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Shielding Jakarta's Household

A Multidimensional Analysis of Climate Maladaptation

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by

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Executive Summary

Flooding represents the most significant threat linked to climate change and requires effective adaptation strategies. It delineates between government-led anticipatory adaptations and autonomous adaptations by households, emphasizing the urgent need for effective local strategy, especially in the Global South, where institutional support may lag. On the other hand, families, as the actors in the frontline, often adapt autonomously within a bounded rationality instead of a rational decision-making process. Compounding with the exacerbated climate change impact, they must actively implement measures to safeguard livelihoods. As more and more households are impacted, their significance in the broader climate adaptation landscape is underscored. However, despite having a favourable condition, maladaptation arises when actions to avoid climate threats inadvertently cause harm or exacerbate their vulnerabilities. Hence, understanding household-level measures is crucial for policymakers to support effective and equitable adaptation strategies.

This thesis focuses on maladaptation—unintended adverse outcomes of adaptation efforts that often worsen vulnerabilities. By exploring household-level responses to flood risks, the thesis highlights the complexities of adaptation decisions influenced by immediate needs and limited resources. This thesis seeks to identify maladaptive outcomes from household adaptation measures and assess the maladaptation of current practices by answering the following: *To what extent do household-level climate change adaptation to flooding result in maladaptive response across urban households, considering their vulnerability to flood risk?*.

Methodology
The mixed-methods approach, which combines qualitative and quantitative research, will be used to comprehensively understand maladaptation through the case study of urban households in Jakarta. Combines the depth of qualitative insights with the predictive capabilities of quantitative analysis to capture the dynamic and complex nature of maladaptation. To assess maladaptation, a literature study was conducted to conceptualise maladaptive behaviours and outcomes, including defining indicators and representation. The IPCC Climate Risk Assessment Framework and Protection Motivation Theory (PMT) were employed and simulated in an agent-based household climate adaptation behaviour model to contextualise the study. Then, maladaptation is evaluated based on the simulation outcome with the predefined indicators.

Research Insights
Through models and simulations, the text reveals how low adaptation intention and capacity constraints lead to maladaptive behaviours like inaction, misperception of flood risks, and false sense of security, even though households view their residences as more than structural entities. A mismatch between adaptation intention and adaptation constraint drives these actions. Inaction is not a beneficial option for low—and middle-income households.

Despite a widespread preference for comprehensive adaptation measures across various income levels, financial barriers pose significant obstacles, especially for low-income families residing in flood-prone areas. This leaves high-income households better equipped to manage flood impacts. In contrast, low-income households face acute vulnerability and limited capabilities for adaptation, highlighting the urgent need for targeted support and intervention across different locations and adaptive capacities. It is consistent across household groups that wet-proofing frequently leads to lock-in and inequality.

Policy Implications to Counter Maladaptation
To overcome inaction, one must understand that perceived risk, external influences, and perceived financial abilities affect one's decisions about adapting to change. In addition, it increases adaptive capacity to make adaptation accessible for all. However, with the economic barriers, targeted financial aid and subsidies should be designed to support the most vulnerable populations. These aids should be tailored to encourage the adoption of effective and comprehensive adaptation measures rather than

perpetuating dependence on inadequate single measures, which also differ across household backgrounds. For instance, low-income households in inner-city neighbourhoods and urban centres might need to be tailored to adapt with complete measure. At the same time, this is not the case for families residing in coastal areas. Social networks can boost adaptation, starting from the massive adaptation of households with higher education or utilising social capital aside from financial capital. Consequently, community and governmental support are crucial in broadening the adaptation options available to all families, especially those in high-risk areas such as coastal areas, inner-city neighbourhoods, and flood-prone zones. Support structures should focus on reducing flood exposure and enabling proactive adaptation measures.

Contents

1
Introduction

1.1. The Grand Challenge

Climate change is intensified across the globe by the worsening weather and increased extreme events, such as flash floods, drought, and heatwaves (IPCC, 2021; Robinson et al., 2021; Zhang et al., 2024). Flooding represents one of the most pressing threats; it is the most visible and highly geographically extensive disaster that has posed urgent threats to livelihood and development progress. Over 1.81 billion people are exposed to flood depths above 0.15 meters (Rentschler et al., 2022). Given the increases in flood frequency and severity due to climate change, it is observed that urban areas are facing more impact of climate change relative to rural areas with higher minimum temperatures, increased runoff intensity, and extreme precipitation due to the altered water cycle, as well as dryness caused by urbanisation (Doblas-Reyes et al., 2021). As future urban development coupled with exacerbated climatic impact, metropolitan areas will experience inevitable devastating floods. This calls for increased adaptation efforts.

Adaptation can be driven by private motives, such as private companies, individuals, households, or public interests, which stands for government, where private and public can adapt with anticipatory and reactive initiatives (IPCC, 2007; Smit et al., 2001). Despite that, anticipatory adaptation, which acts as a strategy initiative, is majorly associated with governments requiring long-term and macro-view planning (Smit et al., 2001). On the other hand, private adaptation corresponds to autonomous adaptation, which aims to maintain livelihoods and reduce the risk of climate change without official interventions (Forsyth & Evans, 2013; Malik et al., 2010). In addition, autonomous adaptation is often reactive or occurs after observing the impact (Malik et al., 2010).

In practice, Petzold et al. (2023) reported that government initiatives in climate adaptation mainly involved planning and coordinating responses. At the same time, implementation regarding the local context is primarily done by private, precise households, and households in the Global South are the least involved in the institutional response Petzold et al. (2023). On the other hand, government initiatives alone cannot provide complete protection (Dewulf et al., 2015; Kievik & Gutteling, 2011). Consequently, planned adaptation is unlikely to be effective, and this is consistent across large coastal cities worldwide (Olazabal & Ruiz De Gopegui, 2021). As a result, the focus of this study is rationalised from the urgency for self-protection and adaptation of coping mechanisms, which falls heavily on the household's adaptive capacity (Serdeczny et al., 2024) and intention to adapt (Noll, Filatova, Need, & Taberna, 2022). They experience day-to-day life disruptions to food production, health and well-being, and settlement, making them a frontier of climate impact (IPCC, 2022; Li et al., 2024).

Though vital, adaptation taken by households also results in maladaptation instead of safeguarding. Adaptation measure often occurs locally autonomously, driven by specific risks and is frequently influenced by bounded rationality (Rahman et al., 2023; Schipper, 2020). While this is considered a robust and low-regret risk management strategy (Koerth et al., 2017), many of these are unlikely to happen in the long term and fail to establish the long-term capacity to adapt (Porter et al., 2014). Some even lead to maladaptation with a risk of exacerbating vulnerability by reinforcing, redistributing, and creating new ones while deepening inequality (Eriksen et al., 2021; Schipper, 2020). Examples include households who reported selling their assets to increase their preparedness for flood, leaving them trapped and vulnerable with only their house as an asset (Schaer, 2015). This can be concerning as households may plausibly choose a suboptimal response and make climate action out of reach due to adaptation barriers. On the other hand, delaying adaptation, also identified as maladaptive thinking, will dramatically raise the cost of adaptation, amplifying severity and increasing the burden for eventual intervention (Sanderson & O'Neill, 2020). Scholars agree that climate change adaptation is context-dependent (Noll, Filatova, Need, & Taberna, 2022; Petzold et al., 2023; Reckien et al., 2023), which implies variation across different situations or environments exists. R. Begum et al. (2022) and Schipper (2020) explains adaptation can succeed if the vulnerability's root cause can be tackled. This shows the necessity of well-informed decisions, which requires a thorough understanding of vulnerability.

Understanding how households respond to flood risks and the unintended consequences of these responses is crucial to forming effective climate adaptation policies, particularly in the global south urban. This thesis aims to identify maladaptation within household-level climate adaptation to flooding across various vulnerabilities and how these responses evolve due to complex system interactions. By understanding these, targeted policies to mitigate maladaptation can be developed, and coordination between governments and households can be strengthened.

1.1.1. Scientific Challenges of Maladaptation Studies

Decades ago, the concept of maladaptation, unintended negative consequences of climate adaptation, emerged in research Scheraga and Grambsch (1998). As the field grow, research primarily relied on qualitative assessment using the predefined framework from Barnett and O'Neill (2013) and Juhola et al. (2016), as it offers multidimensional insights. However, as the dynamic nature of maladaptation has become increasingly recognised (Chi et al., 2021; Magnan, 2014), focusing solely on these indicators without translating them into their context can hinder actionable analysis. This is particularly problematic without clear boundaries for sectors, locations, or timeframes. While maladaptation research recognizes unequal impacts Barnett and O'Neill (2010), previous studies often focus on the broader impacts of maladaptation on regions or sectors rather than examining differences within groups, which this thesis refers to household backgrounds. On the other hand, 1.1 shows that while quantitative methods show predictive capability, quantitative insights are tailored for a niche context, resulting in various metrics to operationalise vulnerability channels in defining maladaptation.

Concerning inferring maladaptive adaptation, the field has moved to recognise that maladaptation exists on a continuum (Magnan et al., 2016; Reckien et al., 2023). This dynamic perspective emphasises the importance of understanding how maladaptation can vary over time in different contexts. This is particularly important as labelling any spotted association with predefined indicators as maladaptation can be misleading. This may erroneously imply that all adaptation efforts are detrimental, hindering the development of practical policy interventions.

This dynamic nature and the limitations of qualitative and quantitative assessments highlight the need for a more comprehensive approach. This may involve combining the specificity merits of quantitative methods with the multidimensional merits of qualitative methods to develop a deeper understanding of the complex phenomenon of maladaptation and inform the development of effective adaptation strategies.

1.1.2. Policy and EPA Relevance

Maladaptation is a remarkably complex and multifaceted challenge; it showcases the interconnected interactions between the nature of climate adaptation and climate change risk to human systems, which often unfold as an adverse effect of their societal objectives (R. Begum et al., 2022; Scheraga & Grambsch, 1998). One way to systematically understand this complex challenge understanding the problem systematically is a way to support the policy-making process (Enserink et al., 2022) by breaking it into smaller, more manageable components complemented by more informed policy-making. This includes gathering more information about household-level climate change adaptation as a potential solution to the challenges of climate adaptation policies in urban coastal cities, which were found to be ineffective and institutional challenges were identified, especially in global south (Olazabal & Ruiz De Gopegui, 2021; Petzold et al., 2023). Household-level climate adaptation is a component of the climate adaptation landscape. At the same time, informed decision-making aims to unfold knowledge of the interaction between climate change risk and the human system, including behaviour and the decision-making process of a household in implementing household-level climate change adaptation. Thus, this thesis is closely tied to the Engineering and Policy Analysis (EPA) study program. It incorporates the system

Table 1.1: Summary of Qualitative and Quantitative Insights into Maladaptation

Aspect	Qualitative Insights into Maladaptation	Quantitative Insights into Maladaptation
Approach	Outcome-based evaluation with narrative processes.	Prediction of maladaptation using contextualized theories within defined system boundaries.
Key Frameworks	**(Barnett & O'Neill, 2010)**: Five criteria (GHG emissions, opportunity cost, impact on vulnerable populations, path dependency, incentive to adapt). **(Juhola et al., 2016)**: Vulnerability-focused.	Various models and metrics depend on context (species distribution, economic cost-benefit, social vulnerability).
Application Examples	**Barnett's Framework**: Snowmaking in tourism (Scott et al., 2024), desalination policy (Tubi & Williams, 2021). **Juhola's Framework**: Seawalls in Fiji (Piggott-McKellar et al., 2020), smallholder farmers in Ghana (Asare-Nuamah et al., 2021).	**Environmental**: Species adaptation (Cobben et al., 2012; Gougherty et al., 2021), crop yield (Yu et al., 2021). **Economic**: Flooding impacts (Han et al., 2020), flood risk management (Abebe et al., 2019). **Social**: Vulnerability reinforcement (Antoci et al., 2024), behavioural adaptation (Zander et al., 2024).

thinking view into the policy-making process for societal needs by empowering stakeholders, primarily policymakers, to position themselves towards household-level climate adaptation while minimizing the risk of maladaptation.

1.2. Thesis Structure

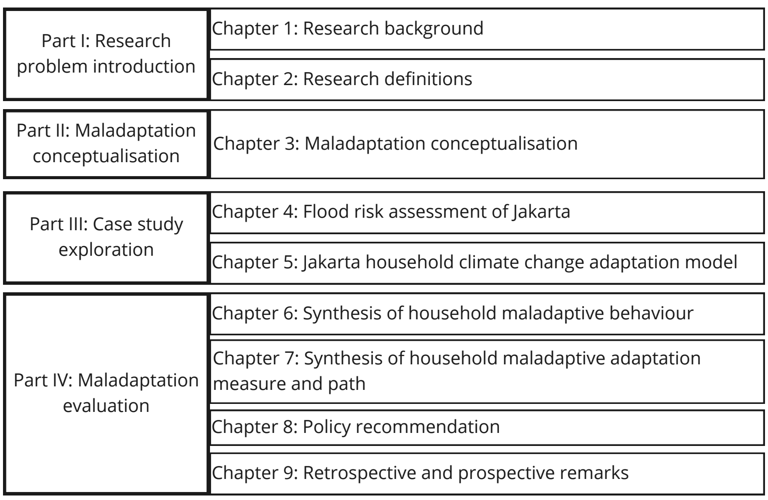

Figure 1.1: Thesis outline

This thesis is divided into four parts as outlined in 1.1. The first part introduces the research background and design to fill the research gap. This part details the specific approach to unfolding insights into maladaptive behaviour and maladaptive outcomes of household-level climate adaptation.

Part II aims to obtain specific indicators and representations of maladaptation that will be used in the case study. To this aim, chapter 3 starts with an in-depth analysis of the scientific approach to quantifying maladaptation. Further, it operationalises maladaptation by introducing the selected metrics and elaborates on the representation of maladaptation from the chosen metrics.

The case study exploration part encapsulates the contextual understanding of the case study. It introduces a case study in Chapter 4 by elaborating on the interaction of flood hazards and vulnerability using a flood risk assessment framework. As this chapter is contextually heavy, it develops multidimensional attributes to evaluate maladaptive responses and lays the building blocks for the household-level climate change adaptation model, which the implementation explained in-depth in Chapter 5.

Finally, Part IV focuses on evaluating maladaptation. It begins by synthesising the indication of maladaptive behaviour as conceptualised in Part II in Chapter 6. Chapter 6 analyzes household behaviour, while Chapter 7 assesses the specific actions taken by households. Both chapters employ a multidimensional approach to understand household adaptation barriers better. With this understanding, Chapters 8 and 9 elaborate reflections based on the insights from the previous chapters, focusing on practical implications and potential avenues for future research.

2 Research Definitions

2.1. Research Questions

The previous section highlights the research gaps below:

Research Gap 1 Lack of comprehensive approach that employs the dynamic nature of maladaptation
Research Gap 2 Lack of maladaptation understanding with the context specificity and social inclusion maladaptation outcomes

The knowledge gap led to the following main research question:

To what extent do household-level climate change adaptation to flooding result in maladaptive responses across urban households, considering their vulnerability to flood risk?

Focusing on the relation between urban household-level climate adaptation to flood risk and maladaptation, this research question aims to unveil a comprehensive understanding of the current practice of household attempts to adapt to floods and identify the characteristics of households that implement potentially maladaptive action, considering that understanding household-level adaptation contribute to a more informed climate adaptation initiatives. The primary research question can be addressed by answering three sub-research questions.

Sub-Research Question 1: What are the measurable indicators and representation of maladaptive flood risk response among urban households?

As identified in Table 1.1, quantifying maladaptation can be varied across context and problem formulation. Hence, there is a need to establish a strong foundation in operationalising maladaptation in the context of household adaptation to climate-induced floods. To this aim, the first sub-research question encapsulates three main aspects: measurable variables, representation maladaptation in a temporal view, and multi-dimensional representation of urban household vulnerability to flood risk, which also involves the spatial element. Reckien et al. Reckien et al. (2023) propose that maladaptation can be seen through categorised assessment criteria, such as system-level and equity-related criteria. The requirements may differ or be expandable based on the relevancy of the local context and the intention of the assessment. This underscores contextualising the household flood risk is necessary. This sub-research question positions the inherent risk of maladaptation of household-level climate change adaptation measures within the maladaptation spectrum.

Sub-Research Question 2: What factors drive maladaptive behaviours in urban household-level flood adaptation, and how do these behaviours influence adaptation implementation and distribution across vulnerability to flood risk?

Maladaptation refers to an action that can exacerbate vulnerability, so inaction is included, as maladaptation is categorised as maladaptive behaviour. The outcome of inaction is also an option for climate change adaptation. To explain this maladaptive behaviour, people's intention to adopt influences the outcome of inaction. Hence, sub-research question 2 aims to obtain factors that potentially drive maladaptive behaviour and compare this with the final decision of implemented adaptation measure.

Sub-Research Question 3: From the emerged urban household-level flood adaptation, what patterns and trends can be identified as maladaptive responses, and how do these vary across their vulnerability to flood risk?

Evaluating the action taken distinctively is insufficient to examine the impact of maladaptation. In practice, household adaptation measures can be combined with other measures, which this research further refers to as adaptation paths. Finally, utilising the framework to evaluate maladaptation built in the first sub-research question, the third sub-research question aims to assess the emerged adaptation path across different households. Moreover, this question can also identify which households under which inaction may be more beneficial than maladaptive strategies. By investigating this, we can better understand these household-level adaptations.

2.2. Foundation of Supplementary Theories

This thesis recognises the need to study maladaptation beyond the theory of maladaptation, especially to integrate with flood risk and household-level climate change adaptation. The first subsection explains how maladaptation is positioned within the flood risk framework. It is followed by the behaviour of household-level climate change adaptation to explain the motivation as well as the maladaptive behaviour.

2.2.1. Maladaptation Encapsulated Within Response as Climate Change Risk Framework

Referring to its definition, maladaptation is a concept relevant to vulnerability. According to IPCC (2022), vulnerability entails a range of ideas and elements, encompassing sensitivity or susceptibility to harm and a deficiency in the adaptive capacity or capacity to cope and adapt. Hence, the vulnerability component is associated with the determinant of adaptive capacity (Hinkel, 2011). On the other hand, the discourse on climate change impacts has predominantly been structured around a risk-based approach called "climate change risk." Scholars highlight that in today's highly networked world, there is increasing evidence of the intricate connection between climate change drivers and risks (Pescaroli & Alexander, 2018), for instance, the increased flood risk resulting from the interactions of higher precipitation and rising sea levels.

Recent scholarly efforts have broadened this perspective by incorporating response as a determinant of climate change risk, recognising that the nature of responses to climate change can influence risk levels by interacting with other determinants (R. A. Begum et al., 2022; Simpson et al., 2021). Thus, the Intergovernmental Panel on Climate Change (IPCC) defines differing degrees of risk complexity with four determinants: hazard, exposure, vulnerability, and response, each with drivers that contribute to the overall climate change risk landscape (R. Begum et al., 2022), visualised in Figure 2.1 in the IPCC Risk Assessment Framework outlined box. The nuanced understanding of climate change risk provides a vital setting for reevaluating maladaptation within the bigger context of climate change, which also signals maladaptation as a process. In the new framework, response refers to the role of climate change responses to climate change affecting risk or existing or new risk (Simpson et al., 2021). The potential risks of responding to climate change include the possibility of making maladaptive adjustments, failing to achieve intended objectives, facing trade-offs, or experiencing adverse side effects. This perspective aligns with and enriches discussions on maladaptation. Examining maladaptation through this lens implies maladaptation as a climate change driver is linked to vulnerabilities as climate change determinants.

2.2.2. Protection Motivation Theory: Household Motivation to Adapt

Protection motivation theory (PMT) determines household behaviour and implements adaptation. PMT was initially developed to explain how individuals respond to threats (Rogers, 1975). As climate change adaptation refers to protecting against the climate threat, protection motivation theory is widely used to describe climate adaptation behaviour, particularly at individual levels (Babcicky & Seebauer, 2019; Botzen et al., 2019; Bubeck et al., 2018). The outcome of PMT demonstrates whether to take protective measures or not, which encompasses five maladaptive coping dimensions, including fatalism, avoidance, religious faith, wishful thinking, and hopelessness (Rogers, 1975). Figure 2.1 in the Protection Motivation Theory outlined box exhibit the structural model, the model is operationalised as the intention to adopt specific actions comprised of two pathways that link perception to behaviour: threat appraisal and coping appraisal. These two pathways are further operationalised and driven by components. The perceived severity and vulnerability widely determine threat appraisal. On the other hand, coping appraisal is often defined as response efficacy, self-efficacy, and perceived costs. However, as socioeconomic and external factors influence individuals' irrational decision-making, PMT models have been expanded by incorporating these factors (Noll, Filatova, & Need, 2022).

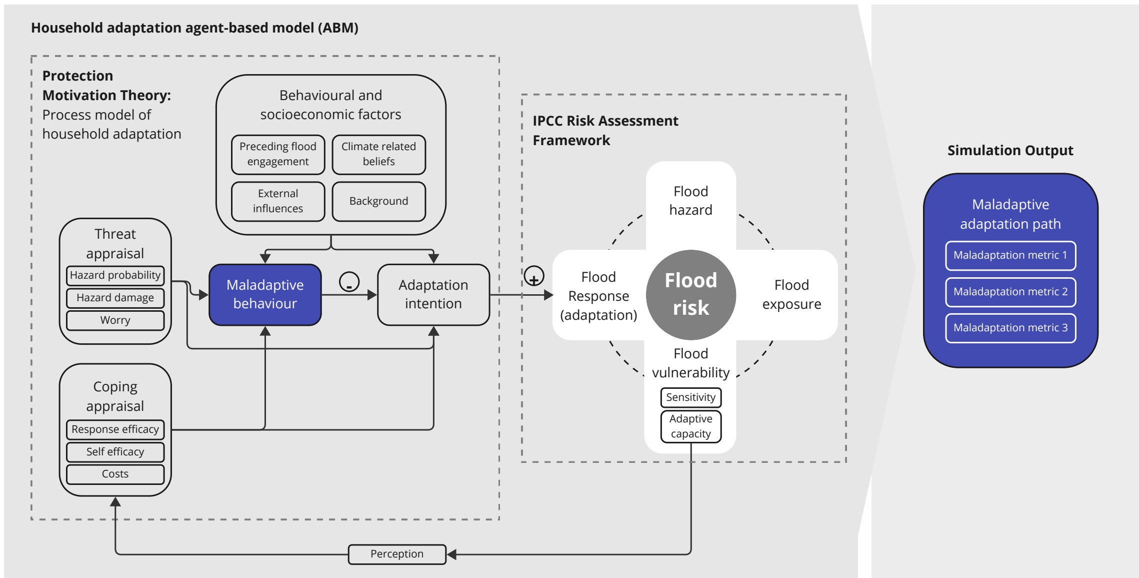

Figure 2.1: *Conceptualisation of research method.* Visualisation of structural PMT model is adapted from Babcicky and Seebauer (2019) and Bubeck et al. (2018).

2.3. Research Methods

The sub-questions above will be answered using different methods. This study will use a mixed-methods approach, which combines the merits of qualitative and quantitative techniques, to understand maladaptation comprehensively.

2.3.1. Research Approach

Agent-Based Modelling: Modelling and Simulation Approach

Barnett and O'Neill (2010) and Magnan et al. (2016) see maladaptation as a cumulative risk that will allow the progress of a household state towards maladapting that, in various articles agreed involves temporal scales. Maladaptation conceptualisation proposed by Magnan et al. (2016) considers its dependency on the previous state, which enables the acknowledgement of multiple measures taken at a time. Hence, a longitudinal model can track changes in household states over time, accounting for the time dependency. Beyond temporal scales, the importance of a multidimensional view in maladaptation requires involving household attributes and spatial scales to identify heterogeneous households. A bottom-up modelling paradigm called Agent-based modelling (ABM) is used for this complex interaction. ABM was initially motivated by complex adaptive systems (CAS) to investigate adaptation and emergence of systems (Macal & North, 2009). ABM enable dependency of state by allowing agents to learn and engage from the dynamic interaction within the model. Moreover, ABM analyzes systems at a granular level (Crooks & Heppenstall, 2012), allowing agents to behave differently, which is especially important for heterogeneous households and a multidimensional analysis of maladaptation. This disaggregated approach enables data collection and management at finer detail (Macal & North, 2009). The ABM model has been widely known as a tool for simulating the decision-making process during the interaction between agent and their environment, which is also applied in climate adaptation in the context of flooding (Abebe et al., 2019; Han et al., 2020). A dedicated study about using ABM in climate adaptation impact for coastal communities found that ABM better allows observation and explains household dynamics while also having scenario testing under various measures (Lawyer et al., 2023).

Building on previous theoretical foundations, Figure 2.1 shows that ABM encapsulates the PMT to represent the agent behaviour and the environment, and the interaction within the model will be represented by the IPCC Risk assessment framework.

Jakarta: Case Study Approach

Due to the highly contextual flood risk assessment and data specificity requirement for ABM, this study employs a case study approach. Jakarta is a metropolitan area with a dense population, growing to 11 million in 2020, the majority located in Central Jakarta with a density of 22 thousand people per km^2 (Unit Pengelola Statistik Dinas Komunikasi, Informatika dan Statistik Provinsi DKI Jakarta, 2021). The Jakarta province administrative area is geographically located in the outer part of Java Island, categorising it as an urban coastal area.

The capital of Indonesia finds itself in a precarious position. Historically, flooding in the capital city of Jakarta is not a new problem. However, as Jakarta's population density grows, flooding in Jakarta is exacerbated by the changes in land use and the vast number of residents impacted (Budiyono et al., 2015). These place immense pressure on urban communities and infrastructure. Disparities are even worse locally, with a Gini ratio of 0.42, higher than the national average (The Jakarta Post, 2023). The disparity in Jakarta suggests that not all its residents can afford the necessary adaptation measures to cope with the intensified flooding. As a result, some do not take any measures, while others focus only on responding to the current flood threat. The natural susceptibility of Jakarta to flooding, compounded by human-induced factors, makes it a compelling case for an in-depth study on maladaptation due to household adaptations in facing the threat of climate-induced flooding.

2.3.2. Research Flows and Deliverables

Figure 2.2 shows research will be conducted in three phases with a continuous flow.

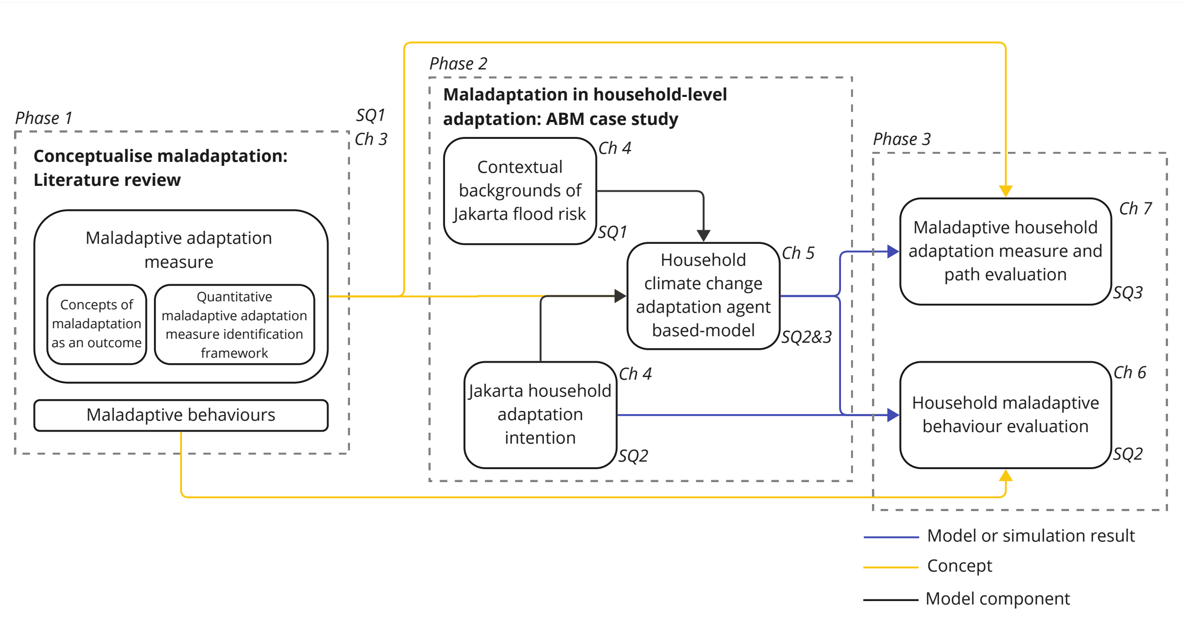

Figure 2.2: *Research flow*

Phase 1
Sub-research question 1 is the first phase and is the research's foundation. It will deliver measurable indicators of maladaptation and a conceptual representation for evaluating maladaptation. To this end, the method involves conducting a literature review to quantify maladaptation and identify maladaptive behaviour, which is documented in Chapter 3.

Phase 2
The second phase of the research acts as the connecter between phases 1 and 3, which cover all sub-research questions—starting by documenting the climate change risk perspective proposed by R. Begum et al. (2022) and Simpson et al. (2021) to acquire a multidimensional view of household vulnerability and explaining data for model purposes. Further derived behavioural factors and actions taken by the household and establishing the household decision-making rules derived from the SCALAR survey (Filatova et al., 2022). From this, logistic regression will be employed to derive behavioural and socioeconomic factors that drive the intention of adaptation. From this data and adaptation decision-making rules, the implementation of ABM is described further, leveraging the CRAB model by Taberna et al. Taberna et al. (2023) of bounded and unbounded rationality of agent in establishing climate adaptation decision-making rule. Moreover, it contextualised maladaptation by setting up the metrics acquired from Phase 1.

Phase 3
Phase 3 addresses sub-research questions 2 and 3 by analysing simulation results. Sub-research question 2 focuses on maladaptive behaviour and aims to identify the gaps between intention and the emergence adaptation measure and paths. Sub-research question 3 aims to identify and generalize the characteristics of households likely to implement maladaptive adaptation measures. By analyzing these measures alongside socioeconomic factors and employing spatial visualization techniques, the research facilitates policymakers' support of families in avoiding maladaptive outcomes.

Ultimately, understanding maladaptation through the outcome and intention of household decisions can inform policymakers and stakeholders to better position themselves in supporting household adaptation measures. Moreover, the multidimensionality of household vulnerabilities can contribute to more-informed climate change adaptation initiatives derived from maladaptation symptoms from empirical evidence at a household level.

3

Maladaptation Conceptualisation

3.1. Approach Used in This Study

This study employs a literature review to acquire the operationalization of maladaptation. To this aim, the search started by identifying the main concepts: “maladaptation”, “climate change adaptation”, “private adaptation”, “household adaptation” and related keywords: “flood adaptation”, “resilience”, “vulnerability”, “risk management”. Building upon this foundation, it developed within the area of the maladaptation subject, as demonstrated in the box below. The search string is employed in various scholarly databases and NGO reports, such as Scopus, Google Scholar, Nature, IPCC, UNFCCC, and World Bank. The article should pass the title and abstract assessment to be included in the review, which results in 40 articles.

Listing 3.1: Search Query 1

```
(”maladaptation” OR ”maladaptive outcomes”) AND (”climate change
   ↪ adaptation” OR ”adaptation to climate change”)
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Listing 3.2: Search Query 2

```
(”private adaptation” OR ”household adaptation”) AND (”climate risks”
   ↪ OR ”climate change risks”)
```

Listing 3.3: Search Query 3

```
(”flood adaptation” OR ”flood resilience”) AND (”household” OR ”private
   ↪ ”) AND (”adaptation strategies” OR ”adaptation measures”)
```

Listing 3.4: Search Query 4

```
(”vulnerability assessment” OR ”risk management”) AND (”climate
   ↪ adaptation” OR ”adaptation measures”) AND (”households” OR ”
   ↪ private sector”)
```

Listing 3.5: Search Query 5

```
(”maladaptation” OR ”adaptive responses”) AND (”climate change
   ↪ adaptation” OR ”private adaptation” OR ”household adaptation”)
   ↪ AND (”flood*” OR ”resilience” OR ”vulnerability” OR ”risk
   ↪ management”)
```

3.2. Conceptualising Maladaptation

The Intergovernmental Panel on Climate Change (IPCC) defines climate adaptation as adjusting human and natural systems to cope with current or expected climate changes and their impacts (IPCC, 2014). Climate adaptation encapsulates the proactive, meaning actions are taken to prepare for future impacts, or reactive, where adjustments are made in response to actual effects.

Climate change impact is beyond political-administrative boundaries. Research suggests that developed countries are not immune to climate change, showing that geographical factors play a more significant role (Lake et al., 2012). Hence, in taking climate adaptation action, the scale and stakeholders' role in adaptation initiatives are usually critical questions to coordinate and collaborate (Vedeld et al., 2016). However, reaching an agreement can be challenging, as climate adaptation is a social process that underpins sociocultural characteristics and the values and power dimensions involved in responding to a changing environment (Wolf, 2011). This emphasizes the significant impact of perception on shaping adaptation in a given situation.

At a household level, perception towards risk could lead to maladaptation (Floyd et al., 2000). This is encapsulated within PMT, as maladaptive behaviour is introduced by Rogers (1975). PMT posits that individuals appraise threats and coping mechanisms, influencing their adaptive or maladaptive behaviours. Adaptive response refers to the decision to take action to prevent. Maladaptation responses have been identified as one of four core elements in the cognitive process of protection motivation theory model (Ghanian et al., 2020). This is consistent with the theory, Rippetoe and Rogers (1987) identified four possible maladaptive coping mechanisms: hopelessness that believes no feasible solution, wishful thinking to treat the solution as unrealistic, avoidance to deny the threat actively, and fatalism to accept the situation as unchangeable by human action. Others encompass five maladaptive coping dimensions: fatalism, avoidance, religious faith, wishful thinking, and hopelessness (Babcicky & Seebauer, 2019; Bubeck et al., 2018; Rogers, 1975). Thus, inaction can be considered maladaptive if the behavioural factors driving this decision are explained.

On the other hand, if households implement adaptation measures, adaptation efforts sometimes backfire, resulting in maladaptation. This term encapsulates actions intended to reduce vulnerability to climate change but instead exacerbate vulnerabilities and pose high risks of adverse consequences (Barnett & O'Neill, 2010; IPCC, 2022; Juhola et al., 2016; Magnan et al., 2016; Schipper, 2020). Eriksen et al. (2021) further explain how a maladaptive adaptation can emerge through three different mechanisms of intervention on vulnerability: reinforcing, redistributing, or creating new vulnerabilities. Moreover, (Juhola et al., 2016) offer typology based on the type of maladaptation: *rebounding vulnerability* exhibits the delayed emergence of negative impact, *shifting vulnerability* shows that the effort does not indeed reduce vulnerability but instead transferred to another part of the system, and *eroding conditions* demonstrate the decrease in vulnerability but damage the system's capacity in the long term. As maladaptive outcomes will be acquired due to an ABM, the subsections below cover two important concepts to evaluate maladaptation.

3.2.1. The Importance of Reference Point: Spatial and Temporal Scales of Maladaptation

Maladaptation encompasses both temporal and spatial scales. Magnan et al. (2016) highlights the four main dimensions to assess the risk of maladaptation, which include spatial scales. They refer spatial scales to the geographical area of the impact of the adaptation initiative, emphasizing that solely considering immediate environs (in situ) where the solution is applied is insufficient, as also highlighted by (Chi et al., 2021). Aside from that, the spatial dimension of maladaptation, in essence, can be framed as a more comparative approach. The well-known maladaptation conceptualisation powerfully demonstrates the involvement of two opposing categories, which reflect the importance of spatial dimension. Spatial, in this case, refers to how objects are positioned and arranged to each other, which also includes the distance expression including *"near"* and *"far"* (Frank, 1992).

Building upon this concept, maladaptation study can be approached as in-situ (internal), self-reference, ex-situ (external), or outside-reference. For ex-situ, maladaptation can be assessed as similar to what has been demonstrated by Magnan et al. (2016) and Juhola et al. (2016) that an adaptation initiative may exacerbate others. Thereby introducing an equity component to the discussion of maladaptation. In addition, ex-situ can also be observed in relation to the temporal dimension by referring to the previous state. Unlike ex-situ, which can be observed with spatial and temporal space, in-situ can only be observed with a temporal dimension by understanding long-term trajectories. The temporal dimension of maladaptation is identified as a dynamic process rather than a discrete impact of an action (Reckien et al., 2023). This process is best understood from the broader context, for instance, through the lens of adaptation pathways as argued by Singh et al. (2016), which allows its evolution over time as Magnan et al. (2016) describe. There is also a feedback loop where maladaptation contributes to vulnerability by increasing exposure and sensitivity Magnan et al. (2016). As vulnerability and the implementation of potentially maladaptive measures increase, so does the risk of maladaptation. These measures fail to increase adaptive capacity, reduce sensitivity, or lessen exposure and negatively impact other systems, social groups, or sectors (Barnett & O'Neill, 2010; Barnett & O'Neill, 2013). In a more complex manner, Chi et al. (2021) indicates a dynamic state of maladaptation with a time-delayed characteristic. These emphasise the importance of temporal dimensions in assessing maladaptation.

Temporal and spatial scales are critical aspects in assessing or identifying maladaptation. These aspects could not be disregarded. According to Barnett and O'Neill (2010), maladaptation can be identified as negatively affecting another system. Based on this understanding, this triggers further questions about to what extent the other system is. Without precise temporal and spatial scales, a climate adaptation can potentially always be viewed as maladaptation, making it hard to discern with non-maladaptive action. Hence, having clear boundaries represented by temporal and spatial scales is critical, which is also emphasised by Magnan et al. (2016). Various approaches to studying maladaptation can result in different inferences based on the definition of the reference point.

3.2.2. Multidimensional Drivers of Maladaptation

As argued by Wolf (2011), climate change adaptation is inherently a social process. This necessitates considering factors beyond the physical impact of climate change; factors such as politics (Eriksen et al., 2015) and equity and impact distribution (Shi et al., 2016) become crucial. From this understanding, maladaptation can be assessed as the result of an adaptation decision. Entities make decisions to formulate responses to climate change, which involves upholding the entity's and system's values (Brink & Wamsler, 2019). From the decision-making process incorporating complex interaction between social, economic, and political systems, maladaptation occurs due to neglecting vulnerability drivers (Magnan et al., 2016).

Despite a growing body of literature supporting the notion that maladaptation is a manifestation of adaptation failure that exacerbates vulnerability and relates to the interconnected topics (Barnett & O'Neill, 2010; Burton, 1997; IPCC, 2012; Magnan et al., 2016; Scheraga & Grambsch, 1998), its practical application remain challenging. The structural challenges that contribute to maladaptation, as identified by Bertana et al. (2022), represent the necessitate to reflect climate adaptation to social, economic, and environmental concerns alongside political factors. This also aligns with Glover and Granberg (2021), which argues for a broader perspective. Decision-makers who only focus on climate impacts might overlook these crucial considerations. Findlater et al. (2022) argues that adaptation should be about protecting fundamental needs like food, water, shelter, and energy. Further, the authors criticize a narrow view of maladaptation as simply a reaction to climate change. This underscores the concept of adaptation as a process that enables organisms or systems to fit into their actively evolving environment from climate-mediated changes (Stein et al., 2013).

The adaptation decision aims for sustenance beyond the climate concerns, which involve multi-dimensionality. This multi-dimensionality has a differential impact on the equity and impact distribution. This aligns with Toole et al. (2016), who further emphasises that adaptation is intertwined with day-to-day life. In addition, the temporal dimension of climate adaptation outcome complicates identifying maladaptation through delayed effect (Chi et al., 2021; Juhola et al., 2016). Maladaptation, therefore, occurs when climate adaptation decisions, which often come from a bounded rationality of social process, produce unintended negative consequences.

3.3. Operationalisation of Maladaptation

Overall, the quantitative approach for maladaptation is utilised for specific usage, with a clear distinction between maladaptation and characteristics of the state that can be identified as maladaptation. With a particular function described in Table 1.1, the quantitative approach offers methods to tackle temporal space with its predictive capability. The qualitative approach provides rich and multidimensional aspects to be incorporated in a thorough assessment of maladaptation with a rich context. Insights derived from Section 3.2, operationalisation of maladaptation is needed to employ a model for maladaptation context, as demonstrated by Reckien et al. (2023) to assess global maladaptation. Two aspects are required to tailor the model for maladaptation study purposes. First, metrics of maladaptation. Maladaptation as an outcome of an adaptation that exacerbates vulnerability needs metrics to determine which vulnerability channel is identified. Having solely metrics to discuss maladaptation is vague without a reference point. Therefore, identifying reference points used in maladaptation study is as essential as having metrics. Below, metrics and reference points commonly used by scholars are discussed.

3.3.1. Indicators of Maladaptation

The pattern within the research on maladaptation reveals that the theoretical foundation of maladaptation has been instrumental in establishing standards for identifying maladaptation, and scholars define it through observable criteria. While qualitative research has benefited from an established foundation, quantitative approaches remain diverse, suggesting a nascent application stage. However, researchers have employed a range of context-specific variables alongside shared ones, summarised in Table 3.1. The variables include:

1. Economic indicators: This reflects the cost-effectiveness of interventions and whether the intervention effectively absorbs the damage. This aligns with the criteria of efficiency of climate adaptation and opportunity cost in undertaking climate adaptation (Han et al., 2020). Moreover, this also aligns with the concept of maladaptation that can exacerbate vulnerability (Schipper, 2020), which translates as damage or loss. The calculation of damage cost due to maladaptation varies depending on the damage proxy and hazard considered.

2. Environmental indicators: Implies environmental degradation due to the changing landscape after the adaptation. One standard observable variable of ecological degradation is emission and the decreasing biodiversity due to extinction or species migration. Despite this, environmental degradation also depends on the context. In the agriculture study, crop failures reduced soil nutrients and access to water (Asare-Nuamah et al., 2021; Findlater et al., 2022). In the coastal study, erosion and changes in the coastal landscape are the observable variables that help identify environmental degradation (Salim et al., 2019). The observed ecosystem service degradation can exacerbate social and economic vulnerabilities.

3. Social Indicators: This relates to the social impact of adaptation measures, including displacement, well-being, livelihood shifts, and conflicts. The quantifiable variable, including the rate of displacement or resettlement following adaptation measures, indicates a change from habitable to uninhabitable areas, whether temporary or permanent. The displacement can further lead to social fragmentation, which also relates to social vulnerability. Like climate change, which can be impacted in various channels, the adaptation project can also affect health. For instance, commodity shifts require more pesticides, increasing the incidence rate of climate-sensitive diseases or disrupting access to clean water.

4. Lock-in indicators: Lock-in highlights entrapment phenomena which applied across various disciplines denoted by *'path dependency'*, *'interlocking situation'*, and *'trapped'* (Goldstein et al., 2023). The entrapment phenomena hinder the ability of a system to adjust. This includes observing reliance on adaptation measures, such as reliance on insurance.

Based on this list, the variables exhibit a deficit-focused assessment of adaptation and often require a reference point. Some indicators can be used in decision-making. This implies not only criteria but also adapting to climate change. For example, migrants who decide to migrate and farmers who shift livelihoods as no other practical choice is assumed to help them remain in the exact location. Besides, reliance on specific measures also depends on maintaining at least the bare minimum level to keep the system functioning. As a result, these indicators can be used if only the decision-making process or maladaptation as the process is enabled.

Scholars assess maladaptation by looking at direct and indirect impacts to capture the full spectrum of unintended consequences of maladaptive actions. Despite recognising the importance of spatial scale, the assessment of the geographic effects remains limited, especially in how these impacts are distributed or manifest across different geographic regions. This showed that existing assessments heavily relied on empirical and observation, seeing the emerging behaviour of the total system. On the other hand, the total system perspective may overlook the redistribution and shift of vulnerability due to maladaptation.

Table 3.1: Summary of Maladaptation Indicators and Measurements

Type of Indicator	Specific Indicators	Examples of Measurement	References
Economic Dimension	Damage cost	Financial losses due to environmental degradation that reduces total gross output	(Antoci et al., 2024)
		Cost of repair due to climate-related failures	(Pritchard & Thielemans, 2014)
		Flood depth-damage loss function estimating damage as a percentage of property values	(Han et al., 2020)
	Adaptation cost	Cumulative expenses across different scenarios	(Han et al., 2020)
		Opportunity costs in a cost-benefit analysis for flood defenses	(Barnett & O'Neill, 2010)
		Standalone project cost compared with GDP for flood defences	(Salim et al., 2019)
	Loss in productivity	Yield comparisons in current and future climates indicating productivity loss	(Yu et al., 2021)
		Less productive tree species due to climate mismatch	(Findlater et al., 2022)
	Livelihood shift	Disruption and forced relocation of small-scale fishing	(Salim et al., 2019)
		Transition from farming to fishing and vice versa due to changing flood patterns	(Naufal et al., 2023)
Environmental Dimension	Loss of biodiversity	Species extinction and migration	(Asare-Nuamah et al., 2021; Cobben et al., 2012; Findlater et al., 2022; Gougherty et al., 2021; Scheraga & Grambsch, 1998; Scott et al., 2024)
		Noted endangered species	(Scott et al., 2024)
	Pollution	Measured pollutants in specific contexts such as industrial effluents	(Asare-Nuamah et al., 2021; Naufal et al., 2023; Scheraga & Grambsch, 1998; Scott et al., 2024)
		Urban runoff	(Naufal et al., 2023)
	Loss of ecosystem services	Agricultural soil nutrient depletion	(Asare-Nuamah et al., 2021; Findlater et al., 2022; Reckien et al., 2023; Salim et al., 2019)
		Water access issues in coastal studies	(Salim et al., 2019)

Continued on next page

Table 3.1 – continued from previous page

Dimensions	**Specific Indicators**	**Examples of Measurement**	**References**
	Increased GHG emissions	Emissions from inappropriate adaptation measures in urban planning	(Barnett & O'Neill, 2010; Juhola et al., 2016; Piggott-McKellar et al., 2020; Reckien et al., 2023; Salim et al., 2019; Scheraga & Grambsch, 1998; Scott et al., 2024; Tubi & Williams, 2021)
		Soil erosion	(Magnan et al., 2016; Mallik & Bandyopadhyay, 2024; Piggott-McKellar et al., 2020; Scott et al., 2024)
Social Dimension	Health issues	Increase in climate-sensitive diseases due to pesticide use	(Schipper, 2020; Scott et al., 2024)
		Disruptions in water sanitation	Scheraga et al., 1998
	Migration and relocation	Displacement rates post-adaptation projects	(Gougherty et al., 2021; Magnan et al., 2016)
	Increase in group conflict	Conflicts triggered by adaptation measures	(Magnan et al., 2016; Pritchard & Thielemans, 2014; Scheraga & Grambsch, 1998; Schipper, 2020; Scott et al., 2024)
	Well-being	Impact on well-being due to adaptation measures	(Antoci et al., 2024)
	Inequality	Impact on social inequality due to adaptation measures	(Antoci et al., 2024; Salim et al., 2019)
Lock-in Indicators	Dependencies of energy infrastructure	Reliance on specific infrastructure adaptations	(Schipper, 2020; Scott et al., 2024)
	Reliance to subsidies and insurance	Dependence on financial aids like subsidies and insurance	(Schipper, 2020; Scott et al., 2024)
	Cost to change existing policy	Costs associated with modifying current policies due to maladaptation	(Findlater et al., 2022)
	Decrease in adaptive capacity	Reduced ability to adjust to further climate impacts	(Juhola et al., 2016; Scott et al., 2024)

3.3.2. Reference Point of Maladaptation Studies

A reference point is essential to identify maladaptation effectively 3.2.1. Distinguishing between adaptive and maladaptive outcomes becomes challenging without a baseline or comparative standard. The most straightforward approach is to use historical data within the same entity as a reference point, allowing for the assessment of absolute or relative changes over time. This method also respects the unique characteristics of each entity.

For example, Yu et al. (2021) pinpoints the reference point to other entities compared to peers facing similar conditions. For instance, the evaluation of agricultural yield performance under changing climatic conditions of two cultivars denoted as Cultivar 1 and Cultivar 2. V0 is the initial yield of Cultivar 1 at time t1. At the same time, V1 and V2 are the yields of Cultivar 2, which is adapted for future climate changes, and Cultivar 1, which is not adapted at a later time, t2, after the changing conditions. The relative improvement or decline in yield due to adaptation, with the formula (V1 - V2)/V0, thus indicating adaptation or maladaptation. Positive values represent adaptation, while maladaptation is represented by negative values, indicating a decline in performance to the original yield of Cultivar 1. However, this method has limitations. It may overlook the unique needs or circumstances of the entities involved, potentially misclassifying the adaptation as maladaptive simply because it does not align with the entity's specific requirements. Furthermore, selecting appropriate entities for comparison remains a significant challenge.

Although not common, other approaches include establishing predetermined criteria as the measure's expected outcome to be considered successful. This can facilitate uniformity and comparability in assessment. Despite the uniformity, this may fail to accommodate the context of adaptation.

Changes in the system can be measured with relative or absolute changes. Absolute changes offer straightforward comparison without directly considering performance relative to others. A similar notion can be found in a qualitative study that observed the changes within the subject study, such as (Asare-Nuamah et al., 2021; Piggott-McKellar et al., 2020; Scott et al., 2024). The deltas allow the evaluation of each entity based on its characteristics. Hence, assuming other variables remain constant, the deltas will allow contextual understanding in answering which condition where adaptation measure is effective or not. On the other hand, the relative changes focus on the difference between two different entities. This is particularly useful for assessing the benefits or lack of specific adaptation measures.

From the household perspective, maladaptation is multidimensional, varying across physical space and within social groups. It exhibits two attributes: location-derived and characteristics-derived. Location-derived attributes are influenced by geographical positioning, which shows a spatial landscape of hazard and resulting physical exposure and vulnerability to climate change risk. Social dimensions influence characteristics, from recognising vulnerability and decision-making to taking adaptation measures.

3.4. Indicators and Representation of Maladaptation

Building upon reference points and multidimensional aspects of maladaptation, scholars employ various indicators to define maladaptation. The literature has four types of shared indicators: economic, environmental, social, and lock-in. These four support the notion of adaptation to protect fundamental needs as argued by Findlater et al. (2022). Hence, this study will employ three indicators from three different indicator types: economic, social, and lock-in, while the environment is not included as the model focuses on household interaction.

3.4.1. Loss Avoidance

Objective: This represent economic indicators combining damage cost as applied by Antoci et al. (2024) and Pritchard and Thielemans (2014) and adaptataion cost as applied by Han et al. (2020). Utilising residual damage variables, loss avoidance aims to be a neutral focus in evaluating the impact of climate adaptation measures on all actions by leveraging the damage cost as commonly applied in maladaptation studies to quantify the cost-effectiveness of adaptation measures. Moreover, this indicator also emphasises the key aspect of reference points in identifying maladaptation.

Identifying maladaptation: This approach utilised inaction as the baseline reference point to compare the impact of adaptation measures. The cost of inaction signifies the escalating damages from allowing uncontrolled climate change (Ackerman & Stanton, 2006). The increasing residual damage denotes the accumulation of effects combined with the socio-economic changes. On the other hand, the cost of adaptation is the total expenditure of investing in the particular adaptation measure and actual spending to recover from the unavoidable climate impact (European Environement Agency, 2023). The effectiveness of adaptation is determined by the concept of avoided loss, which is the reduction in damage compared to the baseline scenario of inaction. Adaptation can be effective in preventing loss or result in maladaptation. Maladaptation occurs when the residual damage exceeds the projected damage under inaction. Figure 3.1 illustrates these relationships; the benefits of adaptation are derived as the avoided loss, effectively reducing damage, and the right panel shows where adaptation inadvertently increases damage.

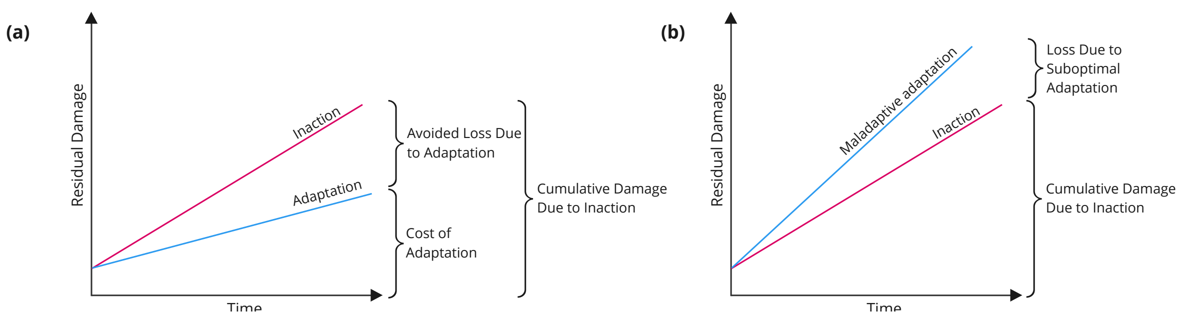

Figure 3.1: *Representation of climate adaptation impact to residual damage of climate adaptation and inaction*: Panel (a) loss avoidance due to effective adaptation and (b) impact of maladaptive adaptation (adapted from European Environement Agency (2023) and UNFCCC (2009)).

3.4.2. Inequality

Objective: Of identified indicators to asses maladaptation (see Table 3.1), inequality represents a social aspect of maladaptation and reflects the importance of including impact distribution within their criteria. Climate change risk and vulnerability are not equally distributed, nor are their adaptive capacities inherently varied (R. Begum et al., 2022; Noll, Filatova, Need, & Taberna, 2022). This indicator aims to evaluate the distributional impacts of climate adaptation measures among different social strata. As Jakarta identified with relatively high inequality (The Jakarta Post, 2023), it is interesting to see the progression of inequality driven by the response or household-level climate change adaptation.

Identifying maladaptation: By utilising net worth to represent the welfare of multiple groups, assessing how adaptation measures impact the stability of various demographic groups, particularly the financial aspect. From this indicator, an increase in inequality after adaptation, indicated by a widening net worth gap between the advantaged and disadvantaged groups, signals that the adaptation measures are not working well (Antoci et al., 2024). This is visualised in Figure 3.2; the diverging net worth growth slopes post-adaptation measure the differential recovery rates, highlighting how some groups may suffer disproportionately. Moreover, Gini index as demonstrated by OECD (2016) is also used to be comparable with the current condition of inequality in a city level.

3.4.3. Lock-In

Objective: Lock-in can manifest in multiple dimensions, including institutional and behavioural dependencies (Goldstein et al., 2023). This study focuses on path dependency as it relates to financial capital availability. Specifically, this study uses available capital as a proxy to gauge household capacity to access domestic private adaptation measures, which often incur significant costs. Financial lock-in occurs when households are constrained by their financial resources, hindering their ability to implement necessary adaptive measures.

Identifying maladaptation: This study employs net worth as the primary metric to assess financial lock-in and its impact on adaptation capability. A household is considered to be in a lock-in situation if it faces financial hardships severe enough that its net worth does not suffice to fund further necessary adaptation measures. This form of financial lock-in represents maladaptation, restricts the household's immediate ability to respond to climate threats and limits long-term resilience by preventing investments in adaptation strategies. This operationalization highlights the critical intersection of economic capacity and adaptive response, underscoring the need for adaptation policies that are financially inclusive to prevent maladaptive outcomes.

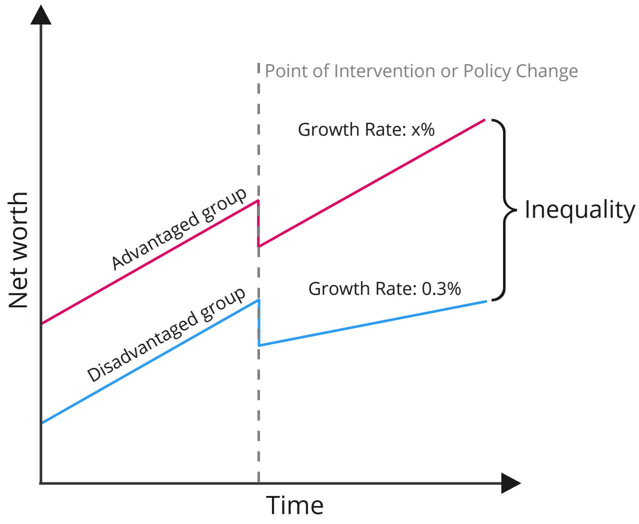

Figure 3.2: *Representation of differential rate of recovery from climate adaptation of advantaged and disadvantaged group* (adapted and developed from Islam and Winkel (2017)).

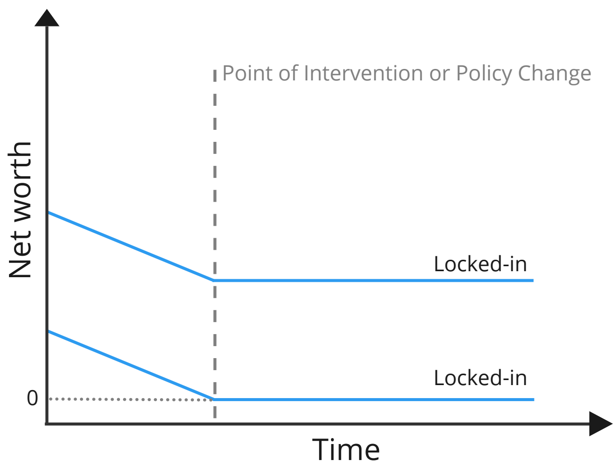

Figure 3.3: *Representation of lock-in situation* (adapted from Goldstein et al. (2023) and Lade et al. (2020)). The blue lines represent two scenarios of lock-in which both identified lock-in if post-adaptation turned into a stagnation period.

4

Jakarta Household Flood Risk Profile

Building upon the developed metrics and representation in assessing maladaptation Section 3.4, three metrics have been designed to evaluate maladaptation and simulate endogenously in Jakarta's flooding by focusing on direct and tangible damage (in monetary terms). To illustrate, flood damage consists of tangible and intangible damage, wherein tangible damage is divisible into direct damage caused to items such as building and inventory items and indirect damage caused by interruption to, for instance, an economic network (Romali et al., 2015). With this aim, the recent development of IPCC's fourth driver is used to exhibit flood risk while measuring the metric involving hazard, exposure, vulnerability, and response.

$$\text{Damage (million IDR)} = \text{Depth-Damage (million IDR/m}^2\text{)} \times \text{Property Size (m}^2\text{)} \tag{4.1}$$

$$\%\text{Damage} = \frac{\text{Damage (million IDR)}}{\text{Property Value (million IDR)}} \tag{4.2}$$

4.1. Contextual Background of Jakarta

Jakarta province includes the Kepulauan Seribu region, a small island in northern Java Island where the remaining areas are located. The population is almost evenly distributed across Java Island regions, with most residing in Central and West Jakarta. As Kepulauan Seribu has different characteristics from other Jakarta regions, this study excludes Kepulauan Seribu to focus on areas within Java Island to understand adaptation in urban households better. This study will have the district as a detailed granularity of spatial resolution.

4.1.1. Poor and Slum Households in Jakarta

Jakarta is known for being central to Indonesia's business and economy, mixing with residential areas. Luxury areas are emerging across the city, predominantly in central Jakarta. This is supported by the varying average house prices, with the higher price not only located in a single region. The Gini coefficient in Jakarta (42%) is higher than the national average (The Jakarta Post, 2023). Jakarta is home to not only wealthy households but also underprivileged households (Rukmana & Ramadhani, 2021). According to Unit Pengelola Statistik Dinas Komunikasi, Informatika dan Statistik Provinsi DKI Jakarta (2021), as of 2020, an average 4% of the population is considered poor, with the highest being 6% located in North Jakarta or the coastal area (Figure 4.1).

Both inequality and intensive population growth result in prolonged unsolved slum areas. Slum areas in Jakarta originated from the illegal settlement of poor households who struggled to afford housing. They are often located in narrow alleys on the river bank, on the edge of the railroad tracks fire, and under the bridge arch. Research by Bidang Statistik Sosial BPS Provinsi DKI Jakarta (2017) shows that slum areas are indicated by their low building quality and poor layout. In addition, they are found to have problems with sanitation; not all households have private sanitation access, access to clean water, and waste management. As of 2017, almost half of the population in the slum area exhibited a lousy habit of disposing of rubbish by throwing it away in holes or burned, throwing it in streams, rivers,

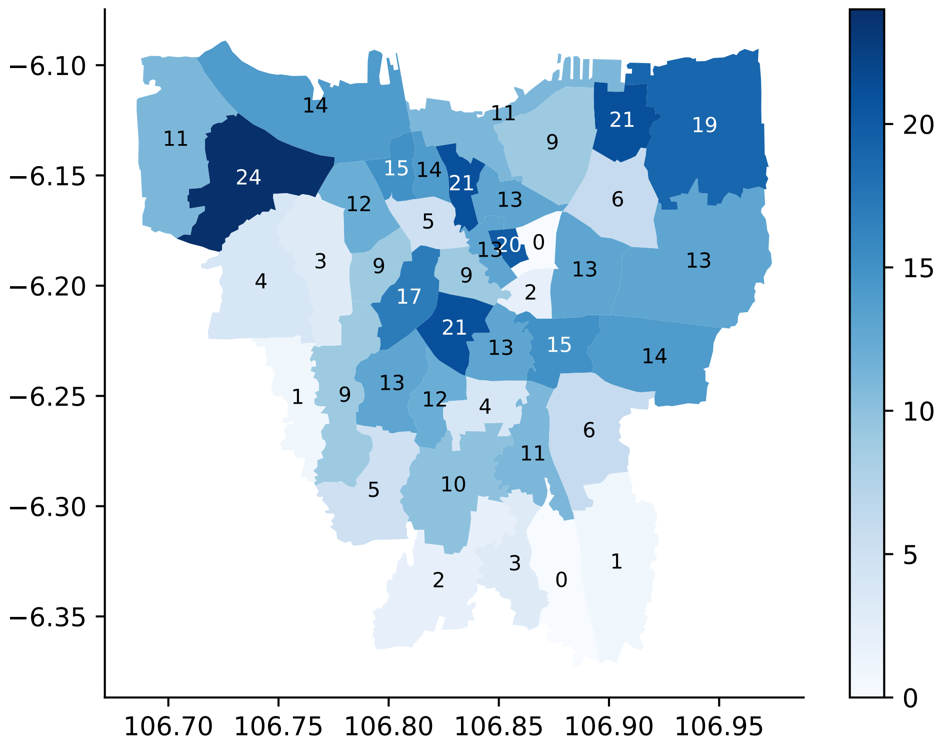

Figure 4.1: *Distribution of Slum Villages Across Jakarta (2023)*. Each district is represented by a polygon, with colour intensity indicating the absolute number of villages classified as slums. *Data from Bidang Data dan Statistik Provinsi DKI Jakarta (n.d.)*

or beaches, and discarding it haphazardly. In addition, in 2017, more than a tenth of the slum villages did not have ditches or culverts to channel the water. However, in slum villages where it was present, it was often observed that most of the water did not flow.

4.1.2. Micro Level Survey Data

The dataset's initialization begins with household survey data by Filatova et al. (2022) (Indonesia, N = 1080). The survey aims to study the adaptation intentions of 18 household flood adaptation measures, including structural and non-structural measures and the explanatory variables that explain the intentions.

prepared through a careful data preparation process, including location filtering and addressing missing data. Understanding the context is crucial to manipulating the data effectively during this preparation phase. Each variable is handled uniquely, though an overarching framework guides the process.

Initially, a filter based on the postcode is applied to isolate data specific to the Jakarta area. To be more intuitive, the area in the postcode was transformed to district name format with the help of lookup data of the district, and the postcode is retrieved from indonesiapostcode.com (2024). Following this, the dataset is examined for missing data across all variables. For any missing entries, an attempt is made to find complementary survey questions with the same intention to complete the data. If missing data persists, the next step is to look for associated variables or related survey questions. For instance, if flood experience data is missing, the respondent's acknowledgement of any damage could indicate that the respondent experienced a flood.

For variables tied to location, missing data is filled in with the mean value per area. This includes variables such as home size, income, and savings, where the average value per region is used to fill in gaps. The global mean fills in the missing data if a variable lacks associated location information. If none of these methods apply, the data points are amputated. This thorough process ensures that 589 data points can be processed and sampled to create a synthetic population. The entire process and metadata details are in the Appendix A.

To synthesise an entire population based on a spatially detailed model, synthetic agents are created using the DataSynthesizer Python package (Ping et al., 2017), which employs the Bayesian Network algorithm. Bayesian Network is selected due to the unavailability of marginal distribution information and the relatively small number of attributes (Yaméogo et al., 2021). The Bayesian Network incorporates conditional dependencies among the variables, and including the district as a node in the network allows for spatial context within the synthetic population. This process creates 3,000 synthetic households, ensuring that the synthetic population reflects the spatial and conditional dependencies of the original dataset with the pairwise mutual information depicted in Figure 4.2. Compared to the population of Jakarta reported in the Unit Pengelola Statistik Dinas Komunikasi, Informatika dan Statistik Provinsi DKI Jakarta (2021), the population distribution across the five regencies is generally similar between the reported population and synthetic datasets. Slight discrepancies are identified. Firstly, the actual population has a slightly higher percentage of people living in regions like the South, West, and North. Additionally, the synthetic population has a more significant proportion of people living in the regency, with the lowest population in the centre, which was the maximum difference with a 10.21% difference.

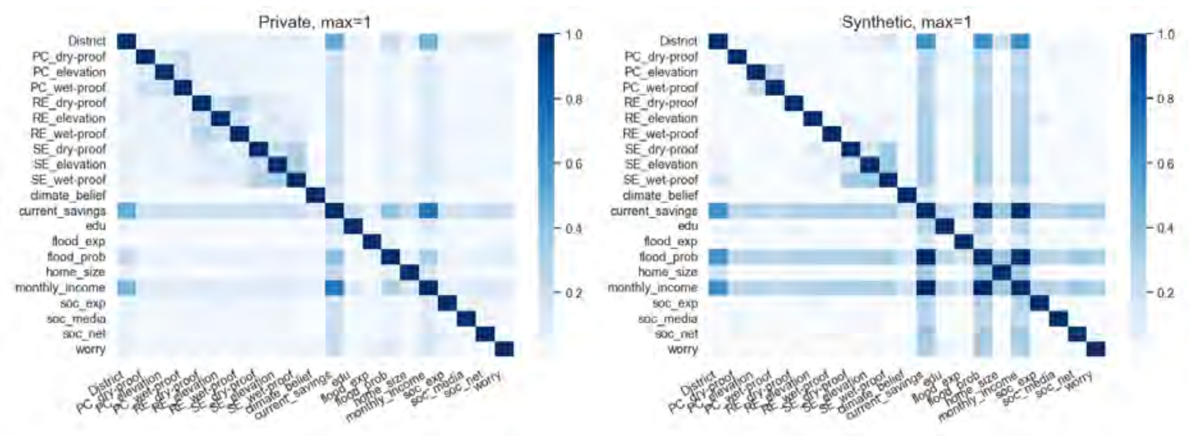

Figure 4.2: *Pairwise mutual information comparison of survey data (left) and synthetic population (right)*

4.2. Hazard: Determining Flood Severity

Jakarta grapples with chronic urban flooding, enduring at least one significant event annually. The Jakarta Provincial Government meticulously records flood events covering rainwater and coastal flooding, including the range of flood depth, duration, and affected villages, on Bidang Data dan Statistik Provinsi DKI Jakarta (n.d.). Flood records from 2017 to 2020 and 2023 (N = 992) indicate that flooding in Jakarta predominantly occurs between the end and the beginning of the following year, coinciding with the rainy season. In July and August 2017, floods occurred during drought in various districts, such as East, South, and West Jakarta. The depth of the floods ranged from 10 to 80 cm. The flooding events were also sparsely geographically distributed, for example, the yearly visual of the January flood as illustrated in Figure 4.3, which also shows the exacerbated impact with the more impacted areas and higher depths. When combined, the figure indicates that nearly all districts, including elevated areas and coastal zones, experienced compound flooding. The severity of these flood events varies across different locations and periods. At the same time, the city centre remains relatively less affected, consistent with Hsiao (2023) and Nasution et al. (2022). Further Nasution et al. (2022) explains the flood pattern in Jakarta's coastal and inner-city areas combined with social issues, including dense population, slum areas, and low education. This susceptibility to flooding is exacerbated by land use changes driven by rapid population growth, compounded by extreme weather events such as heavy rainfall, river overflows, and coastal floods intensified by rising sea levels (Budiyono et al., 2016; Mishra et al., 2018). On the other hand, predicting floods driven by rainfall in Jakarta is challenging due to the warm rain phenomenon and short flood travel time that require high-resolution data and operate on a very short timeframe (Priyambodoho et al., 2021).

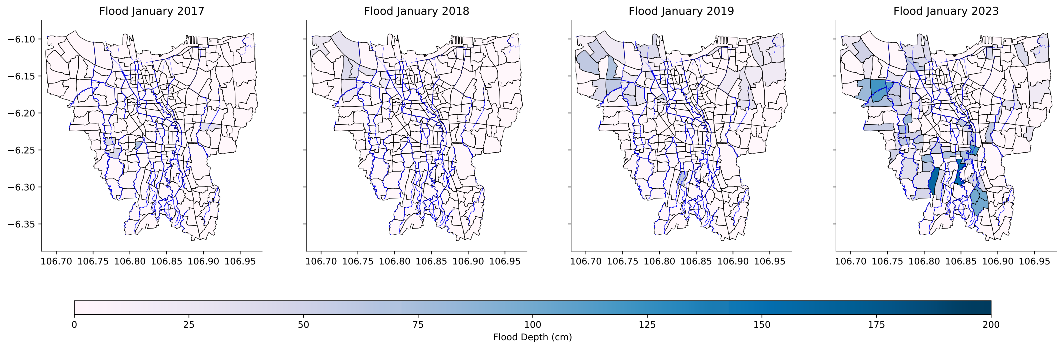

Figure 4.3: *Historical Jakarta floods (2017-2019 and 2023), the polygon represents the district and illustrates the extent of flooding in January.* Different colours indicate varying water depths, while the blue line denotes canals and rivers. *Data from Badan Penanggulangan Bencana Daerah Provinsi DKI Jakarta (n.d.)*

Hence, this study's flood hazard assessment incorporates the variability of flood severity across districts, mapping out areas within Jakarta prone to flooding and utilizing historical flood depth data from 2017 to 2020 and 2023. This study involves the highest recorded depth for each documented flooding event in a particular district in a time window. The highest record of each time window is then transformed as a range for each district. This data is further categorized into tertiles representing different levels of severity: the lowest tertile corresponds to mild flooding. In contrast, the highest tertile indicates severe flooding (Figure 4.4). This categorization allows for nuanced flood risks and their spatial distribution across the city.

4.3. Exposure: Jakarta Household

This study defines household exposure as the combination of the population and infrastructure associated with a given household and the property's physical characteristics (Srivastava & Roy, 2023). Consequently, districts with more families and households owning bigger properties are more exposed to floods. For instance, properties located in coastal areas are generally more susceptible to flooding than those in the city centre, which is an elevated district (Figure 4.4). While flood susceptibility is influenced by location, the size of the property also plays a crucial role in determining exposure, where larger houses may have a more significant potential for damage due to the larger area exposed to floodwaters. Both property size and household location were obtained from survey data Filatova et al. (2022), which data processing is explained in Section 4.1.2. Figure 4.5 illustrates the distribution of households with varying property sizes across Jakarta. The dispersed pattern in the figure suggests that flood risk is a widespread issue affecting various parts of the city rather than being confined to specific areas.

4.4. Vulnerability: Depth-Damage and Adaptive Capacity

Vulnerability is the degree to which a system is affected by sensitivity and responsiveness to or adaptive capacity (Brooks et al., 2003; Cardona et al., 2012). In this study, sensitivity refers to the relationship of the flood hazard with residential infrastructure, which is further defined as depth-damage functions or vulnerability curves (Martínez-Gomariz et al., 2020). The measured damage is specific to residential property as a significant asset associated with the household, leveraging research in the Jakarta context's flood depth-damage curve of residential buildings by Wahab and Tiong (2017) in absolute curves in the form of building and content damage. Unlike previous studies of Jakarta's depth-damage curve, their study obtained it from a multi-variate flood loss model, representing Jakarta as a city affected by mild to severe 2013 January floods. Hence, to transform the absolute value to damage, property price value in the market (2021) from Ismail (2021) and Residential Property Price Index (RPPI) from Bank Indonesia (2022) were used. The explanation of the data processing can be found in Appendix

B.

On the other hand, scholars often include three forms of capital to describe flood adaptive capacity: financial, institutional, and human capital (Ro & Garfin, 2023; Thanvisitthpon et al., 2020). However, the Sixth Assessment Report of the IPCC frames that the enabler of adaptive capacity is also challenged by constraints, which make it harder to implement adaptation (Intergovernmental Panel on Climate Change (IPCC), 2023). Further Serdeczny et al. (2024) defined determinants of adaptive capacity to be reflected as adaptation constraints. These include economic resources, wealth, financial capital, and assets, categorized as financial constraints. In addition, information and skills, the ability to manage information, education, and learning, are classified as human resource constraints. As adaptive capacity is translatable to decision-makers (Engle, 2011), this study focuses on different income and education levels, which serve as two distinct dimensions of adaptive capacity and offer relevant policy recommendations where income (Bidang Statistik Sosial BPS Provinsi DKI Jakarta, 2017; Sholihah & Shaojun, 2018) and education (Chugh, 2005; Quattri & Watkins, 2019) levels have gone hand-in-hand with the issues of urban slums.

4.5. Response: Household Climate Change Adaptation Measures

Future directions of the IPCC risk framework include response to climate change, mitigation or adaptation to complete the previous three determinants. The inclusion of response rationalises from the inherent possibility of not achieving the intended objective or having trade-offs, either caused by uncertainty, maladaptation, or system transitions (R. Begum et al., 2022). As this study focuses on household climate change adaptation, the response refers to adaptation delivered by households as private actors. According to Tompkins and Eakin (2012), private actors take initiatives that can benefit themselves or others, including the community, such as smallholder farmers or individuals. This study evaluates the maladaptation of household climate adaptation measures, particularly on measures that aim to self-reliance to help themselves. As such, the primary focus is on structural adaptation measures, which directly correlate with the exposure and vulnerability of specific building types. Structural measures include three main measure types: elevation, wet-proof, and dry-proof (Botzen et al., 2019). Elevation measures seek to raise the ground level of a building (Aerts, 2018; Attems et al., 2020; Botzen et al., 2019; Lasage et al., 2014). Wet-proof aims to reduce damage while permitting water to enter the house (Aerts, 2018; Attems et al., 2020; Botzen et al., 2019; Lasage et al., 2014). Conversely, dry-proof prevents water from entering a building (Aerts, 2018; Attems et al., 2020; Botzen et al., 2019; Lasage et al., 2014). Table 4.1 exhibits a clear trade-off between damage reduction and implementation among adaptation measure types. Elevation offers the highest damage reduction but is also the most expensive, followed by dry-proof, and finally, wet-proof, which is the most economical measure.

4.5.1. Household Adaptation Behaviours

PMT in household adaptation is applied in logistic regression to predict conditional probabilities using binary outcomes for classification problems like linear regression. In this case, the classification problem refers to the intention to take action for a particular measure. Hence, utilising survey data from Filatova et al. (2022) through data preparation, the data will be replicated, resulting in three independent logistic regression models being built for each measure: dry-proof, wet-proof, and elevation. Figure 4.7 explained the process flow of building the model. Initially, 16 explanatory variables PMT were incorporated in the initial iteration of model building as populated by Noll, Filatova, and Need (2022). The final model has been iterative, looking for better performance with three main metrics: higher accuracy in predicting the take action or True Positive, lower value of Akaike Information Criterion (AIC), and lower value of Bayesian Information Criterion (BIC). To acquire best-fit models for each adaptation measure, interaction effects of the initial explanatory variables were incorporated into the iterations. This is followed by a variable reduction by excluding the lowest explanatory power variables with high p-values and includes the interaction effect. The reports of these metrics of final models can be seen in Appendix C.

Factors Influencing Household Adaptation: A Statistical Analysis

Figure 4.8 of the separate logistic regression model of protection motivation theory shows various predictors of choosing a particular flood adaptation measure: dry-proof, wet-proof, and elevation.

Determining Whether to Implement Dry-Proof Figure 4.8 in the dry-proof column shows the likelihood of households choosing dry-proofing was positively associated with worry about floods *($p<0.01$)*,

Table 4.1: Household climate adaptation measure type in the Jakarta context. Individual measure and categorisation derived from Filatova et al. (2022), Noll, Filatova, and Need (2022), and Noll, Filatova, Need, and Taberna (2022)

Measure Type	Individual Measure	Efficacy	Cost [Million IDR]	Cost Detail
Elevation	Elevating the base level of structures above the expected flood height	100%	36	Implementation cost for elevating the ground floor by at least one meter (Aerts, 2018)
Wet-proof	Reinforcing building foundations, upgrading structural elements with water-resistant materials, and elevating electrical installations	15% (Lowest efficacy among the reduction chance (Kreibich et al., 2015))	0.06 per square meter	Cost per square meter to limit structural damage (Aerts, 2018).
Dry-proof	Fitting non-return valves, installing a pump, and fixing water barriers	25% (Lowest efficacy among the reduction chance (Kreibich et al., 2015))	8.36 per square meter	Cost per square meter to prevent floodwater entry (Aerts, 2018).

belief in climate change *($p<0.01$)*, social media *($p<0.05$)*, exposure to previous floods *($p<0.05$)*, self-efficacy *($p<0.05$)*, external influences *($p<0.01$)*, which refer to social media and the interaction of social network influence. Besides, it was found that monthly income and flood damage are statistically insignificant. Of the three coping appraisal variables (self-efficacy, response efficacy, and perceived cost), response efficacy and perceived cost were negatively associated with dry-proof at non-significant p-values and $p<0.001$ levels, respectively. This implies that households that state they can implement dry-proofing are more likely to do so. However, cost concerns are expected to discourage households from adopting dry-proof. In addition, undergoing another type of measure, either elevation *($p<0.0001$)* or wet-proof *(insignificant)*, negatively influences the choice of dry-proof, which denotes households prefer to choose a single measure and rely on previous investments in flood adaptation.

Determining Whether to Implement Wet-Proof Referring to the Figure 4.8 in the wet-proof column, of three threat appraisals (flood damage, flood probability, and worry), flood damage *($p<0.01$)* and worry *(insignificant)* were found to positively associated with the likelihood of household implementing wet-proof. However, residing in flood-prone areas *($p<0.05$)* discourages households from adopting wet-proof. In coping appraisal, self-efficacy was positively associated with the likelihood of implementing wet-proof even though it was insignificant. On the other hand, perceived cost remains negatively associated with $p<0.01$. The coefficient of undergone elevation *($p<0.05$)* and dry-proof *(insignificant)* were negative, implying that undergoing different measures is likely to discourage households from implementing wet-proof and consistent with the result of the dry-proof model. Socioeconomic factors, represented by monthly income, showed a positive but insignificant relationship with wet-proof adoption. Finally, external factors, including climate belief *($p<0.05$)* and external influences *(insignificant)*, were found to be positively associated with the likelihood of implementing wet-proof.

Determining Whether to Elevate the House Unlike the previous two measures, elevation emerged to better predict by incorporating interaction effects by taking the product of two predictors as shown in the Figure 4.8 in the elevation column. Several contrasting standalone and interaction effects were found in the elevation model. On their own, worry *($p<0.001$)* significantly influences the likelihood of the decision to elevate their house. This suggests that emotional concern about flood damage is a solid motivator for elevating the house. However, flood probability or prior dry-proofing measures did not modify this relationship, as the corresponding interaction terms were insignificant. A similar pattern was also applied to self-efficacy *($p<0.0001$)*, where its standalone effect could significantly influence the likelihood of households elevating their house.

Nevertheless, the beneficial effects of self-efficacy were diminished when combined with response efficacy or prior wet-proofing, as these interactions were insignificant and negative. Besides, a standalone effect of household perceived cost *($p<0.05$)* negatively influenced the likelihood of elevation, as expected. In contrast, the interaction effect of perceived cost with response efficacy and with the social network positively impacted the decision to elevate the house *($p < 0.05$ for both interactions)*. This suggests that social networks' influence and belief in effective response strategies can encourage elevation when households perceive high costs.

4.6. Multidimensional Household Vulnerability for Maladaptation Evaluation

Upon the understanding of Jakarta flood risk, Figure 4.9 visualises the conceptual model of the ABM. Each layer represents the determinants of the flood risk, namely hazard, exposure, vulnerability, and response. Further, as explained above, the contextual data will act as an input for the model. Moreover, with the aim of multidimensional analysis, this research employs dimensions and the category as summarised in Table 4.2. Household-level adaptation measures represent the type of response; household adaptive capacity is defined by education level and income range, while flood risk exposure is determined by location.

Table 4.2: Categories used to evaluate maladaptation to assess multidimensionality of household vulnerability

Household-Level Adaptation Measure	**Education Level**	**Income Range**	**Elevation**
Dry-proof	Basic, Up to junior high school	Up to 5 million IDR	Coastal areas, elevation $\leq$ 5 meters
Wet-proof	Secondary, Completed secondary education	5 - 20 million IDR	City centre, elevation 5 - 25 meters
Elevation	Higher, Minimum Bachelor's degree	More than 20 million IDR	Inner-city, elevation $\geq$ 25 meters

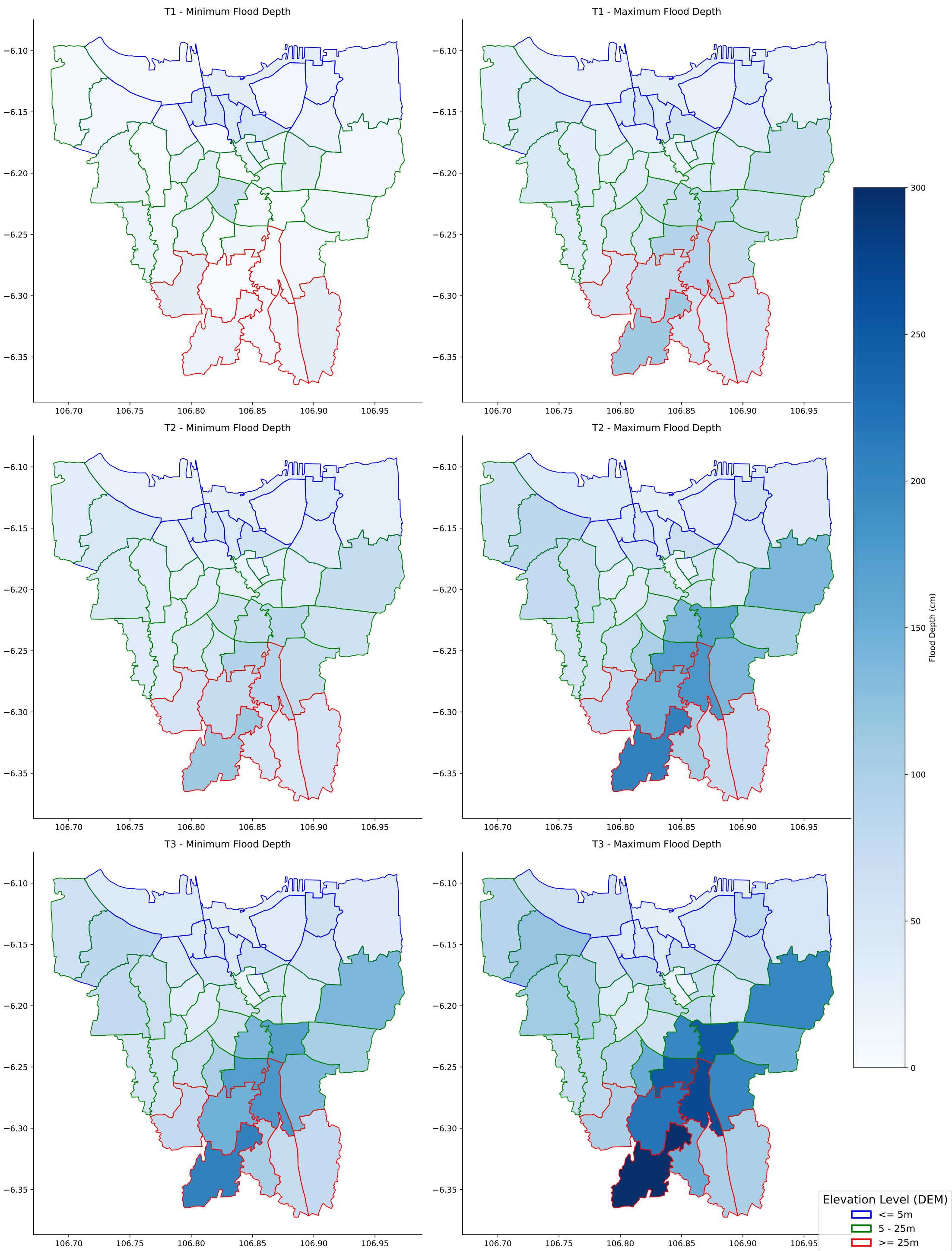

Figure 4.4: *Tertile analysis of flood depths in Jakarta districts (2017-2019 and 2023), showing each tertile's minimum and maximum depths and overlaying elevation contours to indicate flood correlation.* Depth gradation is indicated by colour intensity. *Flood depth data from Badan Penanggulangan Bencana Daerah Provinsi DKI Jakarta (n.d.), Digital elevation model data from Badan Informasi Geospasial (2021) and classified by author*

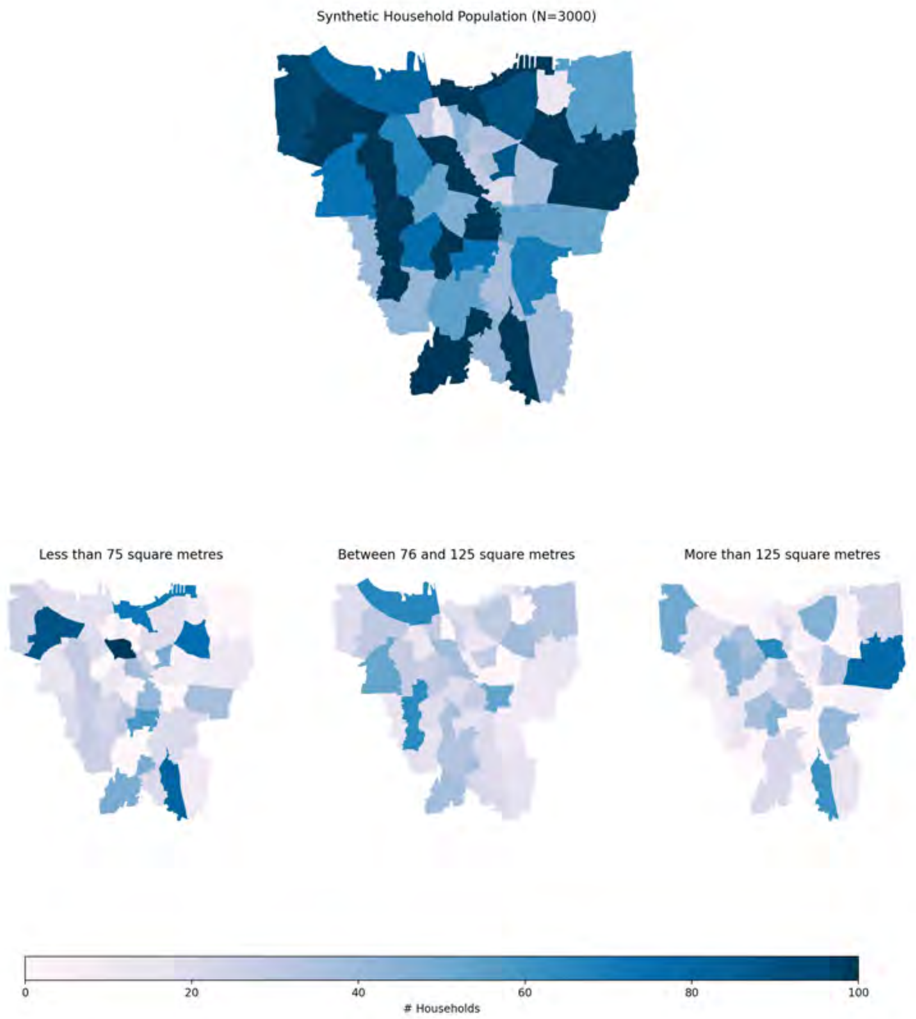

Figure 4.5: *Spatial distribution of household exposure to flood. The number of households represents synthetic household populations across various districts. The top map displays the overall synthetic household population (N=3000).* The bottom maps categorize these households into three classes based on their property size: less than 75 square meters, between 76 and 125 square meters, and more than 125 square meters. Each map utilizes a graduated colour scheme to indicate the density of households within each category.

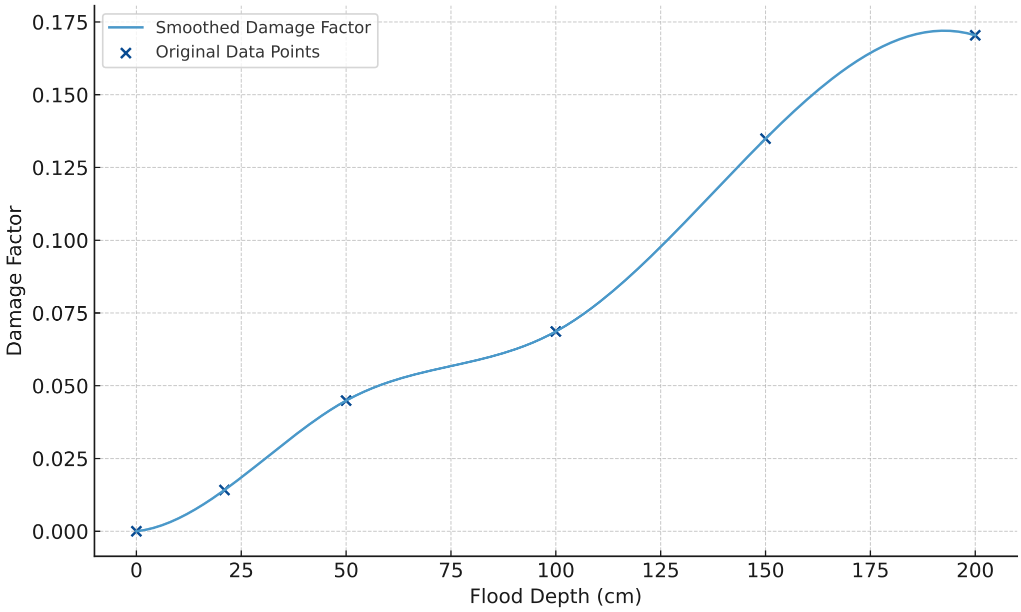

Figure 4.6: *Building flood depth-damage loss function or curves.* The graph presents a smoothed interpolation of damage factors in $millionIDR/m^2$ as a function of flood depth using spline interpolation of empirical data points. *Data adapted from Wahab and Tiong (2017)*

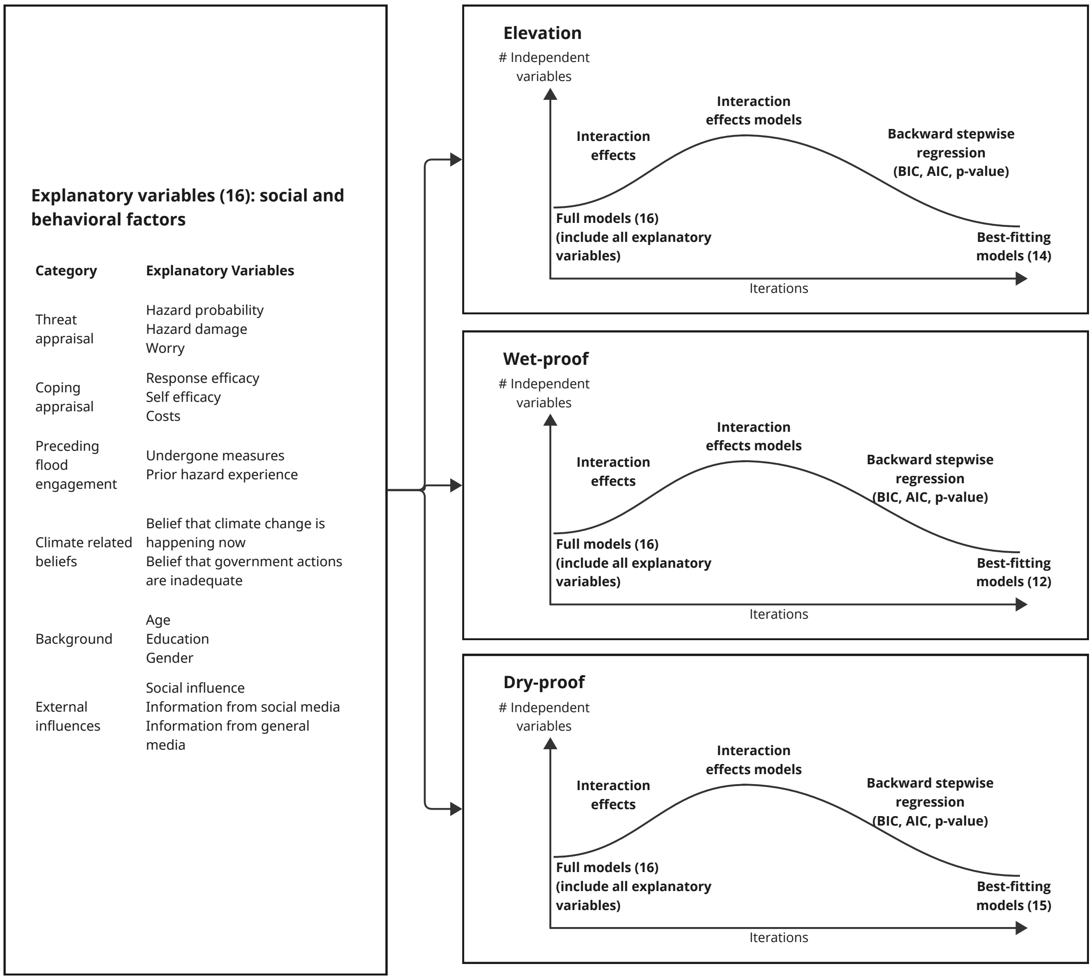

Figure 4.7: *Framework of logistic regressions for adapting elevation, wet-proof, and dry-proof measures.* The explanatory variables are derived from Noll, Filatova, and Need (2022) and Noll, Filatova, Need, and Taberna (2022). The final output is three independent models.

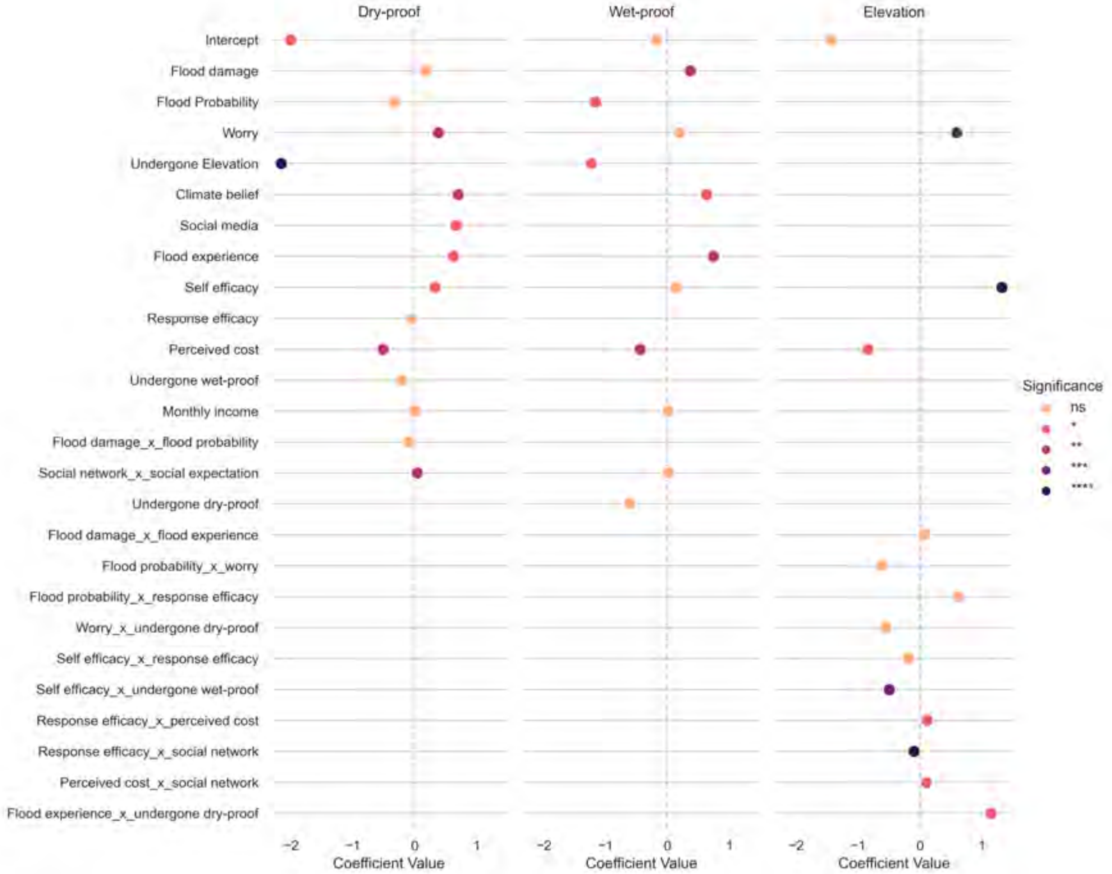

Figure 4.8: *Logit model results of dry-proof, wet-proof, and home elevation.* The ns, *, **, ***, **** indicate significance at the insignificance, 5%, 1%, 0.1%, and 0.01% levels, respectively.

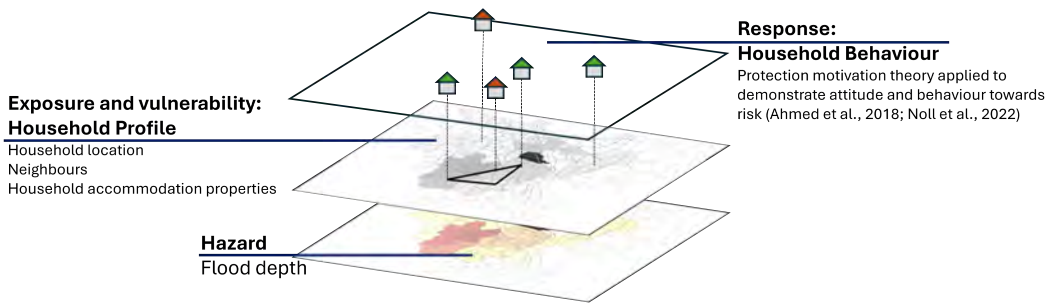

Figure 4.9: *Conceptual model of CRAB model for maladaptation purposes.* Each layer represents climate risk assessment determinants.

5

Jakarta Household-Level Climate Change Adaptation Model

In this study, maladaptation is an outcome where adaptation measures result in negative state changes from a baseline condition. Identifying maladaptation often necessitates a long-term perspective to fully discern the impact of specific interventions. To this end, an agent-based model is employed to simulate the emergent system behaviours resulting from the interactions between household entities, flood hazards, and neighbouring agents in the context of climate change adaptation decisions. Subsequently, an assessment of maladaptation will be conducted using the simulation outputs as proxies for the future states following domestic and private initiatives.

5.1. The Application of the CRAB Model: Simplified and Household Adaptation Focus

The agent-based model is built upon a novel evolutionary economic agent-based model called CRAB, utilising an ABM python-based framework called Mesa (Masad, Kazil, et al., 2015), which has a strong point in representing private climate change adaptation (Taberna et al., 2023). The CRAB model aims to provide insights into the compound risk arising from the dynamic interaction between endogenous economic growth, multi-scale adaptation, and damage caused by repetitive climate-induced shocks. For maladaptation purposes, Figure 5.1 shows that this model is scaled down to focus on the interaction between household adaptation behaviour, household-level adaptation measures, and damage caused by climate-induced floods in Jakarta. Aside from maladaptation metrics, the model output emphasises the emerging adaptation paths to provide policymakers with the maladaptation insights to take the necessary intervention. Utilising the contextual flood risk and household adaptation behaviour acquired from the previous chapter, Figure 4.9 exhibits these layers. This spatial layer not only defines the household location attribute but also defines social interaction as a networked household's neighbours, utilises NetworkX (Hagberg et al., 2008).

5.2. CRAB Model Simplified to Maladaptation Model

Figure **??** describes the input, process, and output of the CRAB model used in this study. The Jakarta flood risk profile is incorporated as the model input and simulation output to represent indicators defined in Chapter 3. This section explains the model specification to describe the model conceptualisation and the end-to-end process of the model following the ODD protocols (Macal & North, 2009). It will initially define the entities, states, and scales used within the model. The algorithm and code snippet are included, followed by how the model schedules the agent and interaction. Model input and model output are explained to enrich their reproducibility and applicability, verified via sensitivity analysis (see Appendix D).

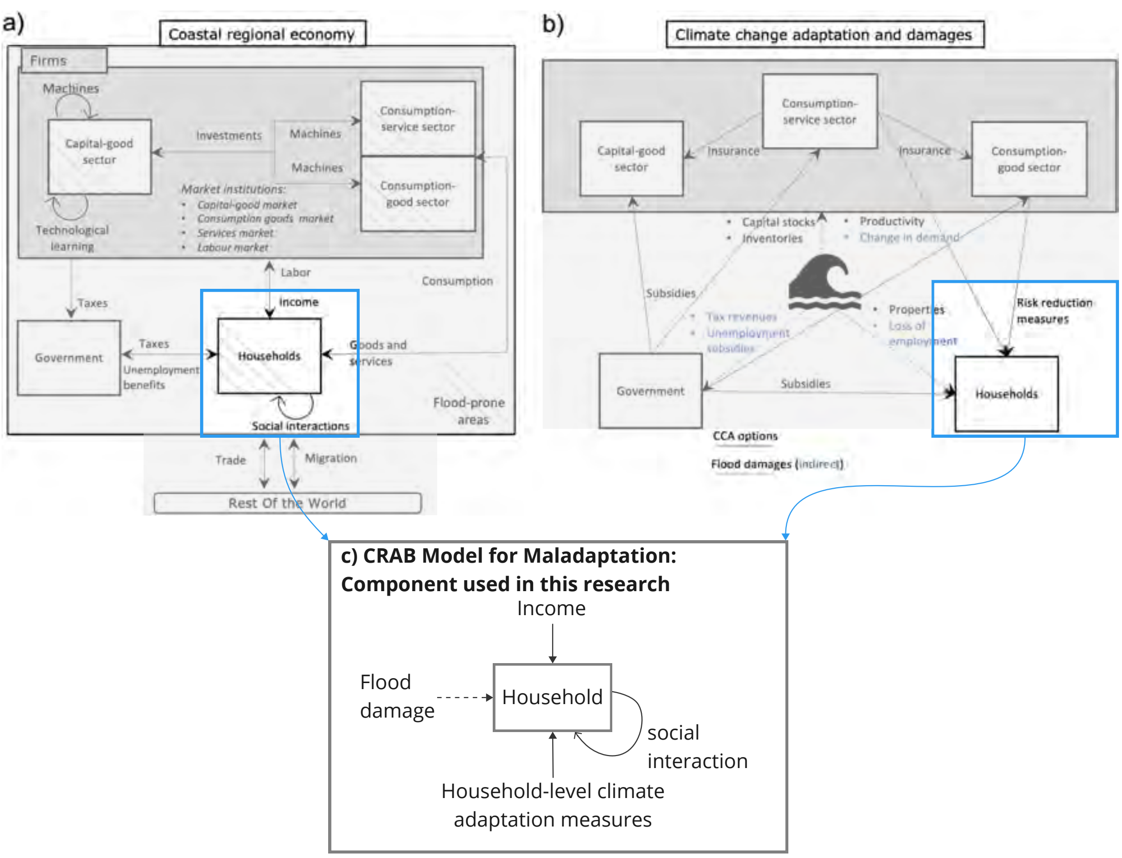

Figure 5.1: *Representation of CRAB model.* Panel (a) presents regional economy representation, (b) presents the conceptual relationship between climate change adaptation and damages Taberna et al. (2023). This model is represented in panel (c), which focuses on household-level adaptation

5.2.1. Entities, State Variables, and Scales

This model comprises individual household states and their environment that represent flood hazards. Household agents represent households, which differ depending on the adaptation measure. They have three types of attributes: (1) socioeconomic attributes, such as savings, wages, and education; (2) residential location attributes, such as district, flood depth, and home size; and (3) attributes related to protection motivation theory, including climate beliefs and social interactions. The second entity is the model, which represents the environment and contains households' flood dynamics depending on location and time depending on the flood scenario.

The model's area is drawn upon spatially explicit space on the Jakarta map, with each polygon representing 41 districts, acquired and processed from indonesiapostcode.com (2024) and pstyd (n.d.). To make it more realistic, a graph representing a social network derived from the adjacency neighbourhood of the Jakarta district. As an agent, each household is positioned based on its District attribution. The individual-based model operates on quarterly time steps. Although the CRAB model used the year as a time tick - see Taberna et al. (2023), this model was set quarterly to get the finest granularity with starting point 2020 as a survey and flood data were available this year. Each household's damage and monetary condition in a unit of a million IDR and implemented adaptation pathways are kept for each time tick.

There are two main state categories. First, the state defines flood occurrence to track the impact on particular districts (True or False). The flooded refers to flood depth beyond 0 cm with the assumption of all households residing in a landed house. This assumption is grounded by more than 80% of the population owning a home, and the property type in Jakarta is either a landed house or an apartment (Badan Pusat Statistik Indonesia, n.d.). Second, adaptation paths are implemented, which flag if specific adaptation measures have been implemented (see Box 5.1). Aside from the status, their

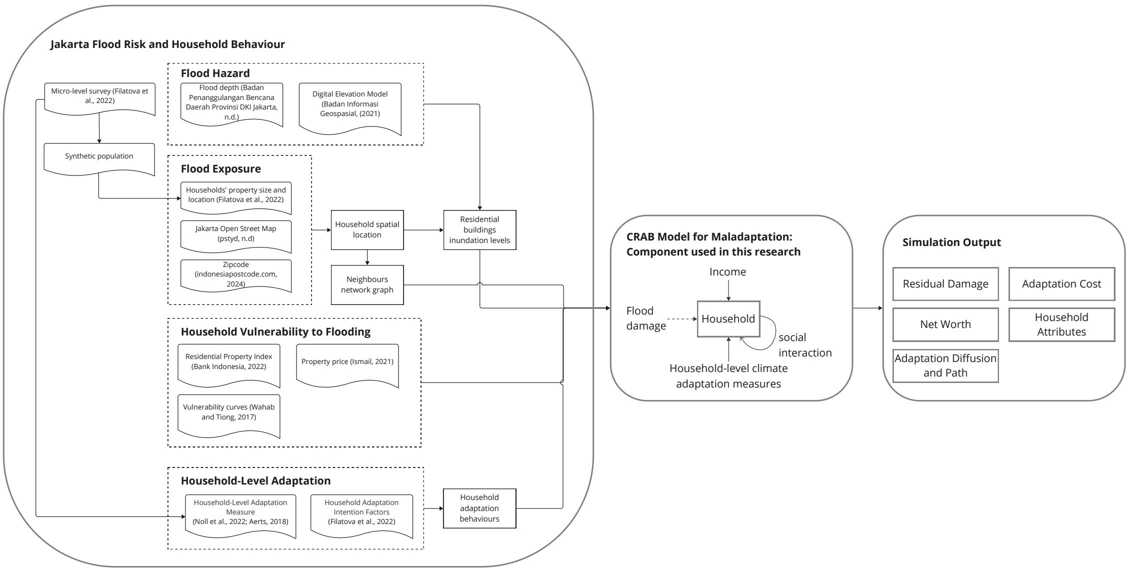

Figure 5.2: *Representation of CRAB model.* Panel (a) presents regional economy representation, (b) presents the conceptual relationship between climate change adaptation and damages Taberna et al. (2023). This model is represented in panel (c), which focuses on household-level adaptation

implemented time tick was also recorded. It is important to emphasise that this model does not allow the model to take multiple measures at the same time.

Custom Box 5.1: Adaptation status across elevation, wet-proof, and dry-proof measure type

- *Do Nothing = False;* the household either has not started implementing or taken the measure.
- *Implemented = True;* household decided to implement the measure.

5.2.2. Process Overview and Scheduling

The model is structured to run through various stages managed using the 'StagedActivatioEnByType' class, which determines the sequence of actions per each time tick. Figure 5.3 details the process of each stage, which refers to:

Stage 0 Damage calculation when a flood occurs. The flood is scheduled with a parameter. If the timestep matches the flood schedule, model entities calculate the flood depth to be further processed by household entities to derive the monetary damage caused by the flood.

Stage 1 Consumption, savings adjustment, and repair expenses are processed internally.

Stage 2 Encapsulates the process of adaptation decisions. This employs logistic regression models for elevation, wet-proof, and dry-proof (see Chapter 4.5.1). As denoted within the flow chart, these three are independent models. The selected measure is derived from the highest measure probability to implement and further decided through Bernoulli trials (see (Taberna et al., 2023)).

A more holistic view, model structure and behaviour are detailed in Figure 5.4, where the process flow mainly occurred within the household class. As this model focuses on the emerging adaptation paths, it assumes a static household number with predetermined adaptation measure options, meaning there is no movement within the spatial space.

5.2.3. Design Concepts

The model is based on principles from agent-based modelling and economic theories of household behaviour. It incorporates the Protection Motivation Theory (PMT) elements to simulate how households

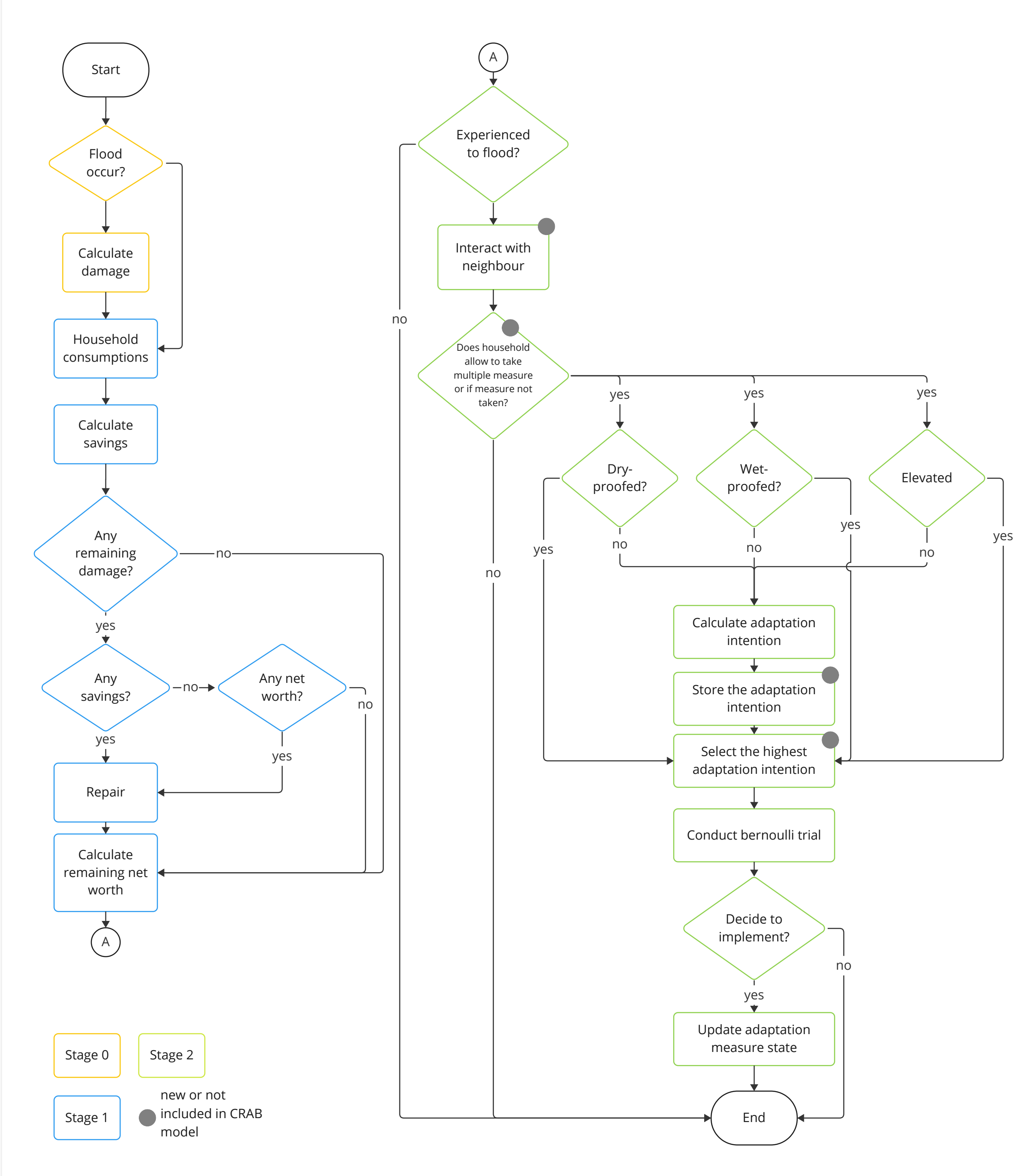

Figure 5.3: *Input, process, the output of CRAB Model for Maladaptation.* Each rounded box represents the component.

decide on adaptation measures like elevation, dry-proof, and wet-proof based on perceived coping appraisal, threat appraisal, and external influences. The emergence of the behaviour is expected to exhibit the dynamics of household behaviour in response to climatic events, in this case, floods. Each household's primary objective is to ensure economic stability and resilience to flood, which is implicitly modelled and significantly influenced by a bounded rational process.

The emergent results include wealth distribution, adaptation decisions derived from the PMT model, maladaptation inequality, and residual damage. The emergent results from individual household decisions depend on the varying economic conditions and flood impacts. In addition to emergent results, imposed results are directly influenced or constrained by the rules and parameters, which in this model are associated with input data. This includes flood severity, adaptation cost, social network, and initial

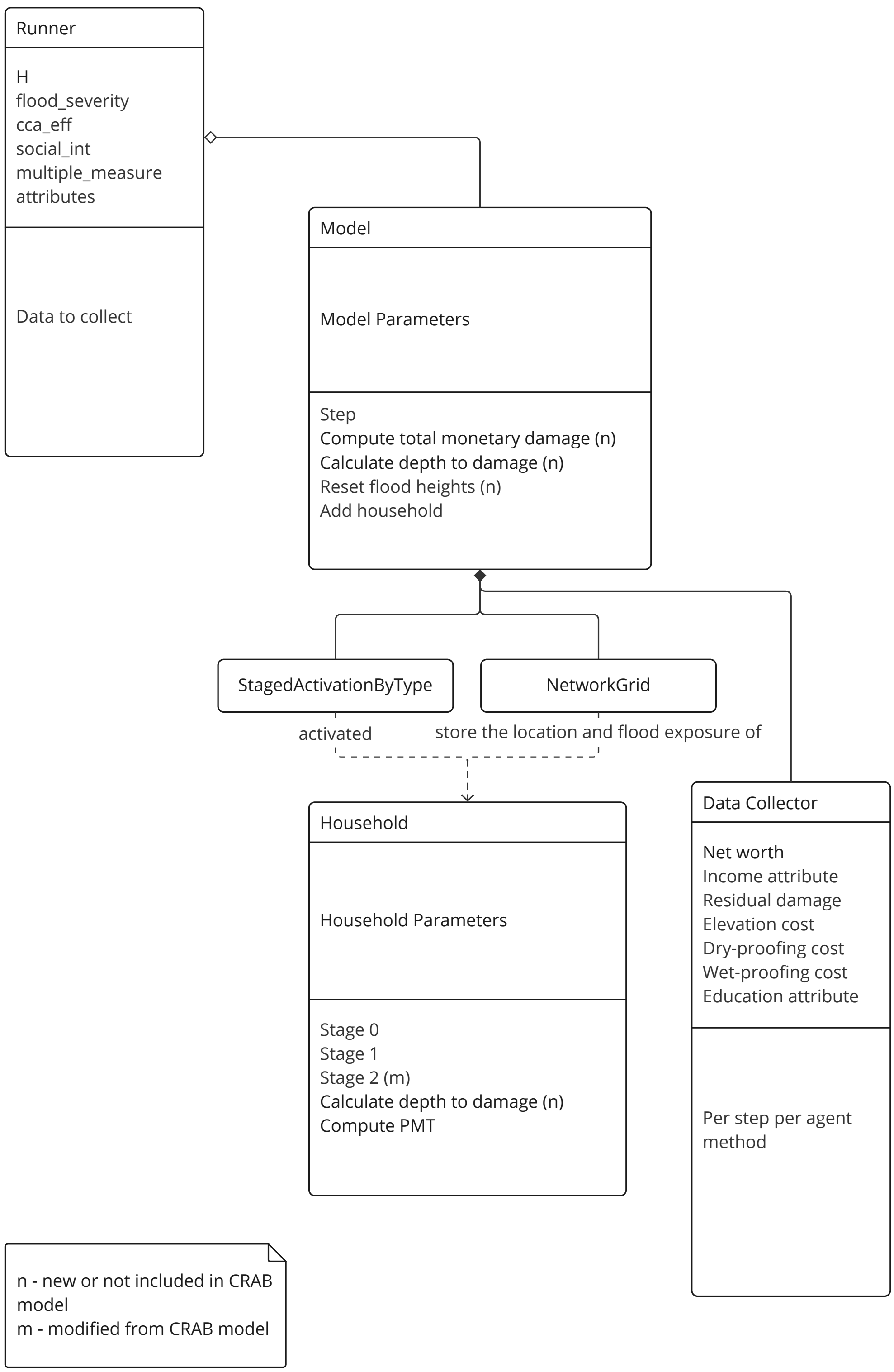

Figure 5.4: *Simplified UML diagram of CRAB-Maladaptation Model adapted from Mesa architecture* (Masad, Kazil, et al., 2015)

household attributes.

5.2.4. Submodels and Detailed Interaction

Figure 5.4 explained in Section 5.2.1, the submodels refer to its class component, environment and household.

Environment Component: Model Class

The model parameters are initialized using a dictionary that includes a flood schedule and the corresponding severity of each scheduled flood. These parameters are pivotal in simulating the timing and impact of flood events within the model. As the model's time aligns with the pre-scheduled flood times, the flood depth for each event is determined. This depth is generated uniformly across all districts based on a specified range associated with the flood's severity. Subsequently, the flood depth is utilized for each district to calculate a damage coefficient through a depth-damage function, which quantifies the potential impact on residential properties.

As referenced from Wahab and Tiong (2017), the depth-damage function is specifically applied to estimate the damage to household properties. The calculated damage per square meter, derived from the depth-damage function, is then multiplied by the house size of the affected property. This computation estimates the total potential damage in monetary terms for each household affected by the flood.

Household Component: Household Class

Upon experiencing a flood, a household assesses the damage in monetary terms (see Pseudocode 1). Here, D_{new} in Equation 5.1 represents the new total monetary damage after calculating the damage for a specific flooding event. Align with Antoci et al. (2024); the damage function holds that if the household chooses not to take any measure, monetary damage is the damage coefficient from depth-damage is then multiplied by the house size of the affected property. On the other hand, if the agent decides to take measures, the multiplication of depth damage with house size is divided by the total weight of the efficacy of protecting against flood. The amount of monetary damage will be handled via immediate responses, including allocating funds from existing savings to repair damages. If the savings are insufficient to cover the repair costs, the unresolved damage costs are deferred to the next time tick, anticipating coverage from future savings accrued from wages. A household's financial status after a flooding event is captured by calculating its net worth. This is determined by subtracting savings, consumption, and damage repair expenditures from total financial resources.

Variables:

- D: `self.monetary_damage` — Rollover monetary damage in a million IDR that could not be covered in the previous time step.
- k: `self.damage_coeff` — Damage coefficient (million IDR/m^2).
- A: `self.house_size` — Area of the house in square meters (m^2).
- r: `total_reduction` — Total reduction factor, starting at one and modified by mitigation measures.
- e: `self.elevation` — Additional reduction due to house elevation.
- d_{dry}: `self.damage_reduction_dry` — Reduction factor for houses that are dry-proofed.
- d_{wet}: `self.damage_reduction_wet` — Reduction factor for houses that are wet-proofed.

Conditionals:

- If the house is elevated (`self.elevated == 1`), $r = 1 + e$.
- If the house is dry-proofed (`self.dry_proofed == 1`), $r = 1 + d_{\text{dry}}$.
- If the house is wet-proofed (`self.wet_proofed == 1`), $r = 1 + d_{\text{wet}}$.

The damage calculation formula incorporates the damage coefficient, the area of the house, and the total reduction due to any mitigation strategies. In equation form, this addition is represented as follows:

$$D_{\text{new}} = D + \left(\frac{k \cdot A}{r}\right) \tag{5.1}$$

If a positive net worth is retained after addressing immediate and rollover damages and necessary expenditures, the household may consider adopting climate change adaptation measures. The decision to adopt such measures is influenced by the household's financial capability to invest in preventative strategies that could absorb future risks. If a decision is made to implement a specific measure, the cost of adaptation will be deducted from the overall net worth. In this case, the cost of the adaptathousehold's financial capability to invest in preventative strategies that could absorb future risks influences the decision to adopt such measuresonstruction.

This study explores decision-making processes in climate adaptation measures grounded in economic and behavioural theories, such as Protection Motivation Theory (PMT) (see Pseudocode 2). Decision-making in climate adaptation is complex and influenced by economic insights and behavioural responses. Protection Motivation Theory suggests bounded rationality, where cognitive and informational limits constrain decisions. This research incorporates these perspectives to model social interactions within and adjacency districts, assessing their impact on adaptation measures.

The main objective of the model is to compare different measures and their combination in the context of maladaptation. The model limits households to adopting no more than one adaptation measure per temporal unit, referred to as a "time tick." Adaptation measures were categorized into three types: dry-proofing, wet-proofing, and elevation. Each category was analyzed using logistic regression to predict the likelihood of adopting specific measures framed within the context of maladaptation risks. The logistic models provided odds ratios, subsequently used in a Bernoulli trial framework to determine the probability of measure adoption. Applying PMT through logistic regression models allows for an analytical separation of adaptation strategies. This framework quantifies the influence of various explanatory variables on decision-making and vividly delineates the likelihood of undertaking specific adaptation measures.

5.2.5. Initialisation

Jakarta's synthetic population, as explained in Chapter 4.1.2, represents the simplified microscopic population. At the start of a simulation, 3000 households were initiated and equipped with their socio-economic, flood risk attitude, and location attributes. The default values, such as flood risk and adaptation details, are incorporated (see Figure 5.5). Besides, flood maps of 41 districts and household networks were imported into the model.

5.3. Experimental Setup

From the intention to adaptation, there is the possibility of not taking any measures and preferences over particular measures. Starting with three available measures and doing nothing, households can choose from sixteen permutations or adaptation paths. Hence, to explore the emergence of this preference, single-measure and multi-measure experiments were formulated. Table 5.1 elaborates on the comparison. Further, the simulation is performed with 3000 households derived from a synthetic population for 120 quarters or 30 years under three flood scenarios: mild, moderate, and severe, and two adaptation approaches: single or multiple measures 5.2. These scenarios run in stochasticity of the tertile analysis explained in Chapter 4.2. The flood is set to happen annually, aligning findings from the documentation of historical flood (Bidang Data dan Statistik Provinsi DKI Jakarta, n.d.). The 30-year was chosen to represent the long-term effect of the interaction between flood risk and household-level adaptation. Erdlenbruch and Bonté (2018) has also used a similar time horizon. Simulation run with (DHPC) (2024), set to produce a big dataframe for each scenario with the output exported into a CSV file, contains a set of variables as mentioned in Figure 5.4 with the example implementation code.

Algorithm 1: Monetary Damage Handling

```
Data: monthly_income, current_savings, education, home_size, district
Result: Updates to monetary_damage, savings, net_worth, and consumption post-flood
Class HouseholdAgent(monthly_income, current_savings, education, home_size, district):
    consumption ← standard_consumption;
    savings ← 0;
    wage ← monthly_income × 3;
    net_worth ← current_savings;
    damage_coeff ← 0;
    monetary_damage ← 0;
    Pncalculate_depth_to_damage() if district in model.district_damage then
        if model.district_damage[district] is None then
            damage_coeff ← 0
        else
            damage_coeff ← model.district_damage[district]
    else
        damage_coeff ← 0
    PnHandleImmediateFloodImpact() if model.is_flood_now then
        calculate_depth_to_damage();
        value_house ← get_property_value(district, house_type, model.time);
        total_reduction ← calculate_total_reduction(elevation, dry_proofed, wet_proofed);
        monetary_damage += damage_coeff × house_size / total_reduction;
        initial_monetary_damage ← monetary_damage;
        total_damage += monetary_damage;
    PnRecoveryAndFinancialAdjustments() consumption ←
     min(standard_consumption, wage);
    savings ← wage - consumption;
    value_house ← get_property_value(district, house_type, model.time);
    if monetary_damage > 0 then
        repair_exp ← min(monetary_damage, max(0, savings));
        monetary_damage -= repair_exp;
        consumption += repair_exp;
        savings ← wage - consumption;
        net_worth += savings;
        if monetary_damage > 0 then
            damage ← max(0, monetary_damage - net_worth);
            net_worth -= monetary_damage;
            monetary_damage ← damage;
```

Algorithm 2: Household Adaptation Decision Process

```
Data: damage_coeff, house_size, house_value, model_parameters, social_interaction,
      adaptation_model
Result: Selected adaptation measures and updates on household properties
Class Household():
    elevated ← 0;
    dry_proofed ← 0;
    wet_proofed ← 0;
    net_worth ← initial_net_worth;
    damage_coeff_old ← damage_coeff;
    total_costs ← 0;
    measure_taken ← False;
    Pnevaluate_adaptation_measures() if damage_coeff > 0 then
        nodes_to_consider ← get_district_and_neighbors();
        if nodes_to_consider is None then
            return;
        foreach node in nodes_to_consider do
            if model.social_interaction then
                ratio_adaptations ← get_adaptation_ratios(node);
            else
                ratio_adaptations ← [0, 0, 0];
        measures ← ["dry_proof", "wet_proof", "elevation"];
        max_odds ← 0;
        selected_measure ← None;
        foreach measure in measures do
            if not self[measure] then
                y_hat ← compute_PMT(measure, ratio_adaptations);
                if y_hat > max_odds then
                    max_odds ← y_hat;
                    selected_measure ← measure;
        if selected_measure is not None and bernoulli_trial(max_odds) then
            apply_measure(selected_measure);
            measure_taken ← True;
    Pnbernoulli_trial(probability) return simulate_bernoulli(probability);
    Function apply_measure(measure):
        net_worth ← net_worth - get_cost(measure);
        self[measure] ← 1;
        total_costs ← total_costs + get_cost(measure);
        update_damage_coeff(measure);
```

		Parameter Name	Description	Default Value
Global	CCA	H	Number of household agents	3000
		cca_eff	Protection measures efficacy	{"Elevation": 1, "Wet_proof": 0.15, "Dry_proof": 0.25}
		cca_cost	Cost per measures (million IDR per meter square)	{"Elevation_cost": 36, "Wet_proof_cost": 0.06, "Dry_proof_cost": 8.36}
		social_int	Enable or disable social network (boolean)	TRUE
		multiple_measure	Boolean for multiple measures	TRUE
		cca_model	Household adaptation model ("PMT" or "EU")	"PMT"
		attributes	Household attributes	"Het"
	Flood risk	flood_severity	Time and severity of flood events {quarter : severity level}	{10: 'mild'}
		flood_prob	Multiplier from the perceived flood probability	0
		district_damage	Dictionary of damage per district	{}
		district_flood_depth	Dictionary of flood depth per district	{}
	Data collection	collect_each	Frequency of data collection	1
	Stochasticity	seed	Seed for random number generator	12345678
Household	Data collection	unique_id	Unique identifier for each household	N/A
		type	Type of agent (Household)	"Household"
	Stage	lifecycle	Life cycle stage of the household	0
	Exposure	district	Location district of the household	attributes["District"]
	Vulnerability	house_size	Size of the house	Calculated based on `home_size` attribute
		house_type	Type of house based on size	Derived from `house_size`
		damage_coeff	Damage coefficient based on flood depth (million IDR per meter square)	0
		flood_depth	Depth of flood water in the household (cm)	0
	Metric	monetary_damage	Cumulative unresolved monetary damage per household (million IDR)	0
		total_damage	Cumulative monetary damage per household (million IDR)	0
		repair_exp	Repair expenditure after flood damage (million IDR)	0
		recovery_time	Time taken to recover after a flood (quarter)	0
	CCA	elevation_cost	Cost of house elevation measure	cca_cost["Elevation_cost"]
		dry_proofing_cost	Cost of house dry-proof measure	cca_cost["Dry_proof_cost"]
		wet_proofing_cost	Cost of house wet-proof measure	cca_cost["Wet_proof_cost"]
		elevation	Elevation measure effectiveness	cca_eff["Elevation"]
		damage_reduction_dry	Damage reduction from dry-proofing	cca_eff["Dry_proof"]
		damage_reduction_wet	Damage reduction from wet-proofing	cca_eff["Wet_proof"]
	Experiment	multiple_measure	Boolean for multiple adaptation measures	TRUE
	Agent state	flooded	Boolean indicating if household is flooded	FALSE
		measure_taken	Boolean indicating if any adaptation measure is taken	FALSE
		elevated	Boolean indicating if the house is elevated	0
		dry_proofed	Boolean indicating if the house is dry-proofed	0
		wet_proofed	Boolean indicating if the house is wet-proofed	0
	Coping appraisal	SE_elev	Perceived self efficacy	(1-I am unable ... 5-I am very able)
		SE_dry	Perceived self efficacy	(1-I am unable ... 5-I am very able)
		SE_wet	Perceived self efficacy	(1-I am unable ... 5-I am very able)
		RE_el	Perceived response efficacy of measure	(1 - Extremely ineffective ... 5 - Extremely effective)
		RE_dry	Perceived response efficacy of measure	(1 - Extremely ineffective ... 5 - Extremely effective)
		RE_wet	Perceived response efficacy of measure	(1 - Extremely ineffective ... 5 - Extremely effective)
		PC_elev	Perceived costs of measure	(1 - Very cheap ... 5 - Very expensive)
		PC_dry	Perceived costs of measure	(1 - Very cheap ... 5 - Very expensive)
		PC_wet	Perceived costs of measure	(1 - Very cheap ... 5 - Very expensive)
	Threat appraisal	perc_p	Perceived probability of flooding	(0, 1)
		worry	Household's level of worry regarding floods	(1 - Not at all worried ... 5 - Very worried)
	Preceding flood engagemt	fl_exp	Household's experience with flooding	(0 - No, 1 - Yes)
	External influence	social_media	Social media engagement	(1 - Very infrequently ... 5 - Very frequently)
	External influence	social_exp	Social experience related to climate change adaptation	(1 - My family, friends and/or social network do NOT expect me to prepare for flooding ... 5 - My family and friends strongly expect me to prepare for flooding)
	Social background	edu	Education level	(1-Primary school (SD) ... 7 Professional higher education (e.g. to qualify as lawyer, accountant))
	Climate beliefs	climate_belief	Belief in climate change	(1 - Global climate change is already happening ... 3 Global climate change won't be felt in the coming decades, but the next generation will experience its consequences)
	Economic background	consumption	Consumption in million IDR	27.6
		savings	Initial savings of the household (million IDR)	0
		wage	Wage in million IDR	(0, inf)
		net_worth	Net worth of the household (million IDR)	(0, inf)

Figure 5.5: *Model parameter.* It consists of global parameters stored in the model class and household parameters.

Table 5.1: *Comparison of experiments setting: single-measure and multi-measure.*

Experiment Name	**Single Measure**	**Multi Measure**
Parameter Setting	multimeasure_false	multimeasure_true
Initial Condition and First Action	Households start from an initial condition and can choose one action (Dry-Proof, Wet-Proof, Elevation, Do Nothing).	Households start from an initial condition and can choose a sequence of actions (Dry-Proof, Wet-Proof, Elevation, Do Nothing).
Action Limitation	Once the first action is taken, no further actions are allowed.	Households are allowed to take multiple actions sequentially. One measure can only be taken once.
Impact on Adaptation Path	Results in a simpler, more limited adaptation path, where the strategy is finalized after the first action.	Leads to a more complex and potentially more effective adaptation strategy, with multiple actions possible.
Examples	• If the first action is Dry-Proof, no further actions (Wet-Proof, Elevation) will be considered. • If the first action is Wet-Proof, no further actions (Dry-Proof, Elevation) will be considered.	• If the first action is Dry-Proof, a household can still consider Wet-Proof, Elevation, or both. • Similarly, after Wet-Proof, Dry-Proof or Elevation can be pursued.

Table 5.2: *Design of Experiment.* Setting of Flood Severity and Measurement Types

Experiment Type	**Flood Severity**	**Occurrence**	**Multiple Measure**	**Replication(Seeds Range)**
Single-measure	Severe	Yearly	FALSE	50(50,100)
	Moderate	Yearly	FALSE	50(50,100)
	Mild	Yearly	FALSE	50(50,100)
Multi-measure	Severe	Yearly	TRUE	50(50,100)
	Moderate	Yearly	TRUE	50(50,100)
	Mild	Yearly	TRUE	50(50,100)

6

Maladaptive Behaviour: Synthesis of Household Adaptation Intention and Emergent Adaptation Path

As revealed in Chapter 3, maladaptation has also been identified by the behaviour itself. Hence, this chapter discusses the maladaptive behaviour of heterogeneous households by analysing the behavioural factors. Initially, this chapter elaborates on the emergence of the household adaptation path. Utilising this, maladaptive behaviour is identified by referring back to Chapter 4.5.1 grounded from work by Rippetoe and Rogers (1987) to explain the adaptation behavioural drivers and the actual adaptation result from single- or multi-measure experiments households. Further, adaptation constraints are identified from the mismatch between intention and actual adaptation. Finally, overall insights are summarised.

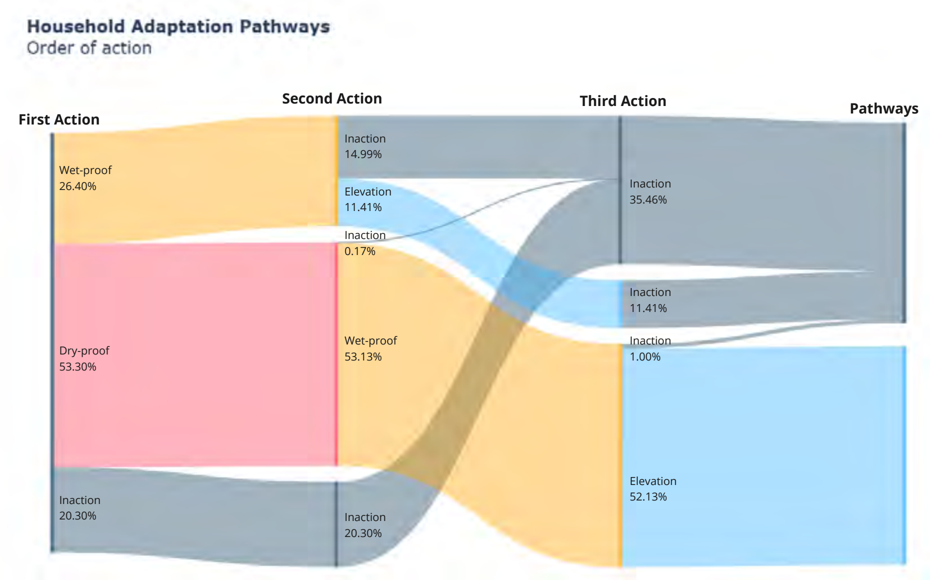

Figure 6.1: *Emerged household-level climate adaptation path*

6.1. The Emergence of Household Adaptation Paths

The emergence of household adaptation from single-measure and multi-measure experiments varied. Implemented measures of single-measure and the first implemented measure of multi-measure experiments are used to compare the emergence. In single-measure experiments, the proportion of households adapting to wet-proof was dominant. In contrast, the initial adaptation action was predominantly dry-proof in multi-measure experiments. Despite the contrast, it is consistent that the elevation measure was not commonly chosen as the first adaptation action in either type of experiment. Instead, elevation was typically the final adaptation measure in multi-measure adaptation paths, with no subsequent measures taken after a household had elevated its house.

In the multi-measure adaptation paths, as referred in Figure 6.1, out of 16 possible ordered combinations, including the option to do nothing at each action point (Figure 6.2), only six adaptation paths emerged. Of 16 adaptation paths, 52.13% of households adapt with more comprehensive paths, which refer to implementing the combination of the available measures. The main adaptation paths implementing all available measures included sequential implementation of dry-proof, wet-proof, and elevation.

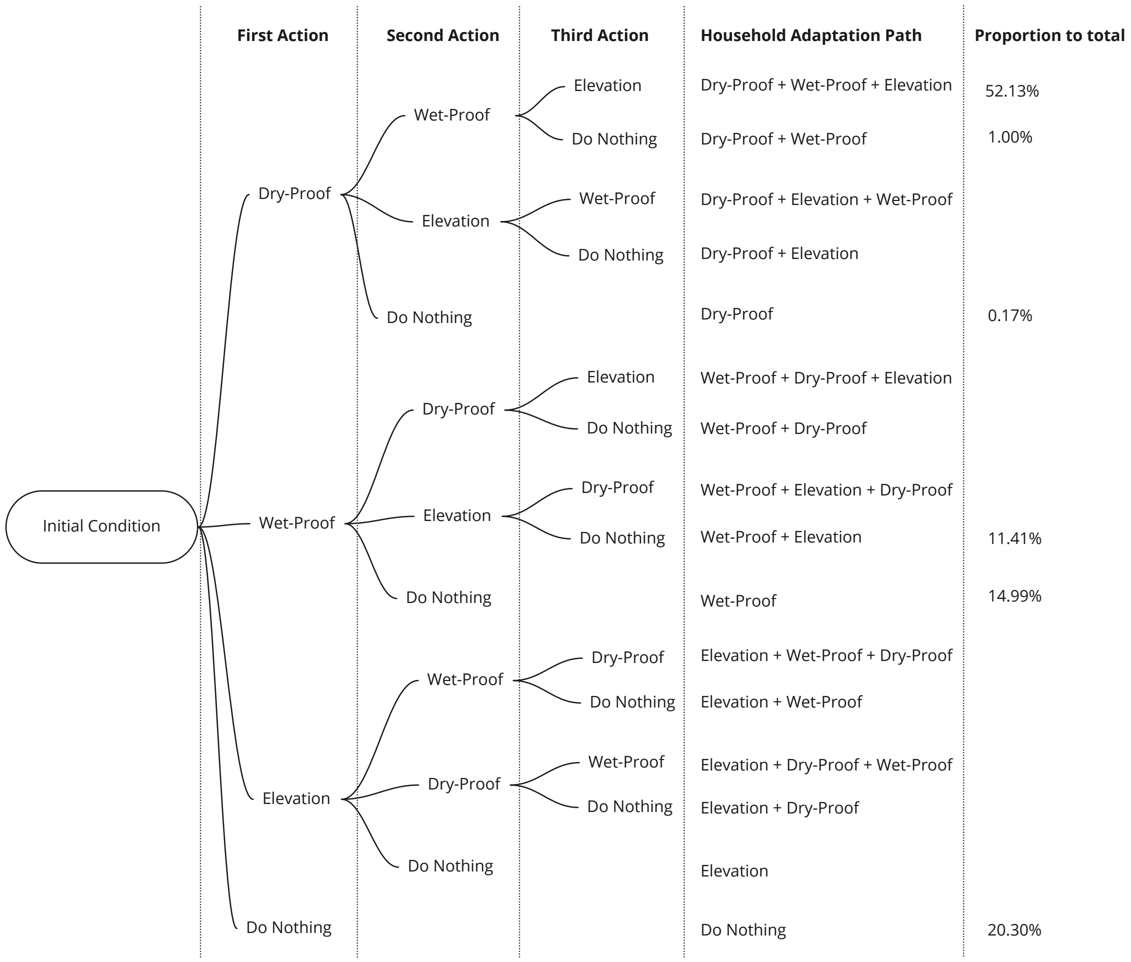

Figure 6.2: *Permutation of possible household adaptation path and the proportion of the emergence pathways.*

6.1.1. Adaptation Diffusion Across Household Vulnerability

Figure 6.3 and Table 6.1 show the distribution of adaptation diffusion was analysed across different educational backgrounds, elevation levels, and income categories. The distribution of adaptation diffusion in single-measure and multi-measure experiments shows similar patterns across different academic backgrounds. It is expected that a household that attends higher education tends to influence its adaptation decision as the proportion of inaction decreases with higher education levels (Figure 6.3), and comprehensive adaptation paths were implemented by households with higher education backgrounds (Table 6.1). This indicates that education can enable more complex adaptations, potentially due to a better understanding of risks or more access to relevant information and resources. However, this might further exploration as in a single-measure experiment, Figure 6.3 panel (a) sub-pane education category, across all education backgrounds favours wet-proof over dry-proof, which has higher efficacy.

Additionally, Figure 6.3 showed that while the spread of adaptation across elevation levels was consistent in multi-measure experiments, single-measure experiments showed slight variations. In this case, households in lower elevations or coastal areas preferred dry-proof over inaction, while those in city centre and inner-city neighbourhoods indicated the opposite preference. However, Table 6.1 unveils that fewer households adapted in the high-elevation areas while, on the other hand, this area is considered to be a flood-prone area. This indicates a misperception of flood hazards.

Adaptation paths vary in household income groups, with consistent patterns found (See Figure 6.3 in income category sub-panel). Most low-income families took no action, which is more likely due to financial constraints. Financial limitations persisted while inaction decreased with increasing income levels. Finances have been widely recognised as one of the adaptation constraints, especially for technological and infrastructural adaptation (Thomas et al., 2021). High-income households exhibited distinct adaptation patterns. Dry-proof was the preferred initial measure, often followed by additional adaptations, indicating a more comprehensive approach. Unlike the single-measure experiment, which preferred wet-proofing, this experiment shows a shift across various household backgrounds, except for the low-income households, to favour dry-proof as their first action.

Hence, it can be inferred that by enabling households to take measures, families were encouraged to take comprehensive measures, which was plausibly influenced by the social network. Moreover, Table 6.1 emphasises the financial constraint as low-income households with primary education employed standalone measures while high-income households with the same education background favoured comprehensive measures.

6.2. Identifying Household Maladaptive Behaviour

Simulation shows inaction as the second highest favoured adaptation path 6.1. The estimated probability of a household taking a particular measure is less than 0.5 if the overall model covariate equals zero with the threat appraisal greater than the coping appraisal (Chapter 4.5.1). Given that the combination of coefficients sums to less than 0.5, the probability is approximately less than is still favourable across different backgrounds except for high-income households. To describe the constraint of adaptation, it is essential to consider it endogenously, influenced by the interplay of values, norms, and culture (Adger et al., 2009). With this view, behaviour can be observed to represent the influence of various social and cultural factors. The influence shapes how households perceive risk, benefits, and the appropriateness of specific actions. This section examines household responses to flood risk through the lens of Protection Motivation Theory (PMT) as a result elaborated in Chapter 4.5.1.

Based on the model, threat appraisal includes perceived flood probability, damage caused by flood, household worry, and the interaction between these three subcomponents. While worrying about flooding strongly predicted adaptation across all measures, which is significant except for wet-proof, the role of perceived flood risk (probability and damage) was less pronounced, consistent with findings by Noll, Filatova, Need, and Taberna (2022). This indicated that households are more inclined to implement adaptation measures if they are worried about potential flood impact. This aligns with local culture, highlighting the importance of home or *'rumah'* as a critical part of their livelihood, establishing relationships between people and their environment beyond a settlement (Wiryomartono, 2014).

A negative coefficient of flood probability, one of the risk variables, suggests a potential underestimation of flood hazards, which aligns with maladaptive coping mechanisms like fatalism and avoidance. This finding is consistent across dry-proof and wet-proof, as well as the interaction effect of flood probability for the elevation model. Moreover, it is supported by the finding that fewer households adapt in higher elevation areas (see Table 6.1). This finding aligns with the more severe flood events experienced in inner-city neighbourhood areas (Section 4.2). While it is consistent that Jakarta has been experiencing floods periodically (Section 4.2), households indicated a misperception in evaluating living in flood-prone areas. This finding also shows that households accepting the flood, as usual, is not surprising, and exacerbated floods are seen as an unchangeable situation, which can result in a fatalistic attitude. This reluctance could stem from a rationale that residing in flood-prone areas may not be enough to prompt voluntary adaptation (Lechowska, 2018). Hence, in the Jakarta context, maladaptive behaviours are still apparent.

The closer a house is to the coastal area, the more likely households are to take action, which

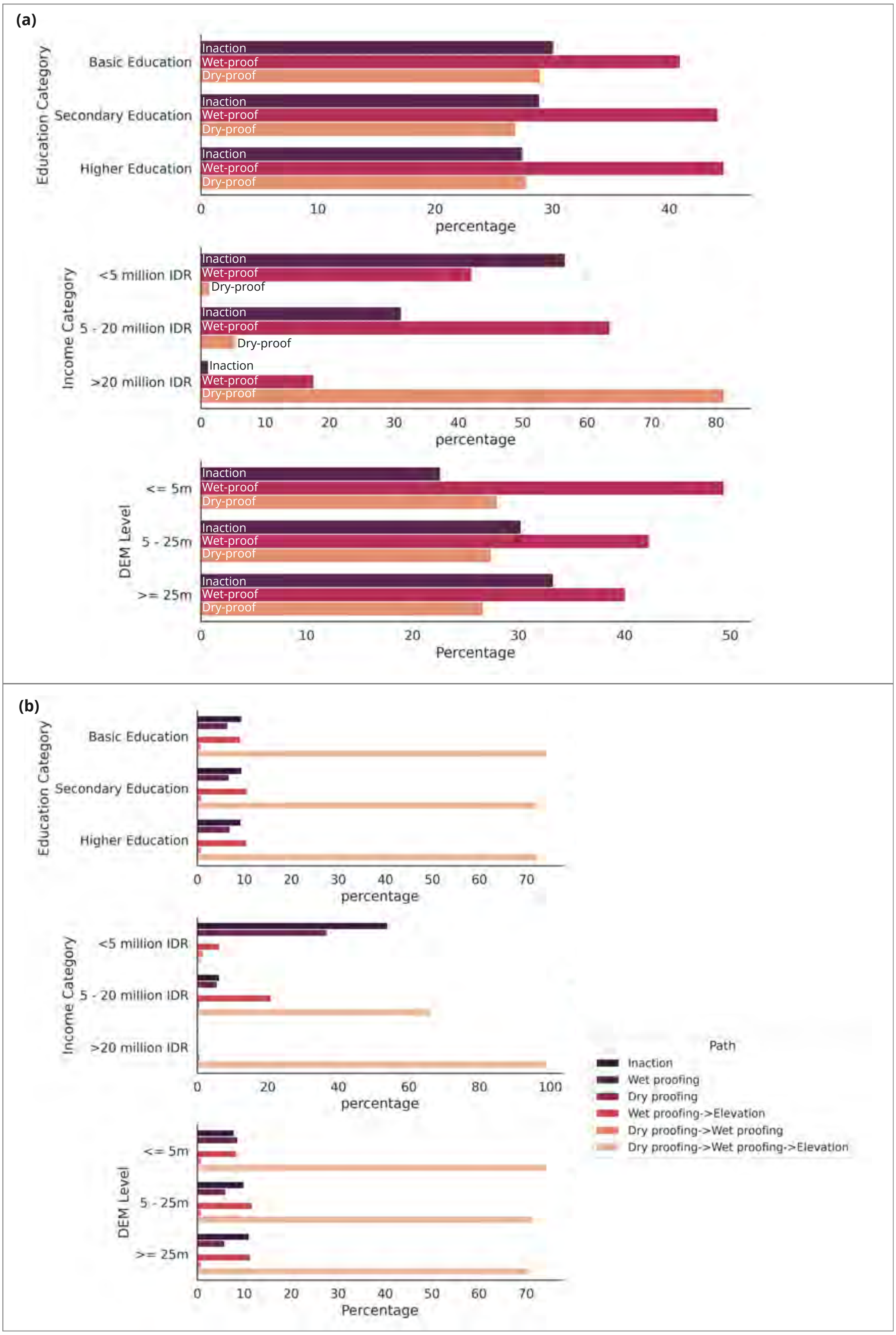

Figure 6.3: *Adaptation decisions by household education, income, and elevation.* Panel (a) represents the result of the single-measure experiment, while (b) exhibits a multi-measure experiment. Bars show the percentage of people choosing adaptation measures (a) or paths (b), with education and income reflecting adaptive capacity.

Table 6.1: The un-implemented household adaptation measures and paths based on elevation and adaptive capacity. *(sm)* refers to single-measure experiments, and *(mm)* refers to multi-measure experiments

Household Adaptation	Low Elevation	Medium Elevation	High Elevation
Inaction			
Wet-proof (sm)			
Dry-proof (sm)			• Low income, basic education
Wet-proof (mm)	• High income, basic education	• High income, basic education	• High income, high education
Dry-proof (mm)		• Low income, basic education	• Low income, basic education
Dry-proof ⇒ Wet-proof			• Low income, basic education • Medium income, basic education
Dry-proof ⇒ Wet-proof ⇒ Elevation	• Low income, basic education • Low income, secondary education	• Low income, basic education	• Low income, basic education
Wet-proof ⇒ Elevation	• Low income, basic education • Low income, secondary education	• Low income, basic education • High income, basic education	• High income, high education • High income, secondary education

suggests a more excellent risk perception as elevation decreases (Plot 'DEM level' in Figure 6.3). To explain this, it can be extended to the historical flooding event across elevation levels as described in Section 4.2. Although residing in flood-prone areas was found to have a negative association with the decision to adapt, it is found that flood experience (*High confidence*) significantly influences the decision to take adaptation measures. For instance, the constant tidal floods caused permanently submerged areas in northern Jakarta, including a mosque in Muara Baru Street Penjaringan district (Hidayatullah, 2021). This led to a continuous reality check with close examples to prompt households to take action. In contrast, even though households at higher elevations experience more severe floods with greater depths, the inundation that temporarily happens may not have as strong an influence as in North Jakarta. As a result, inaction is the second most favoured adaptation measure in the rest of Jakarta. In contrast, the preferred adaptation measure across different geographical locations remains similar, emphasising wet-proof measures.

The findings of the adaptation measure model show a consistent pattern of coping appraisal components across different adaptation measures. First, self-efficacy emerged as a key driver of adaptation, with positive associations across all measures and significant for wet-proof and elevation. This aligns with previous research in Jakarta by Flores et al. (2024) and New York by Botzen et al. (2019). However, a mismatch between perceived and actual adaptive capacity, particularly financial resources, hindered adaptation efforts. High perceived adaptation cost was significantly inversely associated with the odds of adopting the intervention, consistent with earlier studies by Bubeck et al. (2013) and Poussin et al. (2015). This is evident in the data, as high-income households, despite higher savings, also showed inaction rates, although to a lesser extent than other income groups (Figure 6.3 in the income category panel). This discrepancy between perceived and objective capacity underscores the prevalence of avoidant maladaptation (Grothmann & Patt, 2005).

As developed by Noll, Filatova, Need, and Taberna (2022), the PMT expanded to proceeding with flood management, climate-related beliefs, background, and external influences. This study excludes background as it focuses more on the household level. From the extended PMT, another indication of maladaptation is found: households are less inclined to adopt the second measure after implementing other adaptation measures, mainly if the first measure involves elevation. This implies that they solely rely on the undergone measure, which can lead to experiencing a false sense of security and continuing to be vulnerable to climate change (Schipper, 2020). This is worsened in the case of dry-proof measures; the scepticism about dry-proofing's efficacy in reducing damage caused by flood hazards emphasises reliance on the first measure as a one-size-fits-all solution. However, the solution was shown from insights derived from 6.1.1 by enabling households to take multiple measures while also increasing the accessibility of the measure.

6.3. Adaptation Constraint: Adaptation Intention and Capacity Mismatch

Although positive threat and coping appraisal reduced the occurrence of maladaptation (Bechtoldt et al., 2021), actual adaptive capacity enriches the explanation of adopting adaptation measures by describing various resources to seize their perception of high self-efficacy or threat appraisal (Maldonado-Méndez et al., 2022). In both experiment settings, households across all education levels—primary, secondary, and higher—tended to prioritize implementing adaptation measures over inaction, showing that education can help access information or knowledge required to implement the adaptation and process such knowledge (Habtemariam et al., 2019). The popularity of wet-proof in single-measure experiments likely stems from its perceived lower cost and more straightforward implementation compared to dry-proof (Aerts, 2018). While dry-proofing might be more effective, the higher perceived costs may deter adoption. Factors such as flood damage, belief in climate change, and social media influence, as identified in the PMT model, may also contribute to this preference for more economical options.

Besides, adaptation diffusion across actual adaptive capacity found that low-income households displayed higher levels of inaction (Figure 6.3 in the income category sub-panel). This finding highlighted that any household motivated to take measures might not implement measures if they do not have the financial capacity to adapt. In addition, some middle—and high-income households still do not take action. If they decide to undertake a measure, they prefer adapting to the cost-effective measure. Meanwhile, over 80% of high-income households consider dry-proofing the most appropriate measure for their case, which is relatively higher in cost of adaptation than wet-proof and low-income households prefer to adapt to wet-proof initially.

The choice to adopt wet-proof, less efficacy, is often influenced by its perceived affordability and practicality, especially in financially constrained low and middle-income households, as demonstrated in the logit model (Figure 4.8). Wet-proofing, less affected by high perceived costs, is favoured over more costly measures like dry-proofing. Additionally, a stronger correlation exists between flood damage experience and the adoption of wet-proofing, indicating its perceived immediacy and directness in response to flooding and making it a more attractive option for households facing financial constraints, especially in low and middle-income settings. This means capital constraint is more evident in low-income families (see Section 6.1.1). Although insignificant, monthly income was positively associated across all measures. However, increased awareness and preparedness do not necessarily lead to better adaptation decisions, highlighting a gap between intention and effective action, as noted by van Valkengoed et al. (2024).

Moreover, it is shown that people with more income are likely to be more proactive in taking multiple measures, with the proportion of taking complete measures significantly higher than the other income brackets (see Section 6.1.1). In contrast, low-income households favour relying on the absence of adaptation or solely wet-proof measures while showing a decrease in percentages for taking complete or multiple measures. This shows that income levels correspond to a greater adaptation capacity to take various measures, regardless of the household's education category and residing in flood-prone areas. The existence of constraints in climate change adaptation makes the adaptation process difficult and may lead to adaptation limits (Schinko et al., 2024). Capital constraints hinder households from taking adaptation measures. Due to the highest initial investment that should be incurred compared to the other two, the elevation measure is not preferred as the first adopted measure. This is consistent with the logistic regression model that shows how households perceive adaptation cost as a negative relation.

Financial constraints are pivotal in shaping adaptation decisions, especially among economically disadvantaged households. A review underscores that lower initial cash reserves can lead to an aversion to experimentation (Castells-Quintana et al., 2018). The aversion is not merely a preference but can be a necessary caution. Impoverished households cannot afford to risk their limited resources on unproven measures. It is presumed to be a high-stakes decision that can make families unable to afford their needs. Household adaptation is argued to be a low regret strategy (Koerth et al., 2017), but this does not apply to low-income households.

This cautious approach demonstrates how households face uncertainties. Households face uncertainties not only about the outcome of adaptation caused by the impact of climate change but also highlight the mismatch between households' perceived measure efficacy relative to the actual efficacy (Table 6.2). This mismatch can lead households to underestimate the effectiveness of a measure, thereby avoiding its implementation and missing potential benefits. The matrix shown in Table 6.2 also indicates maladaptation where scenarios of high perceived efficacy result in a negative adaptation outcome. Moreover, staying inactive may have favourable results, in some cases, contradicting the research trend that discusses the cost of inaction, which frames the inaction as the villain (Ackerman & Stanton, 2006; Sanderson & O'Neill, 2020; UNFCCC, 2009).

Table 6.2: Scenarios of adaptation outcome based on household adaptation intention

Adaptation Outcome / Household Adaptation Intention Level	Positive Adaptation outcome	Negative Adaptation Outcome
High Adaptation Intention	*Successful adaptation*: Households experienced anticipated benefits from the adaptation.	*Adaptation ineffectiveness (potentially maladaptive)*: Despite high expectations, the adaptation measure did not achieve the intended outcome
Low Adaptation Intention	*Missed adaptation opportunity*: Potential benefits were overlooked due to underestimating measures' efficacy.	*Cautious inaction*: Opted to stay inactive due to perceived low effectiveness while avoiding potential resource wastage.

6.4. Key Insights

Table 6.3: *Scenarios of adaptation outcome based on household adaptation intention and adaptive capacity.*

Adaptive Capacity / Adaptation Intention	High Adaptive Capacity	Low Adaptive Capacity
High Adaptation Intention	Either successful adaptation or maladaptation	Missed opportunity
Low Adaptation Intention	Missed opportunity	Inaction

This chapter unveiled maladaptive behaviour indicated by a high proportion of inaction and reliance on another measure, which plausibly caused elevation not favoured as the initial measure to take and misperception of flood risk, possibly due to a lack of representation. Both coastal and inner-city neighbourhoods with higher elevations appear to be flood-prone, but more households implement adaptation on the coast. Worry, one of the threat appraisal elements, might have an essential role in uplifting maladaptive behaviour supported by the cultural value of *'Rumah'*. At the same time, the perceived adaptation cost is portrayed as a barrier. In addition, this situation, which is complicated by financial constraints, is emphasised in this chapter and is particularly experienced by low-income households. This has led to missed opportunities for adaptation, as illustrated in matrix 6.3.

Furthermore, it is indicated that social networks could influence adaptation strategies, with experiments across various socioeconomic and educational backgrounds showing that middle—and high-income households were likelier to initiate and implement comprehensive adaptation paths. It appears that households of higher education levels were more likely to adopt comprehensive adaptation measures.

7

Maladaptive Outcome: Synthesis of Household Maladaptive Adaptation Measure and Path

Following the previous chapter, this chapter discusses the maladaptive outcome of household-level climate adaptation utilising the indicators and representation in Section 3.4. Wherein the matrix 6.3 spotted in high adaptation intention and adaptive capacity.This chapter elaborates on each indicator across different household vulnerabilities (refer to Table 4.2).

7.1. Loss Avoidance: The Benefit of Adapting

The benefit of adaptation is identified from the area between the curve of residual damage of inaction and the adaptation measure. To do this, the figure showcases the trajectories of residual damage post-adaptation measures. Equation 7.1 assumes that residual damage results from subtracting net worth, which represents the liquid net worth of unrepaired flood damage and damage caused by a current flood.

$$\text{Residual Damage}_{(t)} = \text{Net Worth}_{(t)} - \text{Residual Damage}_{(t-1)} - \text{Repair Expenses}_{(t)} \tag{7.1}$$

Equation 7.1 similar pattern across elevation, education, and income. Inaction shows the worst residual damage, followed by dry-proof, wet-proof, and more comprehensive adaptation paths. In other words, it shows the benefit of undertaking adaptation, which is not marked as a maladaptive measure. For a single-measure path, it shows that post-adaptation of dry-proof begins at a shallow residual damage scale, implying that households took dry-proof before struggling to absorb the damage. In contrast, residual damage from wet-proof started at slightly higher residual damage, indicating that households predominantly took wet-proof after exposure to unavoidable flood damage. As for comprehensive adaptation paths, Figure 7.1 in panel (b) and high-income households that can absorb damage with no residual damage recorded, it is interesting to highlight the differing trends of various income groups shown in Figure 7.2 and Figure 7.3.

While Figure 7.2 unveils a similar pattern, Figure 7.3 exhibits middle-income households with basic education backgrounds potentially experiencing maladaptation. Those household groups residing in coastal areas may find wet-proof has a similar outcome to inaction, and those living in inner-city neighbourhoods may consider inaction. It is interesting to highlight the pattern of households with basic or primary education backgrounds absorbing the damage well. Although they only employ limited paths 6.1, the residual is consistent near 0 throughout the simulations. In contrast, households with higher education levels implement more variation and comprehensive adaptation paths; however, they did not absorb the residual damage well compared to households with primary education. This is notably worse for households with lower incomes as the cost of adapting to comprehensive paths is relatively higher.

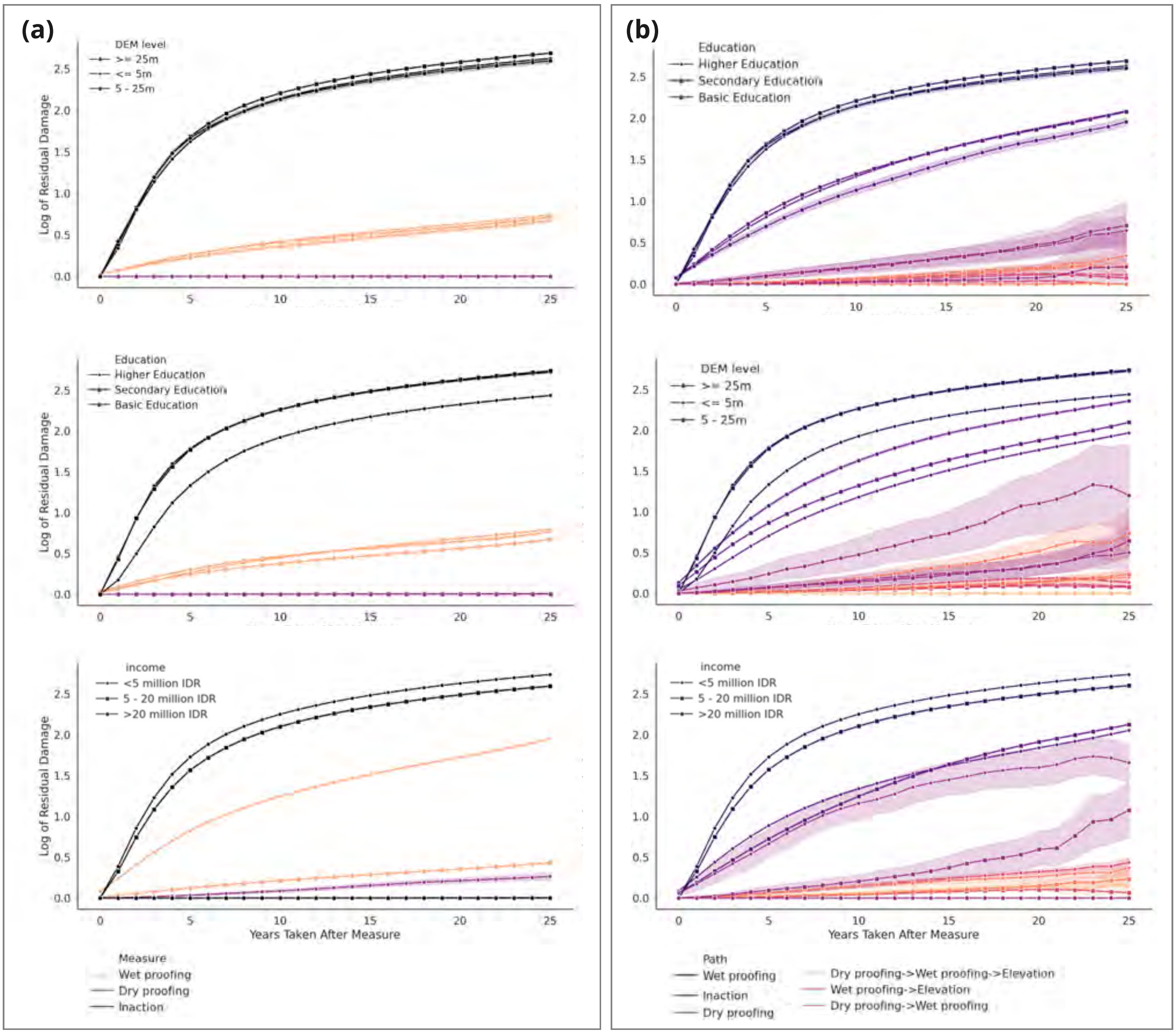

Figure 7.1: *Comparison of log of residual damage projections based on elevation and adaptive capacity Factors Over 25 Years.* The figure displays Panel (a) single-measure experiments and (b) multi-measure experiments with shaded areas indicating a 95% confidence interval. Top Graph: Net worth projections for different elevation levels (DEM levels: ≥ 25m, ≤ 5m, 5-25m). Middle Graph: Net worth projections are differentiated by educational attainment (Higher Education, Secondary Education, Basic Education). Bottom Graph: Net worth projections are categorized by income level (≥ 20 million IDR, 5-20 million IDR, ≤ 5 million IDR).

7.1.1. Lower-Income Household Dilemma: Higher Education and the Challenge of Comprehensive Paths

The previous chapter discussed lower-income households' financial barriers to taking comprehensive measures, as more than 60% remain to do nothing. However, the residual damage shows that lower-income households with higher education backgrounds implemented comprehensive measures but diverted the residual damage less. A similar pattern applies to middle-income households with higher education backgrounds (see Figure 7.3). This shows that education increases the intention to adopt, consistent with the findings in the previous chapter and Habtemariam et al. (2019). However, it challenges the finding that households with higher education tend to adopt better adaptation measures (Alam et al., 2016). Research indicates educated individuals might employ sophisticated and thorough evaluation of options (Dawson et al., 2024; Peters, 2017). Despite these observations, the fact that households with higher education levels still experience significant residual damage, even after implementing comprehensive measures, may be attributed to the timing of implementation. Thorough evaluations, while meticulous, can introduce uncertainties that affect outcomes. In complex situations, including climate change risk, taking more time to decide can sometimes exacerbate the negative effect of complexity and uncertainty (Strittmatter et al., 2022). This also relates to the reported cost of delayed adaptation and stay inaction. Besides, financial barriers experienced by lower-income households may hinder timely decision-making, where they may be in a situation to adapt but are unable to implement due to financial constraints, so they have to wait until a certain amount of money is sufficient to cover the adaptation cost. This delay can lead to increased residual damage. The interplay of timely decision-making, educational background, and financial barriers is beyond the household adaptation model in this study. However, there is a signal to involve education in overcoming such obstacles to utilise resources better.

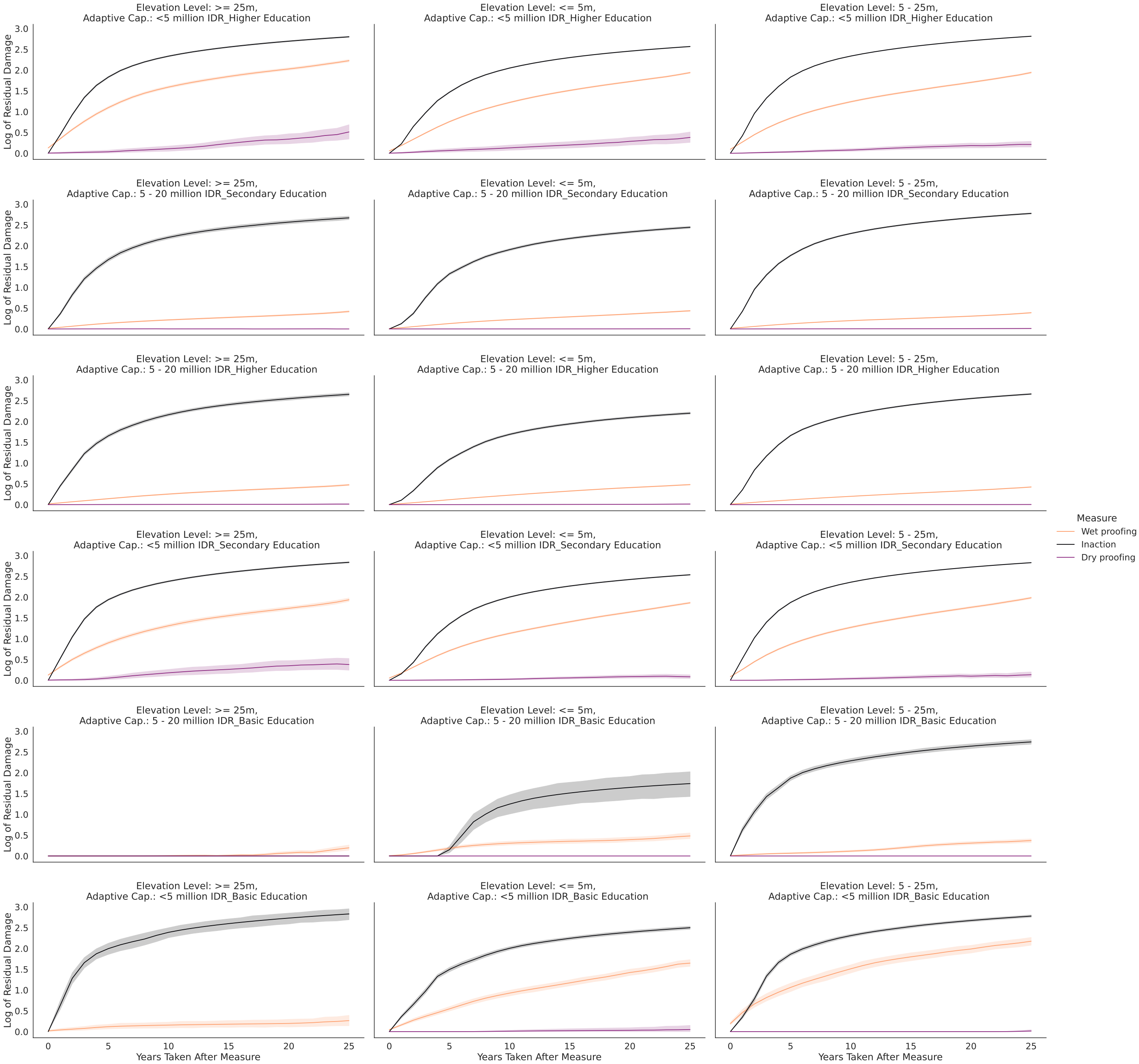

Figure 7.2: *Projected log of residual damage over time based on elevation levels and adaptive capacity with incomes of less than 20 million IDR from the single-measure experiment.* The figure displays the projected net worth (in million IDR) over 25 years, segmented by different elevation levels (≥ 25m, ≤ 5m, 5-25m) and educational attainments (Higher Education, Secondary Education, Basic Education). The pathways considered include emerged adaptation measures. Shaded areas indicate a 95% confidence interval.

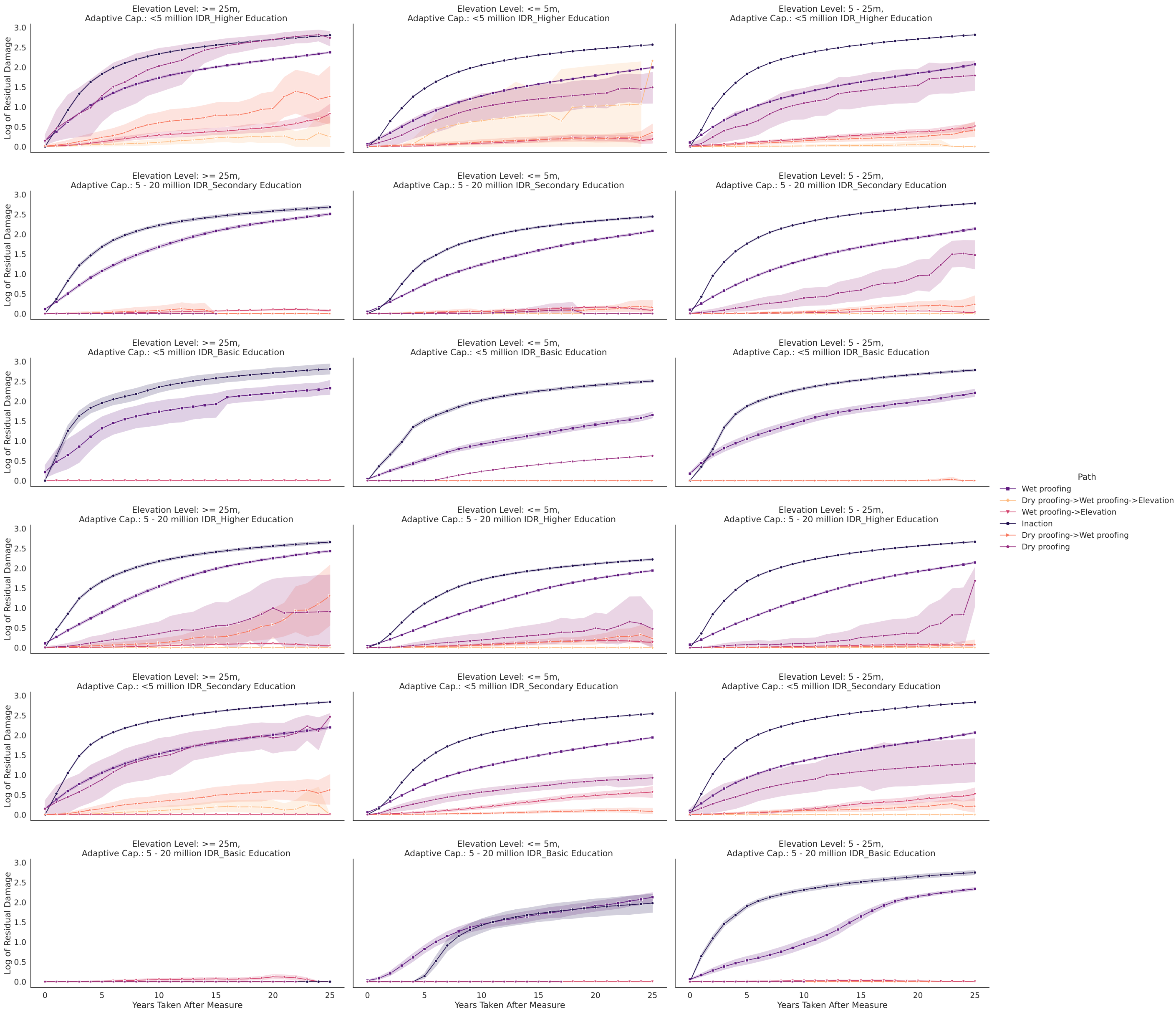

Figure 7.3: *Projected log of residual damage over time based on elevation levels and adaptive capacity with incomes of less than 20 million IDR from the multi-measure experiment.* The figure displays the projected net worth (in million IDR) over 25 years, segmented by different elevation levels (≥ 25m, ≤ 5m, 5-25m) and educational attainments (Higher Education, Secondary Education, Basic Education). The pathways considered include various combinations of dry proofing, wet proofing, elevation, and inaction. Shaded areas indicate a 95% confidence interval.

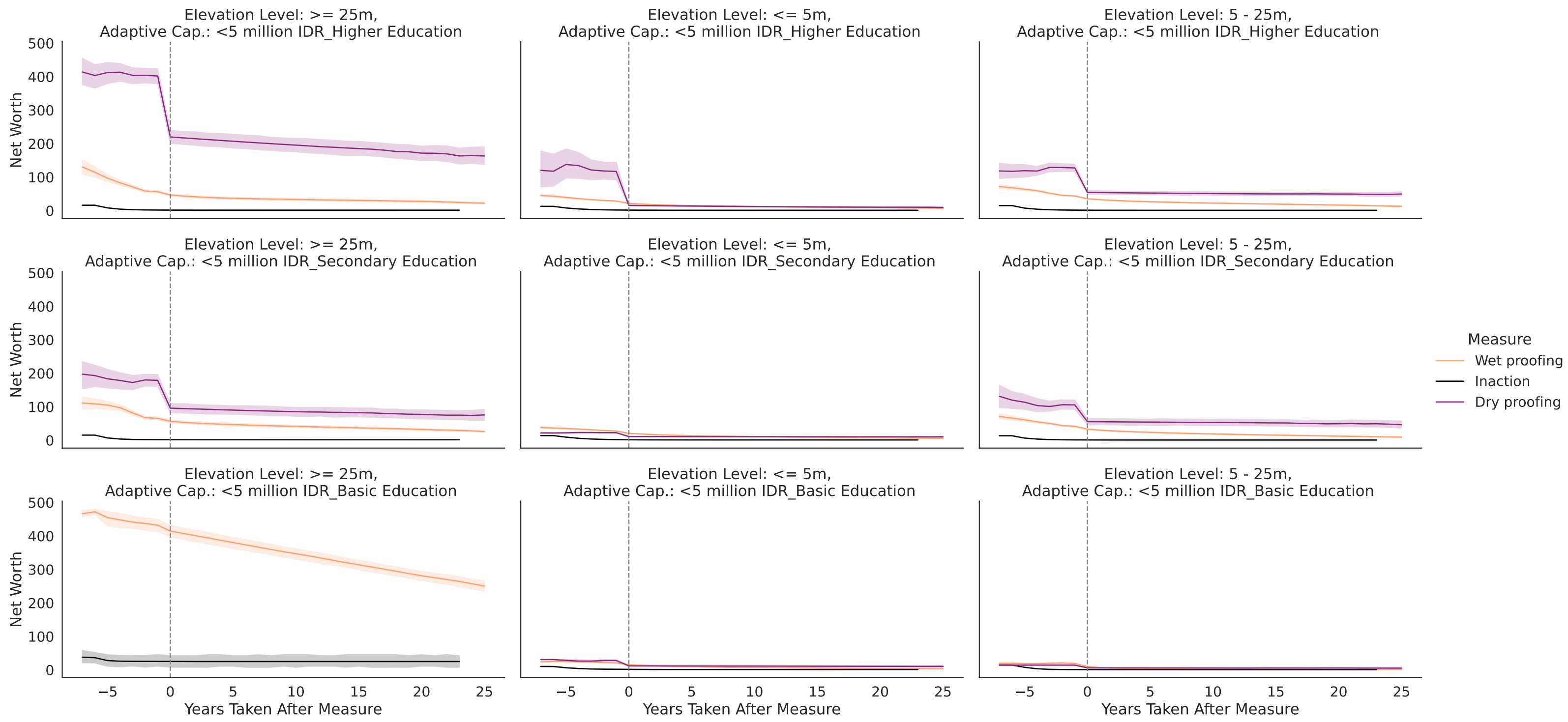

Figure 7.4: *Pre- and post-adaptation impact on projected net worth over time based on elevation levels and adaptive capacity with less than 5 million IDR from the single-measure experiment.* The figure displays the projected net worth (in million IDR) over 25 years, segmented by different elevation levels (≥ 25m, ≤ 5m, 5-25m) and educational attainments (Higher Education, Secondary Education, Basic Education). The measures considered the emerged adaptation measure. Shaded areas indicate a 95% confidence interval.

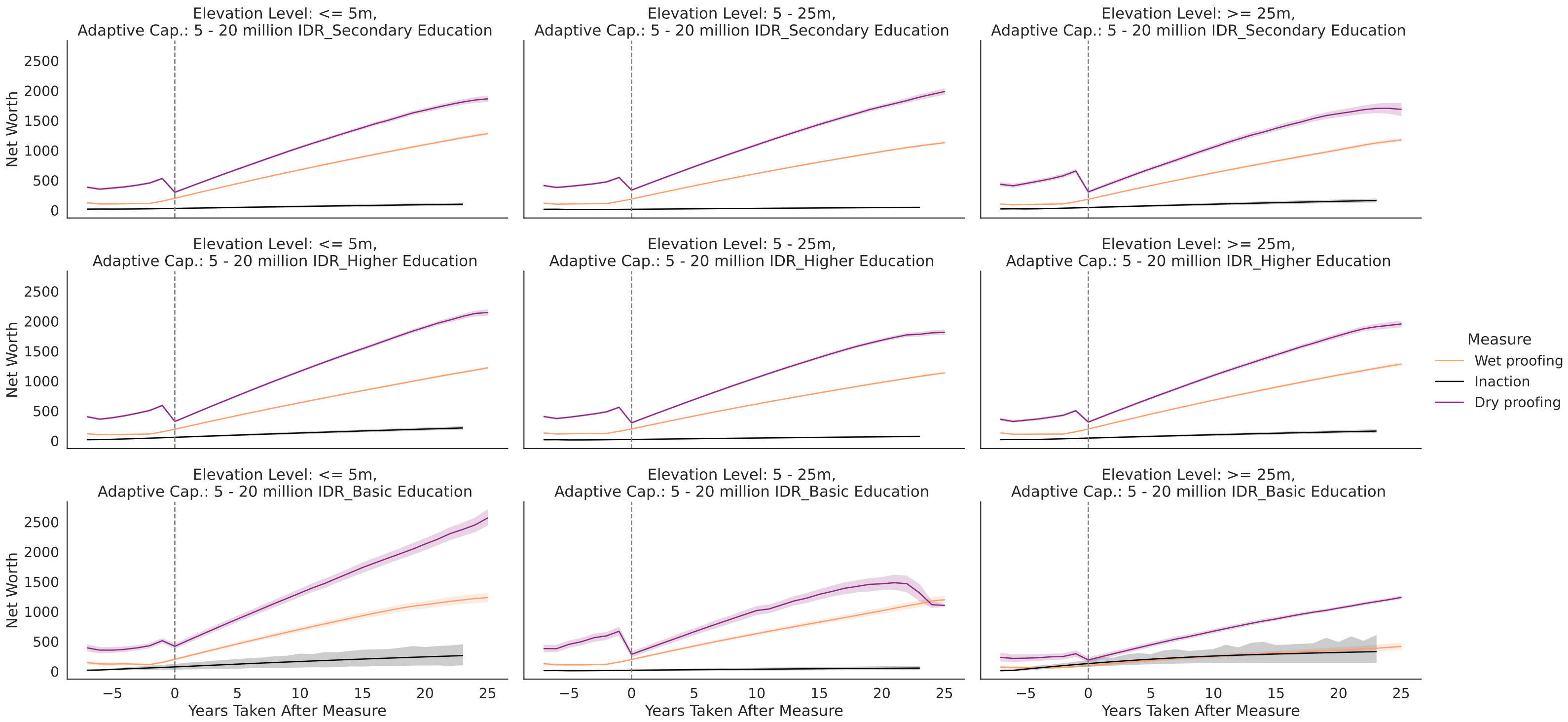

Figure 7.5: *Pre- and post-adaptation impact on projected net worth over time based on elevation levels and adaptive capacity with less than 20 million IDR and over 5 million IDR from the single-measure experiment.* The figure displays the projected net worth (in million IDR) over 25 years, segmented by different elevation levels (≥ 25m, ≤ 5m, 5-25m) and educational attainments (Higher Education, Secondary Education, Basic Education). The measures considered the emerged adaptation measure. Shaded areas indicate a 95% confidence interval.

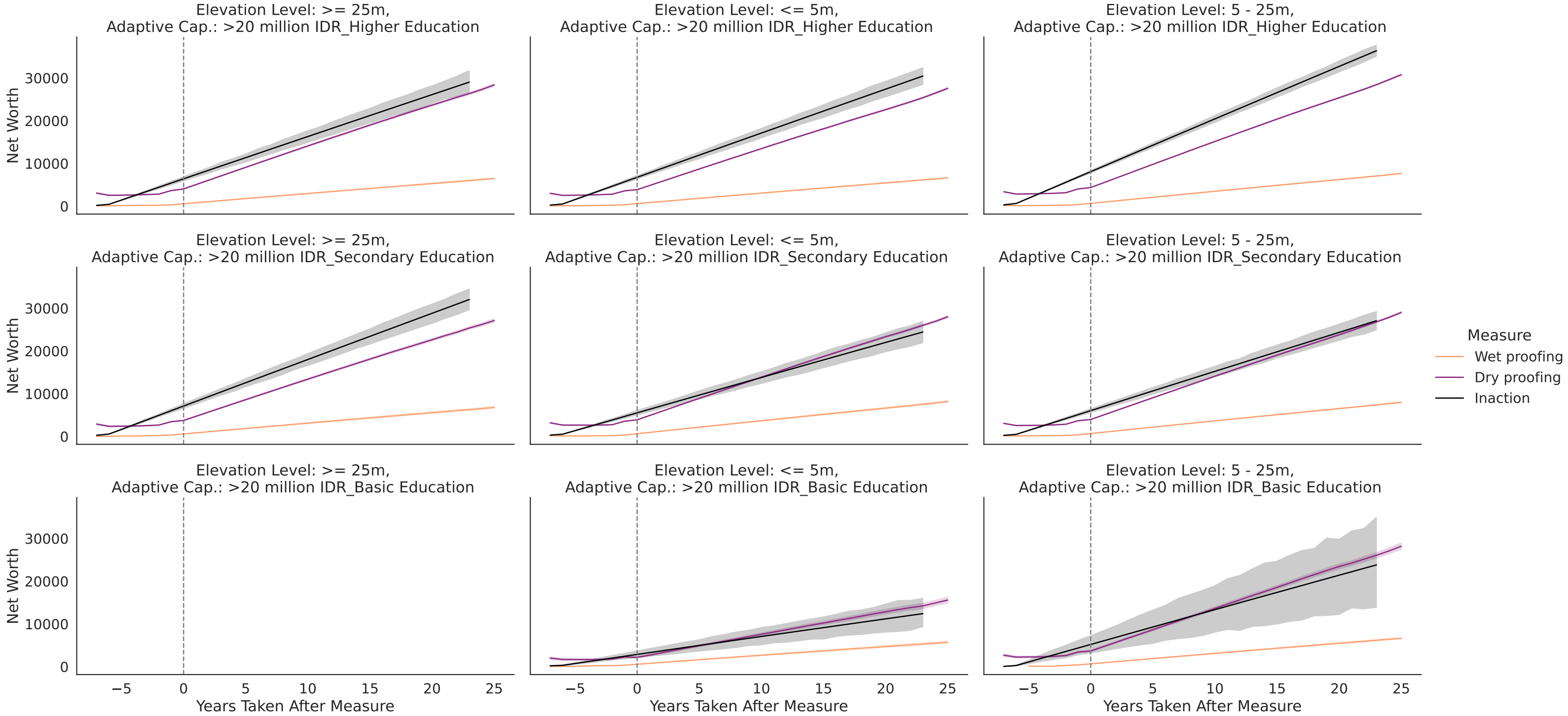

Figure 7.6: *Pre- and post-adaptation impact on projected net worth over time based on elevation levels and adaptive capacity with over 20 million IDR income from the single-measure experiment.* The figure displays the projected net worth (in million IDR) over 25 years, segmented by different elevation levels (≥ 25m, ≤ 5m, 5-25m) and educational attainments (Higher Education, Secondary Education, Basic Education). The measures considered the emerged adaptation measure. Shaded areas indicate a 95% confidence interval.

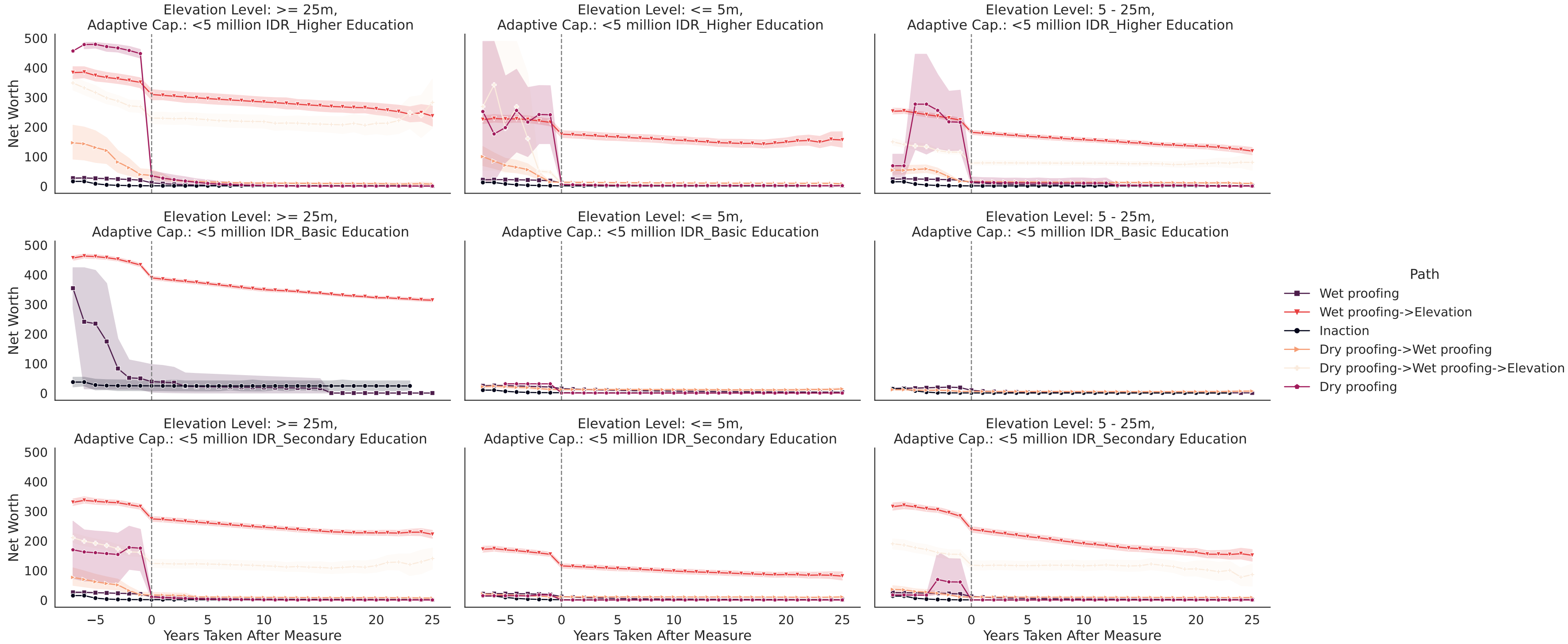

Figure 7.7: *Pre- and post-adaptation impact on projected net worth over time based on elevation levels and adaptive capacity with incomes of less than 5 million IDR from the multi-measure experiment.* The figure displays the projected net worth (in million IDR) over 25 years, segmented by different elevation levels (≥ 25m, ≤ 5m, 5-25m) and educational attainments (Higher Education, Secondary Education, Basic Education). The pathways considered include various combinations of dry-proof, wet-proof, elevation, and inaction. Shaded areas indicate a 95% confidence interval.

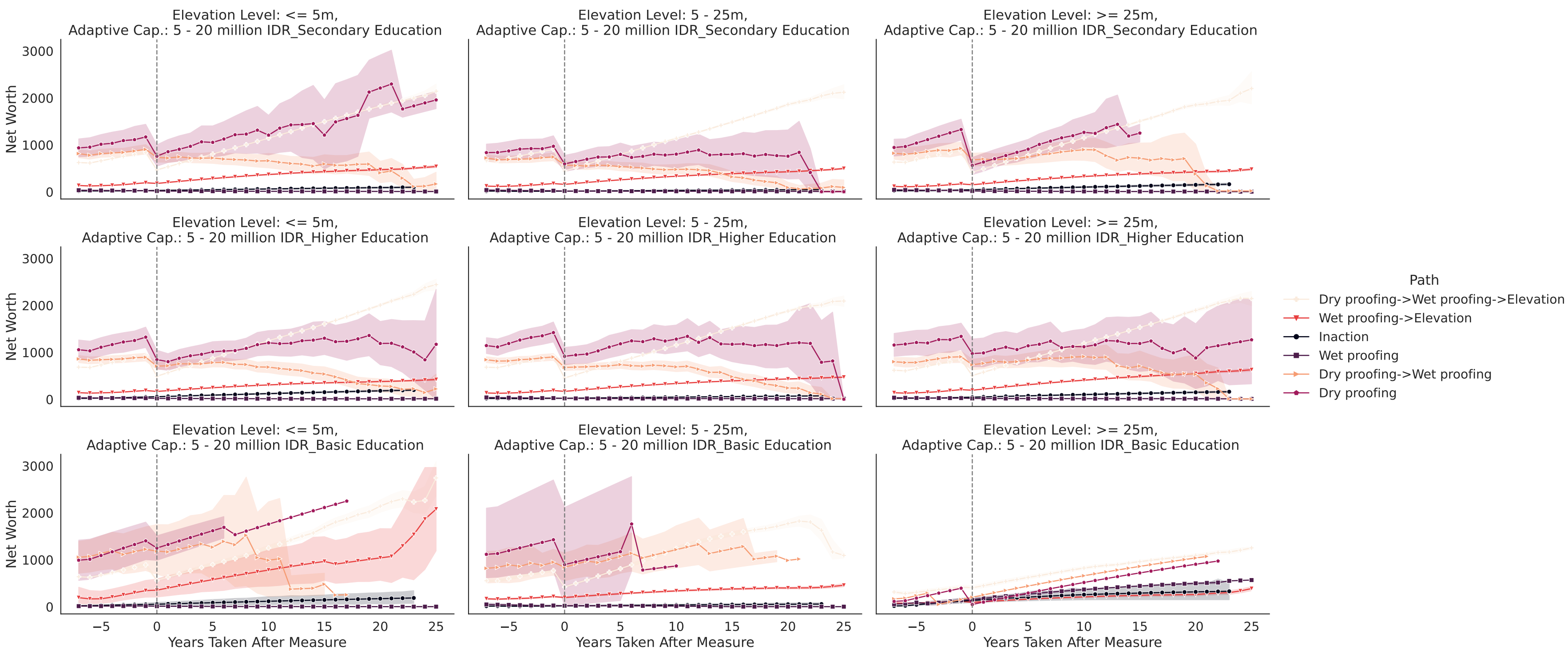

Figure 7.8: *Pre- and post-adaptation impact on projected net worth over time based on elevation levels and adaptive capacity with incomes of less than 20 million IDR and over 5 million IDR from the multi-measure experiment.* The figure displays the projected net worth (in million IDR) over 25 years, segmented by different elevation levels (≥ 25m, ≤ 5m, 5-25m) and educational attainments (Higher Education, Secondary Education, Basic Education). The pathways considered include various dry-proof, wet-proof, elevation, and inaction combinations. Shaded areas indicate a 95% confidence interval.

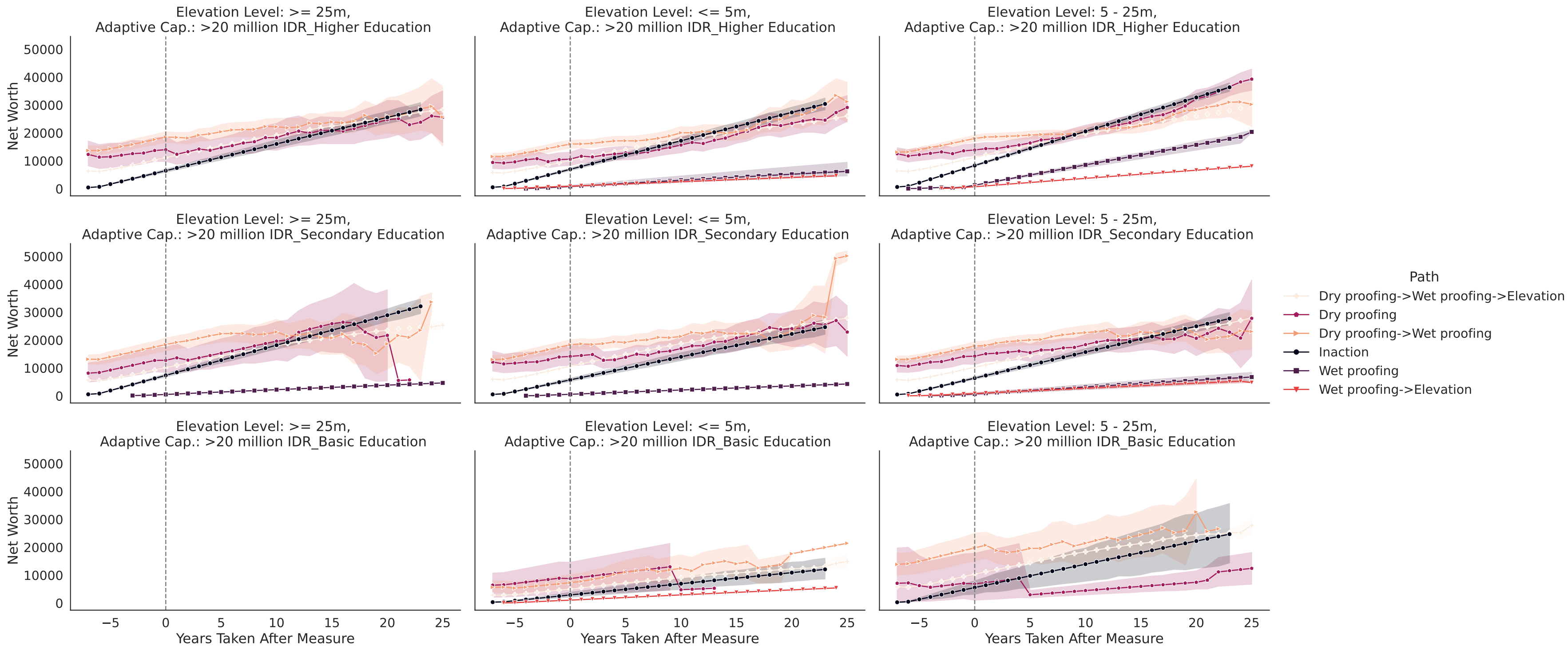

Figure 7.9: *Pre- and post-adaptation impact on projected net worth over time based on elevation levels and adaptive capacity with over 20 million IDR income from the multi-measure experiment.* The figure displays the projected net worth (in million IDR) over 25 years, segmented by different elevation levels (≥ 25m, ≤ 5m, 5-25m) and educational attainments (Higher Education, Secondary Education, Basic Education). The pathways considered include various dry-proof, wet-proof, elevation, and inaction combinations. Shaded areas indicate a 95% confidence interval.

7.2. Household Adaptation Lock-In: Stagnation and Financial Hardship

Lock-in, as defined in this study, refers to a path dependency, synthesised from Goldstein et al. (2023), with existing situations limiting available options (Section 3.4). A lock-in situation occurs when an adaptation measure traps a household in stagnation, as indicated by a flattened net worth curve of post-adaptation-implementation, which can be viewed in temporal scales. Building on this point, the simulation showed that the lock-in condition started after implementation and continued for extended periods. Based on the findings in Table 7.1. It is highlighted that comprehensive adaptation paths do not automatically help households to adapt and avoid maladaptation. Standalone measures, in this case, wet-proof, caused lock-in to more various households than comprehensive measures. However, compared to wet-proof followed by elevation, it is better performed to avoid lock-in than complete measure.

Custom Box 7.1: Summary of financial hardship across household-level adaptation derived from Figure 7.10 and 7.11.

1. Inaction: This affects 80% to 100% of low—and middle-income households with financial hardship, regardless of educational background and location. One exception is for middle-income families who reside in inner-city neighbourhoods and have primary education.

2. Wet-proof: This was found to cause financial hardship in more than 80% of low-income households, consistent in single-measure and multi-measure experiments. In addition, as households were allowed to adapt with comprehensive measures, multi-measure experiments highlighted that wet-proof caused financial hardship to middle-income families, except those with primary education and living in inner-city neighbourhoods.

3. Dry-proof: Although not highlighted in the single-measure experiment setting, standalone dry-proof caused financial hardship for low-income households.

4. Dry-proof, Wet-proof, and Elevation: Interestingly, adaptation paths of complete measure caused financial hardship only for low-income households with higher education backgrounds residing in the coastal areas. These households, despite trying to protect themselves from flood damage, often used expensive strategies that were not very effective. As a result, half of them experienced financial hardship.

Besides assessing a temporal view, a lock-in situation occurs when an adaptation measure financially precludes implementing additional measures and fulfilling the basic needs. Building on this point, it is expected that low-income households are more likely to experience significant, particularly vulnerable in facing long-term economic challenges that diminish their overall wealth. Despite that, to observe the effect of adaptation measures on the lock-in situation, the proportion of households experiencing financial hardship. This measurement was identified by negative delta net worth or with no remaining wealth, which indicates that implementing particular measures to adapt to flooding results in depreciated net worth regardless of income over time. As a result, four household adaptation paths were found to cause significant financial hardship, as summarised in Box 7.1.

Both views of lock-in imply that the lock-in situation varies across different measures and households, with four essential insights. First, the long-term lock-in implications of preference over inaction show a concerning impact. Secondly, repetitive flooding with standalone measures, such as dry-proof or wet-proof, can lead to a lock-in situation, especially for low—and some segments of middle-income households. This suggests that reliance on a standalone measure can be maladaptive and prevent households from considering more comprehensive strategies to mitigate flood damage. Reflecting on the adaptation diffusion in the previous chapter, low-income households favour inaction and wet-proof, which is less effective and more affordable in adapting to flood, which causes them to be trapped in lock-in situations in the long term.

Thirdly, a household adaptation path with house elevation as wet-proof followers will likely help households adapt. However, elevation within complete measure could avoid lock-in only for families residing in higher elevation areas or inner-city neighbourhoods. Inner-city neighbourhoods are more prone to floods, requiring more robust measures to divert the flood damage. On the other hand, with the

Table 7.1: *The effect of household adaptation measure and path on stagnation across adaptive capacity and elevation.* Each cell indicates which household groups are more likely to lock-in due to a particular adaptation path summarised from Figure 7.4, 7.5, 7.6, 7.7, 7.8, and 7.9.

Household Adaptation	**Low Elevation**	**Medium Elevation**	**High Elevation**
Inaction	Low-income households with any educational backgrounds	Low-income households with any educational backgrounds	Low-income households with any educational backgrounds
Wet-proof	• Low-income households with any educational backgrounds • Middle-income households with any educational backgrounds	• Low-income households with any educational backgrounds • Middle-income households with any educational backgrounds	• Low-income households with any educational backgrounds • Middle-income households with higher and secondary educational backgrounds
Dry-proof	Low-income households with any educational backgrounds	Low-income households with any educational backgrounds	Low-income households with any educational backgrounds
Dry-proof ⇒ Wet-proof	Low-income households with any educational backgrounds	Low-income households with any educational backgrounds	Low-income households with any educational backgrounds
Dry-proof ⇒ Wet-proof ⇒ Elevation	Low-income households with any educational backgrounds	Low-income households with any educational backgrounds	
Wet-proof ⇒ Elevation			

relatively high cost of elevation, elevation may be considered a contextual solution for severe floods. This leads to final insights highlighting the need for a cost-effective and accessible household adaptation path to lift the burden of severe floods. Low-income people are identified as more vulnerable to lock-in situations despite adapting to comprehensive adaptation paths.

7.3. Inequality: Disproportionate Effect of Household-Level Adaptation Path

Net worth pre- and post-adaptation were observed to identify maladaptation arising from these interventions. This section focuses on distributive justice or the outcomes of adaptation measures as a sign of exacerbated inequality and highlighting maladaptation. The disproportionate impact of adaptation paths hinders disadvantaged groups' coping and recovery from flood damage setbacks (Swanson, 2021). Figure 7.12 refers to the vertical dashed line at step 0 to indicate the measure's implementation. Pre-adaptation conditions, marked by residual damage due to floods in the absence of adaptation (referred to as 'inaction'), establish a baseline against which to evaluate the impacts of this measure.

The effect of climate change adaptation to inequality can be identified by the difference in recovery rate of the advantaged and disadvantaged group (Islam & Winkel, 2017). Post-adaptation conditions

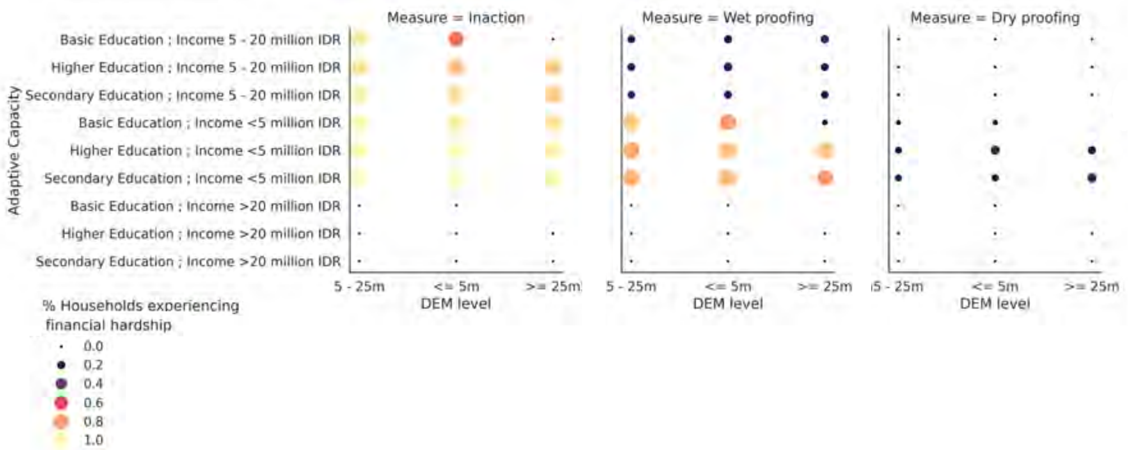

Figure 7.10: *Financial hardship across households by education attainment, income, and elevation, categorized by emerged adaptation measures from the single-measure experiment.* The dot size and colour indicate the percentage of households with 0 net worth at the simulation's end.

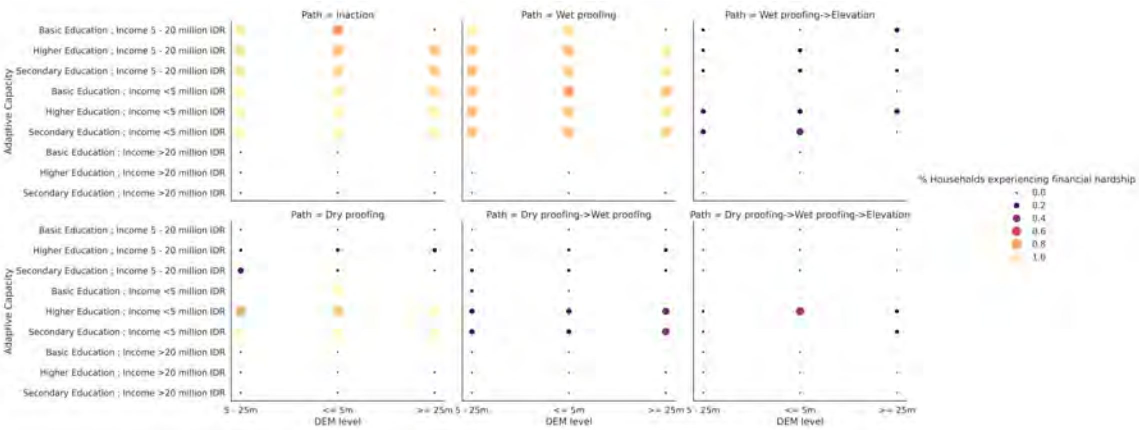

Figure 7.11: *Financial hardship across households by education, income, and elevation, categorized by adaptation paths from the multi-measure experiment.* The dot size and colour indicate the percentage of households with 0 net worth at the simulation's end.

show the impact of adaptation paths; maladaptation is indicated by a widened gap between household groups and their adaptation path. Figure 7.12 demonstrates net worth growth of post-adaptation of standalone wet-proof in single-measure and multi-measure experiments differ across elevation and education level. In addition, the income sub-panel shows that high-income households demonstrate a higher rate of net worth accumulation, positioning them as the advantaged group.

It is well documented that climate change has a disproportionate effect, both geographically and socioeconomically, in which impoverished urban populations often have heightened exposure to flood impact (Winsemius et al., 2018). This pre-adaptation inequality is vividly illustrated by the varying values of residual damage across income and elevation levels by the absence of adaptation measure (see the line labelled 'Inaction' in Figure 7.1). Notably, households with higher incomes experience the most negligible impact from flooding, as indicated by the minimal residual damage of inaction compared to other groups. This is expected, as more financial resources will allow them to recover faster (Wagner et al., 2022). In other words, marginalized groups may need more effective and cost-efficient adaptation measures. Despite this, it is essential to address the unequal socioeconomic structures that drive injustice of climate change impact (Chu & Cannon, 2021). However, as inequality is measured from net worth while income plays a role, the disparity should be inferred carefully using the Gini index.

Inequality has been highlighted in Jakarta and identified by the Gini index. To identify maladaptation caused by household-level climate change adaptation, Figure 7.13 exhibits the pre- and post-

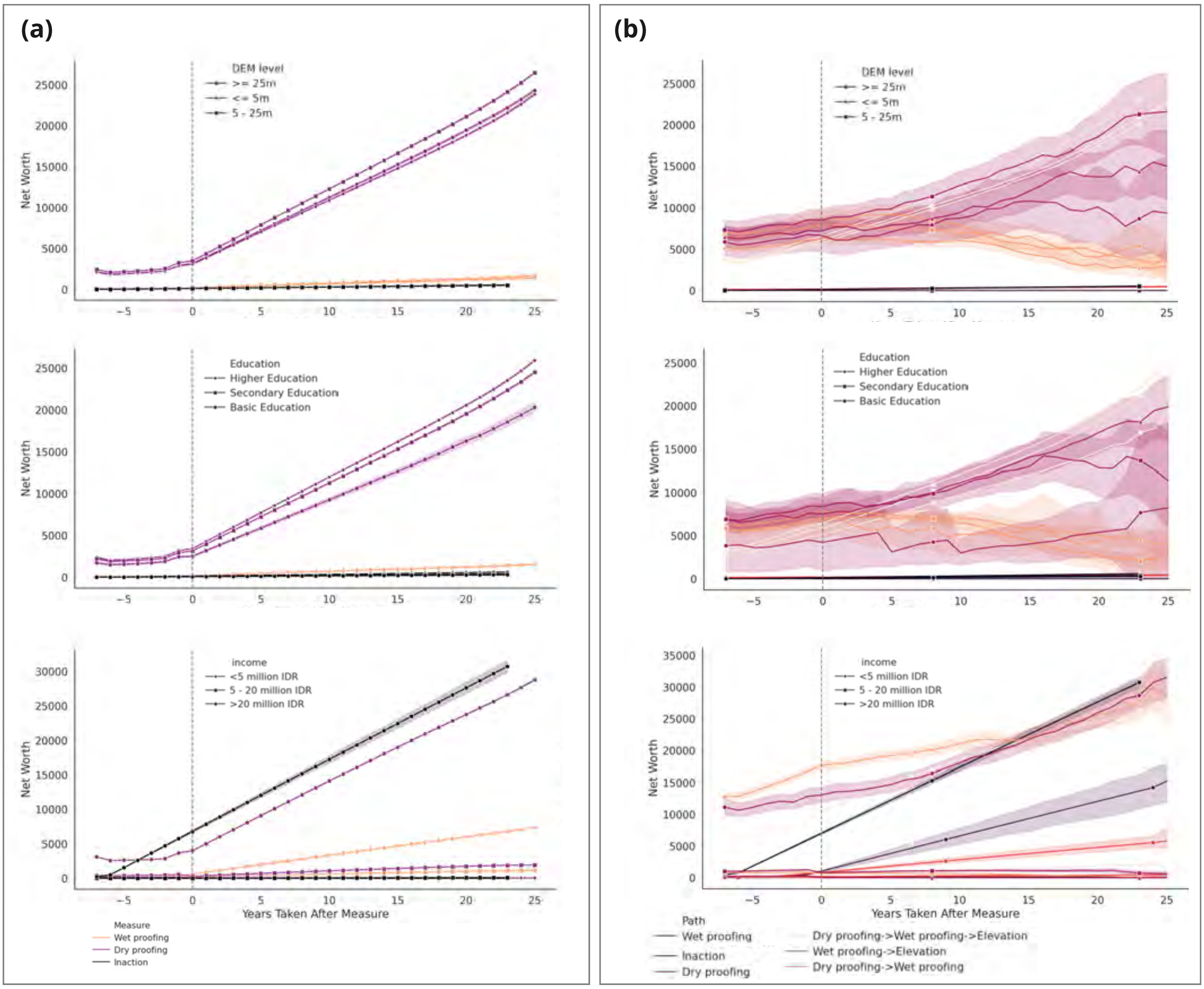

Figure 7.12: *Comparison of pre-and post-adaptation impact on net worth projections based on elevation and adaptive capacity Factors Over 25 Years.* The figure displays Panel (a) single-measure experiments and (b) multi-measure experiments with shaded areas, indicating a 95% confidence interval. Top Graph: Net worth projections for different elevation levels (DEM levels: ≥ 25m, ≤ 5m, 5-25m). Middle Graph: Net worth projections are differentiated by educational attainment (Higher Education, Secondary Education, Basic Education). Bottom Graph: Net worth projections are categorized by income level (≥ 20 million IDR, 5-20 million IDR, ≤ 5 million IDR).

adaptation Gini index across different adaptation paths, summarised in Box 7.2. Overall, most adaptation paths show distinct changes in the Gini index by demonstrating increased inequality. This is particularly significant except for complete-measure adaptation paths with decreasing inequality trends. This implies that combining all measure types may contribute to a more equitable outcome with uniform effect across the population. However, the plateau indicates that the adaptation path has a limited impact on addressing inequality, and effects might be limited over time. This could suggest that while comprehensive, these measures reach a point of diminishing returns where they no longer contribute to further reductions in inequality.

Although highly efficacious, implementing elevation measures within an adaptation path does not necessarily address or maintain inequality levels. On the other hand, both net worth projections and the Gini index show that wet-proofing increases the risk of inequitable outcomes. One possible reason might be its lower efficacy when interacting with economic implementation costs favourable for low-income households. This also explains the benefit of complete measures to manage inequality and why elevation with high efficacy does not necessarily address inequality as indicated by wet-proof followed by elevation. The benefit of elevation is balanced with the efficacy and implementation cost of wet-proof.

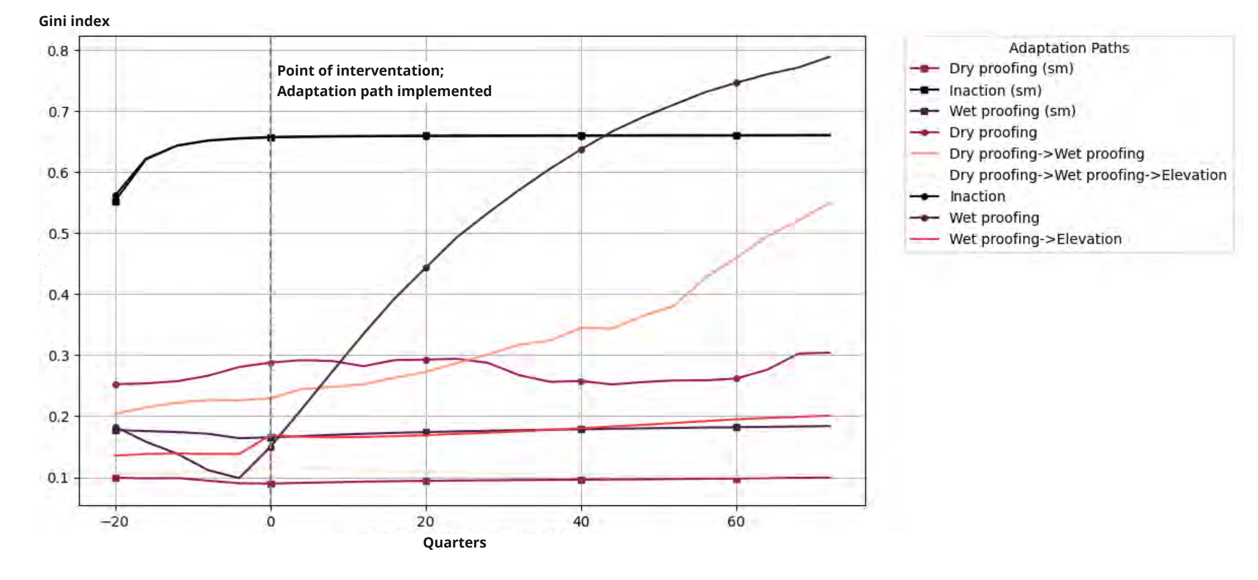

Figure 7.13: *Pre- and post-adaptation impact on GINI index over time.* The figure displays the GINI Index based on different adaptation paths. (sm) indicates single-measure experiments, while others are derived from multi-measure experiments. The dashed line indicates the implementation time.

Custom Box 7.2: Summary of Jakarta Gini index projections across household-level climate change adaptation derived from Figure 7.13.

1. Inaction maintains high inequality, indicating that existing inequalities persist and worsen consistently across single and multi-measure experiments, reaching around 0.65.
2. In single-measure experiments, dry-proof and wet-proof increased with little increase. In multi-measure experiments, post-standalone-measure adaptation showed a significant increase in inequality, especially for wet-proof households, considering that households that implemented wet-proof or dry-proof adaptation decreased in proportion. Moreover, dry-proof slightly decreases in the long-term perspective but then increases again, reaching the Gini index recorded when the adaptation measure was implemented. This suggests that adaptation with standalone measures may exacerbate inequality among areas facing adaptation barriers.
3. Post-wet-proof ⇒ elevation-adaptation exacerbates inequality with a small growth rate.
4. Post-dry-proof ⇒ wet-proof-adaptation revealed a significant increase in inequality.
5. The post-complete adaptation demonstrated a decreasing inequality trend, reaching the initial Gini index after it increased during the pre-adaptation.

7.4. Key Insights

Table 7.2 summarises the maladaptive outcome for each adaptation path across household groups. Some households might become vulnerable by implementing the particular path, as evidenced by the complete filling of all cells in the table. This underscores the necessity for tailored adaptation solutions. However, a general maladaptive trend exists that may be applicable universally. Firstly, wet-proof alone was identified as less residual damage avoidance, lock-in effects, and exacerbation of inequality. It is expected that wet-proof has the lowest measure of efficacy. Similarly, combining it with dry-proofing showed limited benefits. Conversely, augmenting wet-proof with elevation turned out to have diverted residual damage, less proportion of financial hardship and less increase in the Gini index compared to all measures combined. Thus, standalone wet-proof is maladaptive in both the short and long term, but the addition of elevation can mitigate these.

Table 7.2: *Comparison of household-level climate adaptation paths on maladaptive outcome indicators.*

Adaptation Pathways	Residual Damage	Lock-in	Inequality
Dry-proof	Mitigates losses but raises concerns for low-income, especially inner-city neighbourhoods with higher education backgrounds, and middle-income households residing in city centres with higher education.	Predominantly affects low-income households across various educational backgrounds and locations.	Low-income households continue to experience net worth deterioration. On an aggregate level, it increases inequality significantly.
Wet-proof	Wet-proof for low- and middle-income households may lead to more significant long-term damage than inaction, indicating a risk of maladaptation. Even maladaptation occurred for middle-income families with primary education backgrounds residing in the coastal area.	Common among low- and middle-income households from various educational backgrounds in multiple locations.	Low-income households continue to experience net worth deterioration. Impact disparities occur across elevation and educational background. On an aggregate level, it increases inequality significantly.
Wet-proof ⇒ Elevation	While it can significantly avoid loss of inaction, low-income households face increasing residual damage when implementing this pathway, in contrast to other groups.	Affecting financial hardship of 40% of low-income households with secondary education residing in the coastal area.	Low-income households continue to experience net worth deterioration. On an aggregate level, it increases inequality.
Dry-proof ⇒ Wet-proof	Despite the ability to avoid loss of inaction, a rapid increase in residual damage is observed in low-income households, with middle-income households in inner-city neighbourhoods experiencing similar trends.	Affects 20% to 40% of low-income households, especially those in coastal areas with higher and secondary educational backgrounds.	Low-income households continue to experience net worth deterioration. On an aggregate level, it increases inequality.
Dry-proof ⇒ Wet-proof ⇒ Elevation	While it can avoid losses due to inaction by taking action, unlike other households that can divert all residual damage through this comprehensive measure, low-income families continue to suffer, especially in coastal areas.	Lock-in primarily affects low-income households with higher education in coastal areas.	Low-income households continue to experience net worth deterioration. On an aggregate level, it can maintain inequality.

8

Conclusion and Policy Implication: Road to a Tailored Solutions for Household Climate Adaptation

As discussed in Chapters 6 and 7, the experiments' findings called for the community and government to help disadvantaged households that have experienced increased vulnerability due to household-level climate adaptation initiatives. This chapter will discuss the policy implications regarding the caveats in building a tailor-made solution with a context-rich background and inclusiveness, as demonstrated by what can be done for households. Initially, the insights from previous chapters are recalled by answering research questions. Next, policy implications and caveats are discussed.

8.1. Answering Research Questions

Sub-Research Question 1: What are the measurable indicators and representation of maladaptive flood risk response among urban households?

To answer this question, there are two main standings: measurable indicators and representation. Indicators in this study refer to variables, while representation refers to two main things. First, measurable indicators represent maladaptation and diverse flood risk among urban households.

Measurable indicators were found to be diverse in maladaptation, which depends on the context studies but is still grounded from the foundational concept of maladaptation by key leading research Barnett and O'Neill (2010), Juhola et al. (2016), Magnan et al. (2016), and Schipper (2020). As a result, indicators should be selected based on the contextual needs that refer to flood risk. Table 3.1 provides indicators scholars used to define maladaptation. From this, three indicators were selected to cover all categories, which include:

- **Loss avoidance represents an economic dimension.** Inspired by Antoci et al. (2024), Han et al. (2020), and Pritchard and Thielemans (2014), this indicator captures the economic impacts and monetary efficacy of climate adaptation measures.
- **Inequality represent social dimension**. They were grounded from the distributional risks and vulnerabilities associated with climate change, which encapsulates distributional maladaptation impact (R. Begum et al., 2022). These indicators measure the impact on social strata and vulnerability to climate-induced floods. They are particularly relevant in settings where inequalities are identified by uneven adaptive capacity, like Jakarta (The Jakarta Post, 2023).
- **Lock-in**. Adapted from path dependency and trapped concept from Goldstein et al. (2023), households are locked into a state that cannot afford necessary adaptation measures. This perspective is crucial for evaluating the sustainability and dynamic of adaptation paths.

From these indicators, Figure 3.1, 3.2, and 3.3 present the visual representation that encapsulates reference points in defining maladaptation as well as spatial and temporal scale to denotes the dynamic of maladaptation (see 3.2.1).

Moreover, the representation of diverse flood risk among urban households is discussed in Chapter 4, realise Section 3.2.2. Employing the recent development of the IPCC climate risk assessment framework, it includes response as one of its key determinants (R. Begum et al., 2022). Results in four dimensions to be used for evaluating maladaptation (see Figure 4.2))

- Household-level adaptation measure denotes response determinant
- Education level denotes adaptive capacity within vulnerability determinant
- Income Range denotes adaptive capacity within vulnerability determinant
- Elevation denotes exposure determinant

Sub-Research Question 2: What factors drive maladaptive behaviours in urban household-level flood adaptation, and how do these behaviours influence adaptation implementation and distribution across vulnerability to flood risk?

From Protection Motivation Theory (PMT) and its extension to include internal and external factors (Noll, Filatova, Need, & Taberna, 2022), the second sub-research questions define maladaptive behaviour as fatalism, avoidance, religious faith, wishful thinking, and hopelessness (Babcicky & Seebauer, 2019; Bubeck et al., 2018; Rogers, 1975). Logistic regression was employed to acquire an independent household-level climate change adaptation model: elevation, dry-proof, and wet-proof. This model exhibits the adaptation intention, while actual adaptation is acquired from the ABM simulation result (N=3000).

The single-measure and multi-measure experiments, as detailed in Table 5.1, show six out of sixteen adaptation paths emerged with the distribution shown in Figure 6.3 and 6.2. Despite this, three maladaptive behaviours emerged:

- Around 20% of the population remains in action, which denotes low adaptation intention or high intention but limited adaptive capacity.
- False sense of security with reliance on another measure, evident from the negative association between the undertaken measures. Section 4.5.1, reported consistent across dry-proof ($p<0.0001$), wet-proof ($p<0.05$), elevation derived from the interaction of self-efficacy and response efficacy ($p<0.001$). Elevation also emphasised this, as it has the highest efficacy (Aerts, 2018), which was not favoured as the initial measure.
- Misperception of flood risk denoted by the negative association of flood probability (wet-proof reported ($p<0.5$)) and the perceived adaptation cost consistent across all measures, leading to suboptimal measure implementation.

Besides, worry as an element of threat appraisal might have an essential role in uplifting maladaptive behaviour supported by the cultural value of *'Rumah'*. Reflecting from Sjöberg (1998), it is consistent that worry and perceived risk show a weak correlation, indicated by different orientations in this research. Further, Sjöberg (1998) showed different dynamics of risk and worry. This research found that despite coastal and inner-city neighbourhoods appearing flood-prone, more households are implementing adaptations on the coast. At the same time, the perceived adaptation cost is portrayed as a barrier, particularly experienced by low-income families. The gap between adaptation intention and adaptive capacity might result in either inaction or missed opportunity, as illustrated in matrix 6.3. Experiments across various socioeconomic and educational backgrounds showed that middle—and high-income households and households with higher education levels were more likely to adopt comprehensive adaptation measures (see Section 6.1.1).

Sub-Research Question 3: From the emerged urban household-level flood adaptation, what patterns and trends can be identified as maladaptive responses, and how do these vary across their vulnerability to flood risk?

Wet-proofing has been identified as maladaptive, based on three indicators, and consistent across urban household backgrounds and experiments. Particular emphasis is placed on the Gini index, which shows a rapid increase trend of wet-proof compared to other paths, even inaction (see Figure 7.13). On the other hand, it was found that wet-proofing followed by elevation showed better adaptation results than other emerging adaptation paths. However, it is indicated in Table 7.2 that low-income households were more prone to maladaptation compared to middle- and high-income. Furthermore, they were found to be locked in even with a comprehensive adaptation path. This indicates finances are vital as constraints in climate change adaptation make the adaptation process difficult and may lead to adaptation limits (Schinko et al., 2024). This revealed a trade-off between residual damage and adaptation cost, which might disturb households with vulnerable household finances. As low-income families struggle without external hazards, the aftermath of adaptation might deteriorate their net worth. This led to a second trade of off-economic accessibility and effective adaptation. Elevations with relatively higher cost (Aerts, 2018) become limited to households with financial constraints while, in the case of standalone wet-prof, may be destructive beyond the initial. Furthermore, Table 8.1 and 8.2 show different household groups impacted by the household-level adaptation path, implying the uneven impact across the combination of vulnerability dimensions. This table can help as a reference to match the appropriate adaptation with household profiles.

To what extent do household-level climate change adaptation to flooding result in maladaptive responses across urban households, considering their vulnerability to flood risk?

The discussion on maladaptive flood risk responses among urban households centres around measurable indicators and representation grounded in leading research. The study broke down maladaptation into maladaptive behaviours (Rogers, 1975) and maladaptive outcomes. Three primary indicators, loss avoidance, inequality, and lock-in, were identified to assess maladaptive outcomes, including their representations. Following the IPCC's climate risk assessment framework, as explained by R. Begum et al. (2022), household dimensions were derived. In summary, Household-level adaptation to flood risk may result in maladaptation in the long term or even right after implementation.

The study identifies three maladaptive behaviours in urban household-level flood adaptation: about 20% of the population exhibits inaction; a false sense of security is prevalent due to reliance on less effective measures, evidenced by statistically significant negative associations in adaptation choices; and a widespread misperception of flood risk, shown by the negative correlation between flood probability and perceived costs. Finally, Table 8.1 and 8.2 show uneven impact across the combination of vulnerability dimensions with economic trade-offs, particularly between residual damage and adaptation costs, are stark, highlighting significant challenges for financially constrained households, especially low-income families disproportionately affected by inadequate adaptation paths.

8.2. Main Challenges of Household Maladaptation

8.2.1. Mismatch Between Adaptation Intention and Adaptive Capacity

The matrix 6.3 describes inaction that is considered miss-opportunity is driven by either low adaptation intention or adaptive capacity.

Low Adaptation Intention, High Adaptive Capacity

Maladaptive behaviours identify low adaptation intention; consistent with the previous discussion, most household backgrounds could not justify the adaptation with inaction, resulting in most damage and lock-in, except high-income households, regardless of the absence of adaptation measures, have enough capacity to absorb flood damage. However, there is an indication of favour inaction. Hence, inaction as a default action should also be a significant concern, especially for low-income households. It is indicated that an increased education level may not significantly decrease the reluctance to undertake measures and shows that financial factors play a role in this case. From the intention to implement climate adaptation, there is a likelihood that undertaking measures have a significant positive relation with climate belief, self-efficacy, worry, and flood experience (Figure 4.8). Without threat appraisal, coping appraisal cannot motivate households to implement adaptation measures. Policy-makers can start to leverage this positive influence towards the intention of household climate adaptation.

Previously, it was found that despite households receiving houses beyond a settlement, they show a fatalistic attitude by denying the threat of living in flood-prone areas (Section 4.5.1). Research rationale for this situation shows that residing in flood-prone areas may not be enough to prompt voluntary adaptation (Lechowska, 2018). However, as climate impacts intensify, hesitating to adapt could lead households into devastating circumstances, potentially exacerbating the damage and losses when floods occur.

In addition, the all-or-nothing behaviour is indicated across different household backgrounds. It conveys less inclined to adopt a second measure after taking a particular action, mainly after implementing the elevation measure. This suggests the need for massive forces to start implementing adaptation measures and stay inactive, referring to the status quo bias. According to Godefroid et al. (2023), inaction as the status quo becomes an issue when it hinders progress. Further, Godefroid et al. (2023) explains three categories to describe the status quo bias, one of which is a cognitive misperception. As reviewed by Acciarini et al. (2021), cognitive misperception is the cognitive bias that influences perception and decision-making, distorting and misjudging reality based on a pre-conceived response. This, compounded by the indication of misalignment of what is perceived as effective, leads to a suboptimal solution. For instance, favouring and undertaking wet-proof while dry-proof diverted more residual damage, and fewer lock-in cases were found. Other research indicates that the driver of inaction is the difficulty of the decision process (Fleming et al., 2010). Hence, as indicated by Godefroid et al. (2023), manipulating the default to frame the desired option can be one of the countermeasures for cognitive misperception.

High Adaptation Intention, Low Adaptive Capacity
Apart from inaction, low-income households often identified as disadvantaged can also intend to adapt. However, low adaptive capacity or adaptive capacity constraints limit their action.

8.2.2. Adaptation Constraint: Maladaptive Outcome but still Favoured

It is shown that doing nothing is still a significant option taken by households, and if they do take action, not all possible adaptation pathways are chosen. Indications of maladaptation across different indicators are common findings, highlighting no perfect adaptation paths. Standalone wet-proof accounts for 14.99% households adaptation. However, it is found to be a maladaptive outcome consistent across all indicators and household backgrounds. Compared to another measure, wet-proof has the lowest efficacy Aerts (2018).

This results from an interplay between preference and capital constraints; this is particularly true for low-income households, with fewer paths emerging compared to the other group. In addition, households face capital constraints that influence their choice of adaptation measures, with elevation measures often deemed too expensive as initial interventions. Capital constraints exacerbate the adaptation challenge, as households perceive adaptation costs as inversely related to their likelihood of action. Scholars identified increasing adaptive capacity as the most crucial objective of climate change adaptation (Dilling et al., 2019; Neil Adger et al., 2005). One of the determinants of adaptive capacity is financial constraint (Serdeczny et al., 2024).

8.3. Next Step to Prevent Household Maladaptation

Derived from the challenges, it is inferred that the challenges are interconnected. Further, step-by-step in a sequence manner to prevent maladaptation are outlined below:

8.3.1. Handling Low Adaptive Capacity

High-income households were found to be immune, while others or disadvantaged groups may consider financial aid as the solution. Scholars urge a financing scheme for underprivileged and vulnerable populations to ensure equitable access to climate adaptation so that households may not be locked in and can still have various options to adapt (Dilling et al., 2019; Neil Adger et al., 2005). First, unleashing the financial constraint of lower and middle income, particularly those residing in flood-prone areas, can increase their adaptive capacity. Increasing the education level of attainment will not work if it does not align with the increase in financial capacity.

Households might utilise other resources besides financial resources to enable the decision to adopt flood adaptation measures, especially for low-income families who implement adaptation measures. Reflecting on the context of Jakarta, a well-known resource that can be found in the minor neighbourhood structure called Rukun Tetangga (RT) from urban to rural areas in Indonesia includes social capital that is externally sourced to provide mutual assistance, Indonesian commonly called *'Gotong Royong'* (Slikkerveer, 2019). This phenomenon suggests exploring how collective action may help overcome financial barriers while enabling household adaptation measures.

8.3.2. Identify Suitable Adaptation Path

However, financial aid needs to be precisely defined. This is built upon two rationales. First, it is observed that, indeed, households suffer less from financial hardship as income increases, which represents economic resources. However, there are still chances for them to experience financial hardship, as a middle-income household is no exception, indicating that a substantial adaptive capacity gap exists as it requires more wealth to become immune to the flood. Second, the observation above shows that low-income and some segments of middle-income households are experiencing a significant decline in their net worth regardless of their proactive efforts or inaction and long-term financial hardship, particularly in action and wet-proof. For more details, See Chapters 6 and 7.

This indicates that although there is a need to lower financial constraints, aiding households with financial aid may not be effective unless the financial grant is tailored to take specific measures beneficial to the household context, avoiding suboptimal and maladaptive decision-making. As several lock-in situations are identified, monitoring and checking with households is essential to avoid the maladaptive path by balancing investment to implement adaptation and its efficacy. Hence, to broaden household adaptation participation by reducing inaction, the aid may need to be precisely defined, for instance, assistance in taking the adaptation path as formulated in Section Table 8.1 and 8.2.

Adaptation pathways should be tailored to the geographical context and adaptive capacity of households to optimise outcomes from the initial action:

1. For low-income households, taking dual-measure adaptation path, particularly wet-proof followed by elevation. Although ideal, complete-measure pathways are considered unless a financial constraint is addressed. Complete-measure pathways are recommended for households in inner-city neighbourhoods and urban centres.

2. Overall, middle-income households should avoid single-measure pathways, especially wet-proof. If wet-proof is implemented, elevation measures must be followed. If other options are unfeasible, households in coastal areas should favour dry-proof measures due to their higher efficacy. Households in urban centres may initially be sufficient with dry-proof, but eventually, they must supplement dry-proof with another measure to sustain its benefit. In contrast, inner-city neighbourhoods should favour dry-proof as a standalone pathway compared to wet-proof and in combination with wet-proof.

Consequently, in a more holistic view, policymakers may be required to negotiate specific thresholds in accepting the condition of maladaptation; however, this may inadvertently overlook households suffering from maladaptation. If policymakers also want to reduce inequalities, a dedicated strategy is required to solve the inequality problem.

8.3.3. Nudging to Favor Desired Pathways

A nudging mechanism can be employed to ensure households avoid maladaptive paths. Beforehand, the household should be triggered to adapt. The threat appraisal element, Worry, combined with cultural values towards the house and social networks, can enable the selection of an appropriate adaptation path. Along with this threat appraisal, the adaptation path was favoured, which can be started with households of higher education levels being more likely to adopt and utilise social networks to spark adaptation diffusion.

8.3.4. Decrease Flood Exposure Amid Adaptation Path Imperfection

However, no adaptation path is perfect in the context of maladaptation. These insights indicate that more paths with higher efficacy are needed, marked by favouring elevation. However, this implies the dependency of higher efficacy, suggesting unavoidable devastating damage caused by the flood. As floods cover more areas and the flood depth record increases, we should rethink how to decrease flood exposure. A sensitivity analysis report shows sensitivity towards depth-damage curves. Another consideration is that household-level adaptation for low-income beneficiaries indicates insufficient adaptation to climate change's exacerbated impact. A dense population also aggravates this with many low-income populations spread across Jakarta 4.1.1, signalling that many households suffer from this situation and urge the agenda to protect families. This highlights the pressing need for community—and governance-supported adaptation strategies to aid families.

Table 8.1: *Comparison of household-level climate adaptation paths on maladaptive outcome indicators across household groups.* The indicators include loss avoidance and lock-in.

Household Groups	**Loss Avoidance**	**Lock-in**
Low-income, Inner-city	Dry-proof mitigates losses but raises concerns; Wet-proof may lead to significant long-term damage; Increasing residual damage trend due to Wet-proof ⇒ Elevation and Dry-proof ⇒ Wet-proof	Financial hardship caused by inaction and wet-proof; Stagnation due to inaction
Low-income, City Centre, Higher Education	Wet-proof may lead to significant long-term damage; Increasing residual damage trend due to Wet-proof ⇒ Elevation and Dry-proof ⇒ Wet-proof	Financial hardship caused by inaction, dry-proof, and wet-proof; Stagnation due to inaction, and Dry-proof ⇒ Wet-proof ⇒ Elevation
Low-income, City Centre, Secondary Education	Wet-proof may lead to significant long-term damage; Increasing residual damage trend due to Wet-proof ⇒ Elevation and Dry-proof ⇒ Wet-proof	Financial hardship caused by inaction and wet-proof; Stagnation due to inaction
Low-income, City Centre, Primary Education	Wet-proof may lead to significant long-term damage; Increasing residual damage trend due to Wet-proof ⇒ Elevation and Dry-proof ⇒ Wet-proof	Financial hardship caused by inaction and wet-proof; Stagnation due to inaction, wet-proof, dry-proof, Dry-proof ⇒ Wet-proof, and Dry-proof ⇒ Wet-proof ⇒ Elevation
Low-income, Coastal, Higher Education	Wet-proof may lead to significant long-term damage; Increasing residual damage trend due to Wet-proof ⇒ Elevation and Dry-proof ⇒ Wet-proof	Financial hardship caused by inaction, dry-proof, wet-proof, and Dry-proof ⇒ Wet-proof ⇒ Elevation; Stagnation due to inaction, wet-proof, dry-proof, Dry-proof ⇒ Wet-proof, and Dry-proof ⇒ Wet-proof ⇒ Elevation
Low-income, Coastal, Primary and Secondary Education	Wet-proof may lead to significant long-term damage; Increasing residual damage trend due to Wet-proof ⇒ Elevation and Dry-proof ⇒ Wet-proof	Financial hardship caused by inaction, dry-proof, and wet-proof; Stagnation due to inaction, wet-proof, dry-proof, Dry-proof ⇒ Wet-proof, and Dry-proof ⇒ Wet-proof ⇒ Elevation
Middle-income, Inner-city		Financial hardship caused by inaction; Stagnation due to inaction and wet-proof
Middle-income, City Centre, Higher Education	Dry-proof mitigates losses but raises concerns	Financial hardship caused by inaction; Stagnation due to inaction and wet-proof
Middle-income, City Centre, Primary and Secondary Education		Financial hardship caused by inaction; Stagnation due to inaction and wet-proof
Middle-income, Coastal, Secondary and Higher Education		Financial hardship caused by inaction; Stagnation due to inaction and wet-proof
Middle-income, Coastal, Primary Education	Wet-proof unable to divert loss of inaction	Financial hardship caused by inaction; Stagnation due to inaction and wet-proof

Table 8.2: *Comparison of household-level climate adaptation paths on maladaptive outcome indicators across household groups. The indicators include inequality.*

Adaptation paths / Categories	**Inaction**	**Wet-proof**	**Dry-proof ⇒ Wet-proof**	**Dry-proof ⇒ Wet-proof ⇒ Elevation**
Low-income	Disadvantage	Disadvantage	Disadvantage	Disadvantage
Middle-income	Disadvantage	Disadvantage	Disadvantage	Disadvantage
High-income	Advantage	Advantage	Advantage	Advantage
Primary education		Advantage	Advantage	
Secondary education		Advantage	Advantage	
Higher education		Disadvantage	Disadvantage	
Coastal		Disadvantage	Disadvantage	
City-centre		Advantage	Advantage	
Inner-city		Disadvantage	Disadvantage	

9

Retrospective and Prospective of Maladaptation Study

This chapter focuses on reflecting on the research process and acknowledging the limitations and assumptions inherent in the study. Such reflections are crucial for mindfully applying the research findings and understanding this study's position within the broader scientific landscape.

All models are wrong, but some are useful. — George E. P. Box

Acknowledging the imperfections in the current models is crucial; however, their utility in providing structured insights into maladaptation cannot be understated. These models serve as foundational tools for iterative research, aiding in gradually refining adaptation strategies. Reflecting on George E. P. Box's thesis, this research epitomises the practical application of theoretical models in environmental science. It highlights the delicate balance between striving for model perfection and achieving practical utility, advocating for models that, despite inherent flaws, furnish pivotal insights and inform effective policy-making. Despite the research design supported by various research, several limitations and assumptions should be made explicitly to derive future research. This can be grouped into three categories based on its research phase: operationalisation of maladaptation, household climate adaptation modelling, and maladaptation assessment.

Limitation and future direction of operationalisation of maladaptation:

1. Current indicators for defining and assessing maladaptation are narrowly tailored to specific case studies, limiting their broader applicability. However, when deriving the indicators used in this study, the adopted concept is beyond the maladaptation, which reflects the applicability of other climate adaptation evaluation frameworks. Future research should aim to establish a universally applicable framework of indicators that encapsulates a wide array of environmental and socio-economic scenarios.
2. The initial development of maladaptation indicators primarily relied on literature reviews and the subjective insights of the authors, which may overlook critical perspectives recognised within professional practices. Adopting methodologies such as the Delphi technique or expert panels could significantly enrich the indicator development process, ensuring a comprehensive representation of specialist consensus and practical insights and extending the author's worldview upon maladaptation.

Limitation and future direction of household-level climate adaptation modelling:

1. Flood dynamics within the model are simplified from historical floods, demonstrating the most severe floods that have not happened frequently. However, this assumes that in the next 30 years, there will be no flooding beyond the historical data. Simplifying flood dynamics to reflect only historical extremes may fail to anticipate future variations in flood patterns due to evolving climatic conditions. Considering its unique cases, incorporating dynamic climate modelling techniques and predictive analytics by leveraging the hydrologic flow model specific to the Jakarta context could provide more accurate scenarios of flood events beyond the historical scope.

2. Maladaptation is evaluated outside the model, which aims to derive the emerging behaviour. The model seeks to acquire two primary metrics in assessing maladaptation by using households as the actors and households who received the impact. Later, it can be broadened to include the effects of household climate adaptation on other households and how the impact affects the household's decision-making.

Limitation and future direction of maladaptation assessment:

1. Maladaptation is assessed with the predefined indicators with the orientation of long-term dynamics. The fixed approach in evaluating maladaptation may fail to accommodate the ongoing dynamics of climate change, potentially rendering long-term strategies ineffective. It is an evolving and dynamic state; the maladaptation state upon adaptation pathways may be further explored. Adaptive management in maladaptation assessments could facilitate continual adjustments to strategies based on emergent data and changing environmental conditions. Particularly on adaptation pathways that consist of multiple measures; further, the impact may be broken down per measure within the paths.

2. Although multidimensional, the emerging findings primarily use income groups associated with the household. This can be attributed to the main metrics, which are monetary terms, signalling the reliance on financial terms as primary metrics. This observation suggests a pivotal opportunity to extend the metrics dynamic beyond monetised metrics.

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A

Survey Data Processing

Table A.1: Survey Metadata Descriptions and Value Labels

Variable Label	Description	Value labels
Q0_education_ID	What is the highest level of education you have completed?	1-Primary school (SD) to 7-Professional higher education (e.g., to qualify as a lawyer, accountant), 97-None of these
Q0_postcode	Zipcode or postal code	
Q4_home_size_CN_ID_NL	How many square meters is your accommodation? If you don't know for sure, please provide your best estimation.	1 - Less than 50 square metres to 6-More than 151 square metres, 98 Don't know
Q18_flood_exp	Have you ever personally experienced a flood of any kind?	Yes, No
Q19_flood_affect_ID	Were you affected by the floods in January 2020?	Yes, No
Q22_gov_measures	Do you think the current measures that the municipal government in your area have implemented are sufficient to stop the risks of floods and heavy rain?	1-Yes – they are sufficient and will last for the foreseeable future (30+ years) to 3-No – they are not currently sufficient, 98 Don't know
R03_perc_damage	In the event of a major flood such as the flooding from the [Name of flood depending on country] how severe (or not) do you think the physical damage to your house would be?	1 - Not at all severe to 5-Very Severe, 98-Don't know
Q26_flood_damage_ID	You said you were affected by the 2020 Jakarta Flood. How severe was the damage to your house after the floods?	1 - Not at all severe to 5-Very Severe, 98-Don't know
Q27_perc_prob_30y	Imagine you stay in your house for the next 30 years what is the likelihood you believe your household will experience a flood? Please enter your answer as a percentage (e.g., 25%).	

Continued on next page

Table A.1 Continued

Variable Label	Description	Value labels
R05_worry	How worried or not are you about the potential impact of flooding on your home?	1-Not at all worried to 5-Very worried
Q31a_media_trust	From the general media	1 - Do not trust at all to 5 - Trust completely
Q31b_social_media_trust	From social media (i.e., Facebook, Instagram, WeChat, Weibo, etc.)	1 - Do not trust at all to 5 - Trust completely
Q32_climate_belief	There is a lot of discussion about global climate change and its connection to extreme weather events. Which of the following statements do you most agree with?	1-Global climate change is already happening to 3-Global climate change won't be felt in the coming decades, but the next generation will experience its consequences
R1a_self_efficacy_SM1 to SM7	Various actions to prevent flood damage	1 - I am unable to 5 - I am very able
R1b_resp_efficacy_SM1 to SM7	Various responses to flood risk	1 - Extremely ineffective to 5 - Extremely effective
R1c_perc_cost_SM1 to SM7	Cost perceptions of flood protection measures	1 - Very cheap to 5 - Very expensive
R2_implementation_SM1 to SM7	Implementation of structural measures	1 - I have already implemented this structural measure to 6 - I do not intend to implement this structural measure
Q44_social_expectation	Do your family, friends and/or social network expect you to prepare your household for flooding?	1 - My family, friends and/or social network do NOT expect me to prepare for flooding to 5 - My family and friends strongly expect me to prepare for flooding
R07_adaptation_others	Thinking about your friends, families, and neighbours, how many households have taken some adaptive action towards flooding?	1 - None of them to 7 - More than five, 98 - Don't know
Q53_income_ID	Please fill in your TOTAL annual income in Rupiah.	
R08_economic_comfort	When considering your salary along with your expenses, how would you describe your level of 'economic comfort'?	1 - Very difficult to live to 5 - Living very comfortably, 99- Prefer not to say
Q58_savings	With regards to your household's savings, what statement most closely reflects your current household situation?	My household has little to no savings. We use practically all of the money we earn each month.

Data preparation aims to ensure the survey data fits the study context. The processed dataframe is described in Table A.2 with the processing step is explained below.

Table A.2: Summary of the DataFrame

#	Column	Non-Null Count	Dtype
0	flood_prob	589 non-null	float64
1	worry	589 non-null	int64
2	SE_elevation	589 non-null	int64
3	RE_elevation	589 non-null	int64
4	PC_elevation	589 non-null	int64
5	soc_exp	589 non-null	int64
6	soc_net	589 non-null	float64
7	edu	589 non-null	float64
8	home_size	589 non-null	float64
9	climate_belief	589 non-null	float64
10	soc_media	589 non-null	int64
11	District	589 non-null	object
12	flood_exp	589 non-null	int64
13	SE_wet-proof	589 non-null	float64
14	SE_dry-proof	589 non-null	float64
15	RE_wet-proof	589 non-null	float64
16	RE_dry-proof	589 non-null	float64
17	PC_wet-proof	589 non-null	float64
18	PC_dry-proof	589 non-null	float64
19	monthly_income	589 non-null	float64
20	current_savings	589 non-null	float64

A.0.1. Transforming the Measure Type

Adaptation measure type grouping is applied from the Table A.1. Four data types need to be transformed: self-efficacy, response-efficacy, perceived cost, and previous implementation. Transformation of the coping mechanism is shown in the listing below, which is applied to self-efficacy, response-efficacy, and perceived cost. For previous implementations, transformed into binary denotes yes and no. It is set to yes if at least one measure has been implemented for each measure.

Listing A.1: Self Efficacy Calculation

```
# Self efficacy
df_merged['SE_wet-proof'] = df_merged[['R1a_self_efficacy_SM2',
        'R1a_self_efficacy_SM3',
        'R1a_self_efficacy_SM4'
                  ]].mean(axis=1)

df_merged['SE_dry-proof'] = df_merged[['R1a_self_efficacy_SM5',
        'R1a_self_efficacy_SM6',
        'R1a_self_efficacy_SM7'
                  ]].mean(axis=1)

df_merged = df_merged.rename(columns=
                      {'R1a_self_efficacy_SM1': 'SE_elevation'})
```

A.1. Complementary Information

Overlap the information of Q26_flood_damage_ID and R03_perc_damage, which indicated complementary. Similarly, it applies to Q19_flood_affect_ID and Q18_flood_exp.

A.2. Handling Nonresponse Items with Location Attribute

The metadata indicates that several survey questions can be answered with nonresponse, for instance, 'Don't know' and 'Prefer not to say'. In handling this data, it is assumed that data is missing, while several data can be filled with averaged values per regency. By acknowledging the variation within the regency, the data can maintain its variations. This is applied to data that can be associated with its geographical condition, including Q22_gov_measures, Q4_home_size_CN_ID_NL, Q53_income_ID, Q58_savings.

A.3. Handling Missing Data and Export

In this step, each row with missing data is counted initially. If the missing data for a row is more than or equal to four, the data points are dropped. Otherwise, the missing data is filled with the averaged value of the overall survey data type.

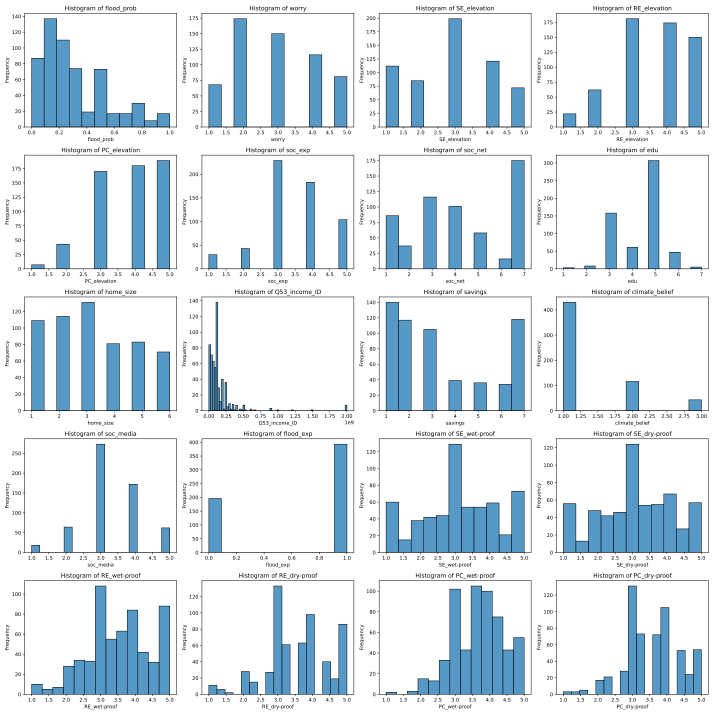


Figure A.1: Distribution plot of metadata

B

Property Value

Property price is used to acquire the proportion of damage to the total property value, as described in Equation 4.1. The property value was acquired by Ismail (2021) in 2021 by scrapping Lamudi.com, an online real estate marketplace. This data is assumed to represent house pricing in Jakarta in 2021. Considering the necessity for a temporal scale quarterly surveyed Residential Property Price Index (RPPI) from Bank Indonesia (2022) can be utilised to exhibit the pricing dynamics. RPPI was derived from 18 cities in Indonesia, including Jakarta, dividing the houses into small, medium, and large house types based on their size.

B.1. Spatial Scale: Property Price

Property price data (N=4738) was derived and processed as it has several data quality issues regarding unmatched addresses with actual district names. Data was manually processed to identify the district based on the listing description or amputated, which resulted in 4411 data points.

B.2. Temporal Scale: Residential Property Price Index

For the acquired data, Figure B.4 shows a rapidly increased trend of RPPI in Jakarta, especially for small and medium housing types. Types of houses were classified based on the width of the house, namely: small/moderate type house less than 36m^2 property area, medium type house which area bigger than 36m^{2}and less than 70m^2, and large type house.

The forecasting method was initially applied as the model expanded beyond the RPPI temporal scale:

- Optimization analysis for ARIMA models on small house type RPPI, selecting the ARIMA(0,1,0)(0,0,1)[4] as the best model based on AIC criteria (Figure B.5). The analysis, conducted over a smaller sample of 24 observations, underscores the effectiveness of including a seasonal MA component at lag 4. The SARIMAX results validate the model's suitability through significant coefficients and diagnostics such as the Ljung-Box test and heteroskedasticity assessments.
- Comprehensive search through various ARIMA model configurations to identify the lowest AIC for medium house type RPPI, significantly focusing on different intercept terms and their impacts on model fit (Figure B.6). The best model, ARIMA(0,1,1)(0,0,0)[4] with intercept, achieved an AIC of 18.456 over 24 observations. The detailed selection process emphasizes the consideration of less frequent differencing coupled with a simple moving average component.
- Results of the stepwise procedure to minimize the Akaike Information Criterion (AIC) for time series data from large house type RPPI (Figure B.7). The optimal model selected was ARIMA(0,1,0)(0,1,0)[4] with an AIC of 4.220, suggesting minimal differencing and seasonal orders necessary to model the data effectively.

However, as the models are insignificant, the model assumes that the residential price index will increase by one point annually from the previous year for small and medium housing types while biennial for large houses.

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,0)[4] intercept   : AIC=3.804, Time=0.17 sec
 ARIMA(1,1,0)(1,0,0)[4] intercept   : AIC=5.697, Time=0.24 sec
 ARIMA(0,1,1)(0,0,1)[4] intercept   : AIC=4.652, Time=0.17 sec
 ARIMA(0,1,0)(0,0,0)[4]             : AIC=39.701, Time=0.03 sec
 ARIMA(0,1,0)(1,0,0)[4] intercept   : AIC=3.783, Time=0.16 sec
 ARIMA(0,1,0)(2,0,0)[4] intercept   : AIC=4.348, Time=0.33 sec
 ARIMA(0,1,0)(1,0,1)[4] intercept   : AIC=5.002, Time=0.30 sec
 ARIMA(0,1,0)(0,0,1)[4] intercept   : AIC=3.016, Time=0.08 sec
 ARIMA(0,1,0)(0,0,2)[4] intercept   : AIC=4.982, Time=0.14 sec
 ARIMA(0,1,0)(1,0,2)[4] intercept   : AIC=6.863, Time=0.21 sec
 ARIMA(1,1,0)(0,0,1)[4] intercept   : AIC=4.829, Time=0.10 sec
 ARIMA(1,1,1)(0,0,1)[4] intercept   : AIC=5.195, Time=0.35 sec
 ARIMA(0,1,0)(0,0,1)[4]             : AIC=inf, Time=0.14 sec

Best model:  ARIMA(0,1,0)(0,0,1)[4] intercept
Total fit time: 2.502 seconds
                                      SARIMAX Results
===========================================================================================
Dep. Variable:                                    y   No. Observations:                  24
Model:             SARIMAX(0, 1, 0)x(0, 0, [1], 4)   Log Likelihood                  1.492
Date:                              Fri, 24 May 2024   AIC                             3.016
Time:                                      15:55:44   BIC                             6.422
Sample:                                  03-31-2018   HQIC                            3.872
                                       - 12-31-2023
Covariance Type:                                opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      0.4997      0.080      6.255      0.000       0.343       0.656
ma.S.L4        0.4664      0.324      1.440      0.150      -0.168       1.101
sigma2         0.0493      0.017      2.916      0.004       0.016       0.082
===================================================================================
Ljung-Box (L1) (Q):                   0.14   Jarque-Bera (JB):                 1.49
Prob(Q):                              0.70   Prob(JB):                         0.47
Heteroskedasticity (H):               2.37   Skew:                             0.62
Prob(H) (two-sided):                  0.24   Kurtosis:                         2.80
===================================================================================
```

Figure B.1: Average property price of small housing type per district (2021). Data from Ismail (2021)

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,0)[4] intercept   : AIC=19.115, Time=0.02 sec
 ARIMA(1,1,0)(1,0,0)[4] intercept   : AIC=21.066, Time=0.18 sec
 ARIMA(0,1,1)(0,0,1)[4] intercept   : AIC=20.441, Time=0.09 sec
 ARIMA(0,1,0)(0,0,0)[4]             : AIC=50.289, Time=0.03 sec
 ARIMA(0,1,0)(1,0,0)[4] intercept   : AIC=21.095, Time=0.13 sec
 ARIMA(0,1,0)(0,0,1)[4] intercept   : AIC=21.089, Time=0.05 sec
 ARIMA(0,1,0)(1,0,1)[4] intercept   : AIC=inf, Time=0.43 sec
 ARIMA(1,1,0)(0,0,0)[4] intercept   : AIC=19.093, Time=0.07 sec
 ARIMA(1,1,0)(0,0,1)[4] intercept   : AIC=21.061, Time=0.16 sec
 ARIMA(1,1,0)(1,0,1)[4] intercept   : AIC=inf, Time=0.37 sec
 ARIMA(2,1,0)(0,0,0)[4] intercept   : AIC=20.779, Time=0.10 sec
 ARIMA(1,1,1)(0,0,0)[4] intercept   : AIC=20.342, Time=0.11 sec
 ARIMA(0,1,1)(0,0,0)[4] intercept   : AIC=18.456, Time=0.03 sec
 ARIMA(0,1,1)(1,0,0)[4] intercept   : AIC=20.443, Time=0.16 sec
 ARIMA(0,1,1)(1,0,1)[4] intercept   : AIC=inf, Time=0.49 sec
 ARIMA(0,1,2)(0,0,0)[4] intercept   : AIC=20.356, Time=0.09 sec
 ARIMA(1,1,2)(0,0,0)[4] intercept   : AIC=22.342, Time=0.17 sec
 ARIMA(0,1,1)(0,0,0)[4]             : AIC=37.152, Time=0.06 sec

Best model:  ARIMA(0,1,1)(0,0,0)[4] intercept
Total fit time: 2.789 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   24
Model:               SARIMAX(0, 1, 1)   Log Likelihood                  -6.228
Date:                Fri, 24 May 2024   AIC                             18.456
Time:                        15:55:53   BIC                             21.863
Sample:                    03-31-2018   HQIC                            19.313
                         - 12-31-2023
```

Figure B.4: Residential Property Price Index (2019-2024). Data from Bank Indonesia (2022)

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,0)[4] intercept   : AIC=3.804, Time=0.17 sec
 ARIMA(1,1,0)(1,0,0)[4] intercept   : AIC=5.697, Time=0.24 sec
 ARIMA(0,1,1)(0,0,1)[4] intercept   : AIC=4.652, Time=0.17 sec
 ARIMA(0,1,0)(0,0,0)[4]             : AIC=39.701, Time=0.03 sec
 ARIMA(0,1,0)(1,0,0)[4] intercept   : AIC=3.783, Time=0.16 sec
 ARIMA(0,1,0)(2,0,0)[4] intercept   : AIC=4.348, Time=0.33 sec
 ARIMA(0,1,0)(1,0,1)[4] intercept   : AIC=5.002, Time=0.30 sec
 ARIMA(0,1,0)(0,0,1)[4] intercept   : AIC=3.016, Time=0.08 sec
 ARIMA(0,1,0)(0,0,2)[4] intercept   : AIC=4.982, Time=0.14 sec
 ARIMA(0,1,0)(1,0,2)[4] intercept   : AIC=6.863, Time=0.21 sec
 ARIMA(1,1,0)(0,0,1)[4] intercept   : AIC=4.829, Time=0.10 sec
 ARIMA(1,1,1)(0,0,1)[4] intercept   : AIC=5.195, Time=0.35 sec
 ARIMA(0,1,0)(0,0,1)[4]             : AIC=inf, Time=0.14 sec

Best model:  ARIMA(0,1,0)(0,0,1)[4] intercept
Total fit time: 2.502 seconds
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                   24
Model:             SARIMAX(0, 1, 0)x(0, 0, [1], 4)   Log Likelihood                   1.492
Date:                            Fri, 24 May 2024   AIC                              3.016
Time:                                    15:55:44   BIC                              6.422
Sample:                                03-31-2018   HQIC                             3.872
                                     - 12-31-2023
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      0.4997      0.080      6.255      0.000       0.343       0.656
ma.S.L4        0.4664      0.324      1.440      0.150      -0.168       1.101
sigma2         0.0493      0.017      2.916      0.004       0.016       0.082
===================================================================================
Ljung-Box (L1) (Q):                   0.14   Jarque-Bera (JB):                 1.49
Prob(Q):                              0.70   Prob(JB):                         0.47
Heteroskedasticity (H):               2.37   Skew:                             0.62
Prob(H) (two-sided):                  0.24   Kurtosis:                         2.80
===================================================================================
```

Figure B.5: Optimization of ARIMA Parameters for Small House Type

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,0)[4] intercept   : AIC=19.115, Time=0.02 sec
 ARIMA(1,1,0)(1,0,0)[4] intercept   : AIC=21.066, Time=0.18 sec
 ARIMA(0,1,1)(0,0,1)[4] intercept   : AIC=20.441, Time=0.09 sec
 ARIMA(0,1,0)(0,0,0)[4]             : AIC=50.289, Time=0.03 sec
 ARIMA(0,1,0)(1,0,0)[4] intercept   : AIC=21.095, Time=0.13 sec
 ARIMA(0,1,0)(0,0,1)[4] intercept   : AIC=21.089, Time=0.05 sec
 ARIMA(0,1,0)(1,0,1)[4] intercept   : AIC=inf, Time=0.43 sec
 ARIMA(1,1,0)(0,0,0)[4] intercept   : AIC=19.093, Time=0.07 sec
 ARIMA(1,1,0)(0,0,1)[4] intercept   : AIC=21.061, Time=0.16 sec
 ARIMA(1,1,0)(1,0,1)[4] intercept   : AIC=inf, Time=0.37 sec
 ARIMA(2,1,0)(0,0,0)[4] intercept   : AIC=20.779, Time=0.10 sec
 ARIMA(1,1,1)(0,0,0)[4] intercept   : AIC=20.342, Time=0.11 sec
 ARIMA(0,1,1)(0,0,0)[4] intercept   : AIC=18.456, Time=0.03 sec
 ARIMA(0,1,1)(1,0,0)[4] intercept   : AIC=20.443, Time=0.16 sec
 ARIMA(0,1,1)(1,0,1)[4] intercept   : AIC=inf, Time=0.49 sec
 ARIMA(0,1,2)(0,0,0)[4] intercept   : AIC=20.356, Time=0.09 sec
 ARIMA(1,1,2)(0,0,0)[4] intercept   : AIC=22.342, Time=0.17 sec
 ARIMA(0,1,1)(0,0,0)[4]             : AIC=37.152, Time=0.06 sec

Best model:  ARIMA(0,1,1)(0,0,0)[4] intercept
Total fit time: 2.789 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   24
Model:               SARIMAX(0, 1, 1)   Log Likelihood                  -6.228
Date:                Fri, 24 May 2024   AIC                             18.456
Time:                        15:55:53   BIC                             21.863
Sample:                    03-31-2018   HQIC                            19.313
                         - 12-31-2023
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      0.6051      0.093      6.521      0.000       0.423       0.787
ma.L1          0.4061      0.211      1.926      0.054      -0.007       0.819
sigma2         0.0998      0.043      2.335      0.020       0.016       0.184
===================================================================================
Ljung-Box (L1) (Q):                   0.06   Jarque-Bera (JB):                 0.66
Prob(Q):                              0.80   Prob(JB):                         0.72
Heteroskedasticity (H):               0.97   Skew:                             0.09
Prob(H) (two-sided):                  0.97   Kurtosis:                         2.19
===================================================================================
```

Figure B.6: Detailed ARIMA Model Selection Process for Medium House Type

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,1,0)[4]             : AIC=4.220, Time=0.06 sec
 ARIMA(1,1,0)(1,1,0)[4]             : AIC=5.302, Time=0.06 sec
 ARIMA(0,1,1)(0,1,1)[4]             : AIC=5.167, Time=0.16 sec
 ARIMA(0,1,0)(1,1,0)[4]             : AIC=4.913, Time=0.06 sec
 ARIMA(0,1,0)(0,1,1)[4]             : AIC=5.055, Time=0.10 sec
 ARIMA(0,1,0)(1,1,1)[4]             : AIC=6.892, Time=0.10 sec
 ARIMA(1,1,0)(0,1,0)[4]             : AIC=5.002, Time=0.03 sec
 ARIMA(0,1,1)(0,1,0)[4]             : AIC=4.799, Time=0.06 sec
 ARIMA(1,1,1)(0,1,0)[4]             : AIC=inf, Time=0.20 sec
 ARIMA(0,1,0)(0,1,0)[4] intercept   : AIC=5.112, Time=0.06 sec

Best model:  ARIMA(0,1,0)(0,1,0)[4]
Total fit time: 0.934 seconds
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                   y   No. Observations:                  24
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 4)   Log Likelihood                  -1.110
Date:                             Fri, 24 May 2024   AIC                              4.220
Time:                                     15:55:54   BIC                              5.164
Sample:                                 03-31-2018   HQIC                             4.380
                                      - 12-31-2023
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2         0.0658      0.024      2.716      0.007       0.018       0.113
===================================================================================
Ljung-Box (L1) (Q):                   0.65   Jarque-Bera (JB):                 0.58
Prob(Q):                              0.42   Prob(JB):                         0.75
Heteroskedasticity (H):               1.70   Skew:                             0.23
Prob(H) (two-sided):                  0.54   Kurtosis:                         2.28
===================================================================================
```

Figure B.7: Stepwise ARIMA Model Selection for Large House Type

C

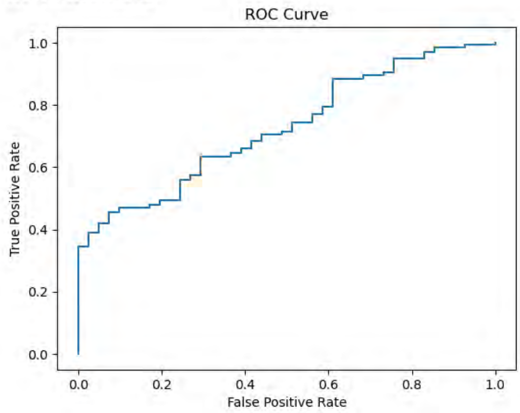
Protection Motivation Theory: Logistic Regression Model

```
Accuracy: 0.7796610169491526
Confusion Matrix:
 [[ 10  31]
 [  8 128]]
F1 Score: 0.8677966101694915
ROC AUC Score: 0.7263271162123386
              precision    recall  f1-score   support

           0       0.56      0.24      0.34        41
           1       0.81      0.94      0.87       136

    accuracy                           0.78       177
   macro avg       0.68      0.59      0.60       177
weighted avg       0.75      0.78      0.75       177

ROC AUC score: 0.7263271162123386
AIC: 210.79510692906865
BIC: 274.3181015805452
```



	Feature	Wet_proof_coeff	p-values	Significance
0	intercept	-0.396519	0.75689	ns
1	flood_dam	0.363569	0.00207	**
2	flood_prob	-1.285311	0.02550	*
3	worry	0.207321	0.09417	ns
4	soc_exp	0.196204	0.43075	ns
5	soc_net	0.104413	0.55689	ns
6	UG_elevation	-1.309832	0.01709	*
7	edu	0.052687	0.67720	ns
8	home_size	-0.058159	0.47899	ns
9	annual_income	0.000673	0.37254	ns
10	savings	-0.053590	0.38148	ns
11	climate_belief	0.575618	0.02488	*
12	media	-0.168904	0.32099	ns
13	soc_media	0.104010	0.52662	ns
14	flood_exp	0.704649	0.01460	*
15	SE	0.222898	0.11413	ns
16	RE	-0.133510	0.36177	ns
17	PC	-0.370822	0.04483	*
18	UG_dry-proof	-0.544678	0.27580	ns
19	soc_exp_x_soc_net	-0.010160	0.84138	ns

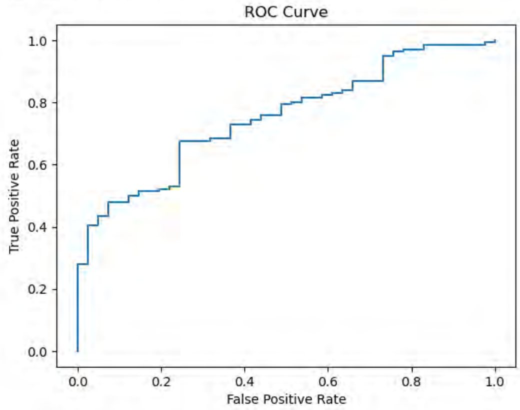
Figure C.1: Initial iteration of the wet-proof model

```
Accuracy: 0.7966101694915254
Confusion Matrix:
 [[ 10  31]
 [  5 131]]
F1 Score: 0.8791946308724832
ROC AUC Score: 0.7523314203730275
              precision    recall  f1-score   support

           0       0.67      0.24      0.36        41
           1       0.81      0.96      0.88       136

    accuracy                           0.80       177
   macro avg       0.74      0.60      0.62       177
weighted avg       0.78      0.80      0.76       177

ROC AUC score: 0.7523314203730275
AIC: 189.23713115987653
BIC: 227.35092795076247
```



	Feature	Wet_proof_coeff	p-values	Significance
0	intercept	-0.176722	0.83397	ns
1	flood_dam	0.368917	0.00148	**
2	flood_prob	-1.167945	0.03902	*
3	worry	0.191045	0.11842	ns
4	UG_elevation	-1.230759	0.02241	*
5	climate_belief	0.632944	0.01141	*
6	flood_exp	0.740960	0.00877	**
7	SE	0.138638	0.23758	ns
8	PC	-0.441182	0.00993	**
9	UG_dry-proof	-0.614320	0.21058	ns
10	monthly_income	0.006647	0.41977	ns
11	soc_exp_x_soc_net	0.019727	0.13948	ns

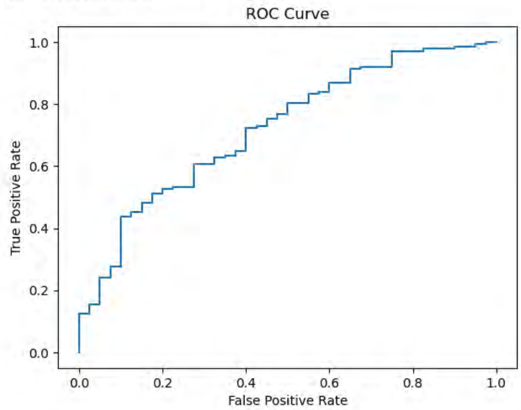
Figure C.2: Final model of wet-proof model

```
Accuracy: 0.7796610169491526
Confusion Matrix:
 [[ 14  26]
 [ 13 124]]
F1 Score: 0.8641114982578397
ROC AUC Score: 0.7215328467153286
              precision    recall  f1-score   support

           0       0.52      0.35      0.42        40
           1       0.83      0.91      0.86       137

    accuracy                           0.78       177
   macro avg       0.67      0.63      0.64       177
weighted avg       0.76      0.78      0.76       177

ROC AUC score: 0.7215328467153286
AIC: 212.17012987090422
BIC: 275.6931245223808
```



	Feature	Dry_proof_coeff	p-values	Significance
0	intercept	-2.049441	0.08274	ns
1	flood_dam	0.176520	0.12812	ns
2	flood_prob	-0.391667	0.49634	ns
3	worry	0.392517	0.00211	**
4	soc_exp	0.058937	0.66730	ns
5	soc_net	0.159264	0.00994	**
6	UG_elevation	-2.046409	0.00000	****
7	edu	0.102615	0.40573	ns
8	home_size	-0.057242	0.47288	ns
9	savings	0.001011	0.99158	ns
10	climate_belief	0.725225	0.00427	**
11	gov_trust	0.151537	0.43877	ns
12	media	-0.279037	0.10014	ns
13	soc_media	0.284473	0.07811	ns
14	flood_exp	0.588438	0.04071	*
15	SE	0.355333	0.01263	*
16	RE	-0.053334	0.73183	ns
17	PC	-0.491098	0.00471	**
18	UG_wet-proof	-0.217616	0.47989	ns
19	monthly_income	0.005978	0.47374	ns

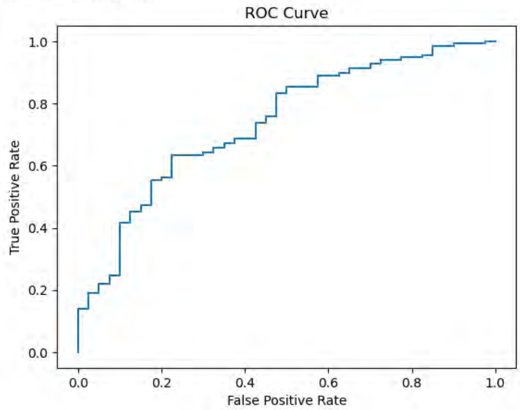
Figure C.3: Initial iteration of dry-proof model

```
Accuracy: 0.7740112994350282
Confusion Matrix:
 [[ 15  25]
 [ 15 122]]
F1 Score: 0.8591549295774648
ROC AUC Score: 0.7377737226277373
              precision    recall  f1-score   support

           0       0.50      0.38      0.43        40
           1       0.83      0.89      0.86       137

    accuracy                           0.77       177
   macro avg       0.66      0.63      0.64       177
weighted avg       0.76      0.77      0.76       177

ROC AUC score: 0.7377737226277373
AIC: 199.67495002809767
BIC: 247.3171960167051
```



	Feature	Dry_proof_coeff	p-values	Significance
0	intercept	-2.032402	0.03247	*
1	flood_dam	0.168726	0.14183	ns
2	flood_prob	-0.331521	0.55631	ns
3	worry	0.382726	0.00259	**
4	UG_elevation	-2.166290	0.00000	****
5	annual_income	0.000620	0.35771	ns
6	climate_belief	0.703157	0.00526	**
7	soc_media	0.667276	0.02870	*
8	flood_exp	0.623559	0.02899	*
9	SE	0.326706	0.01419	*
10	RE	-0.044299	0.77445	ns
11	PC	-0.513120	0.00304	**
12	UG_wet-proof	-0.209493	0.48915	ns
13	flood_dam_x_flood_prob	-0.099365	0.05415	ns
14	soc_net_x_soc_exp	0.038960	0.00474	**

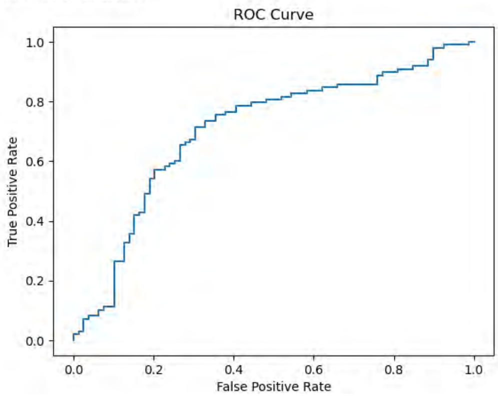
Figure C.4: Final model of dry-proof model

```
Accuracy: 0.7062146892655368
Confusion Matrix:
 [[51 28]
 [24 74]]
F1 Score: 0.74
ROC AUC Score: 0.7043399638336347
              precision    recall  f1-score   support

           0       0.68      0.65      0.66        79
           1       0.73      0.76      0.74        98

    accuracy                           0.71       177
   macro avg       0.70      0.70      0.70       177
weighted avg       0.71      0.71      0.71       177

ROC AUC score: 0.7043399638336347
AIC: 269.63198583434337
BIC: 333.1549804858199
```



	Feature	Dry_proof_coeff	p-values	Significance
0	intercept	-0.785971	0.43465	ns
1	flood_dam	0.177209	0.08500	ns
2	flood_prob	0.083131	0.87113	ns
3	worry	0.142501	0.18453	ns
4	SE	0.353945	0.00150	**
5	RE	-0.176726	0.13126	ns
6	PC	-0.003338	0.97794	ns
7	soc_exp	0.023162	0.84573	ns
8	soc_net	0.050084	0.36404	ns
9	edu	0.017283	0.87508	ns
10	home_size	-0.121179	0.09540	ns
11	savings	-0.026705	0.75784	ns
12	climate_belief	0.009491	0.96070	ns
13	gov_trust	0.041737	0.81084	ns
14	media	-0.234450	0.13065	ns
15	soc_media	0.165994	0.24698	ns
16	flood_exp	0.268745	0.29841	ns
17	UG_wet-proof	-1.568392	0.00000	****
18	UG_dry-proof	-0.458375	0.14155	ns
19	monthly_income	0.014031	0.10649	ns

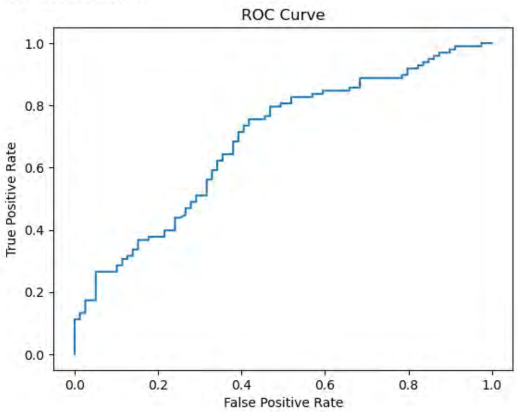
Figure C.5: Initial iteration of elevation model

```
Accuracy: 0.6610169491525424
Confusion Matrix:
 [[47 32]
 [28 70]]
F1 Score: 0.7
ROC AUC Score: 0.6868380263497804
              precision    recall  f1-score   support

           0       0.63      0.59      0.61        79
           1       0.69      0.71      0.70        98

    accuracy                           0.66       177
   macro avg       0.66      0.65      0.66       177
weighted avg       0.66      0.66      0.66       177

ROC AUC score: 0.6868380263497804
AIC: 256.86632005639876
BIC: 301.3324163124324
```



	Feature	Elevation_coeff	p-values	Significance
0	intercept	-1.443867	0.09929	ns
1	worry	0.590631	0.00023	***
2	SE	1.322814	0.00005	****
3	PC	-0.840105	0.01282	*
4	flood_dam_x_flood_exp	0.063012	0.45255	ns
5	flood_prob_x_worry	-0.616917	0.02896	ns
6	flood_prob_x_RE	0.611565	0.02443	ns
7	worry_x_UG_dry-proof	-0.548525	0.00120	ns
8	SE_x_RE	-0.190416	0.01168	ns
9	SE_x_UG_wet-proof	-0.497973	0.00000	***
10	RE_x_PC	0.114723	0.05081	*
11	RE_x_soc_net	-0.096190	0.01217	****
12	PC_x_soc_net	0.102156	0.00478	*
13	flood_exp_x_UG_dry-proof	1.141825	0.08009	*

Figure C.6: Final model of elevation model

D

Sensitivity Analysis

The sensitivity analysis was conducted using the one-factor-at-a-time (OFAT) method (ten Broeke et al., 2016) with ten replications for each scenario that summarised in Table D.1. A sensitivity analysis was conducted per scenario and compared to the baseline to understand the model better.

Table D.1: Comparison of Base Parameters and Parameter Variations

Base Parameter	Base Value	Parameter Variation
Measure Efficacy	Dry-proof: 0.25 Wet-proof: 0.15	Dry-proof: 0.43, 0.85 Wet-proof: 0.41, 0.50 (Aerts, 2018)
Adaptation Cost	Elevation: 36 million IDR Dry-proof: 8.36 million IDR per square meter Wet-proof: 0.06 million IDR per square meter	Elevation: 0 million IDR Dry-proof: 0 million IDR per square meter Wet-proof: 0 million IDR per square meter
Vulnerability Curves	Wahab and Tiong (2017)	Budiyono et al. (2016) and Wijayanti et al. (2014)

From Figure D.3, it is shown two emerging groups. The first group in which it overlaps or slightly deviates from the baseline. On the other hand, the second group significantly differs from the baseline. High and medium measure efficacy show similar patterns, with relatively low deviation from the baseline in both residual damage and net worth. The same goes for subsidy, which results in higher net worth compared to baseline and high measure efficacy. Regarding the model fidelity, it is aligned that with subsidy and higher measure efficacy, the net worth increases faster than the baseline and moderate measure efficacy. This implies that the model is less sensitive to changes in measure efficacy and measure cost despite the model being highly related in monetary terms.

On the other hand, differences in vulnerability curves lead to significant deviations. Two depth-damage curves from Budiyono et al. (2016), Wijayanti et al. (2014), and Wijayanti et al. (2017) show trajectories with similar trends and have a very close net worth range. These scenarios applied identical methodologies to calculate a map of the hazard but from slightly different perspectives or data sets. It is expected that curves by Budiyono et al. (2016) result in more significant residual damage, showing a validation of logic within the model. Despite that, it is revealed that the model is sensitive to the vulnerability.

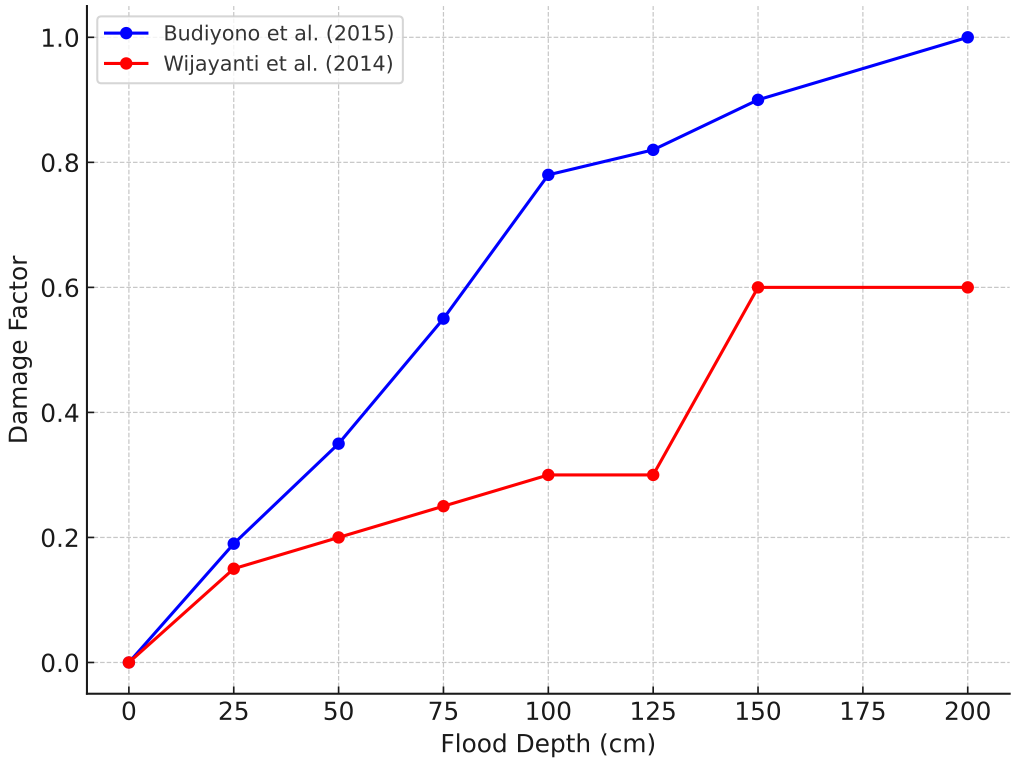


Figure D.1: *Depth-damage curves from Budiyono et al. (2016) and Wijayanti et al. (2014)*

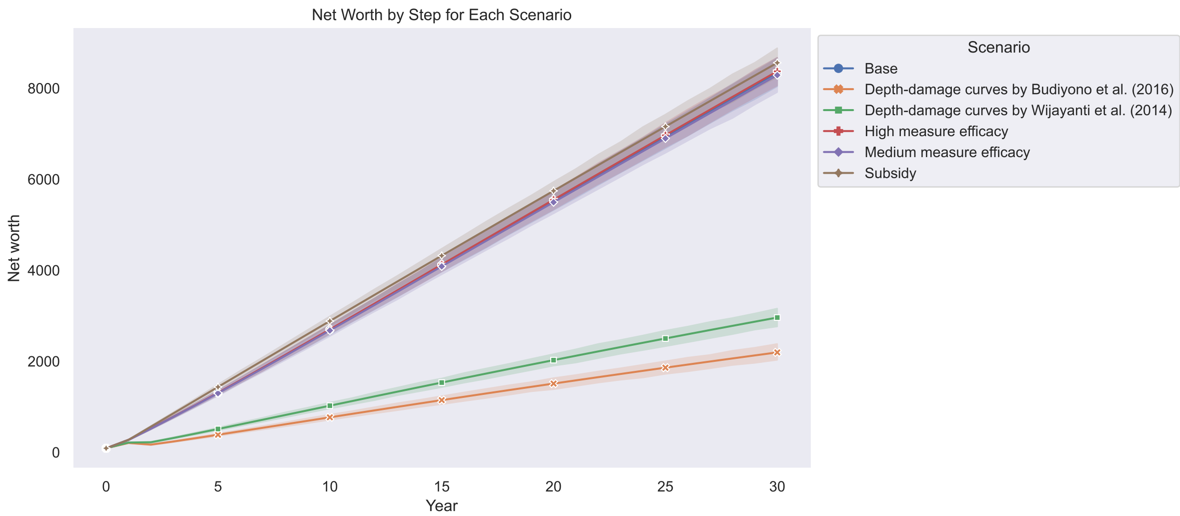


Figure D.2: *Sensitivity result on net worth variable* in million IDR. Shaded color refers to confidence interval of 0.95.

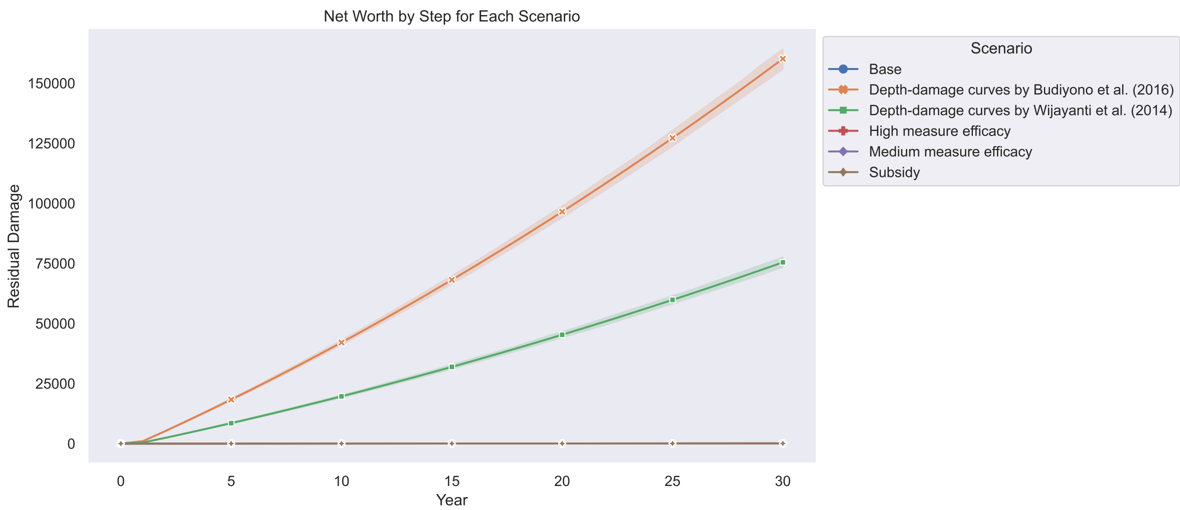


Figure D.3: *Sensitivity result on residual damage variable* in million IDR. Shaded color refers to confidence interval of 0.95.