. In this way, the model is encouraged not only to predict the dominant class but also to pay attention to minority classes and is penalized when it fails to do so.

$$w_c = \frac{n_{\text{samples}}}{n_{\text{classes}} \cdot n_c} \tag{0}$$

where:

$$\begin{aligned} n_{\text{samples}} &= \text{total number of training samples} \\ \mathcal{C} &= \text{set of unique class labels} \\ n_{\text{classes}} &= \text{number of unique classes} \\ n_c &= \text{number of samples in class } c \in \mathcal{C} \\ w_c &= \text{weight assigned to class } c \in \mathcal{C} \end{aligned}$$

Second, the low number of respondents for the hotel, public shelter, and stay-at-home options presents a problem. With only 28 respondents selecting the public shelter option, the sample size is too small to split into a meaningful training and testing set. As a result, the public shelter category is excluded from further analysis. While it is possible to create training and testing sets for the hotel and stay-at-home choices, using only 20 samples per option leads to high variability in outcomes due to the influence of different test set compositions. To address this issue, model performance metrics are calculated over 100 different random splits of the data, and the average values of these metrics are reported. This approach ensures that the evaluation results are robust and not biased by a single favourable split. The downside of this approach is that not a singular model is presented to predict evacuation destination. Instead, it is examined if the relevant factors for evacuation intention are also useful for predicting destination choice.

Model performance is evaluated on the testing sets using standard classification metrics, including accuracy, precision, recall, F1 score, and the confusion matrix, which provides a detailed breakdown of prediction outcomes.

4 Agent-based model

This chapter outlines the development of the agent-based model (ABM). It will explain the key concepts required to create and understand the ABM. Then, these key concepts are integrated into a formalised description of the model. The implemented model is then verified and validated to ensure that it adheres to its intended purpose. Lastly, the experimental design will be presented to generate data for the results.

4.1. Conceptualisation

This section elaborates on the development of the ABM. It begins by explaining the model's purpose, the area of interest, and the storm under investigation. Next, a conceptual overview of the model is provided. Since individual behaviour is a crucial element of the model, the theoretical foundation of this behaviour is explained in greater detail.

4.1.1. Model purpose

The main purpose of the model is to explore and provide insights into the dynamics of evacuation behaviour during hurricanes, specifically in the pre-travel phase. This purpose can be divided into two key aspects. First, the model should offer insight into individual behaviour, including the decision-making phases and evacuation timing. Second, the model should be capable of assessing the effectiveness of different timings of hurricane watch and warnings.

4.1.2. Storm & Area of Interest

The ABM will be applied to model evacuation decision-making prior to the landfall of Hurricane Irma in 2017. According to Cangialosi et al. (2021), Hurricane Irma was a Category 5 storm that began developing on 28 August and intensified to Category 5 on 5 September when it was approximately 500 km from the island of Saint John's. As it approached Florida, the storm gradually weakened until it made landfall on 10 September in Marco Island, Florida. The storm's track and intensity over time are shown in Figure **??**. Notably, from 5 September onward, Irma remained a Category 5 storm for a significant duration, indicating the highest level of hurricane risk and underscoring the critical need to prompt evacuation.

Hurricane Irma presents a particularly interesting case study, as it threatened the metropolitan area of Miami, which is highly prone to flooding. This created a dual threat from both the hurricane itself and the resulting flood risk. Moreover, Irma is one of the few Category 5 hurricanes for which comprehensive data are available, including wind speeds, rainfall, and evacuation warnings. These datasets also include evacuation timing data from evacuees in Florida (Wong et al., 2021), which can be used to validate the model. Finally, among major U.S. cities, Miami is considered the most vulnerable to hurricane-related disasters (Freeman & Ashley, 2017), making its exposure to Irma especially relevant for this study.

Miami-Dade County, outlined by the red polygon in Figure **??**, is the central county of the Miami metropolitan area. Although few hurricane-force winds were recorded in the county, it experienced significant storm surges ranging from 1.2 to 1.8 meters. While no direct casualties were reported, substantial damage was sustained, including damage to approximately 1,000 homes. Importantly, Miami-Dade was at risk of a direct hit, which is

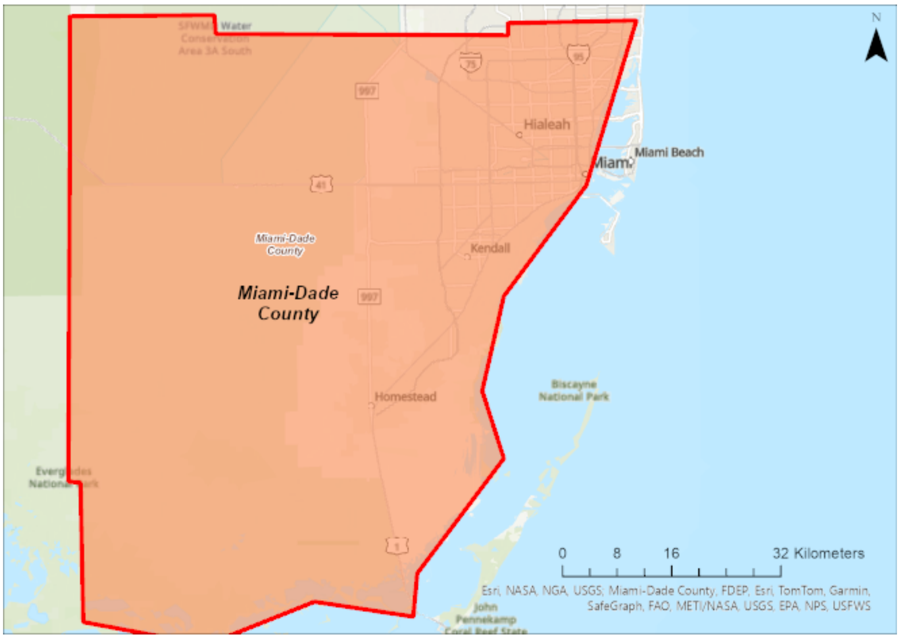

Figure 4.1: Are of interest, Miami-Dade County is indicated by the red area.

particularly relevant for understanding evacuation behaviour prior to landfall. In addition, the county received clearly documented hurricane and storm surge watches and warnings issued by local authorities Cangialosi et al. (2021).

4.1.3. Temporal scope

The first evacuees during Hurricane Irma began evacuating on 3 September (Wong et al., 2021), while the storm made landfall on 10 September at 15:00 (Cangialosi et al., 2021). Therefore, the model will simulate the period from 3 September to 10 September to capture the full duration of evacuation activity. A time step of two hours will be used. A smaller time step would significantly increase computational time without yielding additional insights, as the model does not include detailed information-seeking behaviour at an hourly resolution. Furthermore, evacuation warnings and wind data are updated at six-hour intervals, making a finer time resolution unnecessary. A smaller time step would only be justified if the model included detailed processes such as packing or coordinating with family members.

4.1.4. Conceptual overview model

Figure 4.3 presents the four main components of the model and their interactions. The central component is the individual, who must make the decision to evacuate. The main characteristics of the individual are listed in Table 4.1. The individual is influenced by the storm, the government, the media and social relations.

The storm provides wind and rainfall data over time and determines the timing of landfall. Based on the landfall timing, the individual's propensity to evacuate is updated. The government issues hurricane and storm surge watches and warnings at specific times for designated areas within Miami-Dade County. The media, using various communication channels, conveys cues and updates about the hurricane.

Information from the storm, government, and media affects the individual's risk perception, propensity to act, and attitude toward protective actions. Additionally, individuals communicate with acquaintances, and these social interactions further influence their internal decision-making dynamics.

Throughout the simulation, individuals continuously assess whether they are ready to progress to the next phase in the decision-making process (which will be described later) and whether they are prepared to implement a protective action. Possible actions include evacuating to friends or family, evacuating to a motel or hotel, evacuating to a public shelter, or sheltering in place. The implementation of these characteristics and interactions will be explained in a later section.

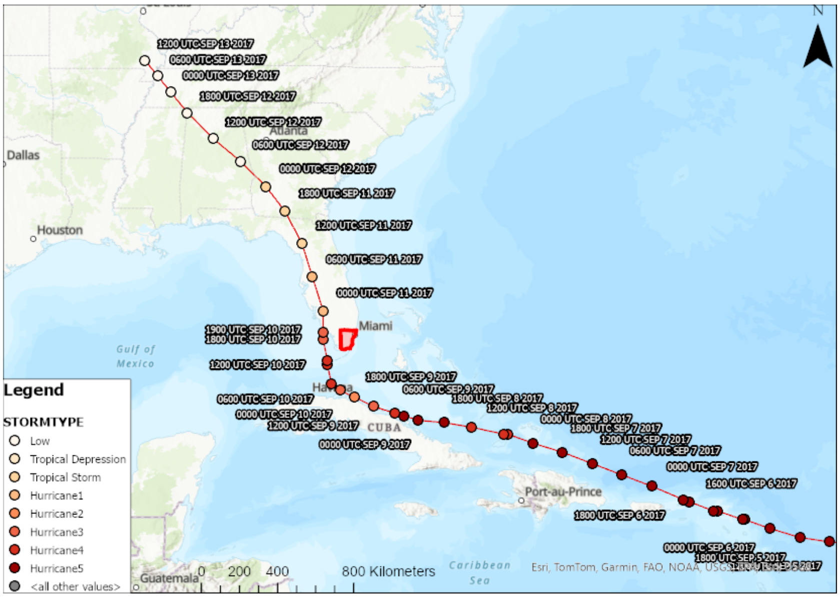

Figure 4.2: Track of Hurricane over time. Colour indicates the intensity of the storm

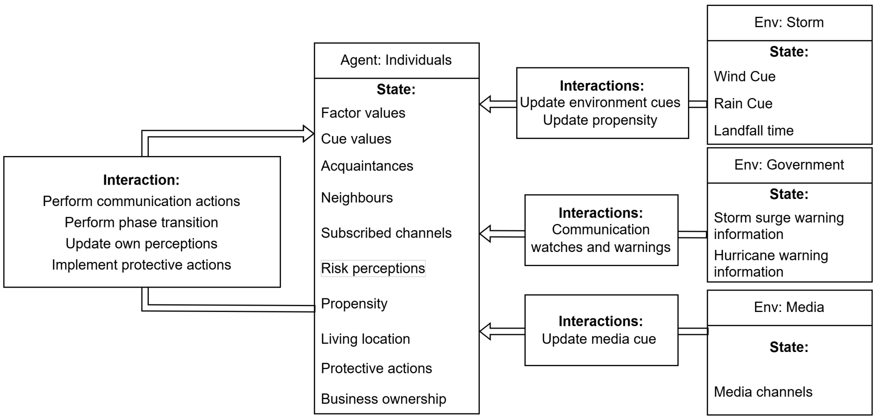

Figure 4.3: Interaction Diagram between the to be modelled components. Env is short for Environment

Characteristics	Description	State
Factor values	Values for the factors relevant to estimate evacuation intention and which are static.	Static
Risk perception	Describe the individual's attitude toward the hurricane	Dynamic
Cue values	The enviromental, media, cue values the Individual is exposed to.	Static
Neighbours	The Individuals which will notice the implementation of evacuation actions	Static
Acquaintances	The Individuals for communciation interactions	Static
Propensity	The inclination of the individual to implement protective actions	Dynamic
Living location	The tract area in which the individual lives	Static
Protective actions	The protective actions the individual can take and its attidude towards them	Dynamic

Table 4.1: Overview characteristics of Individual

4.1.5. Theoretical foundation evacuation behaviour

To translate the eight phases into an agent-based model, it is necessary to merge and simplify certain phases where appropriate. Simplifications will also be applied to the predecisional processes and core perceptions. These simplifications are explained in this section. It must be emphasised that the purpose here is to justify the rationale for simplifying and combining elements, not to explain their implementation. The detailed implementation will be presented in Section 4.2.6.

Predecisional processes & Core perceptions

First, the predecisional processes are simplified. The three original requirements exposure, attention, and comprehension are reduced to exposure only. Hatzis et al. (2024) successfully implemented all three using data from Ripberger et al. (2021). However, that dataset covers attention and comprehension specifically in relation to weather forecasts and warnings, and does not include environmental or social cues. To maintain consistency across all cue types, only exposure is considered. Morss and Hayden (2010) found that the majority of individuals checked weather forecasts four or more times per day. Given the significantly lower barriers to accessing information in the past 15 years, it is reasonable to assume this number is even higher today. Environmental cues such as wind and rain are also considered (Brommer & Senkbeil, 2010), but there is no reliable data on how frequently individuals pay attention to them. Therefore, exposure is assumed to be constant. Exposure to social cues will be modelled explicitly, so no exposure frequency assumption is required in that case.

The core perceptions are included in the model, though in a simplified form. Environmental threat perception is retained, as environmental cues are combined through risk perception, with individual agents having unique interpretations of these cues. Stakeholder perception, however, is not fully incorporated, as it would require explicitly modelling relationships between different actors, such as interactions between governmental and media organisations. Including such actors would require defining their behaviour, which falls outside the scope of this project. Although existing research provides insight into how governmental organisations behave during hurricane events (Cangialosi et al., 2021; Morss, Prestley, et al., 2024), modelling them as dynamic agents is beyond the available time and focus. Since the aim is to simulate the phases of the PADM, detailed governmental behaviour is not essential. Instead, the roles of media and government will be represented more statically, as discussed in the upcoming section 4.2.

Finally, hazard adjustment perception is included, but focused specifically on evacuation-related decisions. The protective actions considered in the model are evacuating to friends or family, evacuating to a hotel or motel, evacuating to a public shelter, or sheltering in place. Perceptions related to these actions will be derived using a logistic regression model given in chapter 5 based on the collected survey data.

Protective action decision-making process

The behaviour of the model is based on the protective action decision-making (PADM) phases. Since these phases were not originally designed for direct implementation in an ABM they are adapted to meet the modelling requirements. This adaptation involves simplifying and merging the eight original phases into five. The original PADM phases are listed in Table 2.2, while the adapted phases are shown in Table **??**.

The risk identification, risk assessment and protective action search phases are largely preserved. The rationale for merging and simplifying specific phases iwill follow now.

Number	Original Phases	Merged Into	Question to Be Answered
1	Risk Identification	Risk Identification	Is there a real threat that I need to pay attention to?
2	Risk Assessment	Risk Assessment	Did the threat reach the severity to consider protective actions?
3	Protective Action Search	Protective Action Search	What can be done to achieve protection?
4, 5	Protective Action Assessment Protective Action Implementation	Protective Action Assessment	What is the best protective action, and does it need to be taken now?
6, 7, 8	Information Needs Assessment Communication Action Assessment Communication Action Implementation	Communication Implementation	What information can I exchange with my environment?

Table 4.2: Merged phases of PADM

The Protective Action Assessment and Protective Action Implementation phases are combined into a single phase, retaining the name Protective Action Assessment. Originally, the Protective Action Assessment phase evaluates which action is most favourable. However, descriptive social norms, such as friends or family evacuating, can influence an individual's attitude toward these actions (Sadri et al., 2017), thereby affecting their preferred choice. The phases will be modelled sequentially, without the possibility of reverting to a previous phase. If modelled separately, individuals who have decided on an action would no longer be influenced by social cues, which contradicts existing research (Huang et al., 2016; Sadri et al., 2017; Van Valkengoed & Steg, 2019). To address this issue, the two phases are combined, allowing individuals to simultaneously adjust their attitudes toward protective actions and decide to implement them.

The Information Needs Assessment, Communication Action Assessment, and Communication Action Implementation phases are merged into a single general phase, referred to as the Information Communication phase. This combination is justified because communication behaviour is closely linked to the phase an individual is currently in. The question of "What information is needed?" varies depending on the individual's phase. From a modelling perspective, it is more logical to integrate information needs assessment into each respective phase, rendering a separate phase unnecessary.

The rationale for excluding an explicit Communication Action Assessment phase is similar. From the collected data, it is possible to determine where individuals gather information. However, this decision is static: it is known which media channels are consulted, how frequently they are used, and the size of individuals' social networks. These attributes are set at the beginning of the model and remain unchanged throughout the simulation. Therefore, there is no need to dynamically determine where or how individuals collect information, as this is already established. The "how" aspect of information access is not considered in the model. Although studies such as Lindell and Perry (2012) and Whitehead et al. (2000) report overloaded cellular networks, while relevant in post-hurricane situations (Booker et al., 2010), it is assumed that, due to recent technological developments, communication channels will remain operational during the pre-hurricane period. Thus, accessing media channels in the model is treated as normal, and individuals who indicate using certain channels are assumed to know how to access them.

The final communication phase is Communication Action Implementation, which concerns when an individual searches for information. As noted by Morss and Hayden (2010), who conducted interviews with victims of Hurricane Ike, the majority of interviewees consulted weather forecasts four or more times per day. It is important to note that this observation was made three days prior to landfall. The frequency of information seeking depends on the ambiguity regarding the timing and location of the threat, which typically becomes clearer over time. Consequently, the frequency of information seeking is likely to change as the threat becomes more specific. However, no existing studies detail how this frequency evolves over time, and the available survey data does not capture this aspect. Therefore, the model assumes that information-seeking behaviour via media remains constant throughout the pre-hurricane period.

4.2. Formalisation

This section provides a description and explanation of how the model can be implemented as a computational model. First, the data resources used will be presented. Next, the formalisation of the protective action decision-making phases will be detailed. Finally, the governmental communication strategies will be formalised.

4.2.1. Data Sources

To ensure that the model produces realistic outputs, it requires accurate and relevant input data. The input data used focuses on three main areas: Storm Irma, the population of Miami-Dade County, and government communication decisions. This section explains the types of data employed and how they are integrated into a single dataset that serves as input for the model. Table 4.3 provides an overview of the data sources used.

Data	**Sources**	**Description**
Wind data	National Hurricane Center	Contains temporal data giving the probabilities of the following three wind speeds: 34, 50, and 64 knots globally.
Inundation data	Kelley, O. (2022)	Contains surface precipitation rates in mm/h for the global surface.
Watch/Warning data	National Hurricane Center	Indicates when and for which areas hurricane and storm surge watches/warnings were issued.
Living locoation	American Community survey	Contains living locations and tract population densities.
Social-psychological factors	PADM-PA survey	Contains data on social influence.
Communication factors	PADM-PA survey	Contains data on frequency and trust of different media channels, and relevant factors like unnecessary evacuation experiences.

Table 4.3: All data sources and the usage of each dataset.

4.2.2. U.S. Census bureau

The ABM will simulate the population of Miami-Dade County. To achieve this realistically, residential locations must be accurately derived. The American Community Survey (ACS) (U.S. Census Bureau, 2023b) provides tract areas along with the number of individuals per tract. Using these tract boundaries and population densities, the ABM can generate agents positioned in locations that realistically represent the county's population distribution. Figure (**fig:tract_areas**) (left side) illustrates the spatial distribution of these tract areas. To integrate various data types, the tract areas will be represented as points, as shown in the figure (right side). This representation facilitates the use of spatial interpolation and sampling techniques to link the weather data with population data.

4.2.3. Wind data

The National Hurricane Center provides temporal vectorized weather data in the form of gridded point features (National Hurricane Center & Central Pacific Hurricane Center, 2017b). Separate datasets exist for wind speeds of 34, 50, and 64 knots, where 34 knots indicate tropical storm-force winds and 64 knots represent hurricane-force winds. For each wind speed category, points indicate the cumulative probability of that wind speed occurring within the next six hours. The left side of Figure 4.5 shows the probability distribution for 64 knots. The points are arranged in a grid-like pattern with a spatial resolution of 50 km.

Before linking the wind speeds to the tract areas, overlapping points within each six-hour time step must be merged. This is done by retaining only the wind speed with the highest probability at each location. The resulting datasets provide the 34, 50, and 64 knot wind speeds along with their corresponding probabilities. To associate the wind data with the tract areas. Laplace interpolation is applied across all time steps, producing a list of wind speeds every six hours for each tract area. The right side of Figure 4.5 displays the wind-speed data points as squares, illustrating that wind values are interpolated from only four points, which reduces the accuracy more

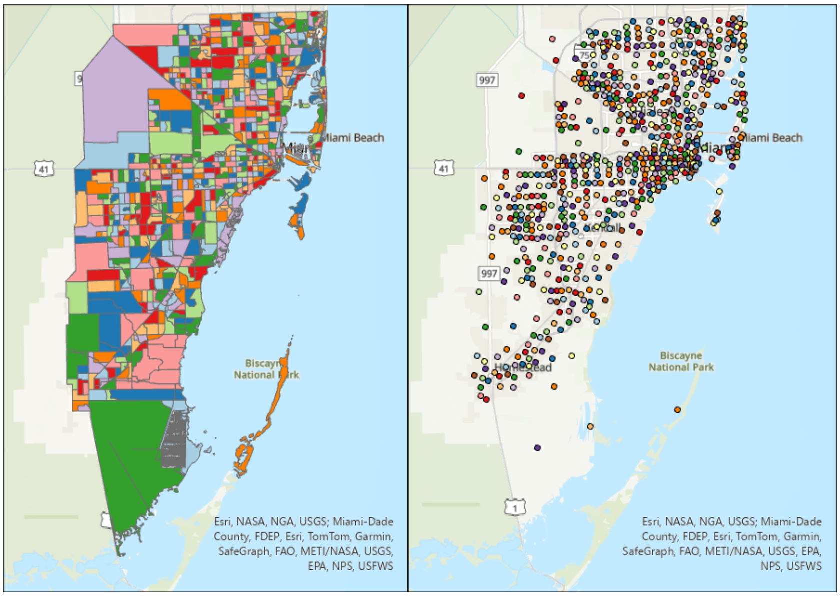

Figure 4.4: Overview of all the included tract areas, distributed using polygons on the left and point on the right.

than desired. Unfortunately, no higher temporal resolution data were available. It must be noted that the colour of the right side living areas do not reflect wind speeds.

4.2.4. Inundation data

Besides wind, the amount of rainfall is an important environmental cue. Kelley (2022) from NASA's Goddard Space Flight Center created a raster dataset containing precipitation rate data for Storm Irma at half-hour intervals. The dataset has a spatial resolution of 10 km, making it more detailed than the wind data; the finer distribution is shown on the right side of Figure 4.6. The original dataset contains ratio data but was converted into nominal categories to better represent how agents perceive the rainfall intensity. The categories used are: less than 2.5 mm/h (light rain); less than 7.5 mm/h (moderate rain); less than 15 mm/h (heavy rain); less than 30 mm/h (intense rain); and more than 30 mm/h (torrential rain). These scales are adapted from Guico et al. (2018). The rainfall data is linked to the tract areas by sampling the grid every two hours, since this aligns with the used time step in the ABM.

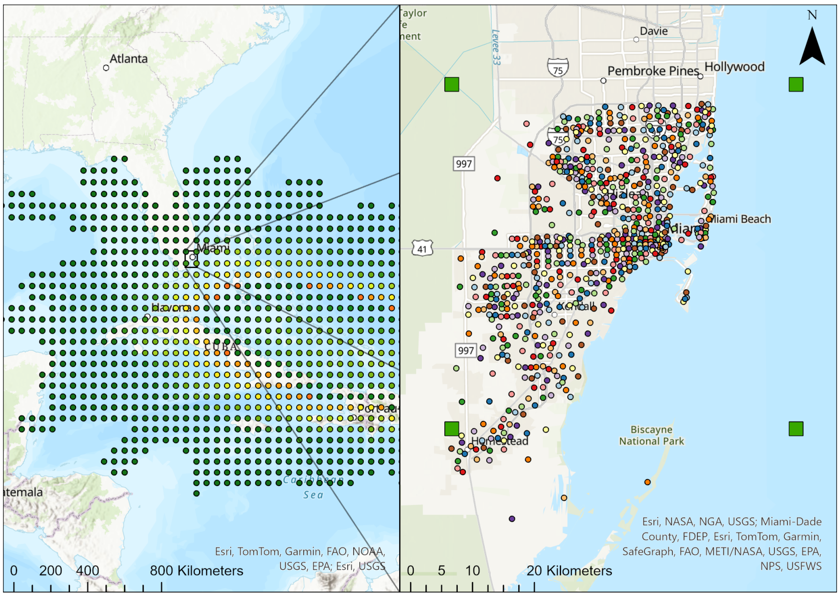

Figure 4.5: Overview of the distribution of wind data. Current views are snapshot of one time instant. The left shows an overview of the distribution for whole Florida. The right is close-up from Miami. The green squares indicate the data points for the wind.

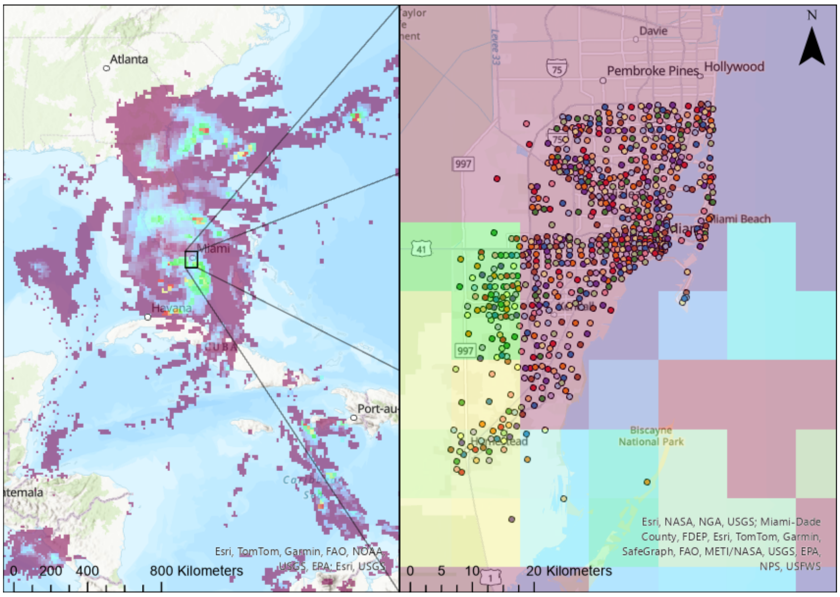

Figure 4.6: Overview of the distribution of rain data. Current views are snapshot of one time instant. The left shows an overview of the distribution for whole Florida. The right is close-up from Miami.

4.2.5. Watch and Warning data

During Storm Irma, the National Weather Service (NWS) was responsible for issuing watches and warnings. According to the NWS, a watch is described as: ”*A watch is used when the risk of a hazardous weather or hydrologic event has increased significantly, but its occurrence, location or timing is still uncertain. It is intended to provide enough lead time so those who need to set their plans in motion can do so. A watch means that hazardous weather is possible. People should have a plan of action in case a storm threatens and they should listen for later information and possible warnings especially when planning travel or outdoor activities.*” (National Hurricane Center, n.d.). In contrast, a warning is described as: *”A warning is issued when a hazardous weather or hydrologic event is occurring, imminent or likely. A warning means weather conditions pose a threat to life or property. People in the path of the storm need to take protective action.”* (National Hurricane Center, n.d.). During Storm Irma, a hurricane watch was issued for Miami on 7 September at 15:00 (Cangialosi et al., 2021). This watch was elevated to a hurricane warning on 8 September at 00:30 (Cangialosi et al., 2021). These hurricane watches and warnings applied uniformly to all tract areas within the county, so no spatial distinctions are necessary. However, this is not the case for storm surge watches and warnings. These alerts are similar in nature to hurricane watches and warnings but specifically address flooding risks caused by storm surges generated by high wind speeds. Storm surge watches and warnings were issued for specific areas within the county in six-hour intervals (National Hurricane Center & Central Pacific Hurricane Center, 2017a). The data is provided using polygons that indicated which areas received a watch or warning. An example for a specific time is shown in Figure 4.7. The left side illustrates that the warnings and watches cover a larger portion of the Florida coast, while the right side shows that the watch/warning is limited to coastal areas. The data is integrated in a manner similar to the rainfall data: every six hours, it is checked whether a point lies within a watch or warning polygon; if not, it is assigned no alert.

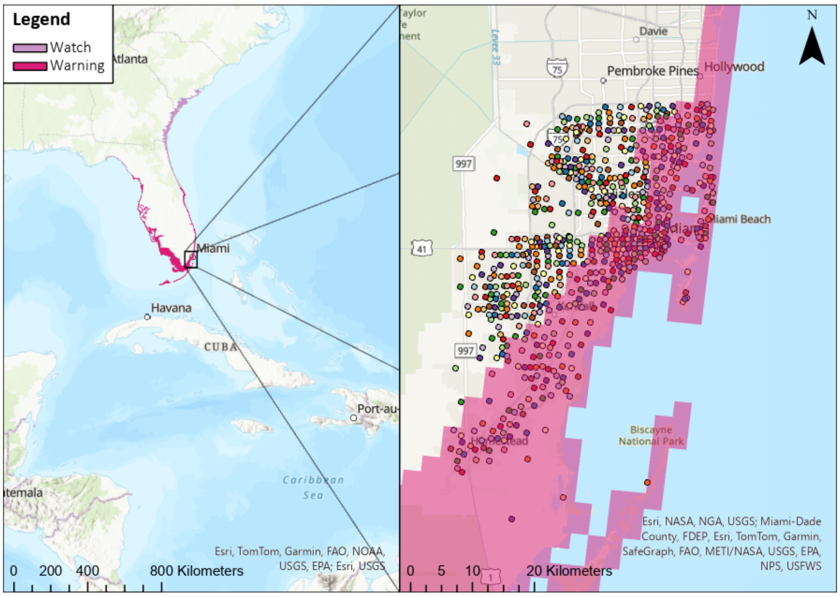

Figure 4.7: Left side shows an overview of the watch and warning areas of the whole of Florida. The right side is focused on Miami and shows that the warning reaches nearly half of the tract areas

4.2.6. Model implementation

This section explains how the adjusted PADM is implemented within the ABM. Each phase defined in Table 4.2 will be modelled individually to achieve this. Since Storm Irma is modelled statically using weather data and without dynamic government agents, the focus will be on one class: the individual, who must decide whether or not to evacuate. This individual progresses through the five phases of the PADM.

Figure 4.8 illustrates the life cycle of an individual and the processes that must be completed before the individual exits the model. It should be noted that the figure includes a dotted section labelled “Individual creation,” which is not part of the decision-making phases themselves but is necessary for initializing the model with individuals. Each of the phases will be described separately, except for the communication implementation phase. Following Lindell and Perry (2012), individuals can communicate during every phase to acquire the information they need, which varies by phase. Therefore, communication behaviour will be explained in conjunction with the other five phases. The model follows a waterfall structure; once individuals progress to the next phase, they cannot return to a previous phase.

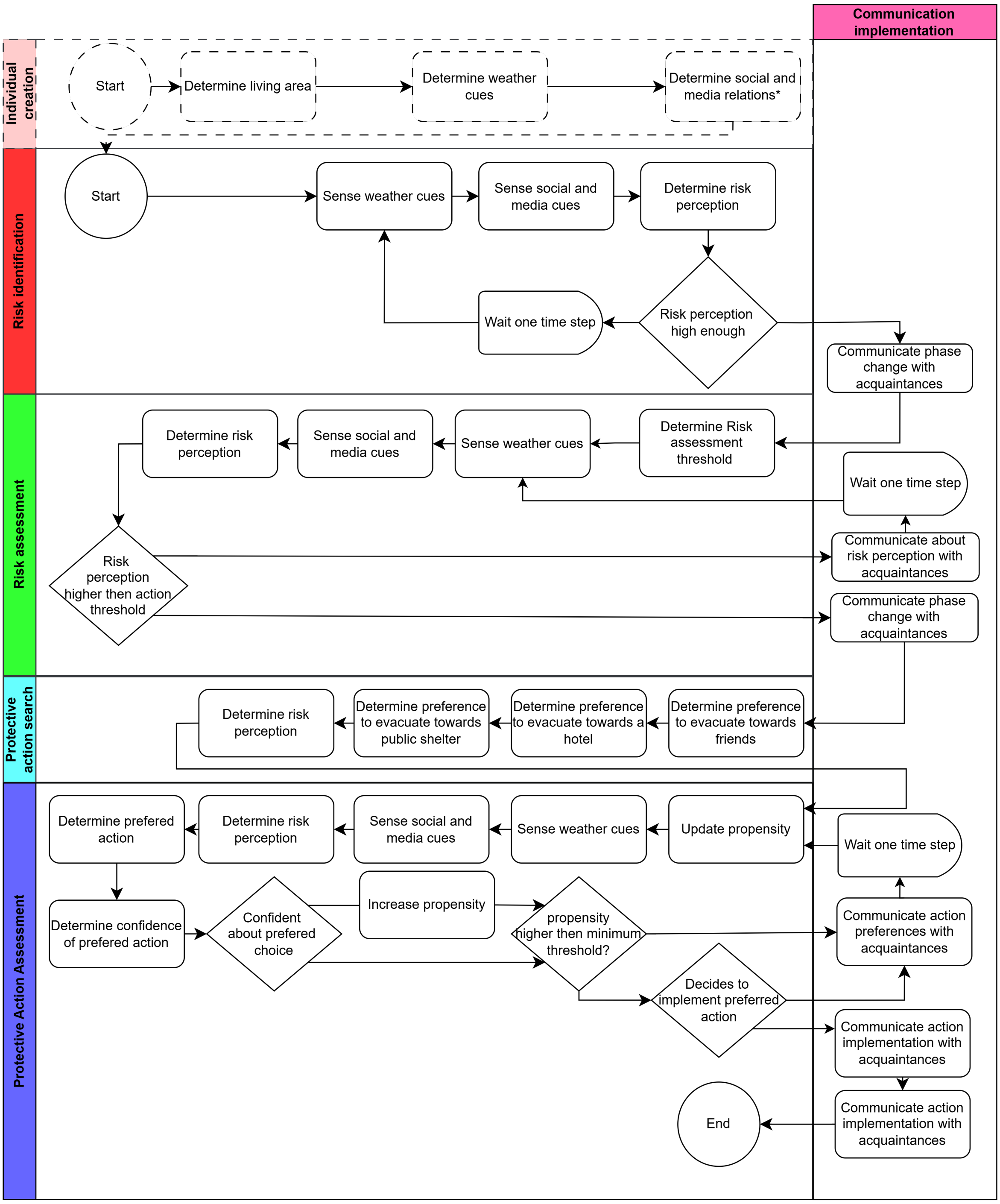

Figure 4.8: Flowchart showing the life cycle of an Individual. The Individual creation section is not part of PADM, but essential from a modelling perspective.

Agent creation

When the model begins simulation, it needs to initialize all the required variables. Table 2.1 provides a general overview; however, to implement the model computationally, these variables must be specified in more detail. This detailed specification of the required variables is provided in Table 4.4 and 4.5.

[H]

Table 4.4: Variable table

Model variables					
Variable	**Value Range**	**Initial value**	**Source**	**Dynamic /static**	**Short description**
number_of_steps	$\mathbb{Z}:[0,\infty]$	96	Wong et al. (2021)	Static	Number of steps, one step is 2 hours
init_individuals	$\mathbb{Z}:[1,\infty]$	1000	-	Static	Number of Individuals in the model
node_connectivity	$\mathbb{Z}:[0,n]$	6	Survey - SN	Static	Determines the number of acquaintances
n_neighbors	$\mathbb{Z}:[0,n]$	10	-	Static	Determines the number of physical neighbors
RI_thresh	$\mathbb{R}:[0,1]$	0,25	-	Static	Threshold when individual acknowledges storm
RA_thresh	$\mathbb{Z}:[0,1]$	0,5	Survey - RA[1,5]	Static	personal threshold indicating action is required against threat
RA_threshold_strength	$\mathbb{R}:[0,1]$	0,4	-	Static	Strength individuals risk assessment value on the threshold
comm_watch_value_risk	$\mathbb{R}:[0,1]$	0,05	-	Static	Influence of watch order on risk
comm_warning_value_risk	$\mathbb{R}:[0,1]$	0,1	-	Static	Influence of warning on risk
comm_watch_value_imm	$\mathbb{R}:[0,1]$	0,01	-	Static	Watch order effect on immediacy
comm_warning_value_imm	$\mathbb{R}:[0,1]$	0,05	-	Static	Influence of warning on immediacy
grow_factor	$\mathbb{R}:[0,\infty]$	30	-	Static	Rate of propensity base value increase
phase_change_factor	$\mathbb{R}:[0,1]$	0,1	-	Static	Communication effect on phase change
action_comm_value_imm	$\mathbb{R}:[0,1]$	0.01	-	Static	Protective actions influence on propensity
action_comm_value	$\mathbb{R}:[0,1]$	0.1	-	Static	Protective actions influence on perception
env_strength	$\mathbb{Z}:[0,1]$	0,18	Survey - ECB[1,3]	Static	How strong environmental cues influence risk perception
media_weight	$\mathbb{Z}:[0,1]$	0,2	-	Static	Determines the influence of media on risk perception
trop_warning_step	$\mathbb{Z}:[0,\infty]$	55	Cangialosi et al. (2021)	Static	Step for hurricane watch
evac_warning_step	$\mathbb{Z}:[0,\infty]$	60	Cangialosi et al. (2021)	Static	Step for hurricane warning

Table 4.5: Agent variables

Agent variables					
Variable	**Possible values**	**Initial values**	**Source**	**Dynamic/ static**	**Short description**
media_cue	$\mathbb{Z} : [0, 1]$	0	-	Dynamic	The perceived information from the media channels
media_freq	$\mathbb{Z} : x \in [0, 1]^{1\times96}$	$[0, 1]$	Survey - MD[1, 5]	Static	
media_trust	$\mathbb{Z} : x \in [0, 1]^{1\times5}$	$[0, 1]$	Survey - MD[6,10]	Static	
cue_perception	$\mathbb{Z} : [0, 1]$	0	-	Dynamic	Combined cue factor for environmental, social and media cues
social_perception	$\mathbb{Z} : [0, 1]$	0	-	Dynamic	Social part of risk perception
risk_perception	$\mathbb{Z} : [0, 1]$	0	-	Dynamic	Assessment of severity and impact threat
rain	$\mathbb{Z} : x \in [0, 1]^{1\times96}$	$[0, 1]^{1\times96}$	Kelley (2022)	Static	The rain cue values over time
rain_cue	$\mathbb{Z} : [0, 1]$	0	Kelley (2022)	Dynamic	The rain cue values current time
wind	$\mathbb{Z} : x \in [0, 1]^{1\times32}$	$[0, 1]^{1\times32}$	NHC (2017a)	Static	The wind cue values over time
wind_cue	$\mathbb{Z} : [0, 1]$	0	NHC (2017a)	Dynamic	The rain cue values current time
storm_surge	$\mathbb{Z} : x \in [0, 1]^{1\times32}$	$[0, 1]^{1\times32}$	NHC (2017a)	Static	The warning/watch values over time
storm_surge_state	$\{0, 1, 2\}$	0	Kelley (2022)	Dynamic	The storm surge warning/watch value current time
evac_friends	$\mathbb{Z} : [0, \infty]$	0	Survey - See Section 5.4		Attitude towards evacuating to family/friends
evac_hotel	$\mathbb{Z} : [0, \infty]$	0	Survey - See Section 5.4		Attitude towards evacuating to hotels
evac_shelter	$\mathbb{Z} : [0, \infty]$	0	Survey - See Section 5.4		Attitude towards evacuating to public shelters
stay	$\mathbb{Z} : [0, \infty]$	0	Survey - See Section 5.4		Attitude towards evacuating to sheltering in place
phase	$\{0, 1, 2\}$	0	-	Static	Current decision phase of the agent
propensity_cum	$\mathbb{Z} : [0, 1]$	0	-		Propensity due influence warnings and social interaction
propensity_base	$\mathbb{Z} : [0, 1]$	0	-		Base value for propensity

The creation of the synthetic population is performed during model initialization. First, bootstrapping was used to increase the number of survey samples to the required number of agents. Since the model runs with 1,000 agents and the original survey sample size is 440, an additional 560 samples were generated through bootstrapping. While this results in a large number of similar agents, it is considered a better approach than creating distributions for the required variables and sampling from those. The latter method could produce individuals with attribute combinations that are not representative of the survey data. Bootstrapping, on the other hand, leads to more realistic agents, with the drawback of duplicated individuals. However, this duplication drawback is mitigated by placing individuals in different living areas, where environmental factors and storm surge watches/warnings vary, making the duplicated agents still unique. The application of the bootstrapped is explained in subsections 4.2.6 and 4.2.6.

To ensure that the bootstrapped data align with the original survey data, the distributions were visually inspected, and a two-sample Kolmogorov–Smirnov test was used to assess their similarity. The two-sample Kolmogorov–Smirnov test evaluates whether the bootstrapped distribution differs significantly from the original survey distribution. A p-value greater than 0.05 indicates no significant difference between the two distributions (Hodges, 1958). Figure 4.9 presents all the distributions of the survey variables used in the ABM. As shown, the bootstrapped and original distributions align well. The p-values from the two-sample Kolmogorov–Smirnov tests support reflects this, with the lowest value being 0.77 for the variable public shelter place attachment variable, indicating strong similarity with the original data.

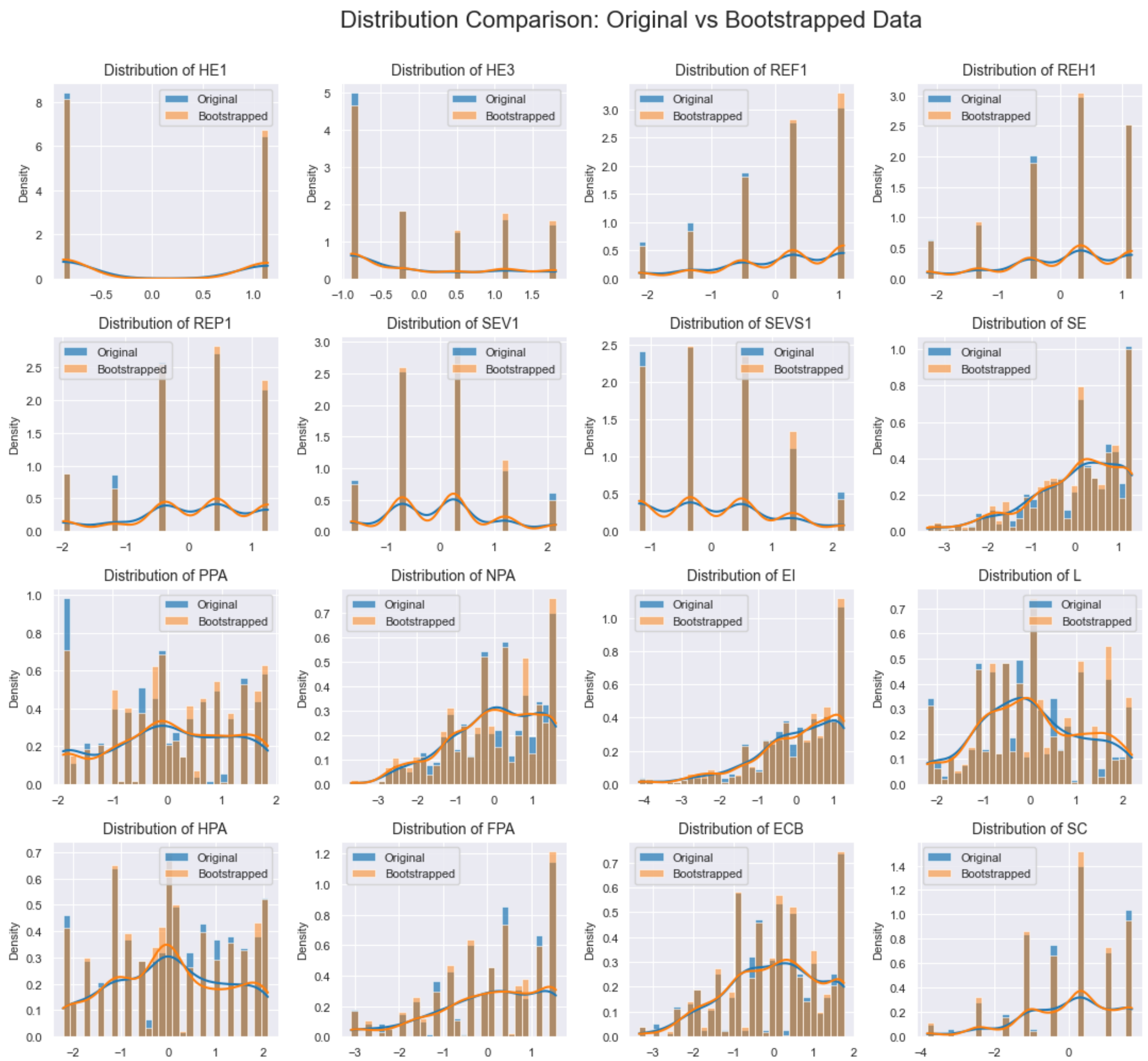

Figure 4.9: Comparison of the distributions of the original and bootstrapped variant of the survey data.

All the living areas are derived using total population per tract area of Miami-Dade county. For each tract, the probability that an individual lives there is calculated by dividing the tract's population by the total county population. Using these probabilities, an individual's living area is assigned. Each tract has unique values for rain and wind cues over time, which are then assigned to the agents residing there. This ensures that all agents within the same tract experience identical weather conditions. Given that the rain and wind data have a spatial resolution of 10 kilometres or more, randomly sampling locations within the tract would have small impact on the model's results. Storm surge watches and warnings do have a significant influence. Individuals living near the coast receive storm surge watches and warnings which influence risk perception.

The final step of the agent creation is assigning social and media relations, which consist of three types: social interactions, neighbour observation, and global broadcast (Du et al., 2017). Social interactions occur between individuals who are acquainted, such as friends, family, or work colleagues. These acquaintances exchange information in person or over the phone throughout the simulation.

The social network is modelled using a Watts-Strogatz graph. A Watts-Strogatz graph arranges all nodes in a ring topology and then connects each node to a predefined number of neighbours Watts and Strogatz (1998). It then iterates over all edges and, with a predefined probability, randomly rewires them. This process creates strongly clustered groups within the small-world network, which is representative of real-world social networks (Usui et al., 2022; Watts & Strogatz, 1998).

Using a Barabási-Albert graph was also considered. This type of random network grows by progressively adding new nodes that preferentially attach to existing nodes with higher connectivity (Barabási & Albert, 1999). However, preferential attachment like this results in the formation of hubs with extremely high numbers of connections and many nodes with very few connections. This is not representative of social network usage during a hurricane, as individuals are more likely to contact close friends rather than their entire social network. The Watts-Strogatz model results in a more balanced distribution of degrees across the nodes, which is why it is used in the model. .

Neighbourhood observation represents the relationship between individuals who can observe the evacuation actions of others nearby. According to Sadri et al. (2017), witnessing others evacuate influences an individual's own decision to evacuate. To determine which individuals can see each other's actions, the model selects the closest neighbours using a k-d tree constructed from the coordinates of their living locations. The number of closest neighbours is an input parameter, which introduces some ambiguity, particularly in the context of evacuation. One might argue that evacuation actions are visible to more people than just those living nearby. However, accurately capturing this would require modelling individuals' evacuation routes, which involves implementing evacuation behaviour itself. Since the model focuses solely on pre-decision-making behaviour, including evacuation paths would greatly increase both the scope and complexity. Furthermore, it would raise computational demands due to the need for pathfinding algorithms and determining when and where individuals observe others evacuating on the roads. This simplification therefore helps avoid unnecessary complexity and computational overhead.

The last relation type is global broadcasting, which defines the connection between media channels and individuals. This relationship is characterized by how frequently an individual consumes a channel and their level of trust in that channel. The media channels considered are social media, television, radio, and the Internet (Du et al., 2017). These channels are assumed to continuously broadcast hurricane-related information. The individual's consumption frequency determines how often they receive information from the channel, while their trust level influences the degree to which the channel affects their perceptions and decisions. Both the trust levels and frequency are derived from the survey.

Phase 1: Risk identification

When all individuals are created, the model will loop over all the agents per time step. In the risk awareness phase, the individual will first sense their environmental and media cues. It assumed that if a individual is exposed to rain and media that it will sense it. An individual can see rain fall from the sky, notice the trees start to shake or feel colder because of the wind. The rain and wind data are assigned to the individual as an array of consecutive values. To update the array with rain value, the array is indexed using the current model step. The wind values are collected every six hours and thus can only be indexed from the array every 3 steps.

The media cue depends on the frequency and trust of the various media channels. Frequency indicates per how many steps the individual gets influenced by that channel. As shown in equation 1, if the t, which represents the current model step, modulus frequency is 0 the value 1 is returned indicating that this channels is consulted this step. This is done for all the channels *i*. Then for all channels *i* the influence is multiplied with the corresponding media trust value and then averaged using the number of channels *n*, as shown in equation2. This gives the incremented value, which is then added to the old media_cue value in equation 3.

$$\forall i, \quad \text{media\_comm}_i = \begin{cases} 1 & \text{if } t \bmod \text{freq}_i = 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$\text{increment} = \frac{1}{n}\sum_{i=0}^{n}(\text{media\_trust}_i \cdot \text{media\_comm}_i) \tag{2}$$

$$\text{media\_cue}_t = \text{media\_cue}_{t-1} + \text{increment} \tag{3}$$

When the cues are updated to their new values they can be used to calculated the risk perception. Here the environmental threat perception and stakeholder perception are used to translate the cues into one risk perception value. The influence of social cues will be added during later communication steps. The base value of risk perception is based on the environmental and media cues. This simply done by define weights per cue which are based on the survey responses. The weights are inspired on Du et al. (2017) and model the core perception of stakeholders as defined in Lindell and Perry (2012). The risk perception is then determined by multiplying the cue values with the corresponding weights, as in 4.

$$\text{risk\_perception} = \frac{1}{n}\sum_{i=0}^{n}(\text{cue}_i \cdot \text{weight}_i) \tag{4}$$

It should be stressed that that this risk_perception is recalculated every step, but will later be heightened by social cues which is calculated in later phases. The risk perception will be compared with a threshold which is a model parameter. If the risk perception is higher then the threshold the individual will move to the next phase and communicates this with its acquaintances. The communication is focused towards the individuals acquaintances. If the individuals has none, nothing happens. Otherwise, the risk perception of the acquaintance gets heightened with certain amount ϕ, as shown in the pseudo-code1. If the threshold is lower, then the agent will not do anything else and until its next step. .

Algorithm 1 Phase Change Communication

```
if individual has any acquaintances then
    for each acquaintance a do
        increase a's risk perception by φ
    end for
end if
```

Phase 2: Risk Assessment

When the individual is convinced a threat is approaching, it will start to assess if the severity of the threat is big enough that action is required. Similar to the risk awareness phase, the environmental cues and media cues get updated first, risk perception is updated, and then compared to a threshold value. The main difference is that the threshold is now based on the characteristics of the individual itself using equation 6. The threshold is based on a static value. Added to this base value is the value from the survey, which represents environmental cue awareness. This value ranges from -1 to 1 and is multiplied by the survey strength coefficient, allowing it to be adjusted to better fit the model.

$$threshold = base\_value + survey_value \cdot survey\_strength \tag{6}$$

As indicated by Lindell and Perry (2012), when the threat is identified, the individual must still decide if the consequences of the threat are grave enough to undertake actions. When the risk perception is higher than the threshold, the individual acknowledges that there is a threat which requires protective actions and moves to the next phase. While going to the next phase, the individual communicates with acquaintances, heightening their risk perception. If the risk perception is lower than the threshold, the agent will gather information from its acquaintances and then will cycle through the risk assessment phase again in the next step. The communication will be focused only on risk perception and is calculated using equation 6 t/m 7. Equation 6 calculates the average risk perception of the acquaintances and then the average of this value and the risk perception of the communicating individual. Then the individual's risk perception gets increased by the difference between the individual's risk perception and the average risk perception. β is a coefficient which can be used to determine the strength of the communication and is used in the sensitivity analyses.

$$R_{\text{avg}} = \frac{R_{\text{own}} + \frac{1}{N}\sum_{i=0}^{N} R_i}{2} \tag{6}$$

$$R_{\text{own}} = R_{\text{own}} + (R_{\text{own}} - R_{\text{avg}}) \cdot \beta \tag{7}$$

where:

R_{avg} = average risk perception acquaintances
R_{own} = agent's own risk perception
R_i = risk perception of acquaintance
N = number of acquaintances
β = model-specific coefficient for risk perception adjustment

Phase 3: Protective action searched

If the individual determines that protective action is necessary, it must then decide which type of action is most favourable. The four main options considered are evacuation to friends or family, evacuation to a hotel, evacuation to a public shelter, or sheltering in place (Bian et al., 2019; Whitehead et al., 2000). During this phase, the individual evaluates their attitude toward each of these four options. This evaluation is carried out using the multinomial logistic regression models described in Chapter 5. These models return the probability of selecting each action based on the individual's characteristics. This probability is interpreted as the individual's willingness to implement the corresponding action.

Since this phase solely involves the computation of these probabilities and does not rely on passing any threshold values, it is not possible for an individual to remain in this phase across multiple time steps. The individual will proceed directly to the protective action assessment phase. It should be noted that this phase also incorporates the ”hazard adjustments perception” component from the core perceptions of the PADM.

Phase 4: Protective action assessment

The fact that individuals recognize that a danger is approaching and that action needs to be taken does not necessarily lead to the implementation of that action Lindell and Perry (2012). The gap between intention and implementation can be explained by two mechanisms. Lindell and Perry (2012) highlights two main points. First, individuals often postpone the implementation of protective actions, believing there is still time left to evacuate later. Second, individuals may doubt which action will lead to the most favourable outcome, resulting in the need for more information. This uncertainty leads to communication with acquaintances. The duration of this communication phase also depends on how much time is perceived to be left before landfall.

The study by Verma et al. (2022) asked participants to fill in the same survey every day for five days. Before each survey round, participants were presented with a forecast map, traffic information, and news articles. They were then asked about their evacuation decision and the certainty of that decision. The results indicated that 84% made an evacuation decision and did not change it throughout the experiment.

Huang et al. (2016) and Lindell and Perry (2012) indicate that individuals often delay their actions until the last possible moment. Additionally, individuals assess the trade-off between the cost of evacuation and the associated risks. However, no studies have investigated how willingness to implement protective action develops from the moment a decision is made until landfall.

Since Huang et al. (2016) and Lindell and Perry (2012) report delayed action, while Verma et al. (2022) shows individuals are confident in their decision, an exponential growth is assumed for the willingness to implement. This is modelled using equation (7). The equation has two variables: the propensity ceiling, which sets a maximum value, and the growth factor, which determines the nonlinearity of the increase. While this forms the base of willingness, the value can further increase through communication with acquaintances or observing neighbours evacuating. The ceiling ensures the value does not exceed one and allows for sensitivity analysis. The maximum value is reached on the date of landfall, so S equals the step corresponding to this date.

$$\omega = c \cdot \frac{(s+1) \cdot \left(\frac{1}{S}\right)}{1 + g \cdot \left(1 - (s+1) \cdot \left(\frac{1}{S}\right)\right)} \tag{7}$$

where:

$\omega =$ willingness
$c =$ propensity ceiling
$s =$ current step
$S =$ number of steps until landfall
$g =$ growth factor

Then, the existing values for environmental cues, media cues, and risk perception are recalculated. While this does not influence the behaviour of the individual itself at this point, these values are still needed during communication with acquaintances.

Next, the willingness is compared to a stochastic threshold. Here, the individual's propensity serves as the threshold value. If a randomly drawn number between zero and one exceeds this threshold, the individual implements its preferred action.

When the individual implements the action, it can influence its environment in various ways. First, if the decision is to evacuate, neighbouring individuals observe this and experience an increase in risk perception, willingness to evacuate, and attitude toward evacuation options. It must be noted that if the individual decides to stay, no such influence occurs. Lastly, the individual will contact its acquaintances and increase their risk perception, willingness to evacuate, and attitude toward the implemented action.

If the individual does not pass either threshold, it will communicate with its acquaintances. Up to this phase, communication only influenced risk perception. Now, it also affects willingness and the attitude toward protective actions. Equations 1 through 2 are used to calculate the new values.

4.3. Convergence analysis

Agent-based models are inherently stochastic; the unique interactions between autonomous agents lead to variation in model outputs across runs. To ensure the reliability of the results, a convergence analysis was conducted to determine the number of iterations required to produce stable averages. The model was executed for 500 iterations. The outputs evacuation time, destination choice for hotel, friends/family, public shelters, and staying at home were standardized across all iterations.

Figure 4.10 shows the running average of these five metrics. The red lines indicate the boundaries of one standard deviation. From approximately iteration 150 onward, the metrics remain within these boundaries, suggesting that the results become sufficiently reliable after this point. Although even greater stability (e.g., within 1 σ) would be preferable, using a threshold of one standard deviation provides a practical balance between computational cost and result accuracy. Notably, the average evacuation time approaches the 1 σ range, further supporting the robustness of the output. All the results produced by the ABM will be based on 150 iteration unless stated otherwise.

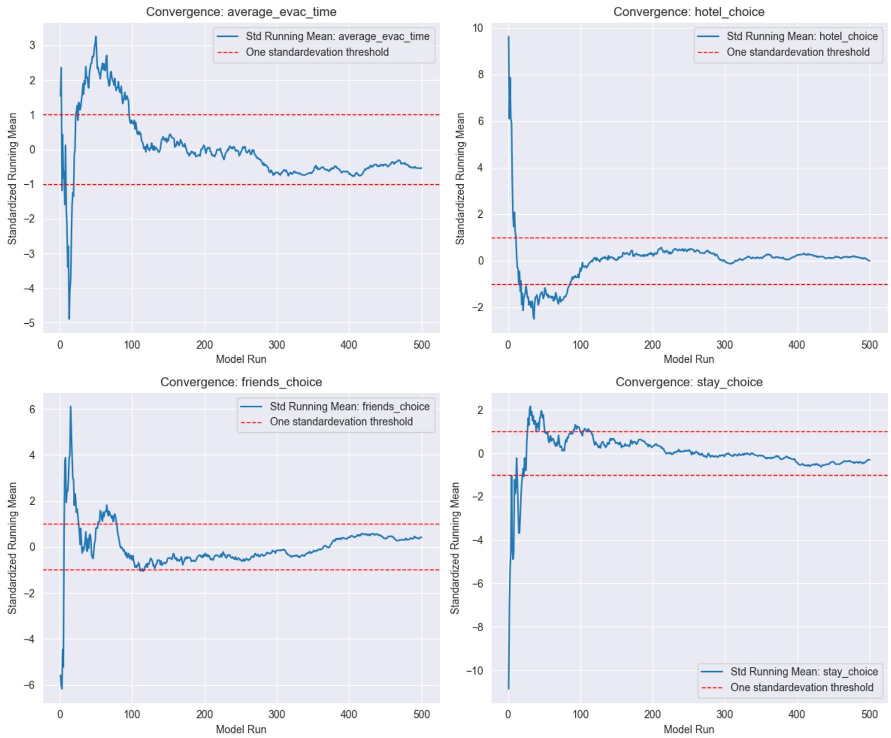

Figure 4.10: Convergence graph for the model outputs: evacuation time, hotel destination choice, friends destination choice, public shelter destination choice, staying home. The red lines indicate one standard deviation boundaries

4.4. Verification

To ensure that the implemented model behaves as expected, as described in Section 4.2, various verification tests were conducted. Following the framework outlined by Dam et al. (2013), these tests include Single-Agent Testing, Minimal Model Testing, and Multi-Agent Testing. Table 4.6 provides an overview of the executed tests.

Test number	Test type	Test description	Observed behaviour	Expected?
C.1.1.1	Single-agent	when using large media frequency and trust values the value should increase swiftly	Media cue reaches 1 at time step 30. Risk perception follows media cue	Yes
C.1.1.2	Single-agent	When using large environmental cue weights risk perception must follow the environmental cues.	The risk perception mimics the trends of the environmental cues	Yes
C.1.1.3	Single-agent	Does the agent follow the correct sequence of phases	All agents start in phase 0. Then go to phase 1. And after phase two they leave the model	Yes
C.1.2.1	Minimal Model	Every phase change the agents must influence each others risk perception	When changing phases agents reach out to acquaintances and increase perception with expected amount.	Yes
C.1.2.2	Minimal Model	Agents influence acquaintances and neighbours risk perception and propensity when implementing action	Acquaintances and neighbours values are changed. For acquaintances only the correct action value and for neighbours only if the action is not staying.	Yes
C.1.2.3	Minimal Model	Does the social network work expected	Networks are made, average degree is as expected.	Partly
C.1.3.1	Multi-agent testing	Do dynamic attributes stay within boundaries	Only social perception exceeds expected range. This, however, is regulated in the risk perception variable	Partly
C.1.3.2	Multi-agent testing	Are the watch/warning timings correct	The watches/warnings are correct for both the hurricane and storm surges.	Yes

Table 4.6: Executed verification tests

4.5. Validation

Validation ensures that the model produces results representative of real-world phenomena. According to Dam et al. (2013), model validation can be achieved by comparing outputs with historical events and existing literature. This model is based on Hurricane Irma and directly integrates data to simulate environmental cues such as wind and rain. Therefore, the values for these cues correspond closely to what residents of Miami experienced during the storm. Similarly, the hurricane watches and warnings, as well as the storm surge alerts, are based on actual data from Hurricane Irma. The timing of the hurricane watches, warnings, and wind probabilities were face-validated using the graphical archive tool of the National Hurricane Center (National hurricane Center, n.d.).

Evacuation decision timings are validated by comparing the model outputs with evacuation timing data collected by the survey conducted by Wong et al. (2021). This survey was distributed in Florida to gather data on evacuation timings during Hurricane Irma. Figure 4.11 shows histograms of the survey results alongside the model results. While the results do not align perfectly, this is expected because the survey responses include individuals who received evacuation orders on 8 and 9 September, resulting in two peaks on those dates, which the model does not reproduce. Both histograms show an increase in evacuation decisions starting around 4 September, with similar growth patterns thereafter. The model exhibits a slightly higher number of decisions made, which can be attributed to its focus on the metropolitan Miami area, where residents tend to have a higher propensity to evacuate compared to more inland regions of Florida.

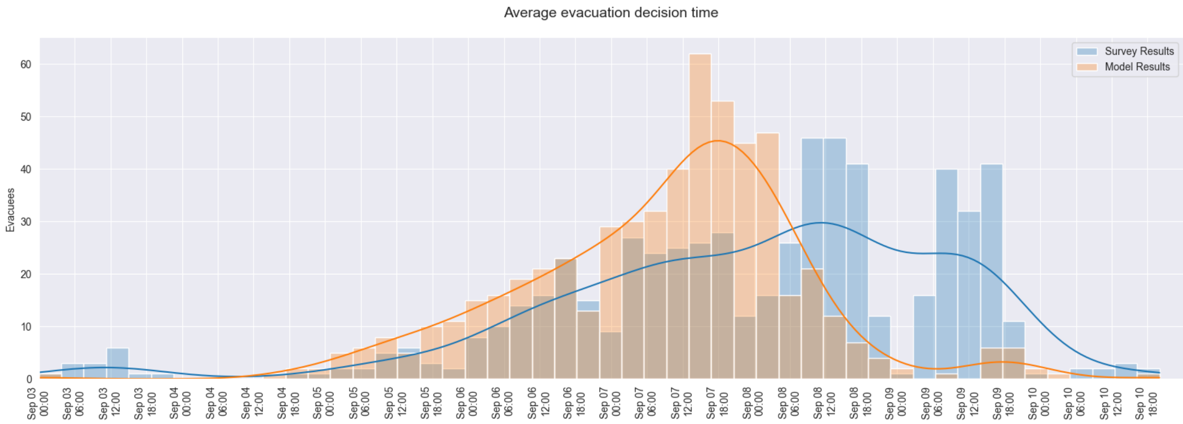

Figure 4.11: Histograms comparing simulated evacuation decision times ("Model Results") with survey-based observations ("Survey Results") during Hurricane Irma. Both distributions show the timing and number of evacuees, allowing for model validation against real-world data. Based on 150 model iterations.

The studies by Wong et al. (2021) and Yin et al. (2014) also provide data on the distribution of evacuees and non-evacuees. Table 4.7 presents this distribution per study. When combining individuals who actively choose to stay with those who are indecisive, the model reports 27.21% non-evacuees, consisting of 21.81% actively staying and 5.40% indecisive agents. This aligns with the study of Wong et al. (2021) which reports a non-evacuation rate of 30.5%. However, a direct comparison with the current ABM is not entirely fair because their survey includes respondents who were not all directly impacted by the hurricane. Fortunately, the study provides county-level data on respondents' residences. Filtering the data for Lee County, an area directly hit by Hurricane Irma, reveals a non-evacuation rate of 21.38%, which still somewhat aligns with the model results.

The agent-based model by Yin et al. (2014), which is based on a hypothetical survey for Miami-Dade County, reports a non-evacuation rate of 11.02%, which differs from the rate produced by the ABM developed in this thesis. This difference can be attributed to the generally weak predictive power of the multinomial logistic model used in both studies, as discussed in Section 5.4, as well as differences in how the potential hurricane threat was described in the respective surveys. The survey used in this thesis did not include a specific description of the severity of the hurricane expected to impact Miami-Dade County. If Yin et al. (2014) included such a description, it may have led to higher perceived threat levels among respondents, resulting in a lower evacuation rate.

Given that the non-evacuation rate produced by the model is reasonably close to the rates reported for the entire state of Florida and for Lee County by Wong et al. (2020), the model's output regarding non-evacuation is considered valid.

Study	Evacuees	Non-evacuees
Model results	72,79%	27,21%
Yin et al. (2014)	88,98%	11,02%
Wong et al. (2020)	69,5%	30,5%
Wong et al. (2020), only Lee County	79,62%	21,38%

Table 4.7: Distribution comparison for evacuees and non-evacuees

Besides the decision to evacuate or not, individuals must also choose their evacuation destination. Table 4.8 presents the distribution of destination choices derived from Wong et al. (2021) and Bian et al. (2019), covering four different hurricanes. While the destination preferences vary somewhat between these events, evacuation to family or friends consistently emerges as the most popular choice, followed by hotels/motels and then public shelters. The model results do have the lowest percentage evacuation towards family/friends and the highest percentages for the other options. This mismatch can be attributed to the weak predictive of the used multinomial logistic model, as discussed in Section 5.4. The model's destination choice distribution aligns well enough with these observed patterns, indicating that the model's output in this aspect can also be considered somewhat valid.

Hurricane	Family/friends	hotel/motel	public shelter	Other
Model result	49%	40%	10%	-
Gustav (2008)	54%	35%	2%	8%
Irene (2011)	83%	10%	1%	6%
Sandy (2012)	83%	7%	4%	6%
Irma (2017)	59%	27%	4%	10%

Table 4.8: Destination types percentages per hurricane

4.6. Sensitivity analysis

The model contains variables that contain a substantial amount of uncertainty. To assess the potential impact of this uncertainty on the model's key metrics, average evacuation timing and destination choice, a sensitivity analysis was performed. For all variables listed in Tables 4.4 and 4.3 without a reference in the Source column, the values were individually adjusted by ±20%. The resulting changes in output metrics were then measured as percentage deviations from the baseline case. Each sensitivity test was run for 150 iterations.

Overall, the sensitivity of these variables, shown in Figure 4.12, is relatively low. This low sensitivity can be explained by the fact that agents are influenced by many different types of cues and processes. Changes in any single variable affect the agent's state but tend to be spread over the agent's entire lifecycle, resulting in minor overall impact.

The first four subplots display the different destination choices. For these choices, the parameter action_comm_value appears insensitive, which is surprising because this parameter controls the influence of acquaintances' implemented actions and the agent's attitude toward those actions. One explanation is that the base effect of this parameter is already strong, so increasing or decreasing it by 20% does not meaningfully affect the agents' decisions when convincing acquaintances.

In contrast, RA_base shows relative sensitivity across all four destination options. Increasing RA_base leads to more individuals evacuating to friends or family and fewer choosing hotels, public shelters, or staying at home. This difference can be explained by two factors. First, RA_base defines the baseline threshold that must be surpassed for an agent to progress through the protective risk assessment phase. This baseline is then adjusted by the individual's unique general risk assessment value, derived from survey data. Agents who prefer evacuation to friends or family tend to have a higher risk perception, which effectively lowers their threshold compared to agents favouring other destinations. As a result, those preferring friends or family destinations are more likely to initiate evacuation earlier and influence acquaintances to adopt the same preference. Decreasing the parameters media_weight_perc, media_weight_trust, and env_strength results in more agents choosing the friends/family destination and fewer choosing the other options. As discussed above, agents preferring friends/family have a lower risk assessment threshold. Reducing these parameters slows down the evacuation decisions of other agents, thereby increasing the window during which friends/family-preferring agents can influence others' destination choices.

Figure 4.12: Every subplot shows the sensitivities for the destination choices for a change of plus-mus twenty percent of uncertain input variable. Based on 150 model iterations.

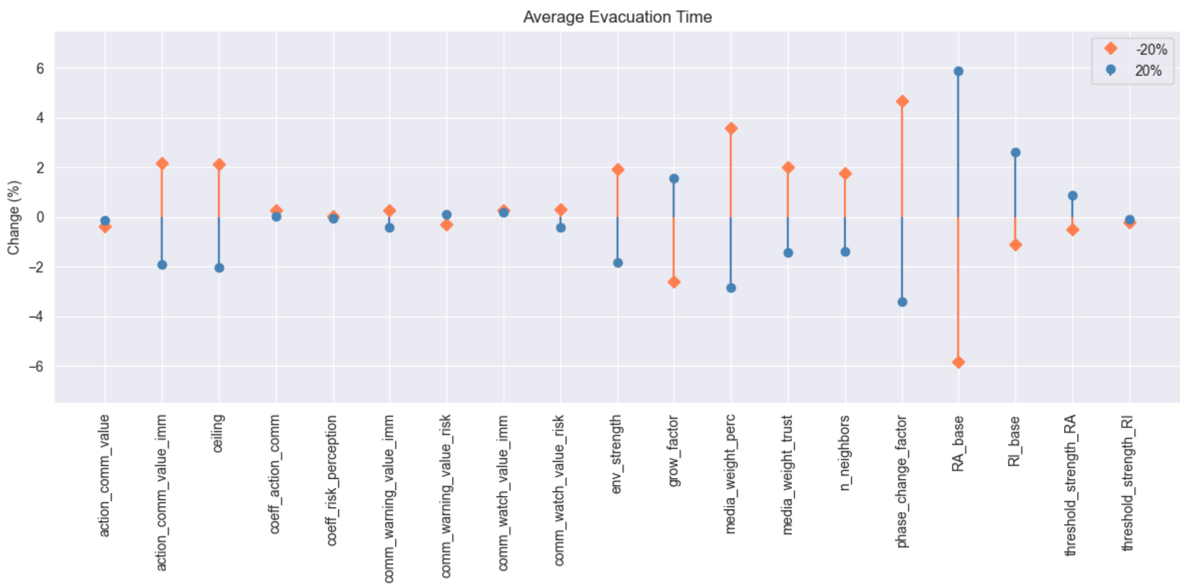

Figure 4.13: Sensitivity of parameters for the output metric of average evacuation decision time. Based on 150 model iterations.

Figure 4.13 shows the sensitivity of the input parameters on the average evacuation decision timing. The parameters action_comm_value, coeff_action_comm, and coeff_risk_perception all relate to how individuals communicate with each other, yet they appear to be insensitive in this context. This can be explained by the fact that within social networks, individuals communicate extensively, causing their influences on one another to converge after a certain point in time. While changing these parameters may affect the timing of this convergence, the sensitivity analysis focuses on the final output metrics, so such differences are not visible. Additionally, action_comm_value is insensitive for evacuation timing because it influences only destination choice, which is not directly relevant to the timing of the evacuation decision itself.

If the parameters action_comm_value_imm, ceiling, and grow_factor increase, the average evacuation decision time decreases, which is expected since these parameters all increase the propensity of individuals to take action. Specifically, grow_factor determines the linearity of the base propensity value. When grow_factor decreases, the relationship becomes more linear, leading to faster growth of propensity and thus a shorter average evacuation time.

The parameters comm_warning_value_imm, comm_warning_value_risk, comm_watch_value_imm, and comm_watch_value_risk control the influence strength of hurricane watches and warnings. Their insensitivity in the analysis may be due to either having negligible effect or their effects being so strong that a ±20% change does not significantly alter outcomes. As shown later in Chapter 6, the watch and warning do have a significant impact on average evacuation decision time.

Risk perception is influenced by media_weight_perc, media_weight_trust, and env_strength, all showing similar sensitivity for average evacuation timing. An increase in these parameters causes individuals to progress through the initial two phases more quickly, thus reducing the average evacuation decision time. The same effect is observed for phase_change_factor, although its influence is even stronger.

Conversely, the parameters RA_Base and RI_Base increase the decision threshold, which results in a longer average evacuation time as their values increase. The parameter threshold_strength_ra has less impact because it varies with individuals' risk assessment values, some individuals have low values that increase the threshold, while others have high values that decrease it. This balancing effect among agents reduces the overall sensitivity of average evacuation timing to this parameter.

4.7. Experimental Design

To gain an overview of evacuation behaviour and the influence of evacuation warnings on this behaviour, experiments need to be conducted and their results analysed. This section outlines the design of these experiments, which focus both on exploring the role of model uncertainties and on evaluating policy interventions.

Following the XLRM framework of Jafino et al. (2021), illustrated in Figure 4.14, model inputs are categorized into external factors (X) and policy levers (L). These inputs interact through model relationships (R) to produce model metrics (M). External factors represent variables outside direct control in the real world, while policy levers correspond to elements that stakeholders can manipulate. In this study, the policy levers are evacuation warnings issued by the Federal Emergency Management Agency (FEMA). The effectiveness of these levers strongly depends on the values of the external factors.

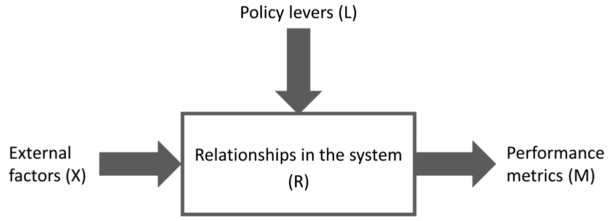

Figure 4.14: XLRM-framework, from Jafino et al. (2021)

The model includes numerous external factors, all of which were incorporated into the sensitivity analysis described in Section 4.6. The sensitivity analysis identified the ceiling, growth factor, media trust factor, and phase change factors as the most sensitive. To ensure that policy interventions remain effective under varying conditions, these external factors are addressed through five scenarios, presented in Table 4.9. Each row represents a scenario in which the default value of one factor is adjusted to a less favourable setting. For example, the

Media Distrust scenario features a reduced media_trust_factor and media_weight_perception value, simulating a situation in which individuals' media usage is less favourable.

Scenario	Ceiling	Growth factor	Media trust factor	Media weight perception	Phase change factor	Base value risk assessment
B: Base	0.4	30	0.04	0.2	0.1	0.5
LT: Low action tendency	0.2	60	0.04	0.2	0.1	0.5
MD: Media distrust	0.4	30	0.02	0.1	0.1	0.5
PC: Low phase communication	0.4	30	0.04	0.2	0.05	0.5
LR: Low risk assessment	0.4	30	0.04	0.2	0.1	0.75

Table 4.9: Scenarios for the external factors (X)

The policy levers (L) are based on hurricane and storm surge watches/warnings. The hurricane watch and warning affect all agents in the model, whereas the storm surge watch and warning influence only those agents living near the coast. These alerts are controlled through two separate policy levers: warning timing and warning gap. The warning timing lever shifts both the evacuation watches and warnings earlier or later on the model timeline. The warning gap lever adjusts the time interval between the evacuation watch and the subsequent evacuation warning. It must be noted that the watch for the hurricane and storm surge is issued nearly identical times. Same applies for the hurricane and storm surge warning.

While optimization algorithms such as the Non-dominated Sorting Genetic Algorithm (NSGA-II) could be employed to identify optimal configurations, this approach is not feasible due to the high computational cost associated with the numerous model iterations required. Instead, a set of predefined policy lever configurations will be tested to evaluate their effectiveness. These policy configurations are presented in Table 4.10. The policy levers are selected to cover the most logical combinations. The values in the Timing column indicate the number of hours by which the watch/warning is advanced, while the Gap column shows the number of additional hours by which the interval between the watch and warning is increased.

Policy code	Timing	Gap
P0-0	0	0
Pn6-0	-6	0
P12-0	12	0
P24-0	24	0
P0-12	0	12
Pn6-12	-6	12
P12-12	12	12
P24-12	24	12
P0-24	0	24
Pn6-24	-6	24
P12-24	12	24
P24-24	24	24

Table 4.10: Policy lever (L) combinations defining the policy configurations

By combining the scenarios for the external factors with the policy configurations of the policy levers, the total number of experiments is determined and presented in Table 4.11. Each experiment represents a combination of one scenario and one policy configuration. The first letters, such as Base Case (B), Low Risk Assessment (LR), and Media Distrust (MD), indicate the scenario, while the following letters and numbers represent the policy configuration. It is important to note that this table does not include all scenarios. As shown in Section **??**, the LR and MD scenarios were identified as the most relevant. To maintain the readability of the policy results, the Low Action Tendency and Low Phase Communication scenarios were excluded from the policy testing.

Base	Risk assessment	Media distrust
BP0-0	LRP0-0	MDP0-0
BPn6-0	LRPn6-0	MDPn6-0
BP12-0	LRP12-0	MDP12-0
BP24-0	LRP24-0	MDP24-0
BP0-12	LRP0-12	MDP0-12
BPn6-12	LRPn6-12	MDPn6-12
BP12-12	LRP12-12	MDP12-12
BP24-12	LRP24-12	MDP24-12
BP0-24	LRP0-24	MDP0-24
BPn6-24	LRPn6-24	MDPn6-24
BP12-24	LRP12-24	MDP12-24
BP24-24	LRP24-24	MDP24-24

Table 4.11: Experimental design for policy interventions

The model uses the experiments as input and translates this input, through the relationships in the system (R), into model metrics (M). These relationships have already been extensively discussed in Sections 4.1 and 4.2. The model metrics include the average evacuation decision time, the spread of evacuation timings, the number of indecisive agents, and the decision to evacuate to a family or friend's home, a hotel, a public shelter, or to stay home.

The average evacuation decision time provides insight into whether the majority of individuals evacuate earlier or later under different scenarios and policy combinations. The spread of evacuation timings is included because this metric indicates whether the entire county evacuates simultaneously or if evacuations are more evenly distributed over time. It is measured through the time between the first and third quantile of the interquartile ranges. The indecisive agents refer to individuals who are unable to progress through all decision-making phases before landfall. Since these individuals do not make an evacuation decision, they do not evacuate.

By combining the number of indecisive individuals with those who actively decide to stay, the total number of individuals who will shelter in place is determined. These include individuals who consciously choose to stay home, convinced it is the appropriate response to the threat, as well as individuals who stay either because they are not convinced that there is a threat requiring action, or because they perceive a threat but do not believe it is serious enough to require evacuation.

4.8. Conclusion of ABM methodology

This chapter partly addresses the sub-question: "*How can these psychosocial and environmental factors be integrated into an agent-based model?*" Section 4.1 outlined how the decision-making phases of the Protective Action Decision Model (PADM) can be combined with the relevant psychosocial and environmental factors, along with the key components involved namely individuals, the storm, media, and government. Subsequently, Section 4.2 detailed the conceptualisation process that translates these theoretical components into a computational framework, including the necessary data sources. The resulting ABM, which has undergone verification and validation, offers a structured approach to incorporate the ten identified factors within an ABM by leveraging the decision phases of PADM.

5
Survey Results

This chapter presents the results of the survey analysis, following the structure outlined in Chapter 3. First, the factors and their suitability are described. Next, the correlations between the relevant variables and the factors related to evacuation intention are discussed. Finally, the logistic regression model is presented and explained.

5.1. Factor Analysis

To identify the expected underlying latent factors in the survey questions, a factor analysis was conducted. The suitability of the data for exploratory factor analysis was assessed using confirmatory factor analysis, the Kaiser-Meyer-Olkin (KMO) test, Bartlett's Test of Sphericity, and by evaluating the communalities of the resulting factors.

Expected Factor	**Variables**
Environmental Cues	ECB1, ECB2, ECB3
Evacuation Intention	EI1, EI2, EI3, EI4, EI5
Neighbourhood Place Attachment	NPA1, NPA2, NPA3, NPA4, NPA5
Friend/Family Place Attachment	FPA1, FPA2, FPA3, FPA4, FPA5
Hotel Place Attachment	HPA1, HPA2, HPA3, HPA4, HPA5
Public Shelter Place Attachment	PPA1, PPA2, PPA3, PPA4, PPA5
Friend/Family Self-Efficacy	SEF1, SEF2
Hotel Self-Efficacy	SEH1, SEH2
Public Shelter Self-Efficacy	SEP1, SEP2
Likelihood Hurricane	LH1, LH2
Likelihood Storm Surge	LS1, LS2
Risk Assessment	RA1, RA2, RA3, RA4, RA5, RA6
Social Cues	SC1, SC2

Table 5.1: Expected factor relationships used in the CFA. Column entries indicate which variables load onto which factors.

5.1.1. Confirmatory factor analysis (CFA)

The confirmatory factor analysis (CFA) used predefined groupings, and the resulting factor loadings are shown in Table 5.2. Loadings below 0.6 are highlighted in bold. The various types of destination place attachment were measured using the same items. Item 1 for the place attachment factors shows loadings greater than one. This is not ideal, as it makes interpretation of the values more difficult. However, in this specific use case, it is not considered problematic. First, since the CFA is used to verify the relationship between the items and the latent factors, a loading greater than one still indicates a valid relationship. The values are only slightly above one, which is likely the result of multicollinearity. FPA1, HPA1, and PPA1 have variance inflation factors (VIF) of 2,2; 3,0; and 3,6, respectively. These VIF scores indicate only mild multicollinearity, but it is sufficient to explain the small increase above one.

Item 4 corresponding to NPA4, FPA4, HPA4, and PPA4 only loads highly for NPA. This item assesses whether individuals feel integrated into the destination location. A possible explanation for the low loadings is that the individuals tend to participate less in neighbourhood activities at their evacuation destination compared to their own neighbourhood, which may reduce their sense of integration.

Since all other items load highly on their expected factors, Item 4 is excluded from the exploratory factor analysis (EFA) for FPA, HPA, and PPA. For evacuation intention, Item EI5 shows a low factor loading and is therefore also excluded from the EFA. Items EI1 through EI4, which demonstrate higher loadings, were derived from Qing et al. (2022). EI5, on the other hand, is an additional item not based on Qing et al. (2022), which may explain its lower loading. In general, the CFA shows that the items belong to the predefined latent factor.

Destination Related Factors								
Place Attachment						**Self-Efficacy**		
Item	1	2	3	4	5	1	2	3
Neighbourhood	0.86	0.81	0.88	0.88	0.86	–	–	–
Hotel	1.05	0.99	0.96	**0.15**	0.9	0.74	0.77	–
Family/Friends	1.03	0.85	0.91	**0.23**	0.97	0.74	0.75	–
Public Shelter	1.06	0.97	0.97	**0.16**	0.97	0.75	0.78	–
Evacuation Intention								
Items	EI1	EI2	EI3	EI4	EI5	EI6		
Loading	0.89	0.98	0.91	0.88	**0.52**	0.97		
Environment Related Factors								
Likelihood Hurricane			**Likelihood Storm Surge**		**Environmental Cues**			
Items	L1	L2	LS1	LS2	ECB1	ECB2	ECB3	
Loading	0.77	0.81	0.79	0.81	0.9	0.76	0.8	
Risk Assessment								
Items	RA1	RA2	RA3	RA4	RA5	RA6		
Loading	0.92	1.01	0.89	0.97	0.81	0.83		
Social Cues								
Items	SC1	SC2						
Loading	0.8	0.8						

Table 5.2: Factor loadings for place attachment, self-efficacy, and other constructs. Values below 0.6 are shown in bold.

5.2. Explorative Factor Analysis (EFA)

The Kaiser-Meyer-Olkin (KMO) test returned a value of 0,907, and Bartlett's Test of Sphericity yielded a p-value smaller than 0,001. These results, combined with the findings from the CFA, confirm the suitability of the data for exploratory factor analysis (EFA). Based on the Kaiser criterion, the optimal number of factors is determined to be ten, as illustrated in Figure 5.1. While the expected number of factors for the CFA was thirteen, the EFA has merged some of these into broader factors.

To assess whether the ten factors adequately represent all items, the communalities were examined. As shown in Figure 5.2, all items have communalities greater than 0.5, except for FPA2, which will therefore be excluded from further analysis. With an explained variance of 0.65, the factors are considered to be reliable and appropriate for further use.

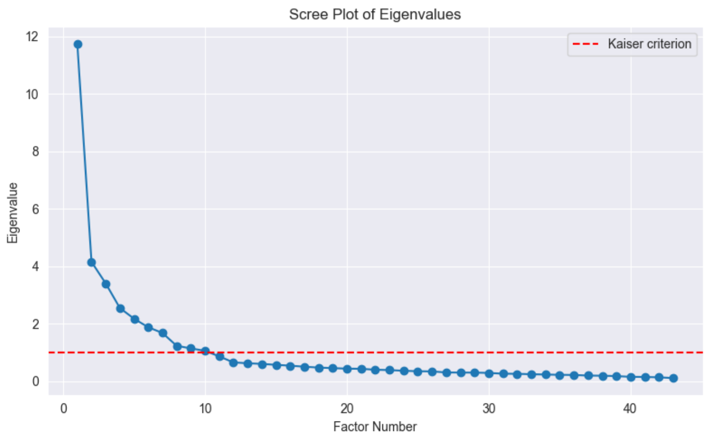

Figure 5.1: Scree plot based on eigenvalues showing when adding extra factors does not add significant explained variance

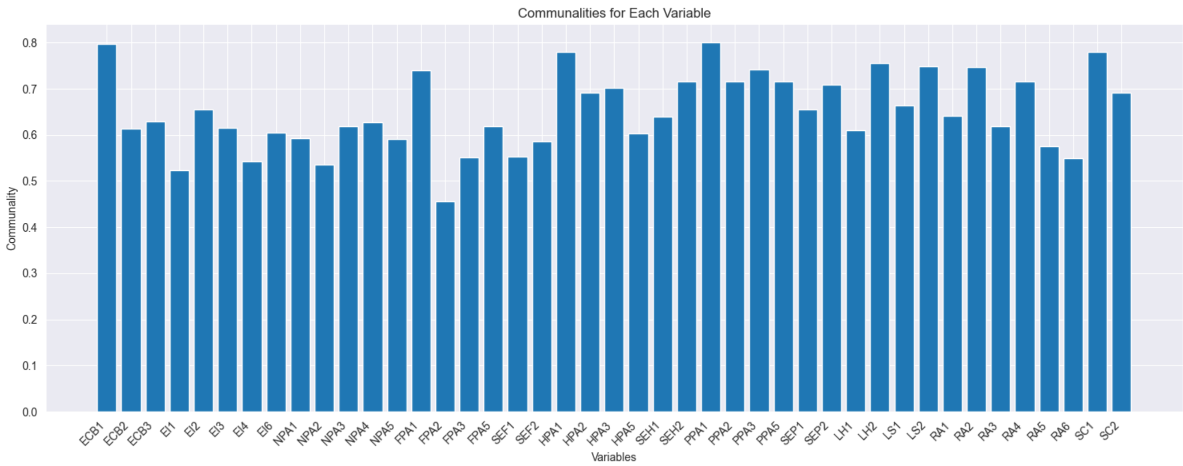

Figure 5.2: Communalities for all the variables

The majority of the factors align with those identified in the CFA. Table 5.3 presents the item loadings for each factor. As expected, the following constructs are clearly represented: social cues, environmental cues, neighbourhood place attachment, family/friends place attachment, hotel place attachment, public shelter place attachment, evacuation intention, and risk assessment.

However, there are some deviations from the initial expectations. The likelihood factor includes items measuring both the perceived likelihood of the hurricane itself and the associated storm surges. The self-efficacy factor includes all destination-specific items, suggesting that participants do not perceive their self-efficacy differently depending on the evacuation destination.

While such a distinction was expected, the loadings of the social cue items (SC1 measuring the influence of acquaintances and SC2 the influence of people in the immediate vicinity) indicate that no clear differentiation is made between these types of social influence. Overall, the strong alignment with CFA expectations and the absence of fragmented factors or significant cross-loadings support the conclusion that the selected items are appropriate and valid for measuring the intended constructs.

Destination Related Factors						
Family/Friends Place Attachment						
Items	FPA1	FPA3	FPA5			
Loading	0.76	0.58	0.70			
Public Shelter Place Attachment						
Items	PPA1	PPA2	PPA3	PPA5		
Loading	0.80	0.79	0.69	0.76		
Hotel Place Attachment						
Items	HPA1	HPA2	HPA3	HPA5		
Loading	0.73	0.67	0.68	0.66		
Neighbourhood Place Attachment						
Items	NPA1	NPA2	NPA3	NPA4	NPA5	
Loading	0.68	0.63	0.71	0.72	0.72	
Self-Efficacy						
Items	SEF1	SEF2	SEH1	SEH2	SEP1	SEP2
Loading	0.63	0.67	0.76	0.79	0.78	0.78
Cue related Factors						
Social Cues						
Items	SC1	SC2				
Loading	0.73	0.64				
Environmental Cues						
Itmes	ECB1	ECB2	ECB3			
Loadings	0.83	0.60	0.71			
Intention and Perception Related Factors						
Likelihood Threat						
Itme	LH1	LH2	LS1	LS2		
Loading	0.74	079	0.73	0.75		
Evacuation Intention						
Items	EI1	EI2	EI3	EI4	EI6	
Loading	0.60	0.77	0.76	0.68	0.67	
Risk Assessment						
Items	RA1	RA2	RA3	RA4	RA5	RA6
Loading	0.79	0.86	0.77	0.83	0.70	0.71

Table 5.3: Factor Loadings for every item grouped per factor

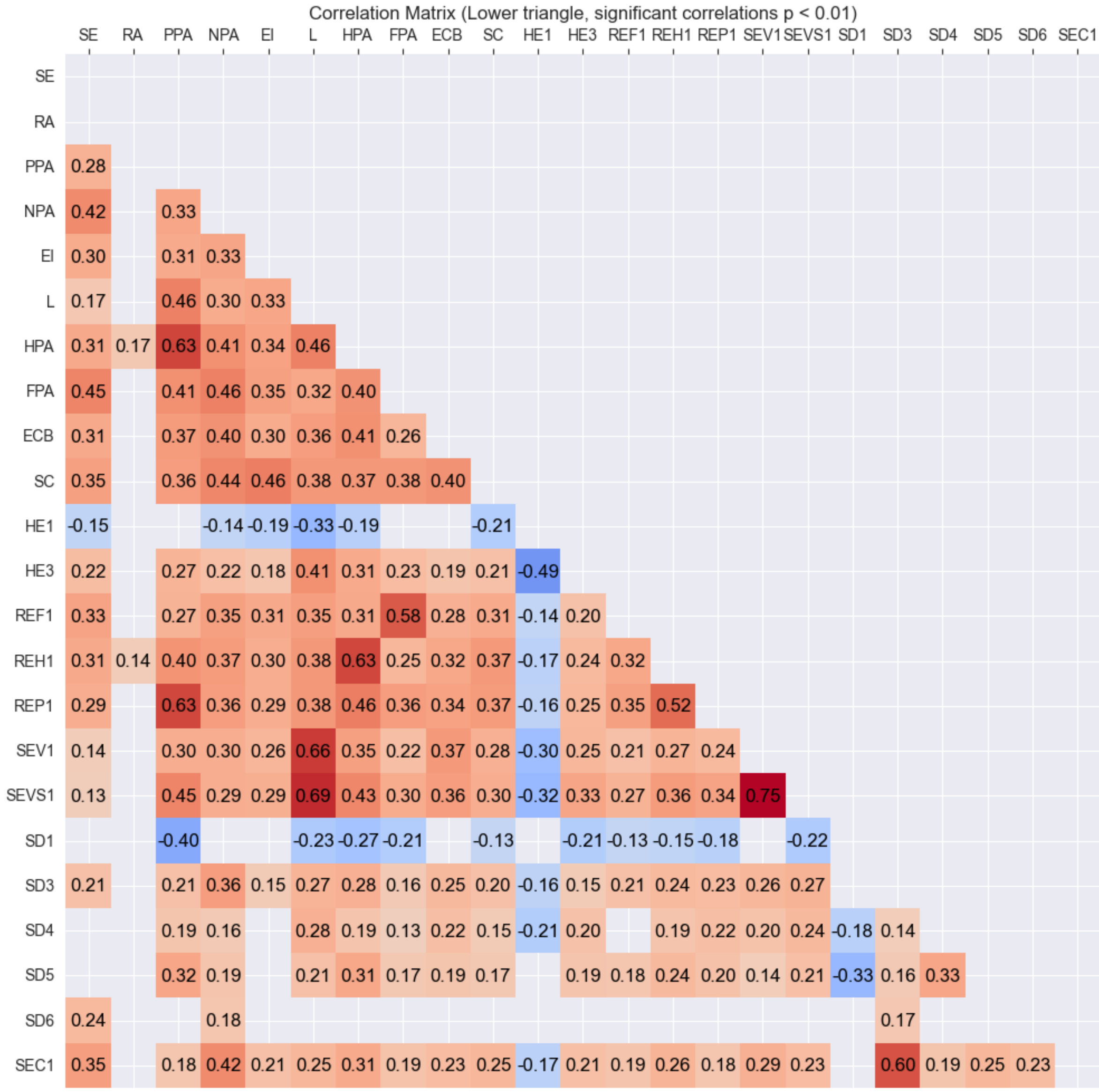

Figure 5.3: Correlation matrix of study variables. Abbreviations: SE = Self-Efficacy; RA = Risk assessment; PPA = Public shelter Place attachment; NPA = Neighbourhood Place Attachment; EI = Evacuation Intention; L = likelihood threat; HPA = Hotel Place Attachment; FPA = Family Place Attachment; ECB = Environmental Cues; SC = Social Clues; HE1 = Hurricane Experience; HE3 = Unnecessary Hurricane evacuation; REF/REH/REP = Response Efficacy (Family/Friends, Hotel, Shelter); SEV: Severity Hurricane; SEVS = Severity Surge; SD1 = Age; SD3 = Education; SD4 = Pet Ownership; SD5 = Household size; SD6 = Car ownership; SEC1 = Income;

5.3. Correlation analysis evacuation intention

Using weighted sum scores with a cut-off value of 0,5, factor scores were calculated, as shown in Table 5.3. These scores were then combined with survey variables that were not part of any latent factor to create a dataset representing all relevant variables for evacuation intention. The correlation matrix for all factors is presented in Table 5.3, showing only statistically significant correlations ($p < 0{,}01$). It is notable that most variables are correlated with each other. However, this is not indicative of multicollinearity. The highest variance inflation factor (VIF) is 3,18 for SEVS1, with an average VIF of 1,8 across all variables, both of which fall within acceptable thresholds. SD2, representing race and ethnicity, was excluded from the matrix because it did not have any significant correlations. Including its dummy variables (White non-Hispanic, Black/African, White Hispanic, and Other) would have significantly reduced the readability of the table.

As anticipated from the literature review in Section 2.1, all variables, except for the socio-demographic variables SD1, SD2, SD4, SD5, and SD6, show significant correlations with evacuation intention. The correlations for FPA, HPA, and PPA are 0,29, 0,32, and 0,31 respectively. These are moderate but meaningful relationships, suggesting that stronger place attachment to a destination is associated with a higher intention to evacuate.

Additionally, it is notable that the place attachment variables are correlated with each other. This suggests that individuals who feel a strong attachment to one destination type are also likely to feel attached to others. This is particularly evident between public shelters and hotels, which show a correlation of 0,64. While most correlations are positive, SD1, representing age, is the only variable with consistently negative correlations. Age is negatively correlated with the place attachment variables, likelihood, and severity, particularly with public shelter place attachment. This suggests that older individuals feel less attachment to public shelters and perceive the threat as less likely or severe. Counter-intuitive, is that both Hurricane Experience (HE1) and Unnecessary Hurricane experience (HE3) have a positive relation with evacuation intention. It would be expected that HE3 would have negative relation since unnecessary evacuating make people hesitant to evacuate again another hurricane. This is, however, not the case and also seen in another study of Huang et al. (2017). Lastly, Risk Assessment (RA) is only significantly correlated with HPA. This isolated correlation is difficult to explain, and the absence of other correlations involving RA is also unexpected.

5.4. Logistic regression for Destination choice

The role of place attachment and evacuation behaviour is inherently location-bound. Therefore, four logistic regression models were trained and evaluated, each corresponding to one of the four evacuation destination locations: staying with family or friends, evacuating to a hotel, evacuating to a public shelter, or staying at home. The models were trained using variables that showed a significant correlation with each specific destination choice. Table 5.4 presents the correlation coefficients and their significance for each destination type.

The stay option shows the highest number of significant correlations. This is not surprising, as individuals identified as stayers tend to score higher on EI6, which asks about the intention to *not* evacuate, compared to EI5, which asks about the willingness to evacuate. As shown in Figure 5.3, evacuation intention correlates with nearly all variables. Therefore, it is logical that the "stay" decision also correlates with many of them. Variables SD1 and SD2, which represent age and education respectively, do not influence the decision to stay.

Regarding the destination choices, the destination-specific variables (FPA, HPA, PPA, REF, REH, and REP) are significantly associated with their corresponding destination options. The variables specific to family and friends are negatively correlated with the hotel destination choice. This suggests that individuals who feel a stronger attachment to family or friends tend to view hotels less favourably. However, no similar relationship is observed for the public shelter choice. Neighbourhood place attachment does not appear to influence the choice of any specific evacuation destination.

Self-efficacy is positively related to the decision to evacuate to family or friends. However, this relationship should be interpreted with caution, as the self-efficacy variable used here is a composite of destination-specific self-efficacy items, as described in Section 5.2. Additionally, unexplained relationships were observed between storm surge severity, perceived threat likelihood, social cues, and the decision to evacuate to a hotel.

Table 5.4: Variables used in logistic regression models. Correlation coefficients with significance levels using the p-value indicated as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Variable	Stay	Family/friends	Hotel	Public shelter
REF1	**-0.2***	**0.23***	**-0.11***	0.08
FPA	**-0.24***	**0.29***	**-0.14***	0.01
REH1	**-0.13**	-0.07	**0.21***	-0.00
HPA	**-0.19***	-0.08	**0.24***	0.06
REP1	**-0.14**	-0.01	0.04	**0.17***
PPA	**-0.19***	-0.00	0.07	**0.19***
NPA	**-0.13**	0.01	0.05	0.08
SE	**-0.12***	**0.10***	-0.02	0.00
HE1	**-0.11***	0.01	-0.06	0.03
HE3	**-0.12***	0.02	0.07	0.02
SEV1	**-0.16**	0.04	0.06	0.06
SEVS1	**-0.22***	0.05	**0.09***	0.06
L	**-0.21***	0.06	**0.10***	0.04
RA	**0.17**	-0.09	0.01	-0.09
ECB	**-0.12***	0.01	0.04	0.08
SC	**-0.22***	0.04	**0.10***	0.07
EI	**-0.51***	**0.24***	**0.17***	0.00

Only 24 samples were obtained from respondents who preferred evacuating to public shelters. This number is too small to reliably train and evaluate a logistic regression model. Therefore, public shelter choice is not included. While including only the previously discussed variables as predictors would be the most logical approach, all available variables were used for model training. Including all variables, resulted in better performance metrics then only considering the significant variables. The reasoning is that non-significant variables can still hold predictive power. The multinomial logistic regression model was trained on 438 samples. The test dataset consisted of 20 true samples per class.

The logistic models demonstrated weak performance. The model achieved an accuracy of 0.573, indicating that approximately 57,3% of the predictions on the test set were correct. Additionally, the precision, recall, and F1 score were all 0.573, reflecting mild inconsistent and mildly unbalanced performance across all evaluation metrics. It does, however predict significantly better then randomly guessing.

The confusion matrix provides extra insight in how the model makes mistakes and is given in Table 5.5. Each row represents the actual class, while each column represents the predicted class. The diagonal elements (10.98, 10.6,12.79) indicate the average number of correct classifications for each class. Misclassification, represented by the off-diagonal elements, were present. The family/friends choice were predicted correct 10.98 times. 9.02 true samples for the family/friends choice were wrongly predicted for the hotel or stay choice. The hotel choice was mostly confused as a family/friends choice with an average 6.39 wrongly predictions. Lastly, the stay option was the most accurately predicted choice with 12.79 correct samples.

Table 5.5: Confusion Matrix

Actual / Predicted	Family/friends	Hotel	Stay
Family/friends	10.98	5.03	3.99
Hotel	6.39	10.6	3.01
Stay	4.2	3.01	12.79

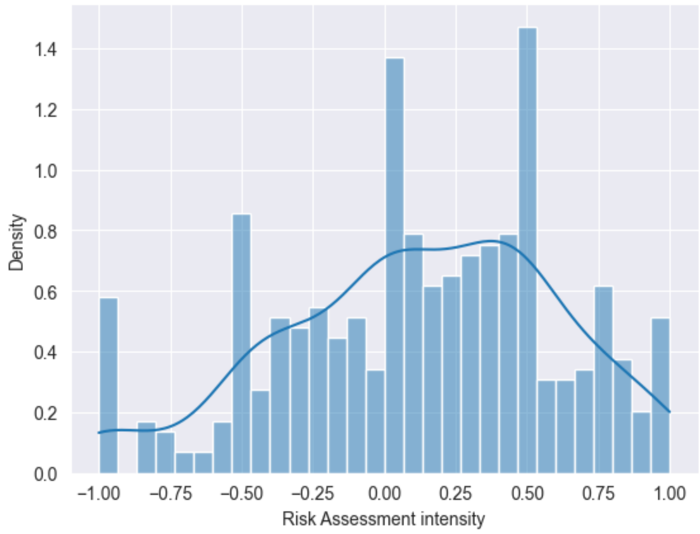

Figure 5.4: Histogram for of the factor scores for risk assessment

5.5. Results for Agent-based model

The survey results are used both to define the Agent-Based Model (ABM) and to provide its input values. This section explains which survey results are utilized for the ABM.

Risk assessment

The risk assessment threshold determines when individuals transition from the risk assessment phase to the protective action decision-making phase. This threshold comprises three components: a base value, an adjustment value, and an adjustment strength value. The base value is used to calibrate the model; the adjustment value is derived from the survey using the factor scores for risk assessment; and the adjustment strength value specifies the extent to which the survey results influence the threshold. Equation 8 defines the final threshold.

$$\text{threshold} = \text{Base Value} + \text{adjustment value} * \text{adjustment strength value} \tag{8}$$

The distribution of the adjustment value, which represents risk assessment, is shown in Figure 5.4. It is important to note that a scaler was applied to set the minimum and maximum values to -1 and 1, respectively. The distribution leans towards the positive side, which, for the agent-based model, means that most agents will have a positive value and, consequently, a higher threshold.

Social Network

The study by Ahmed et al. (2020) indicates that individuals communicate with an average of 4,5 people about the hurricane. In contrast, Yang et al. (2019) developed a model testing network sizes ranging from one to eight people. To ensure realistic representation of social networks, survey question SN:*"With how many friends or family members will you stay in constant contact before the hurricane hits?"* was included. Based on the survey results, individuals reach out to an average of 6.4 people, which falls between the values reported by Ahmed et al. (2020) and Yang et al. (2019). It is important to note that this value has a relatively large standard deviation of 3,4.

Efficacy

Self-efficacy is action-specific. To account for this, the survey included self-efficacy questions, coded SEF, SEH, and SEP, targeted at specific evacuation actions. Factor analysis showed that these questions load onto the same factor, indicating that the type of destination is not significant when considering self-efficacy.

Environmental cues

Individuals will base their risk perception on wind and rain cues. The factor analysis shows that a single latent factor for environmental cues can be used for both wind and rain questions (ECB1, ECB2, ECB3). For the ABM, this means that the weights used to determine the effect of these cues on perception can be combined into a single weight for both wind and rain cues. This is a advantage, as it reduces the number of uncertain variables in the model.

Social cues

Individuals can be influenced through two types of human interactions: by acquaintances or by neighbours in their surroundings. The questions SC1 and SC2 measure both types of interactions. Factor analysis shows that these questions load onto the same factor, indicating that they can be used together to predict the influence of both types of human interactions. This reduces the number of required factors in the model.

Media Cues

Five different media sources can be used to gather information about the hurricane: television, radio, internet, newspapers, and social media. For each of these five options, questions MD1 to MD10 assess how frequently the medium is consulted and how much trust is placed in it. Based on frequency, the number of times per day an individual is influenced is determined. Trust, in turn, determines the strength of that influence when it occurs.

Figure 5.5 presents the results of the survey. The results indicate that the majority of respondents frequently consult all media channels except newspapers. Television and the internet are especially popular. The results regarding media trust show less consistent patterns. Most respondents place a high level of trust in television. A small group of respondents report having little or no trust in newspapers and social media.

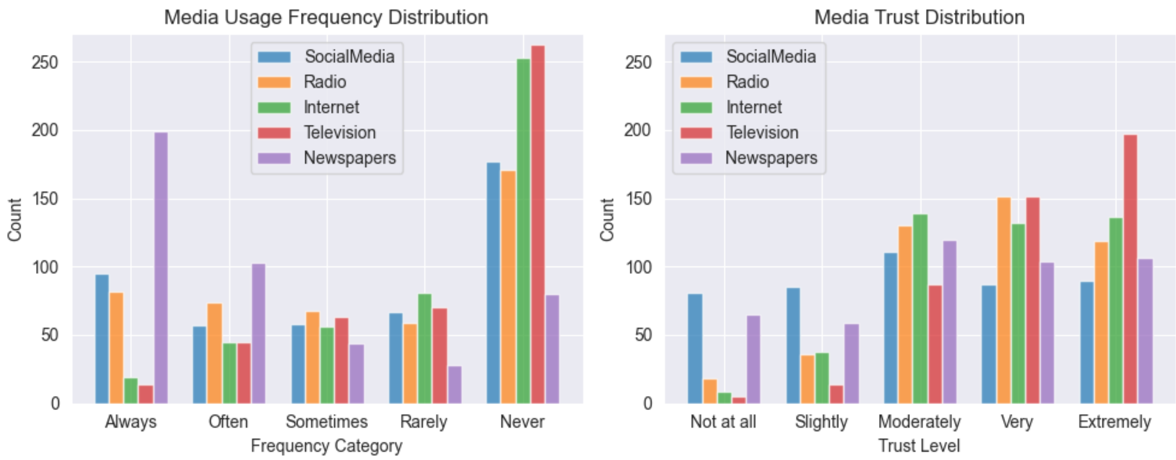

Figure 5.5: Frequency and trust in the media channels: Television, Radio, Internet, Newspaper, social media.

5.6. Conclusion of Survey results

This chapter provided additional insights to address the first sub-question: "*Which psychosocial and environmental factors are required for modelling evacuation behaviour in a hurricane scenario?*" Chapter 2 identified nine relevant psychosocial and environmental factors influencing evacuation decision-making. Analysis of the correlations between these nine factors and evacuation intention revealed that eight are significantly associated with evacuation intention, further confirming their importance for modelling evacuation behaviour. Only the social-demographics showed no significant relations with evacuation intention.

It also addressed the sub-question introduced in Chapter 2: *"How does destination place attachment relate to evacuation intention?"* When examining evacuation destination choices, destination-specific response efficacy, place attachment, and general self-efficacy were found to be relevant. The influence of destination-specific place attachment on destination choice, along with its significant correlation with evacuation intention, shows a clear relationship between destination place attachment and evacuation intention.

6

Simulation results

6.1. Base case: replication of Storm Irma

The base case show the model behaviour using the standard values as shown in Table 4.4 and 4.5, which are used to initialize the model. The purpose of the base case is too replicate the behaviour of the individuals of Miami-Dade county during Hurricane Irma as closely as possible.

6.1.1. Evacuation decision making

Figure 6.1 presents a histogram of evacuation decision timings. The lower axis displays the model steps where each step representing two hours, while the upper axis shows dates corresponding to the actual Storm Irma event, with. During the first 15 steps, no evacuations occur. Thereafter, the number of evacuation decisions gradually increases over time until step 48, after which it starts to increase faster. At step 55, when both the hurricane watch and storm surge watch are issued, a noticeable group of evacuees makes their decision. A similar spike appears at step 60, after which the number of decisions decreases until step 79. At step 79, there is a small increase, followed by a tapering off until step 90, which is twelve hours before landfall. This small increase can be explained when looking at the environmental cues values shown in the later Figure 6.4. Here it is visible that the rain cue drastically increases which results in a few individuals leaving both the risk assessment and protective action assessment phase through due a increased risk perception.

The average evacuation time is 56.4 steps, corresponding to September 7th at 16:00. Notably, the majority of individuals made their decision before the formal evacuation warning was issued, and no one evacuated on the first day.

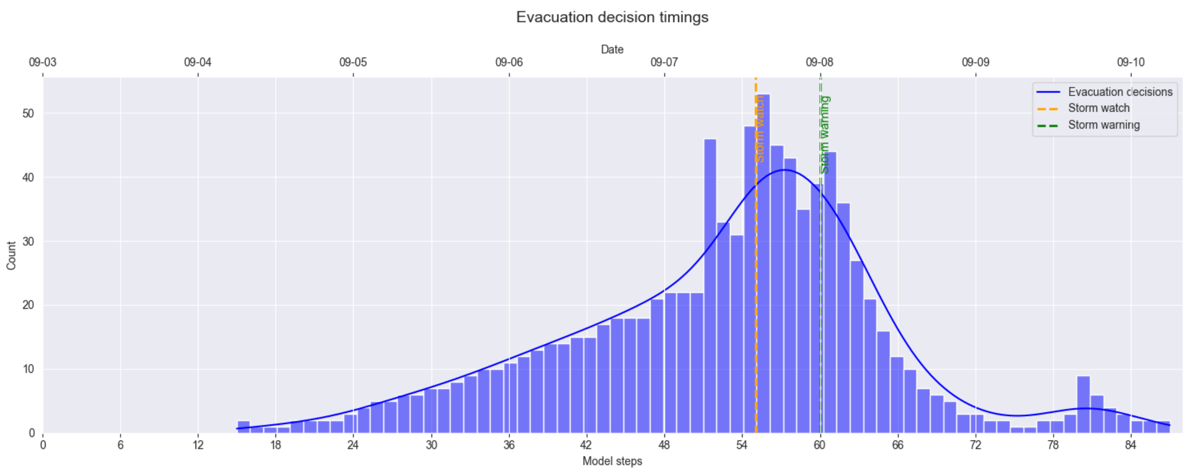

Figure 6.1: Simulated evacuation decision timings, with vertical lines marking storm watch, storm warning, and average decision time. Based on 150 model iterations.

6.1.2. Phase changes

Figure 6.2 illustrates how individuals progress through the decision-making phases before making their final evacuation decision. All individuals begin in the risk identification phase, with none leaving this phase until step 10. After this point, more than 80% move into the risk assessment phase. Upon entering this phase, around 30% also progress beyond risk assessment within a few steps. Another substantial drop in risk assessment occurs around step 24. Overall, the number of individuals in the risk assessment phase gradually decreases over time. The issuance of a hurricane watch has a limited effect on prompting transitions to the next phase, while the effect of the warning is somewhat larger, affecting about 10% of the individuals.

The first individuals enter the protective action assessment phase at step 12. From this point, individuals begin to make their evacuation decisions, with the number of decisions gradually increasing until step 66, after which it starts to decrease. Notably, evacuation watches and warnings appear to have little effect on decision-making. By step 84, a small percentage of individuals remain in the risk assessment phase. This group may be characterized as indecisive or hesitant to take action.

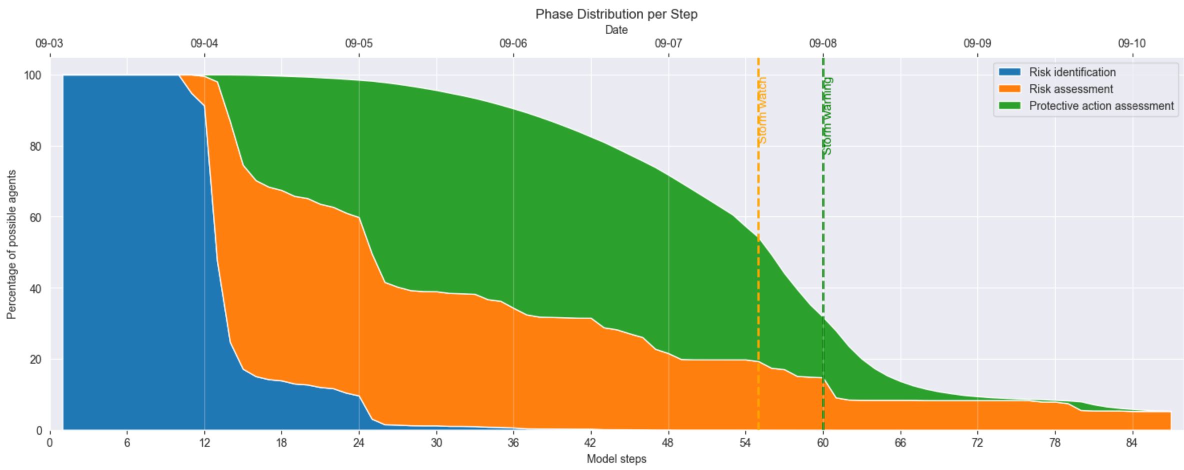

Figure 6.2: Plots the percentage of agents in each decision phase over time. The"hurricane watch" and "hurricane warning" events, are marked using a yellow and green line. The graph includes a second x-axis with dates. Based on 150 model iterations.

Figure **??** shows the number of individuals per phase over time and includes the 95% confidence interval. It should be noted that the confidence intervals are calculated over the 150 model runs, not over the agents of a single run. The number of agents in the risk identification deviates only a little around step 20. So, no significant difference are expected for risk identification. For the risk assessment and protective action phase the deviation are relevant throughout the model but not large enough to expect special model interaction which do not show every run.

6.1.3. Cue and variable evaluation

The evacuation decision and phase transitions are influenced by social, media, and environmental cues, as well as individuals' perceptions of these cues and their propensity to act. Figure 6.4 presents the behaviour of these values over time, including the watches and warnings for both hurricanes and storm surges.

The rain cue peaks three times, around time steps 11, 24, and 47, reaching values of approximately 0.5, which indicates moderate to heavy rainfall. At step 78, it rises sharply to about 0.9, indicating intense to torrential rainfall. Risk perception tends to increase when the rain cue peaks. The wind cue starts increasing from 0.2 at step 20, reaching a value of 1, where 0.2 signifies gale-force winds and 1 indicates hurricane-force winds. The media cue increases steadily from step 0. After step 24, its growth rate slows until all agents receive the maximum media cue of 1 by step 60. Media cues have a substantial impact on risk perception, which displays a similar, though more moderate, growth pattern.

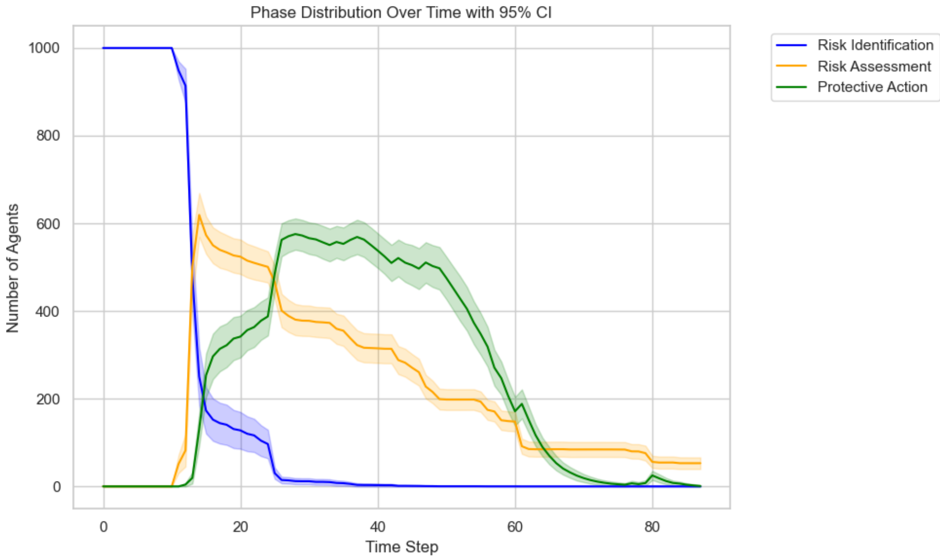

Figure 6.3: The number of individuals per phase over time, including the 95% confidence interval.

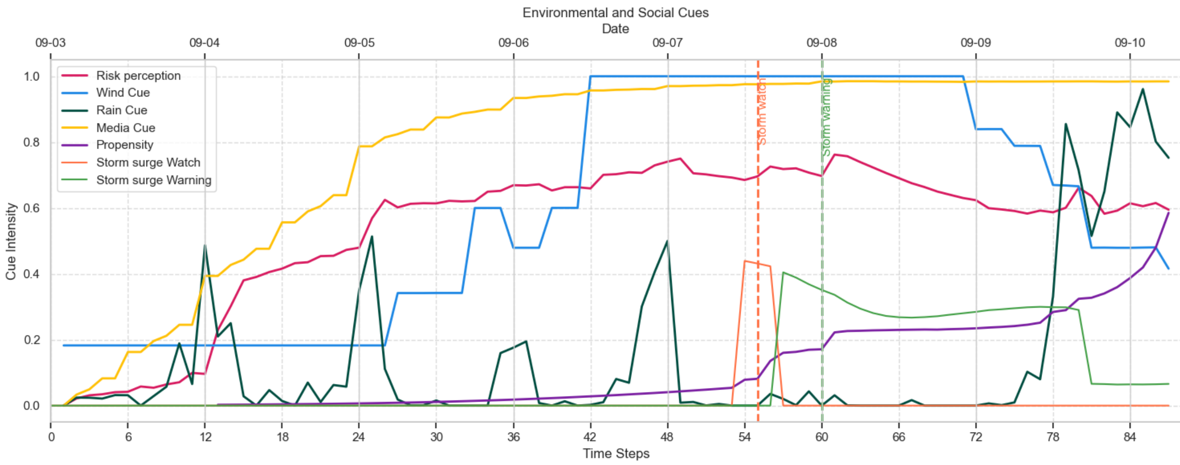

Figure 6.4: The evolution of environmental,social and media cues over time combined with risk perception and propensity. Additionally the watch and warning timing is added for both the hurricane and storm surge. Based on 150 model iterations.

Risk perception is shaped by environmental, media, and social cues. It grows gradually until step 12, where it increases sharply due to strong rain and media cues. As shown in Figure 6.2, many individuals transition between phases at this point and share this information with acquaintances, further increasing risk perception. A similar trend occurs at step 24, when individuals move from risk assessment to protective action assessment. After step 24, risk perception continues to rise slowly, mirroring the gradual phase transition observed in Figure 6.2. The issuance of watches and warnings results in an increase in risk perception, prompting movements into the protective action phase. A small surge in risk perception is also seen around step 80, corresponding to increased rainfall, which motivates a final group of individuals to take action as seen in Figures 6.2 and 6.1.

Propensity remains relatively flat until step 55, then increases sharply as a result of the storm watch and warning. It levels off between steps 60 and 78 before rising steeply until step 96. This increase in propensity is reflected in Figure 6.2 by the steep decline in the number of individuals in the protective action assessment phase after the watch and warning have been issued.

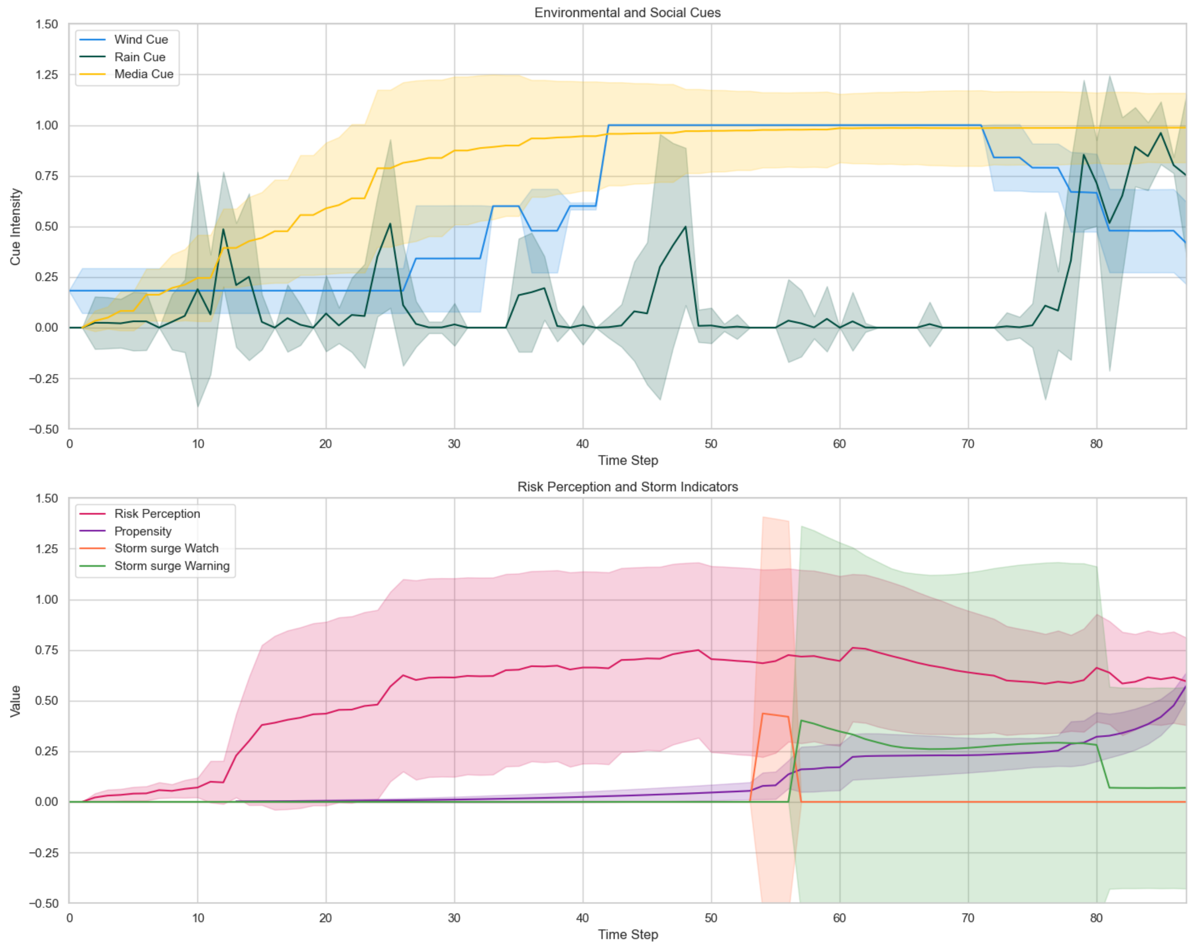

Figure 6.5: The evolution of the 95% confidence interval for the environmental,social and media cues over time combined with risk perception and propensity. Based on 150 model iterations.

To facilitate easier interpretation, Figure 6.4 does not include the 95% confidence intervals, but Figure 6.5 does. It should be noted that the confidence intervals are calculated over the 150 model runs, not over the agents of a single run. The top graph shows the wind, rain, and media cues. For the wind cue, the deviations are moderate, indicating that the experienced wind does not differ significantly between runs. The rain cue shows larger deviations around its peaks while remaining constant everywhere else. These deviations arise because the spatial distribution varies per run, and some runs have more individuals influenced by these peaks. The confidence interval for the media cue increases from step 0 to step 30, then decreases before stabilizing around step 50. This variation can be explained by the randomly assigned media frequency and trust values. Since these values are based on survey data, this shows that using real data impacts the internal model values of the individuals.

The lower graphs show the deviations for risk perception, propensity, and storm surge watch and warning. The confidence interval for risk perception starts small but increases significantly at step 10. This drastic increase corresponds to the rise in both rain and media cues at that step. The variability in these cues propagates and reinforces each other in the risk perception values. After step 10, the confidence interval remains relatively stable until step 60, when it decreases. Propensity deviations remain small, as the largest proportion of the value stays constant throughout the model. The storm surge watch and warning cues show large deviations at the time steps when they are implemented. These warnings are applied only to individuals living in the coastal tract areas, and the number of these individuals varies between runs. This variation explains the observed deviations.

6.1.4. Protective action choices

Figure 6.6 presents the chosen actions in the model compared to the results of the survey. It should be noted that the survey results have been scaled to enable comparison. The Hotel and Shelter choices mostly align. However, the Family and Stay choices do not. This discrepancy can be explained by the use of the multinomial logistic model and the peer influences modelled in the ABM. As shown in Chapter 5, the logistic model is not highly accurate and can partly account for the differences. Peer influence can also lead to deviations from the survey results or amplify inaccuracies introduced by the logistic model.

Excluding the indecisive agents, the Stay option already occurs more frequently in the model than in the survey. Including the indecisive agents increases this difference. Indecisive agents are those who never progressed through all the decision-making phases and thus never actively made an evacuation decision. Because they do not make an active decision, they remain at home. This complicates comparison with the survey, which only asks respondents what they would do if they had to actively make a decision. Since the logistic model is entirely based on the survey data, it does not account for indecisive agents either. This represents a potential source of discrepancy between the model and the survey. It does, however, provide valuable insight that the majority of individuals staying home make this decision actively.

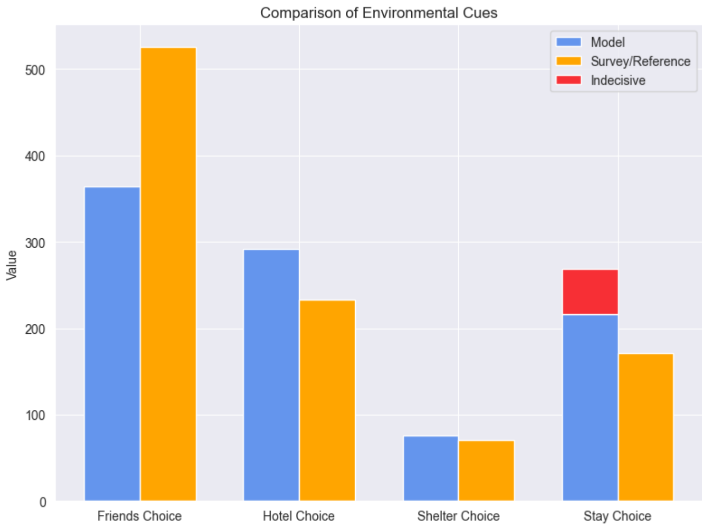

Figure 6.6: Comparison of modelled and surveyed protective action choices. The stay option has an added red bar which indicate the agents who were indecisive and thus also stayed at home. Based on 150 model iterations.

6.2. Scenario comparison

6.2.1. Evacuation decision making

In section 4.7, several scenarios were designed, the results of which are discussed here. Figure 6.7 shows the timing of evacuation decisions over time. All scenarios exhibit similar trends: from step 18 to 54, fewer people make decisions, while after step 54, there is a noticeable peak in the number of decisions made across all scenarios. For the base scenario, as well as the scenarios with low action tendency (AT), media distrust (MD), low phase communication (PC), and low risk assessment (RA), the average decision-making times are 53.08, 59.11, 60.26, 60.06, and 60.81 steps, respectively.

While the scenarios all influence different elements of the model, the evacuation decision timings all show the same change compared to the base case. The gradual increase between steps 6 and 48 is smaller than in the base case. After step 48, it drastically increases, leading to bigger peaks. That the scenarios all show the same trend can be explained by the fact that in the scenarios, most individuals had not yet passed the risk assessment phase, leaving more individuals to be influenced by the evacuation watch or warning than in the base case. So, in the base case, individuals leave earlier between steps 6 and 48 without the push of the warning. In the scenarios, these individuals remain in the risk assessment phase until step 60, where the warning helps them out of the risk assessment phase.

Around step 80, another small peak can be seen, especially for MD, PC and RA scenarios. This peak is the result of an increase of the rain cue, see Figure 6.4. This increases risk perception which leads to more decisions being made. The higher values for the MD, PC and RA scenarios can be explained by the fact that these scenarios still have the most individuals left over who did not make a decision yet.

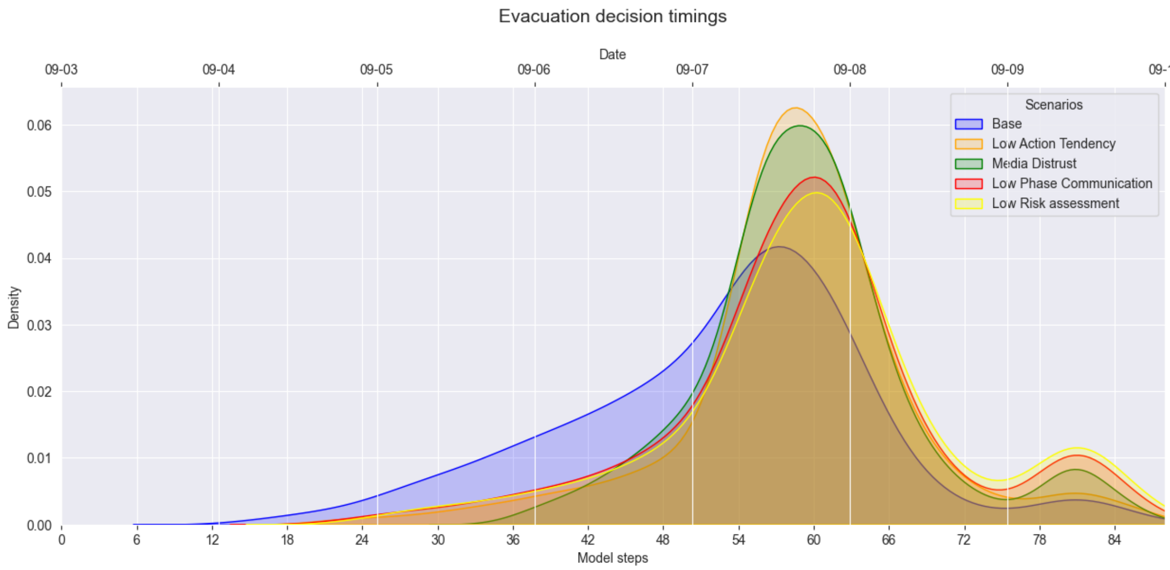

Figure 6.7: Simulated evacuation decision timings for the five different scenarios. Based on 150 model iterations.

6.2.2. Phase changes

That the internal states of the individuals differs becomes clear when examining there phase changes . Figure 6.8 displays three graphs, each illustrating the number of individuals in each phase for every scenario. For the risk identification phase, it is notable that both the PC and MD scenarios keep individuals in the risk identification phase for a longer period. The phase change scenario reduces social influence among acquaintances, indicating that if people communicate less, the risk of a hurricane is recognized later. The media scenario demonstrates that individuals are more dependent on media cues to identify the hurricane threat. The other scenarios do not significantly influence the progression through the risk identification phase. In addition to the PC and MD scenarios, the RA scenario begins to diverge from the base case during the risk assessment phase. In this scenario, individuals who enter the risk assessment phase around step 12 do not progress until step 25; after that, individuals gradually leave the phase. At step 60, when the evacuation warning is issued, a large group progresses, but compared to the other scenarios, many agents remain in the phase and do not progress further. This can be explained by the higher threshold value in the RA scenario, which means some individuals' risk perception never reaches a sufficient height. In the PC scenario, individuals enter the risk assessment phase earlier compared to the MD scenario. However, over time, the number of individuals in this phase converges in both scenarios, and after the evacuation warning at step 60, the numbers become nearly equal. This can be explained by the cumulative loss of risk perception becoming similar across these scenarios as time progresses.

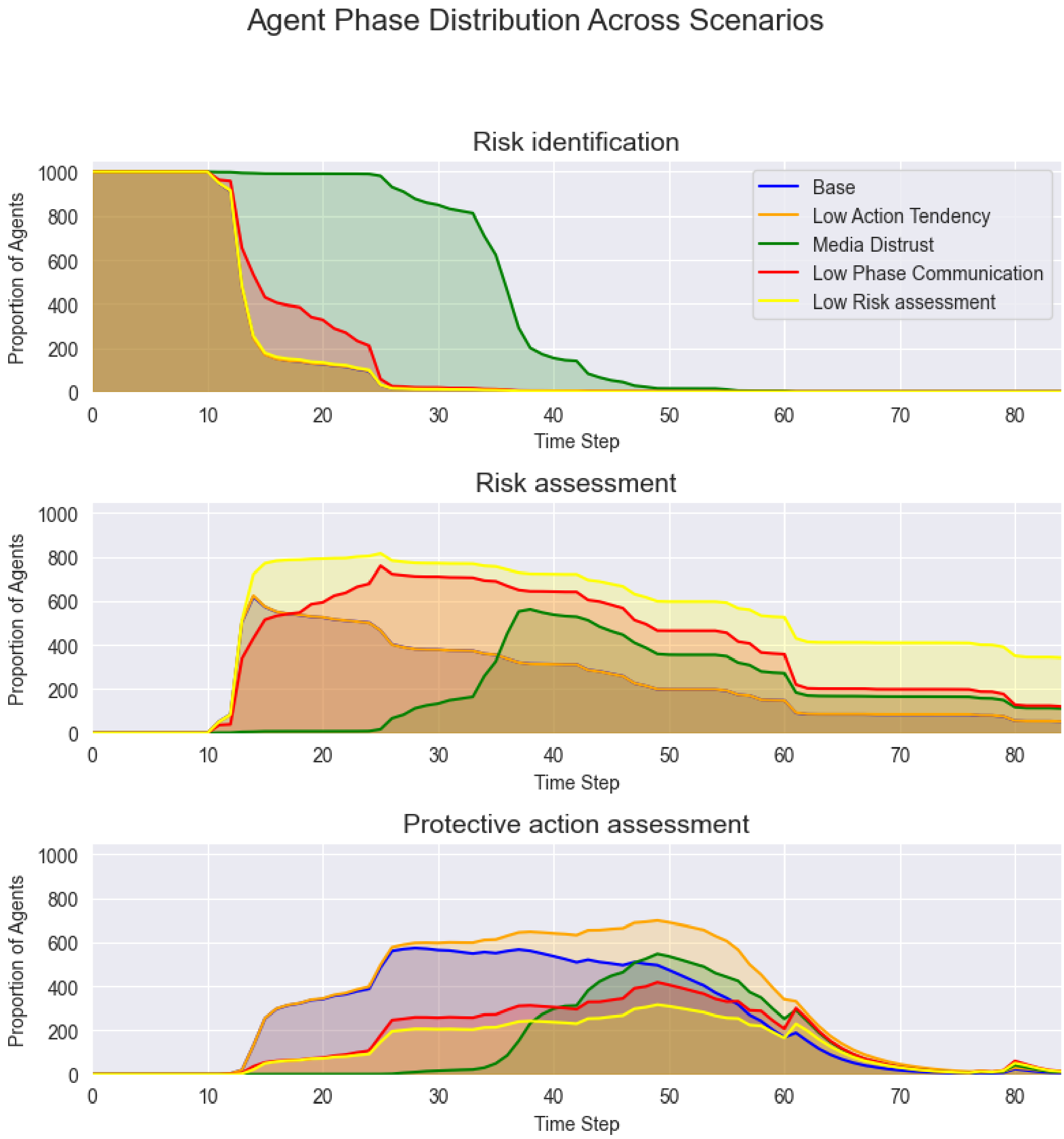

Figure 6.8: Every subplot shows the number of individuals in that phase over time for each scenario. Based on 150 model iterations.

The protective action assessment phase exhibits different behaviours across all scenarios. Since risk perception becomes irrelevant in this phase and the focus shifts to propensity, it is logical that the PC and RA scenarios display exactly the same behaviour. The only difference is that the RA scenario has less people progression trough to this phase then PC. The MD scenario has individuals join the phase later, but the propensity value of the individuals is similar of the MD and PC values and grows exponentially resulting in effect. The Action Tendency (AT) scenario starts to deviate here from the base scenario. Since the propensity grows slower and the maximum value is lower, the individuals leave slower at the beginning. However, at step 55 the values exponential growth becomes to big that the growth factor itself becomes irrelevant. After step 60 the he individuals make their decision at similar rates.

6.2.3. Indecisive agents

Individuals who never leave the Risk assessment phase, show in Figure 6.8 will never make an active decision to evacuate and thus stay home. Figure 6.9 shows the average number of indecisive individuals and agents actively deciding to stay per scenario. The RA scenario has the most indecisive individuals. The changes in the PC and MA scenarios lead to the same decrease of risk perception resulting in similar amount of indecisive agents. The AT scenario does not influence the risk perception which explains the same number of indecisive agents as the base case.

Considering the agents actively choosing to stay, the difference becomes small between the Base and AT scenarios, as well as the MD and PC scenarios, since the proportion of people actively deciding to stay is larger. RA is still significantly higher when combining active and indecisive stayers. In the RA scenario, there are more indecisive than actively staying individuals. This is because indecisive individuals would normally choose to stay but do not reach that point in this scenario.

Figure 6.9: Number of average indecisive agents per scenario and agent actively deciding to stay. Based on 150 model iterations.

Figure 6.10 shows how the number of individuals actively choosing to stay builds up over time. The base case agents begin increasing earlier than those in the other scenarios, as also seen in Figure 6.7. The RA scenario has the lowest number of actively staying individuals. This is because, in this scenario, the majority of individuals are indecisive, see Figure 6.9. The AT, MD, and PC scenarios show a similar build-up of stayers until around step 62, after which notable differences emerge. As with the RA scenario, these differences can be explained by the number of indecisive individuals in each scenario. Notably, around step 77, there is a final increase in the number of staying agents. This can be attributed to a final rise in the rain cue, as shown in Figure 6.4. The lines includes there 95% confidence intervals, which are small indicating that no bug difference exists between model runs.

For the policy testing the RA and MD scenarios will be included. They both result in the most deviating behaviour from the base case making it valuable to see how the watch/warning timing and shifting influence the different behaviours. Additionally, RA scenario has a large number of indecisive agents making it easier to see if the policies will also reduce this high number of indecisive agents.

6.3. Effectiveness of evacuation watch/warnings

The effectiveness of different watch and warning strategies is examined using the experimental designs shown in Table 4.11. Table 6.1 displays the average evacuation decision timing (Evac Dec), the spread of these timings over time (Spread), and the number of indecisive individuals (No Dec). Delaying the evacuation watch and warning by 12 hours, indicated by n6, results in worse average decision timings compared to the base case across all scenarios. The general trend observed is that both issuing watches and warnings earlier and increasing the interval between them lead to improvements in average decision timing.

The spread metric generally improves when the time between the watch and the warning is increased, especially in the LRP scenario. An exception to this is Bn6_0; this intervention combination results in a high spread and a higher evacuation decision timing than the base case. Only advancing the issuance of watch and warning, without

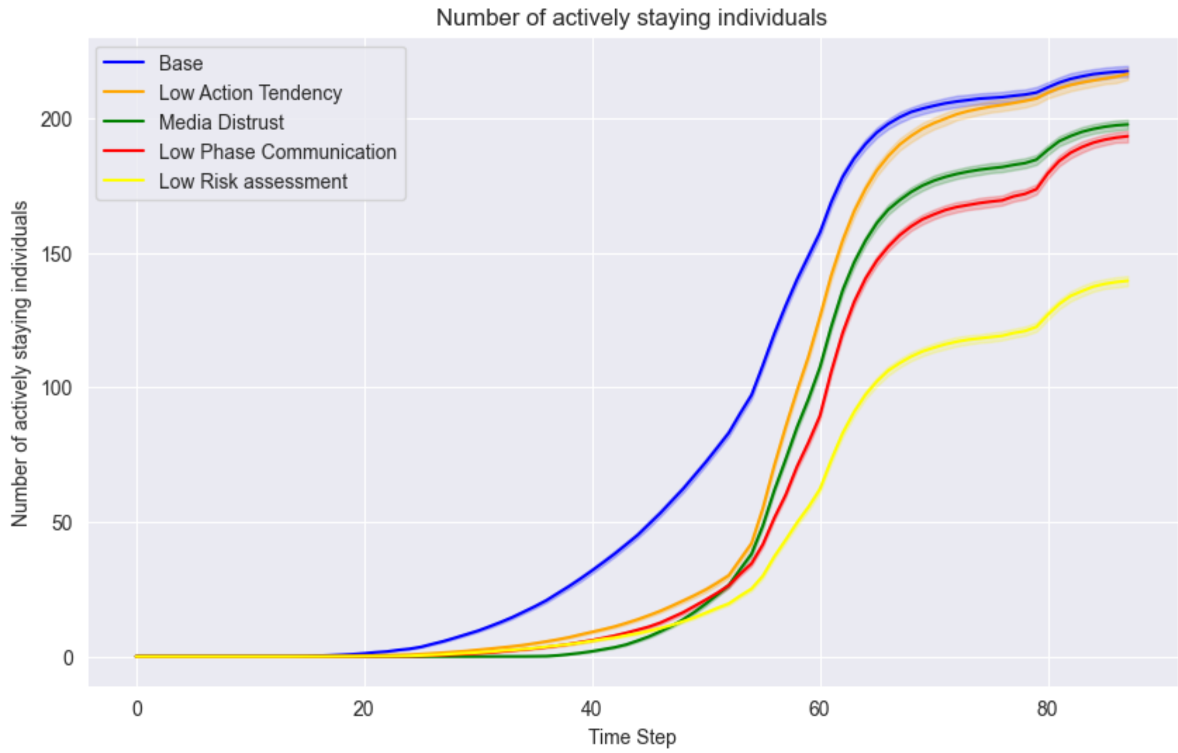

Figure 6.10: Number of actively staying individuals over time per scenario. Based on 150 model iterations.

increasing the gap between them, results in smaller spreads in the BP and MDP scenarios. This decrease is not observed for the LRP scenario.

The number of indecisive individuals is not significantly impacted by these interventions. Comparing the base case and the most optimal intervention for reducing the indecisive individuals metric, the largest differences for the BP, LRP, and MDP scenarios are 6,72, 14.19, and 5,19, respectively. This is less than two percent of the simulated population, making changes due to policy interventions negligible in this regard.

Appendix E provides a scaled version of Table 6.1 and evaluation scores based on average evacuation decision timings and the spread metric. The interventions P12_24 and P24_24 (shown in bold in Table 6.1) are the first and second most effective for all three scenarios. The third most effective intervention for the base case is P24_12, while for scenarios LRP and MDP, the P0_24 intervention ranks third.

To better understand the effectiveness of the identified interventions, the kernel density estimates shown in Figure 6.11 are analysed. The P24_24 intervention displays slightly different behaviours across scenarios. In BP24_24, there is a peak at step twenty and a smaller one at step forty. In contrast, MDP24_24 and LRP24_24 exhibit the reverse pattern: a smaller peak appears first, followed by a larger one. This difference can be explained by how risk perception develops over time. In the MDP scenario, individuals tend to have a lower risk perception at step twenty, while the threshold to leave the risk assessment phase is higher for LRP. Consequently, the gap that needs to be closed between current risk perception and the threshold is bigger in MDP and LRP than in the base case. As a result, issuing the watch has a lesser effect, and more individuals in MDP and LRP remain in the risk assessment phase when the warning is issued, leading to a larger second peak.

The P12_24 intervention shows similar behaviour to P24_24. The main difference is that, generally, the curves shift twelve steps to the right, and the distinction between the first and second peaks is less pronounced. For the base case, BP24_12 produces a first peak similar to BP12_24, but the second peak occurs earlier. Since the first and second peaks are closer together, the spread of evacuation decision timings is reduced, making it a less effective intervention.

The P0_24 intervention is particularly favourable for the MDP and LRP scenarios. For MDP0_24, there is a very large peak at step 40, driven by the effect of the watch. Later, at step 60, the peak resulting from the

Model Metrics Across Scenarios									
	B			**LR**			**MD**		
Index	Evac Dec	Spread	In Dec	Evac Dec	Spread	In Dec	Evac Dec	Spread	In Dec
P0_0	53.69	16.0	54.59	60.77	11.0	342.21	60.44	9.0	112.47
Pn6_0	55.43	20.0	53.42	63.92	14.0	344.27	63.54	12.0	112.51
P12_0	47.08	8.0	50.16	51.16	8.0	337.33	51.25	7.0	111.73
P24_0	38.77	9.0	48.18	42.74	11.0	331.29	42.72	8.0	108.33
P0_12	49.64	11.0	51.82	56.15	16.0	345.60	55.13	14.0	111.04
Pn6_12	53.02	15.0	52.95	61.02	19.0	345.48	59.80	17.0	112.21
P12_12	41.84	14.0	50.69	47.52	15.0	340.58	47.39	13.0	111.40
P24_12	**33.46**	**14.0**	**48.46**	39.79	16.0	332.02	40.12	12.0	107.32
P0_24	43.40	14.0	53.66	**51.32**	**24.0**	**344.31**	**50.09**	**18.0**	**113.15**
Pn6_24	47.02	12.0	54.07	54.73	25.0	346.63	53.13	16.0	113.27
P12_24	**35.12**	**18.0**	**51.05**	**43.54**	**22.0**	**337.88**	**43.30**	**19.0**	**112.02**
P24_24	**29.50**	**20.0**	**47.87**	**37.88**	**19.0**	**332.24**	**35.05**	**20.0**	**107.61**

Table 6.1: Comparison of Evacuation Time (Evac Dec), Decision Spread, and Number of Indecisive Agents (In Dec) across BP, LRP, and MDP models. Bold rows highlight key scenarios.

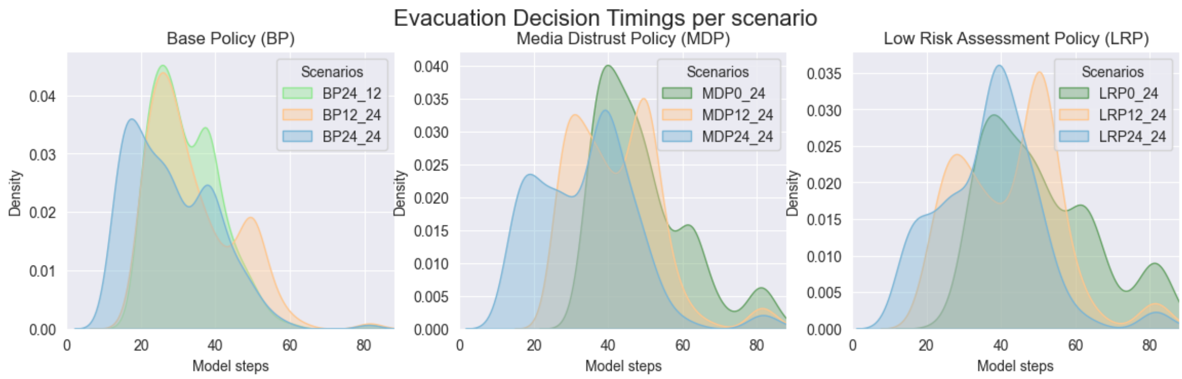

Figure 6.11: Distribution of evacuation decision timings for three policy scenarios: BP, MDP, and LRP. Each curve shows how evacuation decisions are spread across model steps for variants of each policy. Based on 150 model iterations.

warning is much smaller. This occurs because, at step 40, many individuals' risk perception is close to the threshold for leaving the risk assessment phase, and the watch pushes them over this threshold. The subsequent phase communication further increases risk perception, so by the time the warning is issued, fewer people remain to respond, resulting in a much smaller peak. In the case of LRP0_24, the first peak is smaller compared to MDP0_24, which can be explained by a larger gap between average risk perception and the threshold value prior to the watch's issuance. Both MDP0_24 and LRP0_24 result in a higher average evacuation decision time, as the evacuation warning is still issued at the original step, meaning individuals have less time between the warning and the action.

Examining the effect of policy interventions on the decision-making phases, as shown in Figure 6.12, reveals that these interventions do not significantly alter behavioural patterns. Figure 6.12 illustrates the transitions through the decision-making phases. In the MD scenario, for example, interventions advance the timing of phase transitions but do not fundamentally change the behaviour itself. Another notable observation is that the outcomes of different policy interventions often overlap. For the BP scenario, the risk identification and risk assessment phases for BP12_24 and BP24_12 are identical until around step 35; after this point, BP24_12 diverges from BP12_24 and aligns with BP24_24. Across all scenarios and interventions, the number of individuals in the risk assessment phase converges after step 60. Similarly, after step 60, very few agents enter or leave the protective action assessment phase. Therefore, differences in evacuation decision timings are attributable to the timing of the watch/warning rather than to changes in the underlying phase transition patterns.

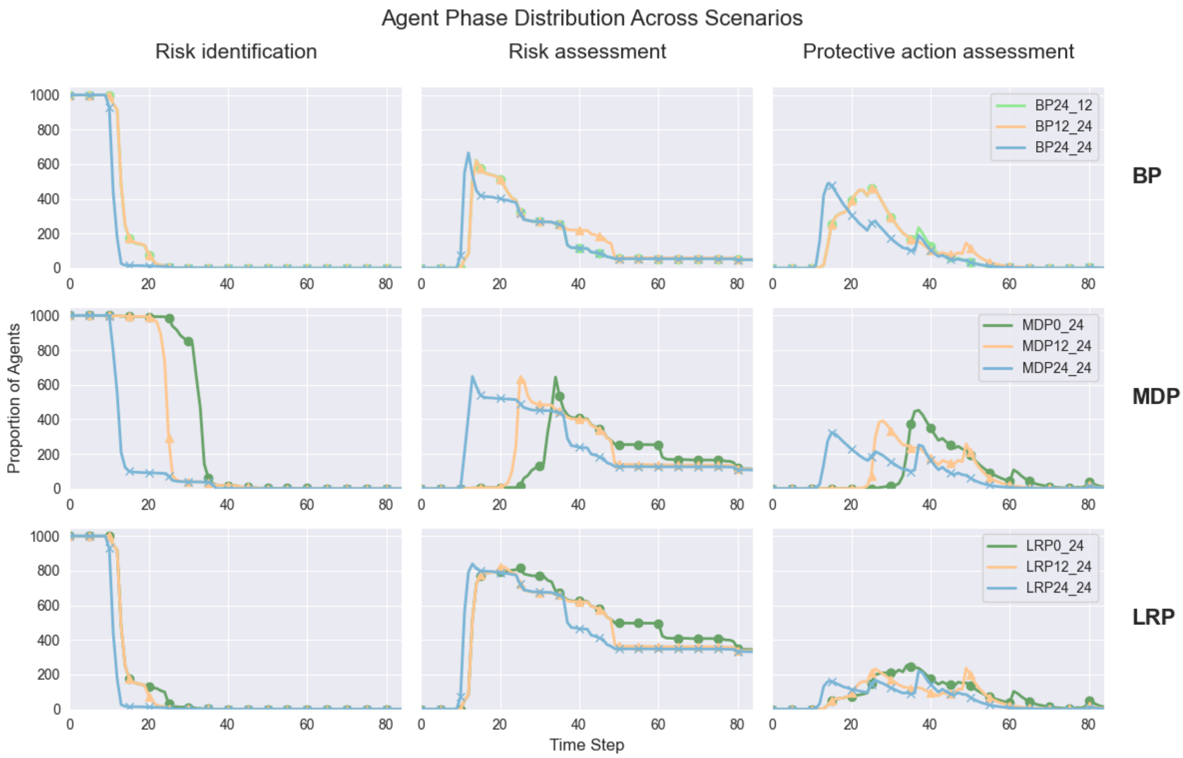

Figure 6.12: Time series of agent distributions across decision-making phases for the three optimal policy intervention divided per scenario. Each subplot shows the average number of agents in a phase over time. The BP24_12 differs from the other scenarios and is therefore indicated with a lighter green. Based on 150 model iterations.

It is logical that different interventions do not fundamentally change behavioural patterns, since these interventions only have a static effect on risk perception. When looking at cumulative risk perception, the timing of the additional risk perception and community effects, when combined at step 60, makes little difference for the majority of individuals. However, it does affect the propensity to make a decision, as the base propensity increases exponentially over time. Thus, in the early steps, interventions have a smaller effect; this is evident in the protective action assessment graphs in Figure 6.8, where the decline is slower at earlier steps and accelerates later. The effect of action communication on propensity, however, remains consistent throughout the simulation. Therefore, if individuals leave earlier, this can drastically increase the propensity of acquaintances to do the same, thereby raising the probability of leaving the protective action assessment phase in the early steps.

6.4. Conclusion of ABM results

Chapter 4 provided a conceptualized, formalized, verified, and validated model demonstrating how psychosocial and environmental factors can be integrated into an ABM. This chapter further addresses the sub-question: ”*How can these psychosocial and environmental factors be integrated into an Agent-Based Model?*” It showed that the ABM is suitable for explaining the influence of different scenarios on agent behaviour. For example, the media trust scenario demonstrated that a decrease in media influence delays agents' departure from the risk identification phase, while the low risk assessment scenario kept agents in the risk assessment phase for a longer period. These scenarios confirmed that the ABM is effective in modelling various possibilities, reinforcing that the identified psychosocial and environmental factors are appropriately integrated for simulating evacuation decision-making.

Section 6.3 answered the sub-question: ”*How do different timings of evacuation warning communication influence evacuation behaviour?”* by evaluating various combinations of advancing or delaying the watch and warning as well as changing the interval between them. Results showed that advancing both the watch and warning and maximizing the interval between them leads to the best average evacuation decision times and the highest spread of decisions made over time. The number of indecisive individuals, however, was not affected by these changes. Overall, these policy interventions did not fundamentally change behavioural patterns, but rather shifted when agents exhibited certain behaviours.

7 Discussion & Conclusion

The goal of this thesis is to explore how coastal communities can become more resilient to hurricanes and flooding, which are expected to become more frequent and intense due to climate change. Specifically, this thesis examined the relationship between psychosocial and environmental factors and evacuation behaviour, as well as how these factors interact with evacuation warnings, by addressing the following research question:

What is the effect of psychosocial factors, environmental factors and evacuation warning communication on evacuation decision making in the case of a hurricane?

It was found that response efficacy, self-efficacy, risk perception, social cues, environmental cues, evacuation experience, media usage, and place attachment all influence evacuation decision-making. Notably, in addition to neighbourhood place attachment, place attachment to the destination location was also found to enhance evacuation intentions.

By implementing the identified factors into an agent-based model (ABM) using the Protective Action Decision Model (PADM), the effects of different watch and warning strategies were tested. The results indicated that advancing the timing of the hurricane and storm surge watches and warnings, and increasing the time interval between them, led to lower average evacuation decision times and a more even distribution of evacuation decisions over time. Advancing the evacuation warnings, however, did not influence the behaviour of the agent itself drastically. It only made them show specific type of behaviour earlier.

Below, the sub-questions are addressed individually and discussed in relation to existing literature. This is followed by a reflection on the strengths and limitations of the thesis. Finally, the practical and theoretical implications of the findings are presented, along with suggestions for future research to build on this study's contributions.

7.1. Addressing the sub-questions

Which psychosocial factors and environmental factors are required for modelling evacuation behaviour in a hurricane scenario?

To answer the research question, a literature review was conducted to examine various factors influencing evacuation intention, followed by a survey analysis based on the identified factors. Drawing from studies that provide overviews of relevant factors as well as those focusing on specific aspects, nine key factors emerged as the most relevant: (1) Response efficacy; (2) Self-efficacy; (3) Risk perception; (4) Social cues; (5) Environmental cues; (6) Evacuation experience; (7) Socioeconomic status; (8) Socio-demographics; and (9) Place attachment. These factors are largely consistent with findings from previous literature reviews Huang et al. (2016), Van Valkengoed and Steg (2019), and Wang et al. (2021), although some studies also indicate the relevance of additional factors.

Regarding the factor of place attachment, it is notable that most applications focus only on attachment to the home or neighbourhood. However, Ariccio et al. (2020) and Villagra et al. (2021) found a significant relationship between place attachment to evacuation destinations and evacuation intention. This aspect of place attachment will be further described in the next sub-question.

The survey analysis largely aligned with expectations based on the literature review. Eight of the nine identified factors were confirmed to influence evacuation intention. However, many socio-demographic variables were found to be insignificant, which is in line with the findings of Huang et al. (2016), who noted that socio-demographics have only marginal influence on evacuation intention. The finding that no significant differences in evacuation intention exist between ethnic groups contrasts with Whitehead et al. (2000).

In the case of environmental cues, the exploratory factor analysis revealed that the perceived likelihood of hurricanes and storm surges can be combined in a general likelihood factor. This differs from Huang et al. (2017), who found a basis to differentiate between meteorological cues (e.g., wind) and hydrological threats.

How does destination place attachment relate to evacuation intention?

Applying confirmatory factor analysis to the items measuring place attachment toward friends/family, hotels, and public shelters showed that the majority of included items measured the expected latent factors. However, Item 4, measured by the statement ”I do not feel integrated in the location [destination specific]”, did not load together with the other items related to destination place attachment. This aligns with the findings of Ariccio et al. (2020), who developed the items and also found that this particular item was not a significant indicator of home place attachment. Similarly, results from the exploratory factor analysis showed that Item 2, measured by the statement ”The home of my family/friends is part of me”, did not adequately describe the latent factor of family/friends place attachment.

Using the resulting factor scores, correlations were calculated with evacuation intention. The three destination place attachment factors for the family/friends, hotel and public shelter destination were found to be positively and significantly correlated with evacuation intention. This is consistent with the findings of Ariccio et al. (2020), Bonaiuto et al. (2016), and Villagra et al. (2021), who reported positive relationships between home, neighbourhood, and evacuation site place attachment and evacuation intention. However, it should be noted that the association with evacuation sites in these studies was based on tsunami threats, which have different characteristics than hurricanes, making direct comparison difficult.

In addition to examining the relationship between place attachment and evacuation intention, the influence of destination-specific place attachment on the corresponding destination choices was also analysed. Place attachment to specific destinations was found to correlate with the likelihood of selecting those destinations. The same applies to response efficacy.

These differences in place attachment and preferences for different locations can be explained by the person, process, and place components of place attachment, as described by Scannell and Gifford (2010). These components highlight that attachment can stem from different sources. For example, an individual might feel strong place attachment to a family member’s home due to positive personal experiences, while another may feel attached to a public shelter because such shelters are often located in community buildings that symbolize safety.

The relationship between destination choice and place attachment in evacuation contexts aligns with findings in tourism research, where individuals develop attachment to vacation locations and choose to revisit them (Hosany et al., 2017; Prayag et al., 2013).

How can these psychosocial factors and environmental factors be integrated into an Agent-based model?

Psychosocial and environmental factors were integrated through a formalized version of PADM. PADM was compared to the Theory of Planned Behaviour (TPB) and Protective Motivation Theory (PMT). PADM was considered more suitable, as it had the greatest overlap with the nine identified factors and provided a temporal description of behaviour, in contrast to the more static nature of TPB and PMT.

The implementation of PADM phases was carried out by simplifying its three key components: the predecisional process, core perceptions, and protective action decision-making. The predecisional process described how individuals had to first be exposed to a cue, pay attention to it, and understand it before it could influence behaviour. However, no existing studies provided a sufficiently structured approach to modelling all three of these predecisional stages. As a result, it was assumed that exposure to a cue automatically resulted in influence. Haer et al. (2016) addressed this by introducing probabilities representing both the likelihood of exposure to information and the likelihood that the information influenced the individual; however, no data were available to implement this approach in this ABM.

The three core perceptions within PADM were threat perception, protective action perception, and stakeholder perception. Self-efficacy and response efficacy were used to represent protective action perception. While Huang et al. (2012, 2016) instead examined protective actions in terms of situational facilitators and impediments, the use of self-efficacy and response efficacy was still applicable . Threat perception was captured through the latent factor of risk perception, operationalized as threat intensity and threat likelihood.

Stakeholder perception, on the other hand, was more challenging to integrate into a model. The social component, particularly communication with neighbours, was modelled using social networks (Du et al., 2017). However, an effective approach for realistic modelling of evacuation coordinators remained unclear, even though conceptual modelling had already been developed (Wang et al., 2021). As highlighted by Wang et al. (2021), coordinators played a crucial role in the evacuation process identifying interesting direction for future work.

PADM defined eight distinct phases, which were reduced to five in order to be integrated into the ABM. The phases risk identification, risk assessment, and protective action search were conceptualized and formalized in line with the original theoretical framework. The protective action assessment and action implementation phases were combined, as the behaviours described in these two phases were closely intertwined and could be effectively modelled as sequential processes.

Similarly, information needs assessment, communication action assessment, and communication action implementation were also merged into a single phase. Together, these described how individuals sought information when their existing knowledge was insufficient to make informed decisions. They were combined due to the lack of sufficient empirical data to accurately model them as separate phases. Unlike the other, more linear stages, this combined phase was revisited at every time step within the model.

Compared to existing studies, this ABM was the first to incorporate the different PADM phases in a structured manner, moving away from static implementations commonly seen in statistical analyses Greer et al. (2023), Li et al. (2024), and Zhang and Borden (2024) or other ABM applications Hatzis et al. (2024), McEligot et al. (2019), and Yeates et al. (2023).

How do different timings of evacuation warning communication influence evacuation behaviour?

Different combinations of watches and warnings were tested by advancing their issuance and increasing the time interval between the watch and the warning. The results showed that issuing the watch and warning as early as possible, and maximizing the time between them, led to the lowest average evacuation decision time and the greatest spread of evacuation decisions over time. However, these timing changes did not result in fundamentally different behaviour among individuals; instead, individuals simply began to exhibit the same behaviours earlier or later, depending on the timing.

The study by Hasan et al. (2013) developed a random-parameter hazard-based model to examine evacuation departure timings. As the model was based on Hurricane Ivan (2004), the results could not be directly compared due to differences in spatial extent and evacuation management. Nevertheless, some similarities could be observed. First, Hasan et al. (2013) found that mandatory or voluntary evacuation notices led to earlier departures. Second, individuals who decided to evacuate later tended to mobilize more quickly. Although not identical, the model in this thesis revealed a related pattern: individuals who left the risk assessment phase later tended to spend less time in the protective action assessment phase. One key difference is that Hasan et al. (2013) identified relationships between socio-demographic characteristics and departure time. An aspect that was not examined in the this study.

Yin et al. (2014) developed an ABM using survey data based on a hypothetical hurricane scenario for Miami-Dade County. As the survey was conducted before Hurricane Irma, the evacuation timings could not be directly compared. However, the model showed a similar progression of evacuation decisions over time, with a slow initial increase followed by the largest surge in decisions occurring during the hurricane watch and warning period. This pattern is consistent with the findings of the ABM presented in this thesis. A notable strength of Yin et al. (2014) was the inclusion of travel behaviour, which enabled the simulation of potential traffic congestion. A limitation, however, was that the study only reported aggregated end results and did not explore behavioural dynamics over time. Additionally, it did not assess the impact of policy interventions. Beyond this, the study was based on a hypothetical hurricane scenario and did not incorporate realistic event data, limiting its applicability to real-world situations.

7.2. Strengths and limitation

During the execution of this thesis, several strengths and limitations were encountered, which should be considered when interpreting the results. These strengths and limitations were observed across the survey analysis, ABM development, and ABM application. The strengths are discussed first.

One key strength of the research was the use of a survey to gather data and insights on which the ABM could be grounded. Relevant information, such as social networks and media usage, could be directly implemented into the model. Additionally, knowledge about the perception of social and environmental cues enabled simplification of the model by combining related factors. For example, the perception of wind and rain cues or the influence of acquaintances and neighbours.

A second strength was the implementation of distinct decision-making phases instead of relying on a static set of behavioural rules. This approach offered more detailed insights into which cues influenced each phase of the decision-making process and how policy interventions affected individual behaviour. For instance, the influence of the media cue was most prominent in the the risk identification phase, while perceived severity and likelihood of the risk changes the duration of individuals in the risk assessment phase.

Another strength was that the ABM was grounded in empirical data from Hurricane Irma. This included spatial-temporal data on wind and storm surge watches/warnings from National Hurricane Center and Central Pacific Hurricane Center (2017b), rain data from Kelley (2022), hurricane warning data from Cangialosi et al. (2021), and residential location data from U.S. Census Bureau (2023a). The use of real-world environmental cue data significantly reduced uncertainty in the input, allowing uncertainty to be concentrated primarily on the behavioural side. This approach also provided an accurate representation of Hurricane Irma, offering a robust foundation for assessing how evacuation outcomes might have been improved.

Despite these strengths, the model also has limitations. The first limitation related to the survey. Although it explored various factors influencing hurricane evacuation behaviour, it did not provide respondents with contextual information about the scenario they were being asked to consider. To improve accuracy, future surveys should include a context description prior to each question. The study by Verma et al. (2022), for example, presents a strong approach by first providing respondents with an overview of available hurricane-related information. Furthermore, the use of hypothetical hurricane scenarios measures evacuation intention rather than actual behaviour. While Huang et al. (2016) suggested that such surveys are valid for predicting behaviour, post-event surveys typically yield more accurate results. Additionally, because the survey was distributed by a third-party company, the distribution process could not be verified, reducing confidence in the quality and representativeness of the data (Marsden & Pingry, 2018).

Limitations within the ABM were identified in the initialization process, the input data, and the experimental design. The synthetic population was initialized using bootstrapping. Since the survey included only 440 responses and the model required 1,000 agents, an additional 560 were generated through bootstrapping. This resulted in a largely duplicated population, which may reinforce the misrepresentation of the original survey data. Another limitation is the misrepresentation in the original survey. The survey failed to capture a sufficient number of respondents with lower educational attainment and/or Hispanic backgrounds, resulting in a skewed picture compared to the actual demographic composition of Miami-Dade County. Additionally, the spatial distribution of respondents is not representative of the county's population. The living locations were randomly assigned to the survey samples, leading to a spatial distribution that is not representative of Miami-Dade County. These issues of population duplication and spatial mismatch could be addressed by using population synthesis tools, such as the one proposed by Sonnenschein et al. (2024), which generates spatially explicit synthetic populations. The misrepresentation of the survey could be mitigated by better targeting low-educated and Hispanic populations, as well as by extending the survey data collection period.

Another limitation stemmed from the fact that although the ABM captured dynamic evacuation behaviour through multiple phases, it was based primarily on knowledge and data from static studies. As noted by both Verma et al. (2022) and the PADM framework itself (Lindell & Perry, 2012), behavioural factors such as risk perception and evacuation propensity evolve over time. However, the way these factors change temporally remains unclear. More empirical research is needed that goes beyond traditional survey methods to track behavioural evolution over time. Verma et al. (2022) suggested innovative methods for such longitudinal behavioural data collection. The current modelling of evacuation propensity relied on textual descriptions from Lindell and Perry (2012) and Morss, Prestley, et al. (2024), rather than empirical measurements. Given that propensity is a central driver of evacuation behaviour, understanding its development over time could substantially enhance both ABM performance and real-world decision-making strategies.

The ABM was also used to test various scenarios and policy interventions using different experimental designs. However, the parameter values used in these experiments were based primarily on the sensitivity analysis and the modeller's interpretation of the system. This so-called ”cherry-picking” of parameter values posed several risks. First, important model behaviours might remain hidden because the modeller's perspective could bias the parameter selection. Second, optimal intervention strategies might be overlooked because not all combinations were tested. Third, this approach risks reinforcing confirmation bias by selecting scenarios that align with the modeller's expectations. These issues could be mitigated using exploratory modelling tools such as the EMA Workbench (Kwakkel, 2017), which offers automated sampling techniques (e.g., Monte Carlo, Latin hypercube) and optimization algorithms like NSGA-II (Non-dominated Sorting Genetic Algorithm II). However, the current ABM's high computational cost prevented efficient use of such tools, presenting a major barrier to their implementation.

7.3. Theoretical relevance

The main scientific contribution of this study is the development of a novel approach to model agent behaviour across distinct decision-making phases. Whereas previous studies, such as McEligot et al. (2019), Yeates et al. (2023), and Hatzis et al. (2024), implemented PADM in a static manner without distinguishing between different phases of decision-making, this study introduces a dynamic, phase-based implementation. The inclusion of these phases provides critical insights into the sequence in which agents consider different variables, enabling a more nuanced understanding of how cues and policy interventions influence behaviour

Additionally, the phase-based structure enhances the explanatory power of the ABM by allowing researchers to target specific stages within the pre-travel decision-making process, thereby facilitating the development of more detailed and realistic behavioural models. Furthermore, the dynamic implementation of PADM provides potential to be defined as an Agent-block. Agent-blocks are generalized ABM components that can be applied across various research domains (Berger et al., 2024). An Agent-block of the presented PADM implementation would lower the barrier for future studies to transition from static implementations of PADM to a dynamic one. The implementation, however, is not done and can be seen as future work.

The departure timings generated by the model, can serve as inputs for other ABMs focused on the travel phase of evacuation. The integration of this pre-travel ABM with models that simulate the travel phase would significantly enhance the overall realism of evacuation modelling, a gap that, as noted by Wang et al. (2021), has yet to be fully addressed.

Besides highlighting the relevance of the ABM, the survey itself yielded valuable insights. The analysis reaffirmed the factors previously identified as relevant. It also found that destination place attachment, specifically towards family and friends, hotels, and public shelters, significantly influences evacuation intention. This builds upon the existing work of Ariccio et al. (2020) and Villagra et al. (2021), which examined shelter place attachment in the context of tsunamis. Lastly, the relevant predictors of evacuation intention proved insufficient for developing an accurate multinomial logistic model to predict destination choice. This provides guidance for other models by indicating which factors may not be necessary.

7.4. Policy relevance

For policymakers, the ABM is relevant in several ways. First, it can be used within a model-based decision-making context to evaluate the effectiveness of advancing hurricane watches and warnings. As demonstrated in Chapter 6, advancing the issuance of watches and warnings and increasing the time gap between them has a favourable impact on both the average evacuation decision time and the temporal spread of decisions. These findings could serve as a valuable foundation for adjusting warning strategies during future hurricanes. Second, the model offers deeper insight into the individual decision-making process, highlighting which factors are most influential at different stages. This allows policymakers to design and test targeted policy interventions based on specific behavioural drivers. For example, policies focused on information dissemination are effective during the risk identification phase by influencing media cues. In contrast, educational policies aimed at improving threat perception are more relevant to the risk assessment phase, as they influence individuals risk assessment.

Lastly, the model's outputs, specifically evacuation decision times and spread of these timings, can be used as inputs for existing travel demand models. For example, it could evaluate how different combinations of watch and warning timings affect evacuation times during the travel phase and reduce road congestion. This integration would enable more realistic simulations of travel behaviour and infrastructure use during evacuations, helping to assess the impact of various hurricane watch and warning strategies on travel demand and traffic flow.

7.5. Future research

Besides addressing the limitations of this thesis, future research could also build upon and extend it. As indicated by Wang et al. (2021), very few studies examine the entire evacuation process from the pre-travel phase through the travel phase to re-entry. Future work could integrate this ABM with a model simulating the travel and re-entry phase, thereby offering a more holistic perspective of the evacuation process. This would enable researchers to assess how pre-travel behaviours influence travel behaviours and congestion patterns during evacuation events and potentially re-entry.

Another point raised by Wang et al. (2021) concerns the essential interactions between emergency coordinators and evacuees. The current model does not account for any feedback mechanisms through which individuals can influence the behaviour of coordinators. Future extensions could include coordinators as independent agents, enabling the simulation of more complex and dynamic policy scenarios. This would enhance the model's capacity to test real-time coordination strategies and evaluate their effectiveness.

Evacuation decision-making behaviour also varies across regions (Huang et al., 2017). This variation raises important questions about how community-specific characteristics shape behavioural responses. Applying the ABM to different geographic regions and storm events would allow for comparative case studies. Such comparisons could reveal the underlying drivers of behavioural differences, thereby enhancing our understanding of region-specific evacuation patterns and enabling the design of more context-sensitive policies.

However, before the study of region-specific evacuation patterns becomes feasible, both the synthetic population and the multinomial logistic model must be improved. As indicated in Section 7.2, population duplication and spatial mismatches result in a non-representative population. Future work should replace the current approach to population synthesis with more effective methods, such as those described in (Sonnenschein et al., 2024). The currently used multinomial logistic model has an F1 score of 0.573, which is not accurate enough to capture region-specific differences. This model could be improved by collecting new data on additional relevant factors, optimizing parameter configurations, or increasing the number of survey responses for less common choices, such as evacuating to a public shelter. Furthermore, the existing survey includes data on responsibility attribution and evacuation destination distance, which could also be used to improve the multinomial logistic model.

Lastly, additional policy types could be incorporated into the model. For example, interventions aimed at improving the dispersion of information via media channels, or public awareness campaigns designed to enhance risk assessment, could be simulated. In addition to exploring new interventions, it is important to consider the trade-offs of advancing evacuation warnings. While earlier departures can reduce risk and improve decision timing, they also impose financial burdens on evacuees who must stay away longer, and they can worsen economic disruption by prolonging local shutdowns. Moreover, issuing premature evacuation warnings may lead to unnecessary evacuations, which could undermine public trust and reduce compliance in future hurricanes (Huang et al., 2016).

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A

Appendix A: Research approach

The thesis will investigate the role of environmental and psychological factors using PADM. To answer this question, a survey will be conducted, based on which an Agent-Based Model (ABM) will be developed. Figure A.1 outlines the steps necessary to address the main research question. The methods align with most of the steps presented in Dam et al. (2013). These steps are used because they break down the development of an ABM into manageable tasks, each with its own goal. In this way, all the relevant elements required to build an ABM will be addressed. Now the approach will be discussed following the division given on the right of Figure A.1, excluding the Introduction since that is already given.

A.1. Literature review

As indicated by Van Valkengoed and Steg (2019) and Huang et al. (2016), many factors are relevant when considering the decision to evacuate and where to evacuate to. With the time scope of thesis thesis, however, it is not feasible to examine all factors. Literature will be reviewed to find factors which are relevant for predicting the choice to evacuate or not. This process will be done while considering the following criteria: (1) Relevant specifically for evacuation decisions, (2) Possible to gather information using a survey for the factor. Besides the factors themselves, a better understanding of PADM must be developed in order to correctly place factors that are found to be relevant but not yet included into the appropriate phase of PADM.

A.2. Survey & Model creation

The literature review will result in a list of factors linked to a certain phase of PADM. This will form the foundation of the development of the survey and the ABM. The survey has to contain questions covering all the identified factors and questions focusing on the intention of individuals to evacuate. The creation of survey questions is challenging since it must be made sure that the question corresponds to only one factor, the question itself is not suggestive in any way, it is formulated in a way understandable manner. Based on the literature review done to identify factors also questions can be derived since most studies reporting on factors also include the corresponding survey setup. For the place attachment to evacuation sites questions will be adapted from the studies of Ariccio et al. (2020), Stancu et al. (2020), and Villagra et al. (2021). To ensure that the survey will capture the correct data, experts will be consulted.

Parallel to the survey development the conceptualization and formalization of the ABM can be done. During the conceptualization the relations of individuals and their behaviour, environment, media and government will be explained. The phases of PADM will form the foundation on which the conceptualization will be based. In addition, it will also be formulated how existing geographical and socio-demographic data will be integrated into the model. The United States census bureau provides data on citizens spatially distributed using the ZIP Code Tabulation Areas (ZCTA). For the ZIP Code Tabulation Areas.

In addition to modeling individuals, the hurricane risk must also be addressed. While modeling the hurricane and the corresponding flooding is appealing, as it offers the opportunity for extensive scenario analyses based on flood severity, it will not be pursued. Instead existing data will be used from **precipitation_processing_system_pps_version_2022** and National Weather Service Forecast Office (2025) to model a hurricane.This approach will be more time-

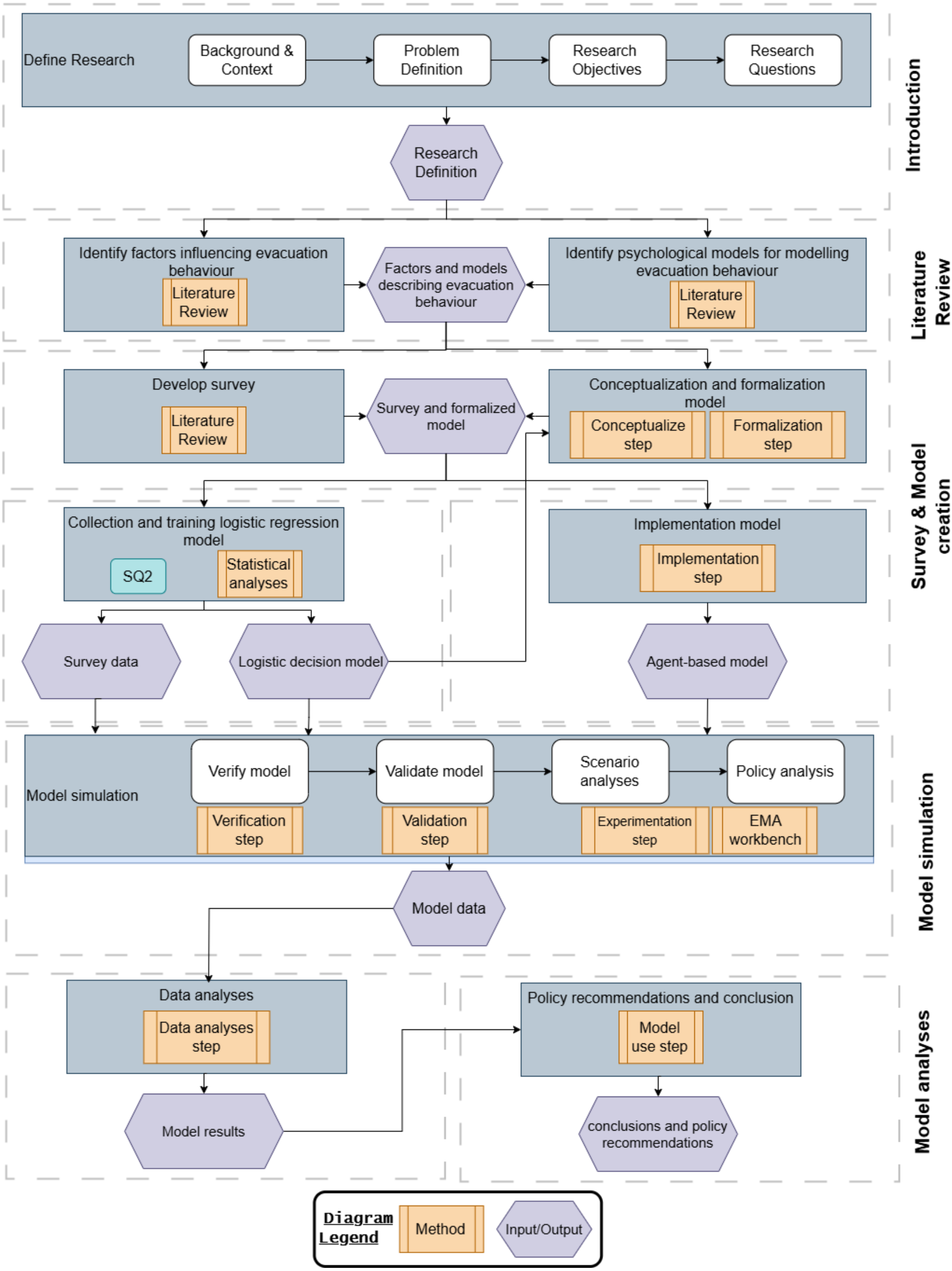


Figure A.1: Overview of approach

efficient and will allow the thesis to focus more on accurately modeling behavior rather than on modeling the storm.

The formulation will translate the conceptualization into something that can computationally modeled. There is a chance that the survey results will indicate that certain factors are not reliable enough to be included into the ABM. This creates the risk that the conceptualization and formalization needs to be changed to align with the survey results. This risk is deemed acceptable since waiting for the results of the survey is not feasible within the time scope. When the survey is finalized it can be distributed using the respondents panel of the survey distribution company. Since areas along the coast are the most vulnerable these will be prioritized (Blake et al., n.d.).

When the data has been gathered it can be used to train logistic regression models which gives the likelihoods of individuals evacuating or not and where to. These models will give an overview of the significance of the included factors to predict evacuation behaviour. The outcome can be used to determine to exclude any factors from the ABM. The computational ABM can be trained using the survey data and the populated using socio-demographic data of U.S. Census Bureau (2023b). To ensure that the model works as intended, the results of the implementation will be verified using the conceptual model. To get insight into which factors have the biggest influence on the model a sensitivity analyses will be conducted using the EMA workbench. Based on the results a experimental setup can be created exploring various scenarios of which some scenarios will be selected to test policies. How these scenarios and policies will be tested will be defined in experimental setup for policies. The data gather using this design will be analyzed and used to answer the main question. Then the final step is to put these results in a policy perspective to create recommendations to make Miami more resilient against hurricanes in the future.

B

Appendix B: Background place attachment

The concept of PA has been extensively researched. Scannell and Gifford (2010) reviewed the literature on PA and defined it using three different dimensions: person, place, and process. The person dimension describes individual and group connections to place. Here, individual attachment forms through experiences a person has had in a certain place or through certain milestones reached. At the group level, places can have religious and historical meaning, creating a symbolic value for the group.

Second is the place dimension, which examines what in the space is the object of attachment. These can be social and/or physical elements. Socially, a person can be connected to a location based on the social relations developed or maintained in that certain location. For example, playing football every Sunday with friends at the sports club. Physical elements can include amenities, like forests, shops, public transport, or larger-scale elements like the local climate.

Lastly, the psychological process dimension of place attachment exists when affection, cognition, and behavior together determine the type of psychological interactions a person has in or with a place. Affection describes the emotional tone towards the location. Is the relationship based on resentment, love, or friendship? Affection also clearly demonstrates that attachment is not always positive. For instance, when being robbed creates a negative bond with the emotion of resentment towards the place where the robbery occurred. Place attachment as cognition. The last dimension is the behavior dimension, describing the actions done in a certain location. When an individual maintains behavior over a longer period of time in the same place, they develop a sense of place attachment, regardless of the type of behavior. A student taking all their exams in a central exam hall may develop an emotionally stressful attachment to that place, representing a negative relationship. A more neutral variant of place attachment could be to the train station the student uses to commute to the university. Here, the travel behavior creates place attachment.

Place attachment is a complex concept since it can be created through multiple factors, but the physical scope and age are also important when considering place attachment (Chamlee-Wright & Storr, 2009; Scannell & Gifford, 2010; Scannell et al., 2016). An individual can feel place attachment towards various scopes of locations. Small-scope locations include bedrooms, sports halls, and churches. Larger scopes would encompass the surroundings of these smaller locations. For example, a bedroom is a place in a neighborhood to which an individual can be attached. The scope can increase to the size of cities, countries, or even continents. The role of age is explained by Scannell et al. (2016). Young children's place attachment is often linked to locations around the parental home. As children grow older, they become more independent and can access locations that were previously inaccessible. Adolescents begin to develop new place attachments towards commercial or cultural locations, such as libraries, bars, cinemas, or churches. This shifts the scope of place attachment from a small neighborhood focus to a broader city perspective. Additionally, some place attachment dimensions gain more prominence. Adolescents start to achieve new milestones, such as getting their first job at a café or attending their first concert, and some places become meeting spots for groups. In this way, the person dimension becomes more relevant. As individuals mature, the dynamics of place attachment can start to shift again.

B.0.1. The role of Place attachment during evacuations

Regardless of how place attachment is developed, home and neighborhood influence the evacuation behavior of evacuees during disaster evacuations. Chamlee-Wright and Storr (2009) found that place attachment (PA) is a strong motivator for individuals to return to their previous place of residence after their home area was struck by flooding. Most studies have focused on the choice to leave home and risk perception. Bird et al. (2011) researched risk perception and emergency response knowledge in relation to the eruption risk of the Katla Volcano in Iceland. Here, rural residents were more attached to their homes and took a more proactive role in emergency response, making them less vulnerable than urban residents. Bonaiuto et al. (2011) found that neighborhood attachment increases risk perception and advising neighbors, indicating that neighborhood attachment can lead to higher vulnerability.

The research review by Bonaiuto et al. (2016) aligns with the findings of Chamlee-Wright and Storr (2009) and Bird et al. (2011), but it also raises two interesting points.. First, it states that risk perception lacks a standardized method of operationalization. Different studies focus on different factors, such as perception, knowledge, concern, or awareness. Second, place attachment can have a negative effect on risk perception in some cases. Individuals tend to underestimate risks when they threaten their home or community to which they are attached (Armaş, 2006; Donovan et al., 2012). The concept of insideness, as explained by Relph (1976), can help explain this negative relationship. Insideness suggests that the more an individual feels ”inside” a place, the less they feel threatened by it (Seamon & Sowers, 2008).

B.0.2. Moving away from home place attachment

The meta-analyses Van Valkengoed and Steg (2019) indicates that the role place attachment is not analyzed extensively and the focus is on home PA. This raises the question what the role PA towards other locations is.

While it is under-explored in evacuation literature, it has been explored in the tourism domain. Prayag et al. (2013) analyzed the link between satisfaction and behavior intentions. It stated that tourist who was satisfied by its visit to a certain destination will show more favorable behavioral intentions and thus a higher change to return or recommended the destination. In 2017, Hosany et al. examined the link between emotions, satisfaction and behavioral intentions further and analyzed the explicit role of PA. If tourist experienced emotions like love and pleasure then they develop a attachment to the locations where these emotions were felt. The findings of Hosany et al. are inline with the theory of Morgan (2010) which describes how PA can develop through interaction with the environment. Interesting result of Hosany is that negative emotions still lead to a positive development of PA. This can be explained by the 'rosy view' phenomenon. The rosy view explains how individuals can mitigate the role of negative emotions emphasize the role of positive emotions (**mitchell_temporal_19**).

The role of place attachment (PA) toward evacuation destinations has recently emerged as an area of interest in the literature. Although substantial attention has been given to the influence of home PA on evacuation willingness (Bonaiuto et al., 2016), comparatively little research has addressed PA in relation to evacuation sites. Recent findings suggest that PA to an evacuation site can significantly influence the decision to evacuate to that location (Ariccio et al., 2020).

Stancu et al. (2020) expands on the findings related to evacuation site PA by examining the role of PA styles and risk coping strategies. Using the attachment styles conceptualized by Lewicka (2011) and Quinn et al. (2018), the study found that different attachment styles result in the use of different risk coping strategies. Additionally, Stancu et al. (2020) examined the importance of PA intensity, or the strength of the bond between person and place Williams and Roggenbuck (1989). It was found that PA intensity has a significant effect on perceptions of risk and distress.

Villagra et al. (2021) study combined the traditional view of the evacuation process using Geographic Information Systems simulations and mathematical modeling with findings on evacuation site PA . It explored how psychological and spatial indicators relate to each other and influence the intention to evacuate to designated sites. Comparing the spatial and psychological optimal areas, the study found significant overlap between them. The two main challenges identified were: 1) the need for better communication among organizations involved in the evacuation process, and 2) the improvement of routes to evacuation sites, including equipping natural areas with emergency facilities. This study is the first to connect evacuation site PA with research in the field of Geographic Information Science.

A later study by Ariccio et al. (2021) on evacuation site PA refocused on the work of Ariccio et al. (2020) and Stancu et al. (2020) by gathering empirical evidence that the satisfaction of psychological needs is a requirement for the development of PA. The study found that satisfying psychological needs based on Self-Determination Theory and PA Theory leads to place bonding.

The next three studies primarily focus on how to increase community resilience. Spaccatini et al. (2022) found that risk perception is lower when individuals dislike adaptation measures designed to reduce risk. Furthermore, individuals with less prior knowledge and lower trust in science often have negative attitudes towards adaptive measures, leading to a reduced perception of risk. Villagra et al. (2023) developed a serious game aimed at improving participants' cognitive, emotional, and behavioral responses. While the game increased resilience, it had an unintended effect: it heightened home-PA, making it more difficult for evacuees to leave there home. The serious game is just one of many measures to enhance resilience. Villagra et al. (2024) reviewed literature on resilience measures across various domains and categorized them into ten areas. The study identified specific domains where resilience planning for the coast of Chile is lacking.

C

Appendix C: Model details

C.1. Model verification

The purpose of verifying the model is ensure that the formalisation is implemented as expected and the model works as expected Dam et al. (2013).

C.1.1. Single-agent test

These test are focused on the behaviour and state of one particular agent. All the single-agent test are done for the agent with *AgentId* 42,273, 22 and based on 100 model iterations with 1000 agents.

Media cue tracking

To see if the media cue is influences the risk perception. The media weight and influence factor is heightened and the the cue value and risk perception is evaluated, see Figure C.2. The dotted lines indicate risk perception while the full lines indicate the cue perception. The values are shown for the three agents individually. In C.2 it visible that between step 0 and 20 the media cue grows quickly and that the risk per perceptions follows the same trend in increase indication it responsiveness to the media cue. When the media cues maxes out at value 1 at step 20 the increase of risk perception stops as well.

Environmental cue tracking

To test if the agents are able to respond well to the environmental cues it is tested how risk perception compares to the cues when the environment cues are heightened to extreme values. Figure C.2 shows the wind cue and risk perception on the left side and the rain cue and risk perception on the right side. For both it is clear that the risk perception (dotted lines) follow the trends of the cue values (full lines). This indicates that the agents are able to process the environmental cues.

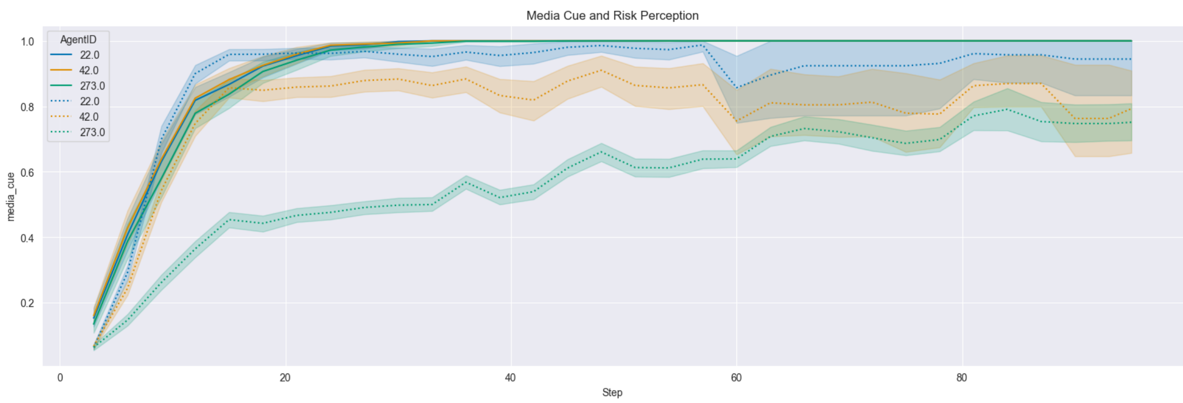


Figure C.1: Extreme media cue influence over time for risk perception

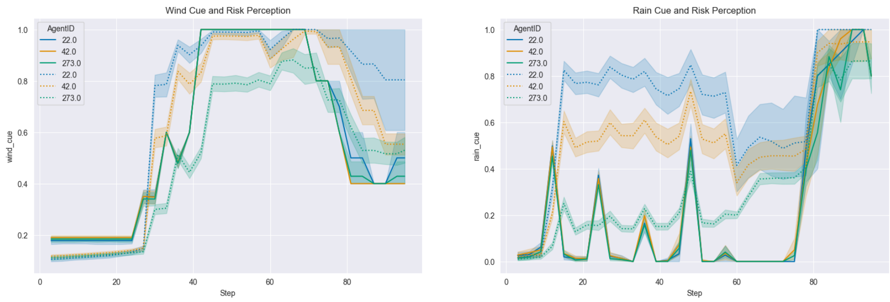


Figure C.2: Relation between wind cues (right side) and rain cues (right side) with risk perception. It must be noted that the weight for both cues is assigned a extreme value to make it easy to see if the risk perception reacts to the cues. The dashed lines are for the risk perception, while the full are for the cue values.

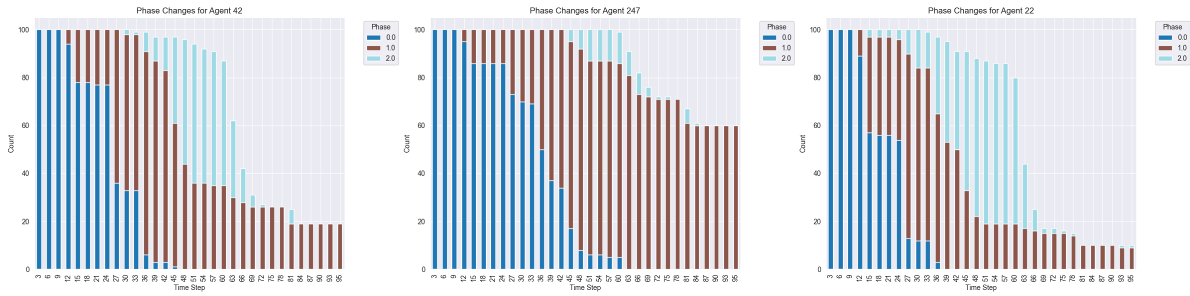


Figure C.3: Phases over time for three specific agents for 100 iterations

Phase change

The protective action decision phases are sequential: after moving to the next phase the agent can not go back. Additionally, the agent ca not skip phases. To make sure that this is the case the phase change behaviour is examined for three individual agents over 100 iterations and given in Figure C.3. The values of 0,1,2 represent the risk identification, risk assessment and protective action assessment phase respectively. For three agents it is visible that the order is correct and no agents go back to a previous phase. When the agent implements an action it leaves the model explaining why, at the later steps, the count does not add up to one hundred.

C.1.2. Minimal model testing

The minimal model test tests the interaction between a small set of agents. The model is run with only twelve agents and a neighbour of five. This way all the interactions between the agents can be monitored in a clear and isolated manner. The model will not run multiple times since makes following the sequence of actions ambiguous.

Phase change communication

To ensure that the agent executes the right communication behaviour after a phase change, print statements were added to the code to visualise the communication process. A snipped of the out put is given in C.1 showing the communication of four state changes. On line 1, agent communicates its phase change from phase 0 (risk identification phase). Identifies the agents with ids 1, 4, 6, 7, 8 as acquaintances and communicates with them increasing there risk perception as shown in line 2 to 12. Agent 4 also changes from phase 0, but only reaches out to Agent 1. Same goes for Agent 2 and Agent 9 who move from phase 1. All the influenced agents received an increase of 0.02, which is the expected amount.

Listing C.1: Code Snippet: Output for phase communication verifcation

```
Agent 9 communicates phase 0 change!
Agent 9 reaches out to: Agent [1, 4, 6, 7, 8]
Perception Agent 1 before: 0.02
Perception Agent 1 after: 0.04
Perception Agent 4 before: 0.02
Perception Agent 4 after: 0.04
Perception Agent 6 before: 0.02
Perception Agent 6 after: 0.04
Perception Agent 7 before: 0
Perception Agent 7 after: 0.02
Perception Agent 8 before: 0
Perception Agent 8 after: 0.02
Agent 9 new phase is 1!

Agent 4 communicates phase 0 change!
Agent 4 reaches out to: Agent [1]
Perception Agent 1 before: 0.04
Perception Agent 1 after: 0.06
Agent 4 new phase is 1!

Agent 2 communicates phase 1change!
Agent 2 reaches out to: Agent [1]
Perception Agent 1 before: 0.3900542031023606
Perception Agent 1 after: 0.4100542031023606
Agent 2 new phase is 2!

Agent 9 communicates phase 1change!
Agent 9 reaches out to: Agent [1, 4, 6, 7, 8]
Perception Agent 1 before: 0.4100542031023606
Perception Agent 1 after: 0.43005420310236064
Perception Agent 4 before: 0.08109888726190428
Perception Agent 4 after: 0.10109888726190429
Perception Agent 6 before: 0.16090513282153213
Perception Agent 6 after: 0.18090513282153212
Perception Agent 7 before: 0.21218390863556078
Perception Agent 7 after: 0.23218390863556077
Perception Agent 8 before: 0.09872420413370417
Perception Agent 8 after: 0.11872420413370417
Agent 9 new phase is 2!
```

Action implementation communication

When an agent implements a specific action, it influences both its acquaintances' attitudes towards that action and their propensity to implement it. Print statements were integrated into the simulation to expose this internal communication behaviour. A section of the output is shown in Snippet C.2.

In line 1, Agent 5 decides to implement the `stay` action (shelter in place). It communicates this decision to its only acquaintance, Agent 1, as shown in line 2. As a result of this communication, Agent 1's *attitude* towards the stay action increases from `0.26284` to `0.28784`, and the *propensity* from `0.46159` to `0.48159` (lines 3–6).

Later, in line 8, Agent 1 implements the `evac_shelter` action. However, it has no explicitly defined acquaintances to communicate with, as indicated in line 9. Instead, the action is *observed* by nearby agents Agent 8 and Agent), as noted in line 10. Consequently, their attitude and propensity values are updated. For Agent 8, these values change from `(0, 0, 0, 0.12188)` to `(0.025, 0.025, 0.025, 0.13188)` (lines 11–12). Similarly, Agent 2's values increase from `(0, 0, 0, 0.13472)` to `(0.025, 0.025, 0.025, 0.14472)` (lines 13–14).

Listing C.2: Code Snippet: Agent Action Execution

```
Agent 5 will implement the stay action!
Agent 5 reaches out to acquaintances: Agent [1]
Attitude towards stay action for Agent 1 before: 0.26284
Propensity value of Agent 1 before: 0.46159
Attitude towards stay action for Agent 1 after: 0.28784
Propensity value of Agent 1 after: 0.48159

Agent 1 will implement the evac_shelter action!
Agent 1 reaches out to acquaintances: Agent []
Agent 1 seen by neighbours: Agent [8, 2]
Attitude and propensity values of Agent 8 before: (0, 0, 0,
    0.1218804480311658)
Attitude and propensity values of Agent 8 after: (0.025, 0.025, 0.025,
    0.1318804480311658)
Attitude and propensity values of Agent 2 before: (0, 0, 0,
    0.134721101752683)
Attitude and propensity values of Agent 2 after: (0.025, 0.025, 0.025,
    0.14472110175268302)
```

Social relation assignment

The social relations are defined using graphs were nodes represent agents and the edges the relations between them. To verify if the relations are created as expected the model is initiated four times with different number of agents while keeping the average number of edges per agent at the value of 5. It is notable that the 12 agent graph has an incorrect average degree of 6.83. This is due to how barabasi-albert graphs are constructed, where for the first agents cannot create the required number of edges. This problem becomes smaller when the graph size increases. The deviation for 500 individuals is already 9.90 and so not a significant problem. A downside of using barabasi-albert graphs is that specific nodes get a extremely high degree which is not preventative of real world communication for emergencies since one agent has 64 connections in the 500 agents graph.

C.1.3. Multi-agent testing

During the multi-agents testing the aggregated model outcomes will be specified running XXX number of agents for 1000 model runs.

Variable range test

During the model formalisation the ranges are given for the variables. The dynamic ranges change overtime. To ensure that the dynamic variables only take on expected values the model is run 1000 times and the minium value and maximum value are then compared to the expected ranges. Table C.1 shows the expected and actual variable range. Only, social perception exceeds its expected range. This, however, is not troublesome. The social cues gets processed into risk perception and a check is implemented which reduces it to one before it is used for the decision-making of the agent as shown in:

```
self.risk_perception = min(self.cue_perception + self.social_perception, 1)
```

Evacuation warnings

The model examines the role of warnings. To ensure that the warnings communication follows the real process of Storm Irma (2017) a graph is made showing when the Hurricane and storm surge watches/warnings were issued. The figure C.5 shows that watch and warning happens at step at 55 and 60 respectively. The storm surge warning is counted per agent since not all agents receive them. The timing are similar and derived from the agent attributes indicating that the agents sense the watches/warnings.

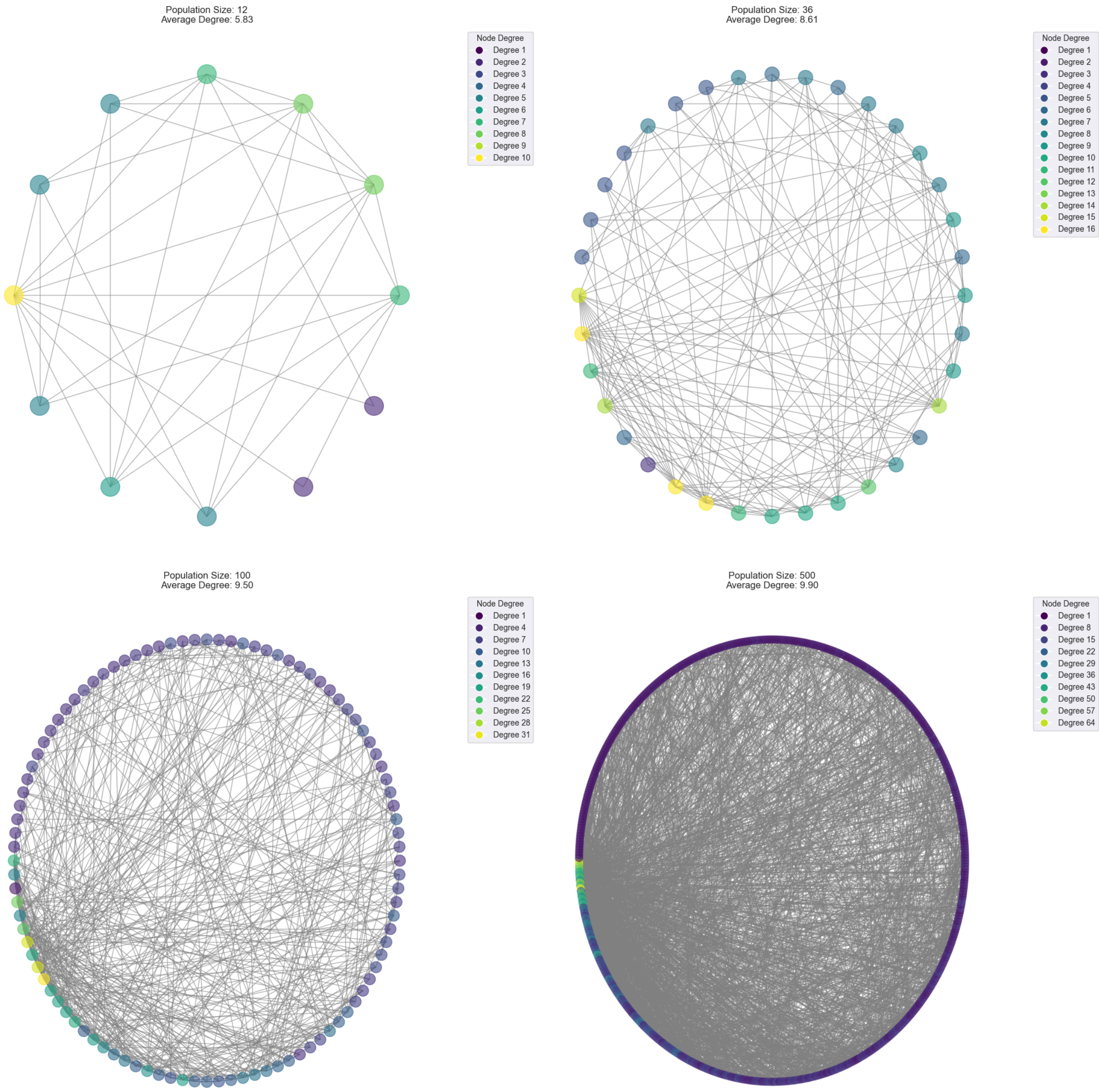


Figure C.4: Shows the used social graphs for a model with 12, 36, 100 and 500 agents. The model shows the degree per agent and the average degree.

Table C.1: Comparison of expected value ranges and actual variable value ranges after 500 iterations.

Variable	Range	Min	Max
cue_perception	$\mathbb{Z}:[0,1]$	0.0	0.811847
social_perception	$\mathbb{Z}:[0,1]$	0.0	1.0
media_cue	$\mathbb{Z}:[0,1]$	0.0	1.0
rain_cue	$\mathbb{Z}:[0,1]$	0.0	1.0
wind_cue	$\mathbb{Z}:[0,1]$	0.0	1.0
storm_surge_state	$\{0,1,2\}$	0.0	1.0
risk_perception	$\mathbb{Z}:[0,1]$	0.0	1.0
evac_friends	$\mathbb{Z}:[0,\infty]$	0.0	1.233714
evac_hotel	$\mathbb{Z}:[0,\infty]$	0.0	1.289577
evac_shelter	$\mathbb{Z}:[0,\infty]$	0.0	1.299905
stay	$\mathbb{Z}:[0,\infty]$	0.0	1.137429
phase	$\{0,1,2\}$	0.0	2.0

Figure C.5: Plot shows the watch/warning timings for the hurricane and storm surges.

C.2. Model assumptions & simplification

The purpose of the ABM is to provide insight into evacuation behaviour. Translating human behaviour into an computer model can not be done 100%, hence assumptions and simplification must be done. These assumptions and simplifications are done for different parts of the model itself and the process of developing the ABM. Underneath the assumptions are given per category:

Agent State:

- The values for self and response efficacy are modelled static while these normally depend on social and environmental cues
- The initialisation of state variables are all done individually and in isolation. This result in agents which are representative of the real world. For example, an agent can be assigned the age of 18 while having an income of 200,000+ dollar per year.
- Situational impediments are not considered. When choosing to evacuate the availability of a travel mode is essential to execute the action. It must be noted that this indirectly checked through self-efficacy

- Media cues are modelled linearly. It assumed that the information flow over time stays constant.
- The moment the individuals decides to implement an action it directly evacuates. In reality people often have to prepare before they leave. This is not considered in the model.

Agent interaction:

- Lindell and Perry (2012) describes that individuals must be exposed, pay attention and understand cues before they can be influenced by the cues. The assumption is made that if an agent is exposed, it will be influenced.
- Within a individuals social networks no differences are made between communication, so communication between all agent is the same. In reality, it can be expected that not everyone communicates similar and to same intensity.
- When the individual implements an action it leaves the model and therefore stops communication with surrounding agents.
- When evacuating individuals will drive through the city alerting individuals they pass. Currently individuals only influence selected people in the vicinity of the living area.

Experimental design:

- Model results are based on 150 Iteration which leaves model outcome differences of one standard deviation. In general results can be seen as reliable, but 150 iteration does not exactly replicate the same values.
- The design for the sensitivity analysis is manually created and combination effects are not examined
- The testing of policy interventions is done using manually selected values instead of using an optimisation algorithm like Non-dominated Sorting Genetic Algorithm II.

C.3. Sensitivity analysis

The sensitivity analysis is done for all uncertain variables. Figure X shows the sensitivity for the model metrics. The overall sensitivity is quite low. The most sensitive values are: It is notable that XXXX are more sensitive for the evacuation timings while xxxx are more sentive for XXXX.

D

Appendix D: Survey

Introduction

You are invited to participate in a survey about pre-evacuation behaviour. The research is part of a master thesis graduation project. The goal is to gain insight into evacuation behaviour and decision making before a hurricane disaster, and will take approximately 10 minutes to complete. Your participation is entirely voluntary and you can withdraw at any time without giving a reason.

To the best of our ability your answers in this study will remain confidential and securely stored. We will minimize any risks by ensuring that your survey data is stored anonymously and securely at Delft University of Technology storage services for at least 10 years.

For more information, questions or complaints regarding the survey the following contact information can be used

By proceeding and completing this survey, you acknowledge and agree to the terms outlined in this Opening Statement.

○ I have read the information and agree to take part

Surrounding awereness

To what extent do you pay attention to weather conditions such as wind in your daily life?

- Not at all
- Slightly
- Moderately
- Very much
- Extremely

To what extent do you pay attention to weather conditions, such as wave strength or water turbulence, in your daily life?

- Not at all
- Slightly
- Moderately
- Very much
- Extremely

To what extent do you pay attention to the likelihood or intensity of rain in your daily life?

- Not at all
- Slightly
- Moderately
- Very much
- Extremely

Evacuation intention

To what extent would you agree with the following statements?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Faced with the threat of a hurricane, if the people close to me have evacuated, I am willing to evacuate	○	○	○	○	○
Faced with the threat of a hurricane, I will not evacuate	○	○	○	○	○
Faced with the threat of a hurricane, I will evacuate	○	○	○	○	○
Faced with the threat of a hurricane, if the government forces me to evacuate, I am willing to evacuate	○	○	○	○	○
Facing with the threat of a hurricane, if the government gives a certain subsidy, I am willing to evacuate	○	○	○	○	○

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Faced with the threat of a hurricane, without considering other people, if I am allowed to evacuate voluntarily, I am willing to evacuate	○	○	○	○	○

PA neighborhood

To what extent would you agree with the following statements about the neighborhood you live in?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
My neighborhood is my favorite place to be	○	○	○	○	○
My neighborhood reflects the type of person I am	○	○	○	○	○
I believe that residents in my neighborhood can be trusted	○	○	○	○	○
I feel that I am a member of my neighborhood community	○	○	○	○	○

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Being in this neighborhood gives me a lot of pleasure.	○	○	○	○	○

PA Destination

Consider a location where you might seek refuge during a hurricane—whether it's a family member's or friend's home, a hotel, or a community shelter—and reflect on the following factors for each option.

Family/Friends - To what extent do you agree with the following statements?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
My family/friends are well-informed that I will seek shelter at their location when a hurricane occurs	○	○	○	○	○
My family/friends will expect me to seek refuge when a hurricane occurs	○	○	○	○	○
I do not feel integrated in the neighborhood of my families/friends home .	○	○	○	○	○

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
The home of my families/friends home is part of me.	○	○	○	○	○
My families/friends home is the ideal evacuation place for me.	○	○	○	○	○

How likely is it that evacuating towards the families/friends home would be effective to reduce harm to yourself and your family?

- ○ Extremely unlikely
- ○ Somewhat unlikely
- ○ Neither likely nor unlikely
- ○ Somewhat likely
- ○ Extremely likely

Do you have the ability to evacuate to family or friends by yourself?

- ○ Definitely not
- ○ Probably not
- ○ Might or might not
- ○ Probably yes
- ○ Definitely yes

Do you have the ability to help someone else evacuate to a family or friend's place?

- Definitely not
- Probably not
- Might or might not
- Probably yes
- Definitely yes

Hotel/motel - To what extent do you agree with the following statements?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
The hotel is the ideal evacuation place for me.	○	○	○	○	○
The hotel is well-informed that I will seek shelter at their location when a hurricane occurs	○	○	○	○	○
The hotel willl expect me seeking refuge when a hurricane occurs	○	○	○	○	○
I do not feel integrated in the location of my hotel.	○	○	○	○	○
The neighborhood of the hotel is part of me.	○	○	○	○	○

How likely is it that evacuating to a hotel would effectively reduce harm to you and your family

- Extremely unlikely

- Somewhat unlikely
- Neither likely nor unlikely
- Somewhat likely
- Extremely likely

Do you have the ability to evacuate to a hotel by yourself?

- Definitely not
- Probably not
- Might or might not
- Probably yes
- Definitely yes

Do you have the ability to help someone else evacuate to a hotel?

- Definitely not
- Probably not
- Might or might not
- Probably yes
- Definitely yes

Public shelter - To what extent do you agree with the following statements?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
The public shelter is well-informed that I will seek shelter at their location when a hurricane occurs	○	○	○	○	○
The public shelter is the ideal evacuation place for me.	○	○	○	○	○
I do not feel integrated in the location of the public shelter.	○	○	○	○	○
The public shelter willl expect me seeking refuge when a hurricane occurs	○	○	○	○	○
The location of the public shelter is part of me.	○	○	○	○	○

How likely is it that evacuating to a public shelter would effectively reduce harm to you and your family?

- ○ Extremely unlikely
- ○ Somewhat unlikely
- ○ Neither likely nor unlikely
- ○ Somewhat likely
- ○ Extremely likely

Do you have the ability to evacuate to a public shelter by yourself?

- ○ Definitely not
- ○ Probably not

- Might or might not
- Probably yes
- Definitely yes

Do you have the ability to help someone else evacuate to a public shelter?

- Definitely not
- Probably not
- Might or might not
- Probably yes
- Definitely yes

Protective action search

To which state will you evacuate? If you are not sure, choose the option that is the most likely location.

- Stay in Florida
- Lousiana
- Arkansas
- Oklahoma
- Missouri
- Kansas
- Colorado
- New Mexico
- Mexico (country)
- Texas
- Georgia

- Alabama
- Mississippi
- South Carolina
- Tennessee
- Other

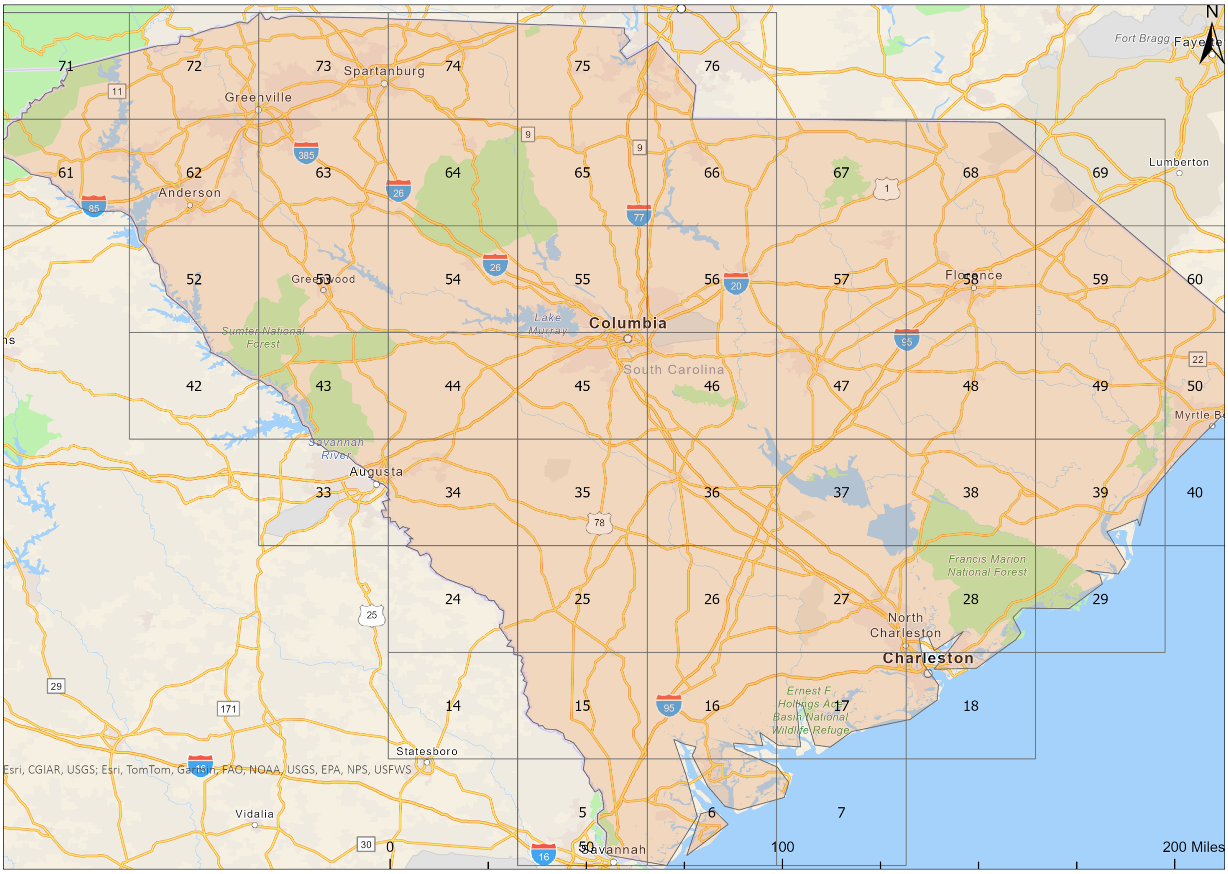
What is the most likely location that you would evacuate towards?

- Family/friends
- Hotel/motel
- Public shelter
- Other
- Not know

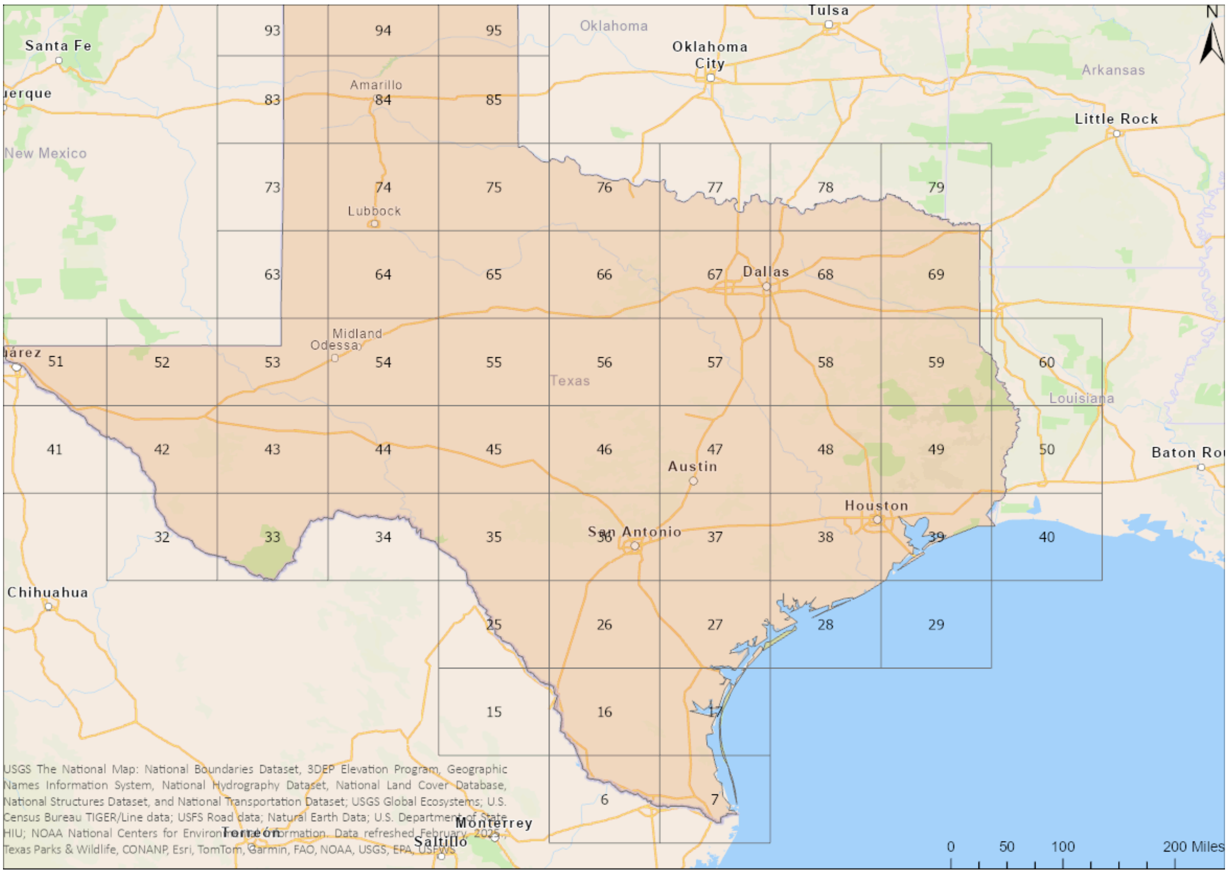
To which type of location will you prefer to evacuate?

- Family/friends
- Hotel/motel
- Public shelter
- Other
- Not know

The map below shows the state you want to evacuate in. Choose the number of the square which contains your evacuation destination to which you would be most likely to evacuate. Use the number to answer the next question.



The map below shows the state you want to evacuate in. Choose the number of the square which contains your evacuation destination to which you would be most likely to evacuate. Use the number to answer the next question.



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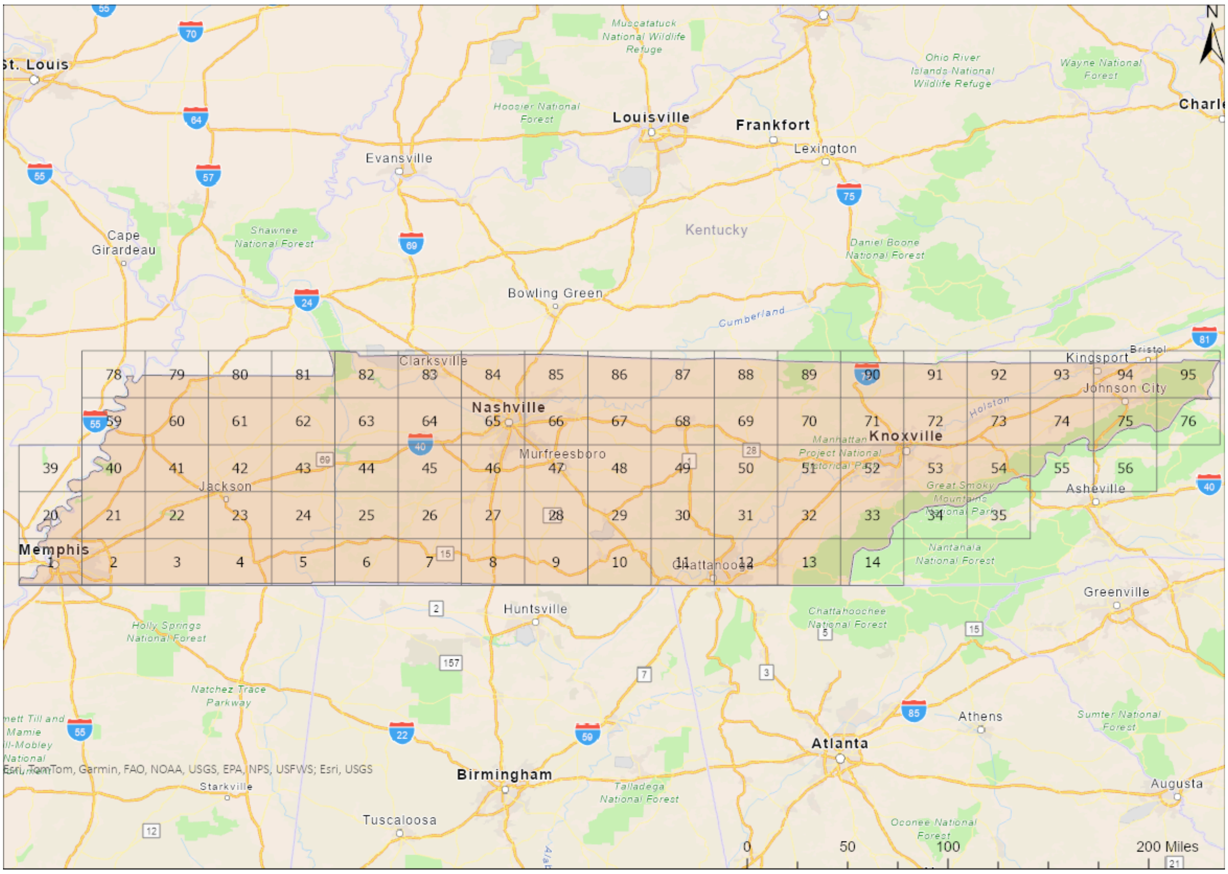

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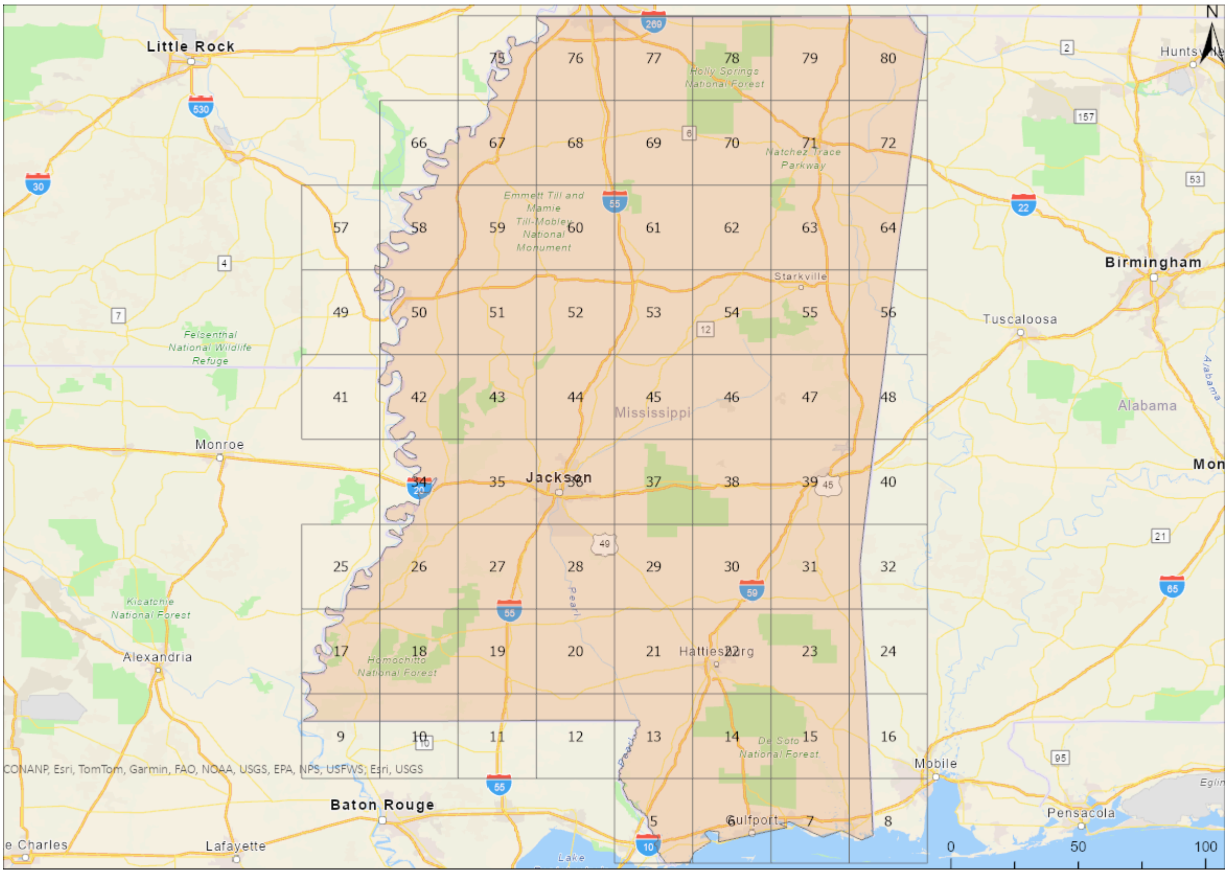

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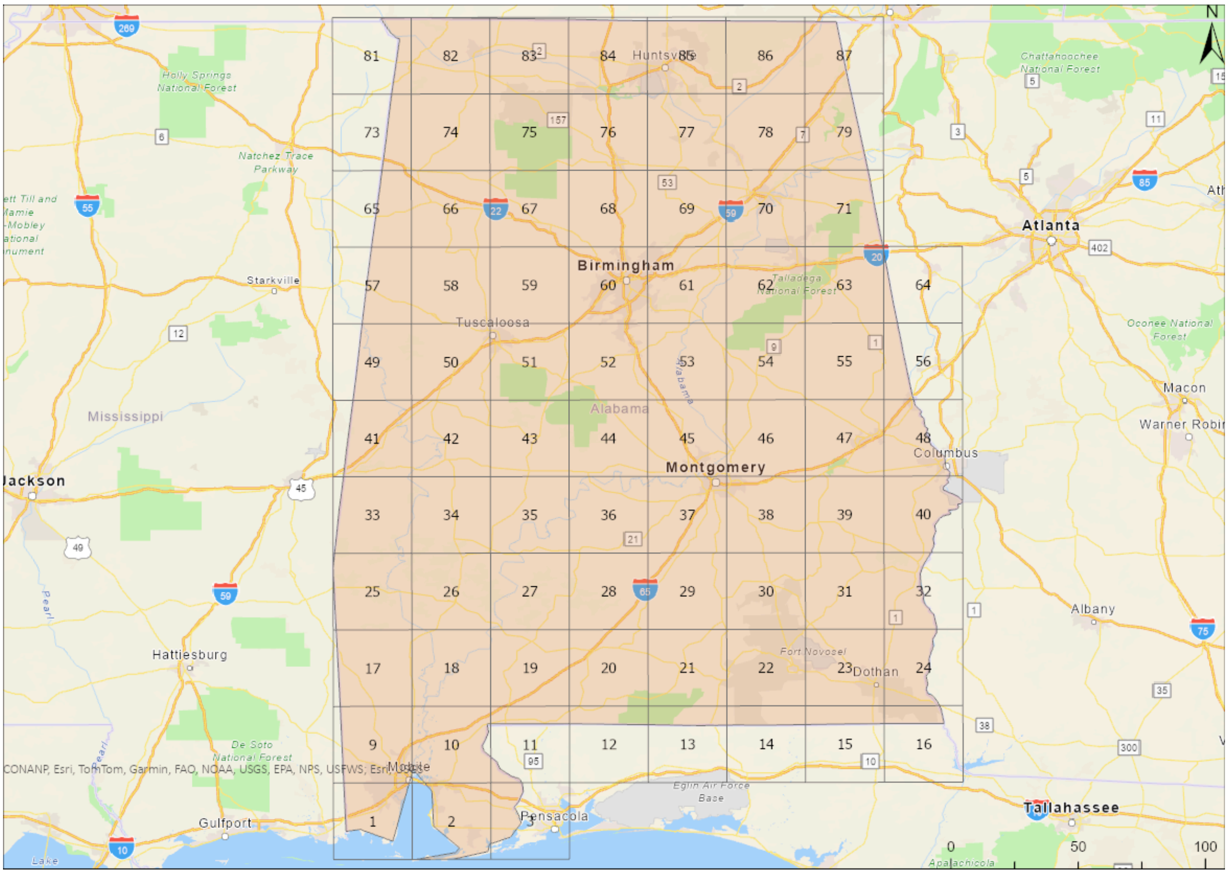

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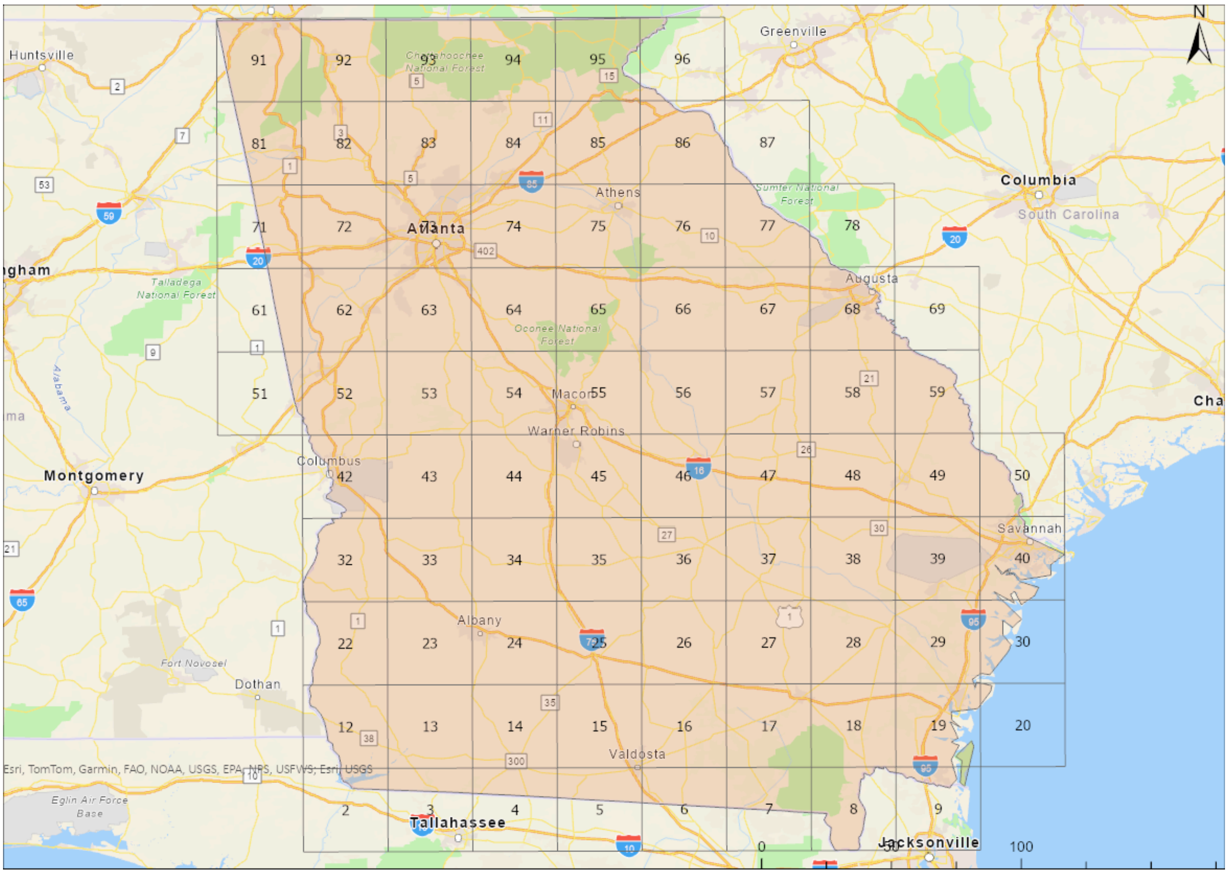

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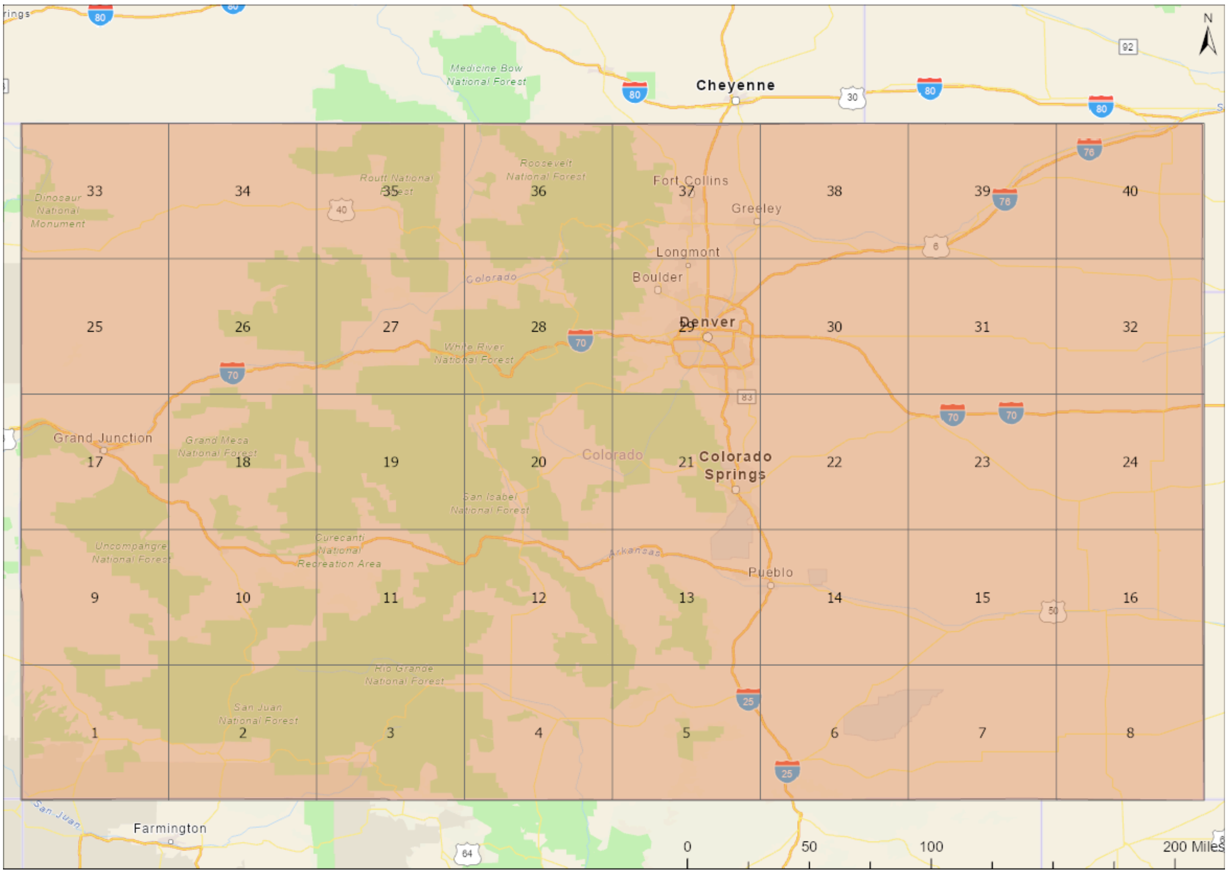

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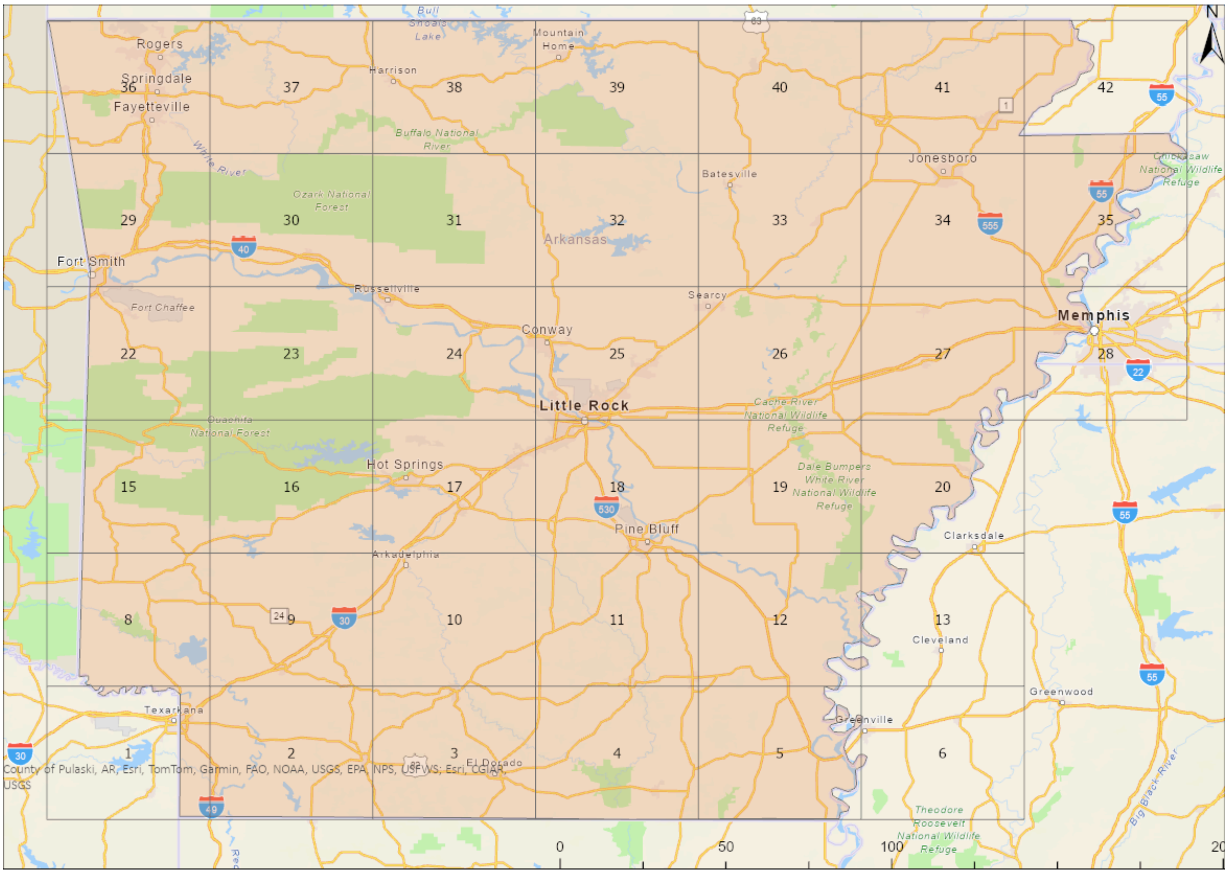

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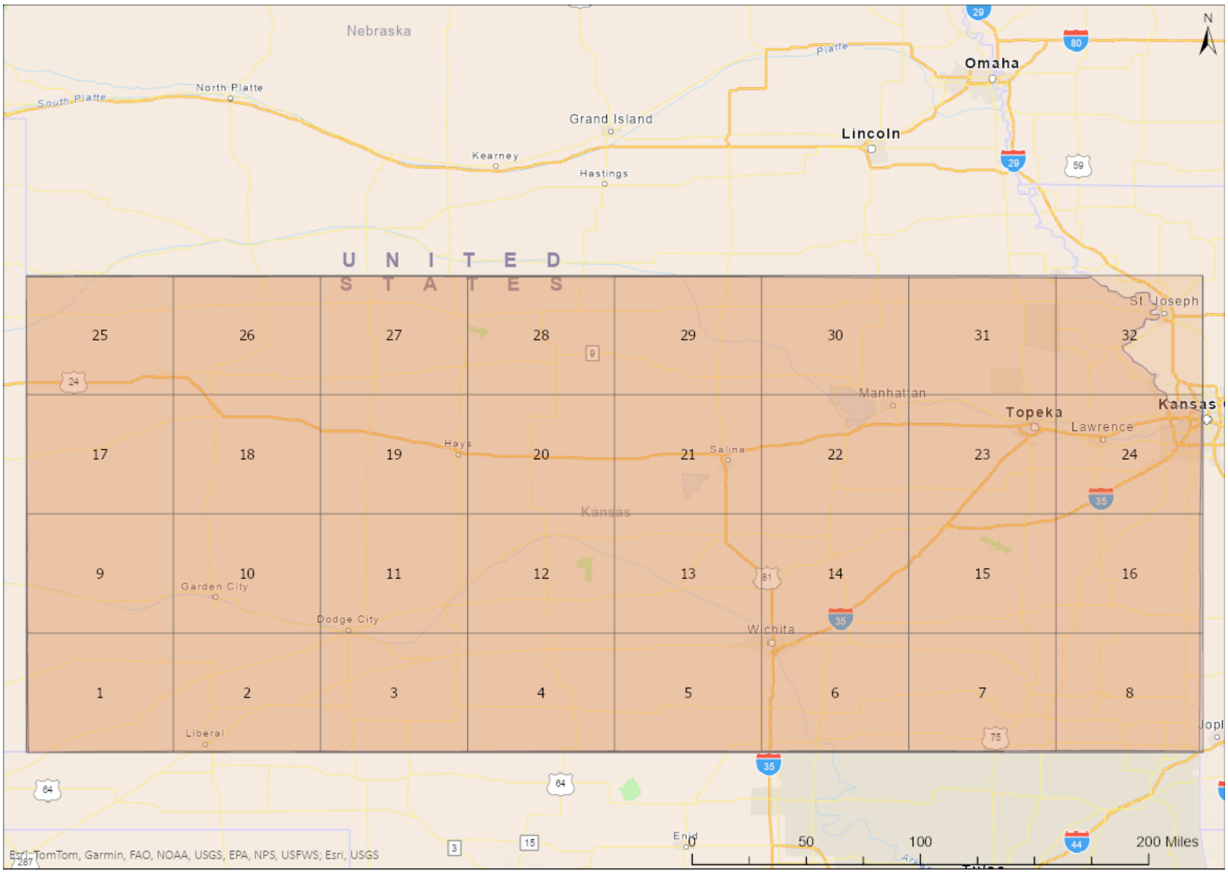

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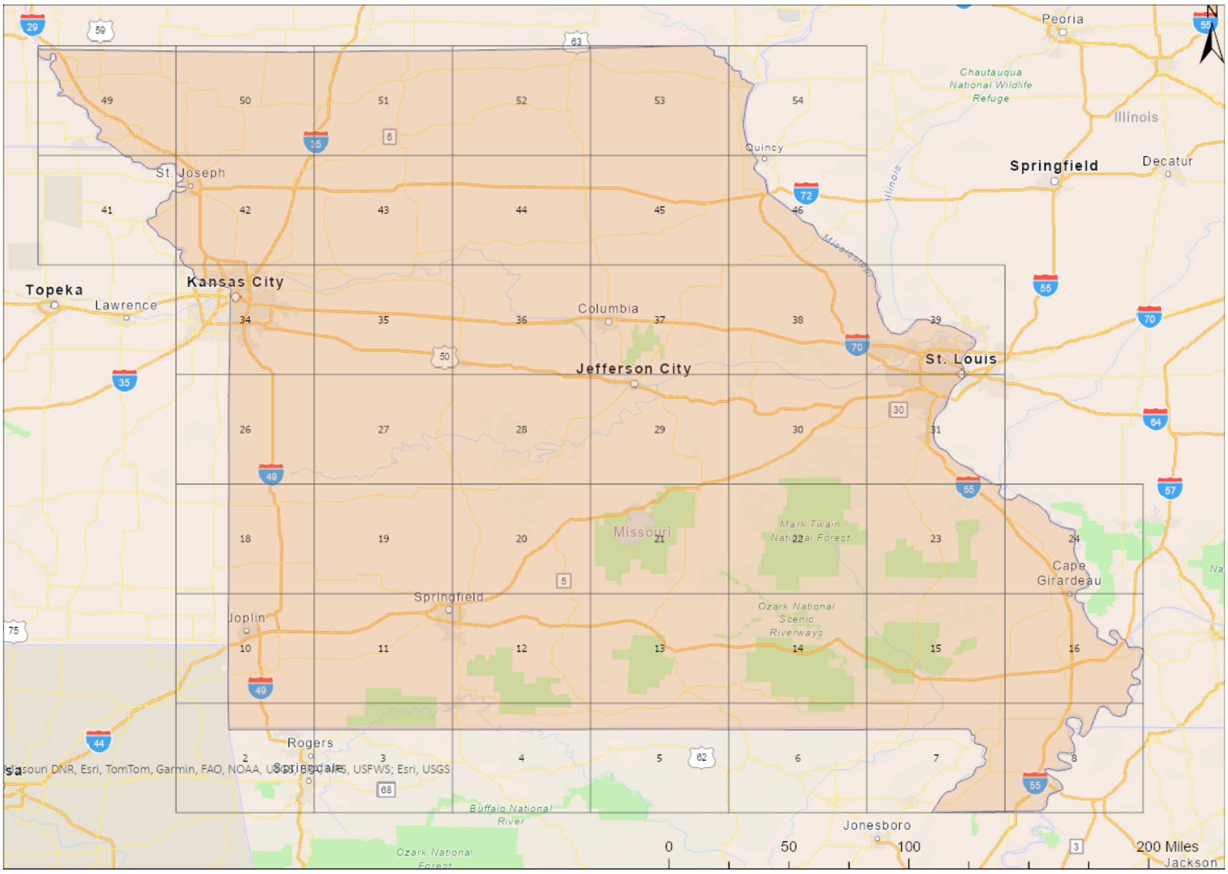

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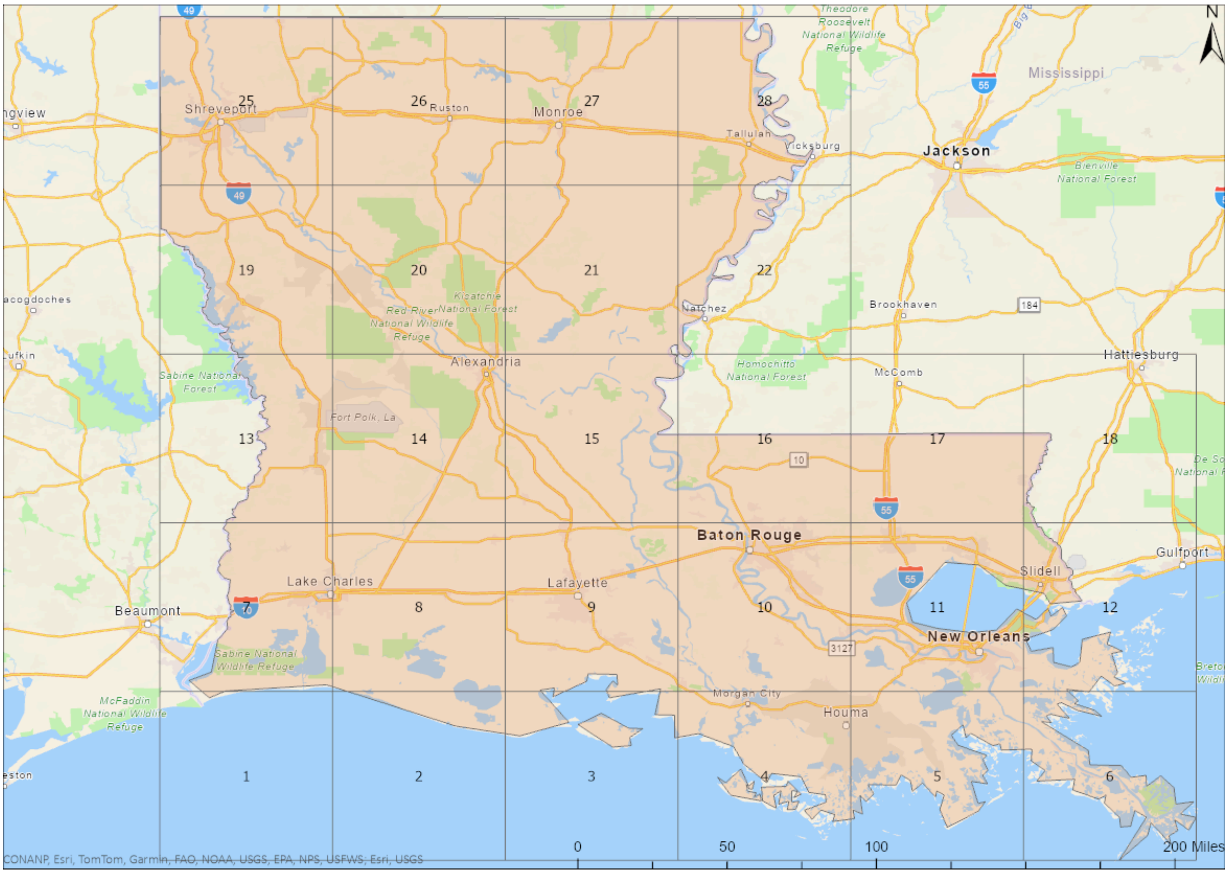

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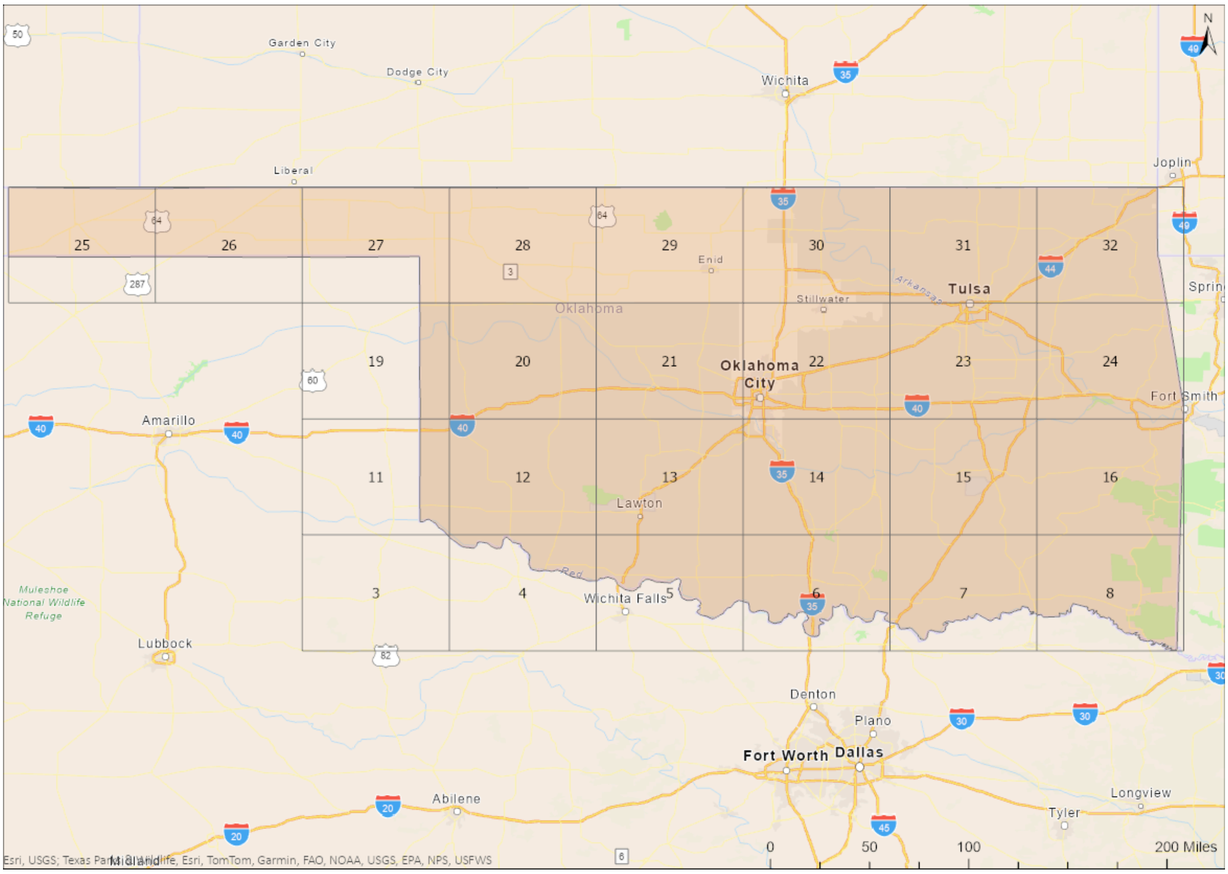
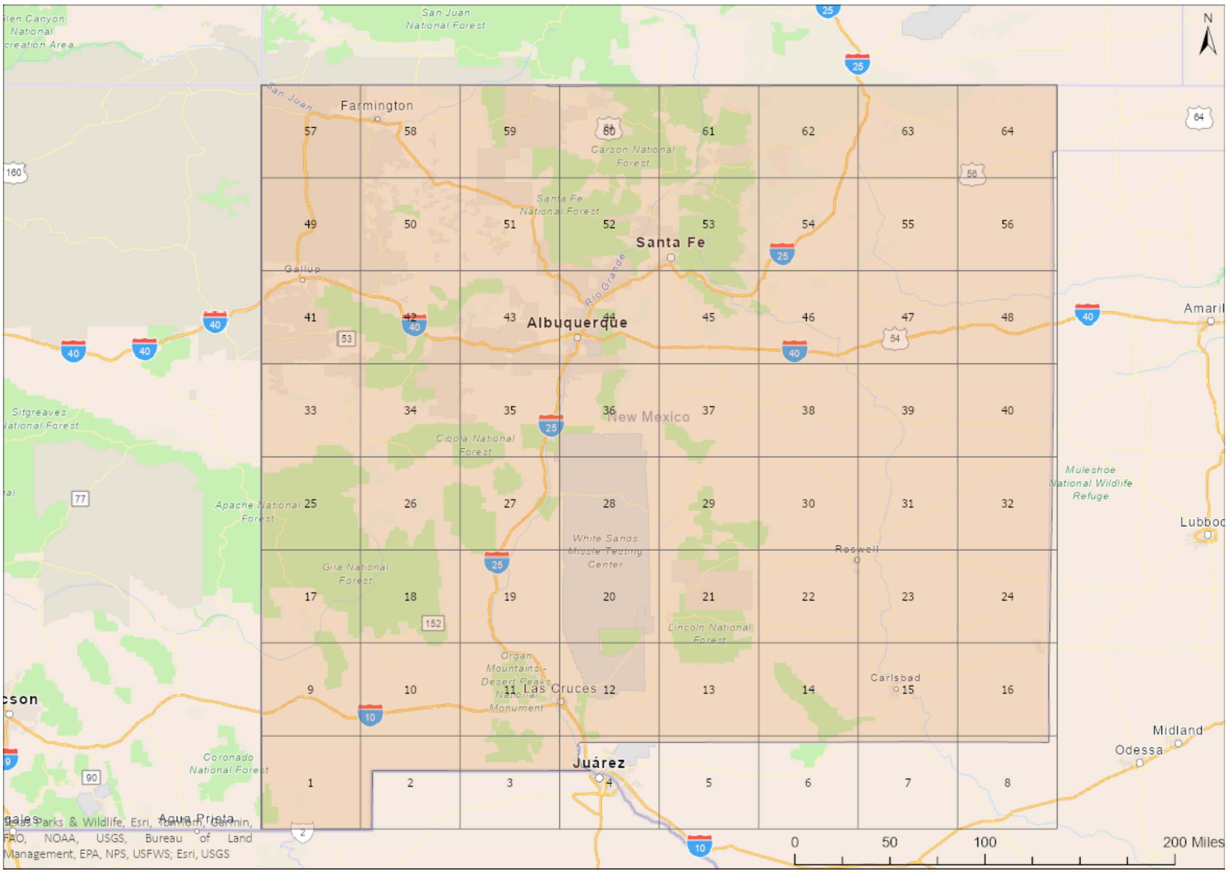


The map below shows the state you want to evacuate in. Choose the number of the square which contains your evacuation destination. Use the number to answer the next question.



What is the number of the square which contains your evacuation destination?

Risk identification

To what extent do you agree with the following statements?

	Very unlikely	Unlikely	Neutral	Likely	Very likely
Imagine you stay in your home during this storm. How likely do you think it is that you could get hurt by the **storm**?	◯	◯	◯	◯	◯
How likely is it that your home would be affected by this **storm**?	◯	◯	◯	◯	◯
How likely is it that your home would be affected by the **storm surge**?	◯	◯	◯	◯	◯
Imagine you stay in your home during this storm. How likely do you think it is that you could get hurt by the **storm surge**?	◯	◯	◯	◯	◯

How severe would the storm damage your home?

- ◯ None
- ◯ Mild
- ◯ Moderate
- ◯ Severe
- ◯ Very Severe

How severe would the storm surge damage your home?

- ◯ None
- ◯ Mild
- ◯ Moderate
- ◯ Severe

○ Very severe

Risk assessment

To what extent do you agree with the following statements?

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I think being careful about a **storm surge** is important. However, as long as the **impact** is not severe when it reaches my neighborhood, I will not take any action.	○	○	○	○	○
I think being careful about a **hurricane** is important. However, as long as the **impact** is not severe when it reaches my neighborhood, I will not take any action.	○	○	○	○	○
I think being careful about a **hurricane** is important. However, as long as it does not seem **likely** to hit my neighborhood, I will not take any action.	○	○	○	○	○
Seeing businesses in the area close does not mean my neighborhood is in danger and I will not take action.	○	○	○	○	○
When friends, relatives, neighbors, or coworkers evacuate, it does not mean my neighborhood is in danger and I will not take action.	○	○	○	○	○
I think being careful about a **storm surge** is important. However, as long as it does not seem **likely** to hit my neighborhood, I will not take any action.	○	○	○	○	○

The people who remained in an evacuation zone after the evacuation order acted irresponsibly.

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

People who do not heed the evacuation orders are responsible for what happens to them.

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

People are responsible for seeking information about the risks posed to them and their property.

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

Surrounding awareness

To what extent would you consider the following statements during a Hurricane?

	Not at all	Slightly	Moderately	Very	Extremely
Sensing weather, such as wave strength or water turbulence	○	○	○	○	○
Seeing businesses in the area close	○	○	○	○	○
Sensing weather conditions, such as winds	○	○	○	○	○
Seeing friends, relatives, neighbors, or coworkers evacuating in your surroundings	○	○	○	○	○
Hearing of friends, relatives, neighbors, or coworkers evacuating on different media	○	○	○	○	○
Sensing weather conditions such as increased rain	○	○	○	○	○

Communication

How frequently would you consult the following media channels for hurricane information

	Never	Once a day	Twice a day	Four times a day	Constantly
Internet	○	○	○	○	○

	Never	Once a day	Twice a day	Four times a day	Constantly
Radio	○	○	○	○	○
Television	○	○	○	○	○
Newspapers	○	○	○	○	○
Social media	○	○	○	○	○

How much do you trust the following media channels for hurricane information?

	Not at all	Slightly	Moderately	Very	Extremely
Social media	○	○	○	○	○
Radio	○	○	○	○	○
Internet	○	○	○	○	○
Television	○	○	○	○	○
Newspapers	○	○	○	○	○

Indicate to what extent you would communicate about the following aspects with people in person or over the telephone.

	Very Unlikely	Unlikely	Neutral	Likely	Very Likely
Severity of storm surges	○	○	○	○	○
Severity of the hurricane	○	○	○	○	○
When I plan to leave	○	○	○	○	○

	Very Unlikely	Unlikely	Neutral	Likely	Very Likely
What I will do during the storm	○	○	○	○	○
Where I plan to stay	○	○	○	○	○

Socio-demo and PAS

What is your age group?

What is your race and ethnicity?

- White - not hispanic
- Black or African American - not hispanic
- American Indian and Alaska Native - not hispanic
- other - not hispanic
- White alone - hispanic
- Black or African American alone - hispanic
- Other - hispanic

Highest completed education

How man pets do you own?

- None
- 1

- ○ 2
- ○ 3
- ○ 4
- ○ More than 5

What was your total household income before taxes during the past 12 months?

How many people live or stay in this household at least half of the time (excluding your self)

Do you own a car with which you can evacuate?

- ○ No
- ○ Yes

Are you responsible for a relative or friend with major medical needs?

- ○ Yes
- ○ No

Have you ever evacuated from a hurricane in your past?

- ○ Yes
- ○ No

Have you evacuated from storm Harvey in 2017?

- No
- Yes

Have you ever evacuated your home during a hurricane in the past when it was not necessary?

- Definitely not
- Probably not
- Might or might not
- Probably yes
- Definitely yes

With how many friends or family members will you stay in constant contact before the hurricane hits?

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E

Appendix E: Policy scores

E.1. Policy scores

Model Metrics Across Scenarios

	BP				**LRP**				**MDP**			
Index	Evac	Spread	No Dec	Score	Evac	Spread	No Dec	Score	Evac	Spread	No Dec	Score
0_0	1.00	0.53	0.01	1.54	1.00	0.94	0.03	1.97	1.00	0.92	0.07	1.99
n6_0	0.88	0.33	0.00	1.22	0.91	0.18	0.02	1.10	**0.87**	**0.00**	**0.07**	**0.94**
12_0	0.76	1.00	0.96	2.71	0.59	1.00	0.92	2.52	0.64	1.00	0.94	2.58
24_0	0.38	1.00	1.00	2.38	0.15	0.88	1.00	2.03	0.24	0.92	1.00	2.16
0_12	**0.56**	**0.33**	**0.01**	**0.91**	**0.59**	**0.41**	**0.00**	**1.00**	0.60	0.54	0.05	1.18
n6_12	**0.54**	**0.00**	**0.05**	**0.59**	**0.66**	**0.00**	**0.07**	**0.73**	**0.64**	**0.23**	**0.00**	**0.87**
12_12	0.52	0.60	0.23	1.35	0.43	0.65	0.25	1.33	0.48	0.69	0.28	1.46
24_12	0.14	0.60	0.72	1.46	0.04	0.65	0.76	1.44	0.15	0.69	0.83	1.67
0_24	0.59	0.53	0.60	1.72	0.62	0.06	0.64	1.32	0.61	0.15	0.56	1.32
n6_24	0.73	0.73	0.54	2.00	0.73	0.12	0.68	1.53	0.70	0.38	0.58	1.66
12_24	0.18	0.40	0.41	1.00	0.14	0.47	0.51	1.12	0.25	0.46	0.57	1.28
24_24	**0.00**	**0.33**	**0.33**	**0.66**	**0.00**	**0.53**	**0.38**	**0.91**	**0.00**	**0.31**	**0.49**	**0.79**

Table E.1: Comparison of Evacuation Time (Evac), Decision Spread, Number of Indecisive Agents (No Dec), and Scores across BP, LRP, and MDP models.