Simulating the Delta

Finding the best modeling approach for simulating disaggregated impacts during salinity intrusion in the Vietnamese Mekong Delta

Engineering & Policy Analysis

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by

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https://rainforestjournalismfund.org/sites/default/files/styles/orig_optimized/public/inline-images/image_574.jpeg.webp?itok=u-taYN75

TU Delft

Preface

This document is the final document I need to submit before graduating. However, I would not have been able to complete it without all the wonderful people around me, and so I would like to take a moment to express my gratitude.

It all started in November 2024 when I spoke with Maaike about this topic. Without any knowledge of water systems, river deltas, or even non-Western cultures, she gave me her trust that day. I am grateful for the opportunity she gave me to do my internship at Deltares. Thank you so much for the guidance, for thinking along with me, and for all your knowledge. I also want to thank all the colleagues who shared their ideas, gave me motivation, and answered all of my (sometimes stupid) questions. I have learned a lot from all of you, thank you! Finally, thank you to Jari, it was an honor to be interns together. Thank you for listening during all those cups of tea and hot chocolate.

I would also like to thank my graduation committee. Alexander, thank you for offering different perspectives, for thinking with me when I couldn't see a way forward, and for all the feedback on (sometimes rather unstructured) work I had done. Without your structure and expertise, this thesis would not exist. Natalie, thank you especially for contributing on the psychological side, for the feedback during our meetings, and most of all for the optimism you gave me at the end.

Thank you to everyone who made the time for an interview. All your different perspectives helped me better understand the system.

Lastly, thank you to all my friends, my boyfriend, and my family. Thank you for writing our theses side by side, for giggling in the back of lecture halls, grabbing tea during breaks, or simply calling to share a new insight. You know everything about the Vietnamese Mekong Delta now, without reading my thesis. Thank you to my sister for proofreading at the last minute and offering advice, and thanks to Mum and Dad for trusting me and giving me the confidence. The final thanks to my boyfriend, I have lost count of how many times you said, 'Just take it one step at a time, and it will all be fine'. It will not surprise you all, but that was indeed true.

Enjoy reading!

J.A.M. van Alst
Delft, July 2025

Summary

This thesis studied which modeling approach is most suitable to simulate the human behavior of inhabitants in river deltas during environmental changes. The Vietnamese Mekong Delta (VMD) was chosen as the test case. River deltas are currently experiencing an increase in salinity levels due to sea level rise, land subsidence, and groundwater extraction. To assess the impacts on local populations, the following research question is addressed: *"What are the advantages and disadvantages of different socioeconomic response modeling techniques in assessing the disaggregated or distributional impacts for different subgroups in light of environmental change now and in future scenarios, tested in the Vietnamese Mekong Delta?"*. System Dynamics (SD), Discrete-Event Simulation (DES), and Agent-Based Modeling (ABM) were compared. There were too few advantages of DES compared to SD and ABM for this case, and therefore, only models were created in ABM and SD.

The ABM offers several advantages, such as the ability to realistically simulate individual human behavior, including emergent behavior. It allows for clear differentiation between household types and supports spatial modeling. However, not only is there a risk of overfitting given the current level of data, but the model is also more complex to understand. In addition, due to its stochastic nature, multiple runs are required to produce reliable results.

The SD model, on the other hand, is easier to understand, requires only a single run because it is deterministic, and needs only aggregate-level data. The stock-flow structure provides a clear overview of system dynamics, and the interactive dashboard with sliders makes the model more accessible. But, this level of aggregation also has limitations: it is not possible to model individual behavior, and the individuals cannot interact with each other. Instead, fixed probabilities determine the actions of population fractions.

Due to the strengths and limitations of both techniques, the results of the two models differ considerably. Nevertheless, the ABM model provides a more realistic representation, and it is therefore recommended to the employees at Deltares to develop a model in ABM. It might even be useful to use NetLogo for this, since technique combines the behavioral aspects of ABM with the visual clarity and slider-based interaction of SD. SD can still be used, for example, to validate the data before using it in the ABM. It is also advised to conduct long-term field research in which structured data is collected over several years through targeted surveys that can serve as model input.

This is one of the few studies that developed both an ABM and an SD model using the exact same variables and it is the first one related to river deltas and farmers. Moreover, an ABM that incorporates salinity, yield, income, livelihoods, and migration had never been created before for the VMD. Little has been explored yet regarding the use of SD for the socioeconomic aspects of the local population. This study can be seen as a stepping stone for Deltares to continue its research towards developing a socioeconomic model to simulate the impacts of inhabitants in the VMD.

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1 Introduction

River deltas play a crucial role in ensuring food security, but their function is currently at risk (Scown et al., 2023). Deltas offer many advantages: they are flat, have fertile soils for agriculture, and have access to fresh and salt water (Kuenzer & Renaud, 2012). In addition, river deltas contribute significantly to a country's GDP (Loucks, 2019). However, because these deltas are lying low, they are vulnerable to flooding, sea level rise, and salinization (Scown et al., 2023). Combined with intensive development in these regions, river deltas are becoming less sustainable (Loucks, 2019). More than 500 million people live in river deltas worldwide, and the growing environmental impacts are causing an increasing demand for change to prevent disasters (Kuenzer & Renaud, 2012). Despite that, the dominance of agricultural land in the deltas leaves little room for alternative uses (Nicholls et al., 2020). Many people are migrating to cities, and the key characteristics that make river deltas so valuable are beginning to fade (Nicholls et al., 2020).

One of the main challenges in river deltas is salinity (Mukhopadhyay et al., 2021). According to Rahman et al. (2019), salinization refers to the accumulation of salt in the soil and freshwater systems, making it unsuitable for drinking or agricultural use. The low land in the river deltas, in combination with dikes, allows saltwater to move easily inland during the dry season, increasing the salinization of the land and water (Xuan et al., 2022). Moreover, groundwater is extracted faster than it can be restored, leading to salinity. Increasing urbanization worsens the degradation of the land and, consequently, also contributes to salinity. (Stouthamer et al., n.d.). Over time, not only does salinity increase, but "salinity shocks" occur more often as well. During these shocks, the salinity will increase drastically for a few days, causing crop failures. These shocks are expected to occur more frequently, and according to Vu et al. (2018), action is required to prevent severe disasters.

The focus of this research is the Vietnamese Mekong Delta (VMD). The area has more than 17 million inhabitants, consisting of agricultural and aqua-cultural farmers, wage workers, and people who migrated from rural areas to Ho Chi Min, the main city in VMD. The main crop in VMD is rice, and 90 percent of the country's rice for export is produced there (Dang et al., 2021). The VMD is chosen because it is already heavily impacted by climate change (Kontgis et al., 2019). The delta is only 0.8 meters above sea level today, while it was 2.6 meters in the past (Minderhoud et al., 2019). There is no long-term strategy to mitigate this problem of salinity in the VMD (Dang et al., 2021).

The problem is that Deltares currently does not know how to best model the impact of environmental changes in the VMD. Several comparative studies have been conducted that evaluate different modeling approaches, for example Maidstone (2012), but it is unclear what effect these will have when applied specifically to the VMD. In addition, Deltares currently has experience with System Dynamics (SD), but less with Agent-Based Modeling (ABM). Therefore, this research can be seen as a starting point for Deltares in developing ABMs.

When looking at the current literature on simulations for the VMD, most of the studies are mainly environmental. They focus on land subsidence, salinization, or groundwater extraction (Tran et al., 2022a; Tran et al., 2024; Vu et al., 2018). This approach is effective for studying environmental changes, but human behavior is often neglected. The only simulation models related to human behavior are created by Nguyen et al. (2021), Trinh and Munro (2023), and Truong et al. (2023). A limitation of these studies is, among others, that they focus only on the cumulative level instead of the individual. For example, in the model of Truong et al. (2023), each agent has the same amount of land, and the focus is solely on the cumulative income per province, but the possibility of migration is not taken into account. Nguyen et al. (2021) and Trinh and Munro (2023) did incorporate migration, but did not focus on the changes in labor, income, or adaptation strategies that residents might implement. In addition, most studies focused only on a few regions in the VMD instead of the entire delta.

There is no general model available that takes into account all factors of the system. Furthermore, only ABMs or statistical or stakeholder analysis have been performed (Quyen et al., 2017; Trinh & Munro, 2023; Van Aalst et al., 2023), and no one has developed a human behavior system dynamics model (SD) or a discrete event simulation (DES) for the inhabitants of the VMD.

This study contributes by studying the most promising socioeconomic modeling approach to model human behavior in river deltas, using VMD as a test case. For two simulation approaches, conceptual models have been created, and multiple computational models have been simulated. A distinction was made between different subgroups, such as lower-skilled wage workers and rice farmers, as they each respond differently to drought and salinity. Through this research, a larger model can be developed in the future to simulate the behavior of inhabitants of river deltas. This can be seen as a first step for creating socio-economic behavioral models in The Deltares Toolset for simulating and understanding river deltas.

Based on the knowledge gap, the following research question will be answered:

What are the advantages and disadvantages of different socioeconomic response modeling techniques in assessing the disaggregated or distributional impacts for different subgroups in light of environmental change now and in future scenarios, tested on the Vietnamese Mekong Delta?

The goal is to create an overview of the disadvantages and advantages of promising socio-economic modeling approaches for simulating the inhabitants of river deltas. Two models are made and their results are compared to identify the disadvantages and advantages of these models for the inhabitants of the VMD.

To answer the main research question, four sub-questions have been formulated, which are explained below.

Sub-question 1: *What are promising different modeling tools and approaches?*
Three simulation approaches were distinguished: DES, ABM, and SD. The advantages and disadvantages of these methods were studied, as well as the levels of aggregation at which they can be applied. This has been done by conducting a literature review. Furthermore, a requirements document has been created, together with Deltares, to see what they prefer in the simulation model. In the end, an overview of the methods, aggregation levels, and their pros and cons will be provided.

Sub-question 2: *How can these promising approaches be conceptualized, combined with their data requirements?*
After the approaches and tools were studied, conceptual models were created for two of the modeling approaches. Furthermore, the conceptual models provided information on the data requirements. This data was collected using the available datasets and analyzed to formalize and run the models.

Sub-question 3: *How do ABMs and SD models differ in representing disaggregated impacts between subgroups of farmers under environmental changes*
Two computational models have been created, with the exact same variables, to simulate the inhabitants of the VMD. The model output and sensitivities are also compared to each other.

To answer the sub-questions and subsequently the main research question, it was important to get an overview of life in river deltas, especially in the VMD. First, a literature study was conducted; despite this, gaining insight into the drivers of behavior and household dynamics of the inhabitants proved challenging due to limited available data. Therefore, various interviews have been conducted with colleagues who are experts in the field and have experience with the area. These explained, for example, how debts work, what the area looks like, and what decisions farmers make in the VMD. Appendix A gives an overview of these people, their function, and the date of contact.

Chapter 2 provides a complete system overview based on analyzed data, interviews with colleagues, and literature. In Chapter 3, three simulation approaches are compared, and requirements are established that the final model must meet. Next, Chapter 4 presents the conceptualization of the ABM model, and Chapter 5 discusses the results of the ABM model.

Chapter 6 presents the conceptualization of the SD model, and Chapter 7 shows the results of the SD model. The results of the ABM and SD models are compared in Chapter 8, together with the sensitivities of the model. Finally, conclusions and a discussion are presented in Chapter 9.

[1]

[1]During the development of the models and the writing of this document, two artificial intelligence-using software tools were used. First, Writefull was used in Overleaf, this tool corrects grammatical errors and improves the structure of sentences. This enhances the overall flow of the text. Each of the suggestions given by Writefull was considered individually and only accepted when appropriate to ensure that the intended meaning of the text was maintained.

Second, ChatGPT was used to translate words and phrases from Dutch to English. ChapGPT also helped debug the ABM, work with spatial data in QGIS, and help create some visual overviews. Although ChatGPT provided some good support, the most valuable insights came from personal trial and error and individual problem-solving.

2 System Description

A literature review was conducted, and colleagues from Deltares and other researchers were interviewed to gain insight into daily life in rural areas of VMD. The system will be explained based on four factors: inhabitants, environment, governmental impact, and migrations. When research is already conducted on a topic or a model is created, this is also mentioned.

2.1. Inhabitants

2.1.1. Demographic characteristics and education

In terms of demography, the VMD has a high concentration of children and the elderly. Looking at data from the 2019 Pop Housing Census [1] for rural areas, a quarter of the population is under the age of 15. This trend has only intensified in recent years. Compared to a study by Huynh (2011), the share of the working population has decreased (from 68 percent in 2009 to 62.5% in 2019), while the proportion of the elderly has increased (from 8 to 13.5%). This demographic change can be explained by the migration of youth.

Between age groups, there are large differences in the level of education. Based on Pop Housing Census 2009, it is striking to see that 17% of the people older than 59 years have no education, and over fifty percent are below primary level. The percentages below the primary level in the groups 16-45 and 46-59 are also notably high (28 and 47 percent). Moreover, the share of people with education beyond primary level is very low: only a quarter in the 16-45 years old group, and 11 percent in the age group of 46-59. Nowadays, children have better access to education, and it is expected that these levels will only increase over the years.

2.1.2. Occupations

The working population of the VMD is often divided into seven groups. Table 2.1 shows these types, a short description, and an example.

However, unpublished data from Deltares (personal communication, March 2025) showed that there have been many labor shifts in the past years, due to, among others, the salinity shock in 2016. When looking at the number of people per occupation, only 57% of the people who defined themselves as 'agricultural crop' in 2016 were still in this sector in 2018. The lowest retention rate between 2014 and 2018 was in the "Low-skilled Agri Wage" group: only 42% remained. This suggests that this group experienced the greatest impact from the salinity shock.

In an interview with a Vietnamese sociologist (personal communication, April 2025), it was revealed that efforts have been made in the VMD to introduce city life to rural areas to reduce outmigration. This has been done by establishing factories in the countryside. According to M. van Aalst (personal communication, April 2025), the goal of the VMD is to become a high-value agriculture business, where the focus is on agriculture-related manufacturing. This is achieved, for instance, by processing mangoes to make juice or jam. Based on VHLSS2020 data, 43% of the landless households main income source is based on the processing of food.

[1] Pop Housing Census and VHLSS are purchased datasets that are not publicly available and were provided by Deltares

Table 2.1: Seven types of occupations in the VMD

Occupation type	Description	Example
Agricultural crop	People who own land and grow agricultural crops	Rice farmers, Maize farmers
Aquaculture	People who own land and earn an income from aquaculture	Shrimp farmers, pangasius farmers
Low-skilled Agri Wage	People who do not own land, but work on farms as laborer, but have little expertise	Rice wage worker, aquaculture wage worker
Skilled Agri Wage / Business	People without land, but who work in agricultural sector or have their own business, but they have expertise	People working in IT, farm workers who fix machines
Low-skilled Non-Agri Wage	People who do not own land and do not work in agricultural sector, and have limited intellectual abilities	Cleaners, domestic helpers and workers in mining
Other income	People who do not own land or a business and do not work in the agricultural sector	Officers, governmental members
Non-Laborer	These people are not employed	Children, women caring for children, elderly

In recent years, investors of the VMD have also tried other industries, such as textile production. However, these have not yet taken off. Based on the interview with M. Van Aalst (personal communication, April 2025), the VMD is mainly known for its agriculture and is less attractive to investors from other sectors.

2.1.3. Ethnic and religious diversity

There are different types of ethnicity in the VMD. The Kinh is the largest group in Vietnam Nam and the Khmer is one of the ethnic minorities. The Khmer live especially in the VMD, and 7 percent of the VMD inhabitants are Khmer (Tuan et al., 2023). A study by Tung (2018) shows that the Khmer have significantly lower income than, for example, the Kinh, which can be declared by the fact that they have less land and a lower level of education. Furthermore, Vietnamese is not their mother tongue, which can cause language barriers.

In addition to ethnicity, there are also various religions in the VMD. However, little research has been done, as religion is often considered a non-essential aspect of life in this region (Nguyen et al., 2020). As a result, there is limited research on the influence of religion. There are multiple traditional native religions, but Buddhism and Christianity are also widely practiced (Nguyen et al., 2020). Catholicism has a growing influence and, in addition to working (which is important in every religion), Catholics are known for the emphasis on justice and charity (Ngô, 2023). Due to the lack of available research and expert input suggesting that religion is not the most important factor to be considered, this factor was not included in the current analysis (V. Sharma & M. van Aalst, personal communication, March 2025).

2.2. Environment

The pictures shown in the interviews show that the landscape looks quite similar to that of the Netherlands (V. Sharma & M. van Aalst, personal communication, March 2025). There are pieces of land separated by ditches to provide water to all farmers, as captured in Figure 2.1.

Figure 2.1: Environment in the VMD, captured by M. van Aalst

These small canals make it possible to pump water directly from the river. The rest of the environment in the VMD can be described by multiple factors. The most important is salinity, which causes crops to fail. However, dikes and sluices can influence salinity levels, and there are different types of crops, and groundwater extraction and urbanization make these problems worse. In addition, these land uses are changing over time.

2.2.1. Salinity

Figure 2.2 shows the salinity levels of the VMD in 2014. This is the newest data available at Deltares, provided by S. Eslami (personal communication, April 2025). When looking at the distribution of salinity, the southern and coastal areas are particularly saline. This can be declared by the fact that they are close to the sea, and saltwater is intruding inland. In 2016 and 2020, salinity shocks occurred, causing salinity levels to increase for a few days. Crops that are sensitive to salt cannot survive these shocks, leading to failed harvests.

In recent years, much research has been done on salinity levels in VMD. For example, Tran et al. (2024) found that salinity started each dry season earlier and became more intense in the last 25 years. This is in line with the research of Eslami et al. (2021), who also found that the VMD is becoming more vulnerable, even during mild events. Multiple models are created to simulate salinity levels, for example, in combination with groundwater distribution, or to simulate the salinity levels since the Pleistocene era (Gunnink et al., 2021; Pham et al., 2022). Trung et al. (2020) found that the loss of sediment and nutrient transport and the decrease in water quality are the biggest changes caused by the increase in salinity. The rise in sea level leads to saltwater intrusion (Vu et al., 2018). Using Machine Learning, Tran et al. (2022b) made it possible to predict the intrusion of salinity in the VMD. In addition, Tran et al. (2023) found a way to combine satellite data with numerical simulations and made it possible to predict salinity levels as well.

Truong et al. (2023) created an ABM to study land use and adaptation strategies. They found that there will be a decrease in income in the future for farmers due to failing crops during salinity increases. When looking at the income decreases for different types of inhabitants in the VMD, households with a lower socioeconomic status were more vulnerable to the impacts of salinity (Van Aalst et al., 2023). Hua et al. (2024) created an ABM and found that collective government intervention was a useful strategy to mitigate this problem.

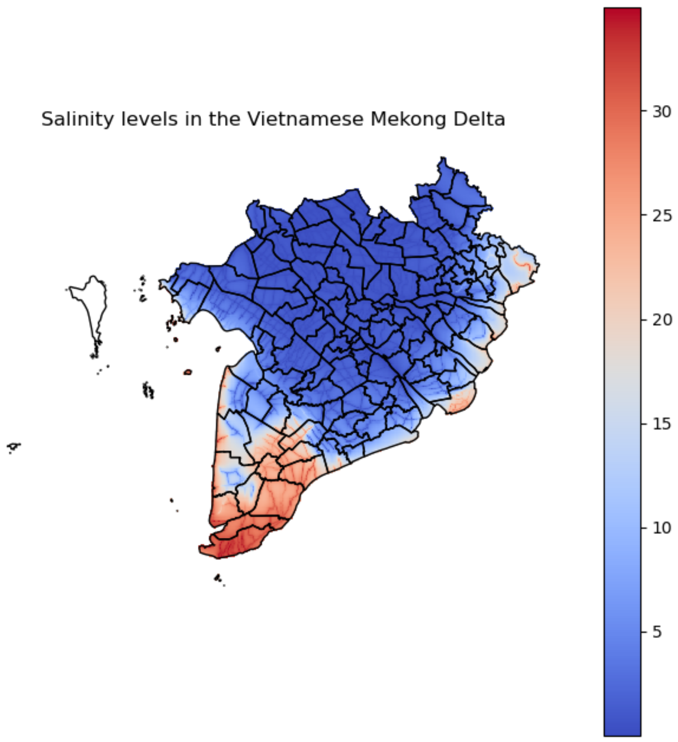


Figure 2.2: Salinity levels in the VMD, in 2014

2.2.2. Dikes and sluice

Farmers can have low or high dikes, and both were originally created to protect rice from flooding (Xuan et al., 2022). When a farmer has low dikes, the land floods once a year, while high dikes prevent the land from flooding all year long. van Aalst et al. (2023) found that rice cultivation per season is higher when a farmer has low dikes: 8.1 tons/ha/season, while high dikes lead to 7.5 tons/ha/season. However, only double rice cultivation is possible with low dikes (a farmer can harvest rice two times a year), while triple rice is possible with high dikes. This causes the overall water demand to be lower near low dikes: 54 USD/ha/year, compared to 72 USD/ha/year (van Aalst et al., 2023). Lastly, high dikes use more fertilizer and pesticides, and the profitability of these farms is decreasing due to high production costs (Tran et al., 2018).

In addition to the dikes, there are sluice gate systems to regulate the water levels. They are used for agricultural resilience, flood management, and the prevention of salinity intrusion. The sluice allows the farm to be closed for saline water or make more freshwater available for irrigation (Duy et al., 2025). The interview with S. Eslami showed that the closing of gates could decrease the impact of the salinity shock. However, a disadvantage of the sluices is that when someone more upstream in the river closes their sluices, more downstream farms also have less water available (L. Hermans, personal communication, April 2025).

The interview with a S. Eslami also revealed that most people pump their water out of the river, and farmers do not use a lot of groundwater (personal communication, April 2025). Some farmers have their own pumping systems, others have a contract with a farmer community, and have to go to a community irrigation point (V. Sharma, M. van Aalst, personal communication, March 2025).

2.2.3. Groundwater and urbanization

The groundwater extraction and urbanization lead to the subsidence of land in the VMD, which increases salinity levels (Tran et al., 2022a). The disturbance of groundwater over the last 25 years has been studied, and the subsidence of the land will be between 1.1 and 2.5 cm per year due to groundwater extraction (Minderhoud et al., 2017). Several studies have been conducted on this topic, such as Minderhoud et al. (2020), and research is conducted on how to inform stakeholders about the problem as well (Hoan et al., 2022; Tran et al., 2022a). They also analyze the impact of groundwater levels, and it is indicated that a lower pumping rate is needed to restore groundwater levels (Tran et al., 2022a).

2.2.4. Land use

Multiple types of crops are cultivated in the VMD. These can be divided into different groups, such as rice, annual crops, perennial crops, and aquaculture. Additionally, it is possible to combine crops, for example, rice and shrimp, while forestry and livestock keeping are also common. Below is an overview of examples based on the VHLSS2020 questionnaire.

- Rice can be divided into single, double, or triple cropping systems. This refers to the number of rice crops that a farmer cultivates each year. The difference in double and triple rice is the extra crop in November. Moreover, there are multiple types of rice, for instance salt tolerance rice, glutinous rice, and specialty rice.

- Annual crops are all the crops that can be harvested annually, but are not rice. Examples are maize, sweet potato, and cassava.

- Perennial crops are crops that take multiple years to grow. These are primarily tree crops, such as citrus, coconut, mango, and durian.

- Aquaculture is mainly focused on shrimp and pangasius. Within shrimp, it is possible to choose extensive, intensive, or mangrove shrimp farming. Intensive shrimp leads to a higher yield, but also more risks and more chemical inputs (Joffre et al., 2015a). Mangrove shrimp means that there is a mangrove forest, where the shrimp swim between trees. Lastly, it is possible to combine shrimp with rice, where rice is grown during the rainy season and shrimp during the dry season. The biggest disadvantage of aquaculture is the increased chance of diseases. These can be cured by using antibiotics, but this also leads to a lock-in effect: the antibiotics penetrate into the ground, and after 5-10 years, the ground is so polluted that the yield is not successful anymore. The advantage of aquaculture is that it is salt-tolerant, and brackish water can be used (N. Mulder, personal communication, April 2025).

- Livestock and hunting are common in the VMD, animals kept include horses, horses, goats, chickens, ducks and pigs.

There are different perceptions about the impact of the use of pesticides and antibiotics, as well as the effects on surrounding farms. Some experts believed that a shrimp farm can co-exist next to a rice farm without major problems. Others stated that neighboring farmers often feel forced to switch to shrimp due to rising soil salinity and antibiotic contamination. In addition, pesticides used in rice farming were mentioned as a factor that negatively affects shrimp quality (E. Eslami, N. Mulder, L. Hermans, personal communication, 2025).

2.2.5. Land use changes over time

When looking at land use, this is in line with the salinity levels in the VMD. In the southern and coastal regions, the focus is on aquaculture, while in other areas, double and triple rice is cultivated. An additional effect of the environmental changes and increase in salinity levels affects food production negatively (Mukhopadhyay et al., 2021). According to Wassmann et al. (2019), 44 percent of the total rice area is prone to salinity. Vu et al. (2018) found that a salinity of 4 grams/liter will impact the rice and that the salinity will penetrate 50-60 km of the river. That salinity can influence crop production is also established by Anh et al. (2018) and Dang et al. (2020). Truong et al. (2023) found that it is best to significantly reduce water use during the dry season. This also results in lower income. Unfortunately, increasing irrigation and fertilization cannot prevent yield losses (Kontgis et al., 2019). But Tran et al. (2018) found that the use of fertilizers and pesticides is increasing. Farms with more diversified crops, behind lower dikes, are less impacted. In addition to salinity, farmers are also affected by sudden colds, floods, and heavy rain, which also affect food production in a negative way (Huế, 2024).

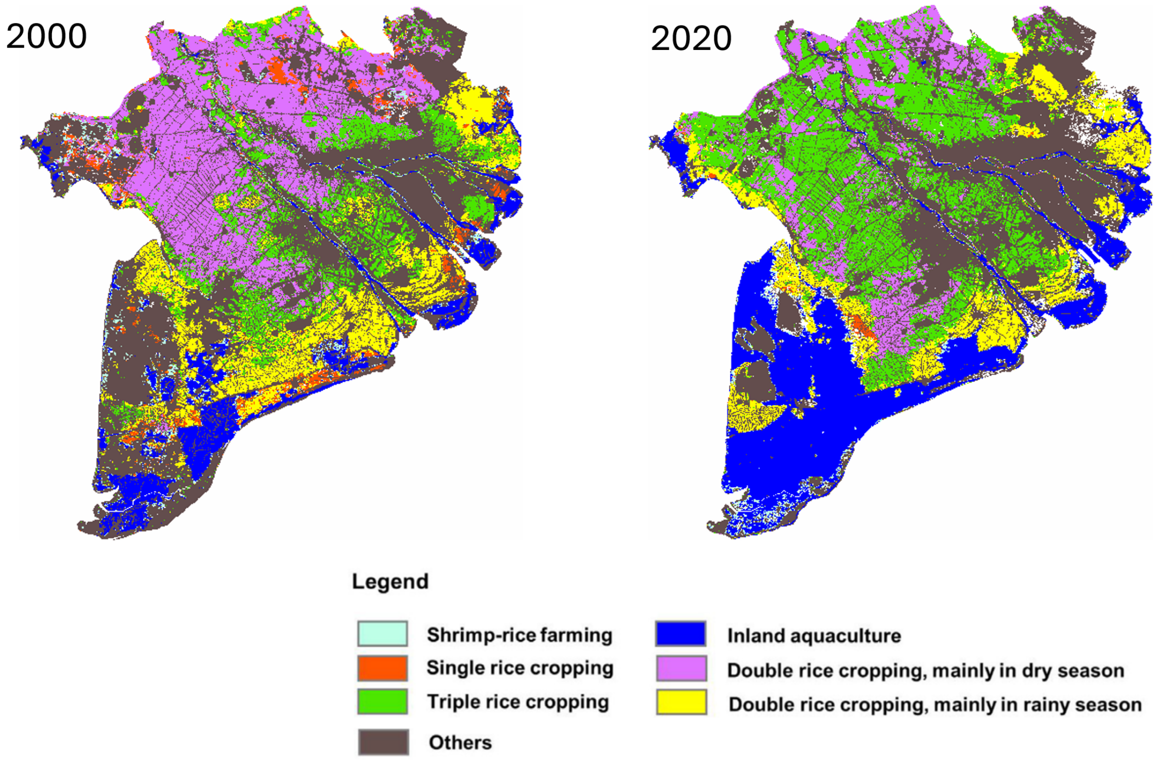


Figure 2.3: Land use changes between 2000 and 2020 by Vu et al. (2022)

Due to the environmental changes, there have been changes in land use in the past 25 years (Vu et al., 2022). In 2001, the vast majority of the land was still used for double rice cultivation, both in the rainy and dry seasons. In the southern part of the VMD, there were small areas of aquaculture, but also some land was used for ’other’ crops, such as perennial or annual crops. By 2020, the share of aquaculture, mainly in the southern part of the region, had increased significantly. In addition, more farmers switched from double to triple rice cultivation. These changes are mapped by Vu et al. (2022), and shown in Figure 2.3. This can be explained by the fact that salinity levels have been increasing in the south, as shown in Figure 2.2, and inland aquaculture is salt-tolerant.

A study by Le et al. (2024) found that out of all rice farmers, 44 percent switched to safe rice, 33 percent to fruits, and 6 percent to vegetables. Also, 13 percent of the vegetable farmers switched to fruit trees. Reasons to switch were higher profits and reduced water resources available. This is in line with the research by Vu et al. (2022).

2.3. Governmental impact

In the VMD, there is a local government, a central government, and the Communist Party. The central government is aware that a sustainable delta is required. However, the local government is several years behind in its thinking and still favors triple rice cropping (M. van Aalst, personal communication, March 2025). In the 1990s, there was a ”rice first” policy, where farmers were expected to grow rice (Tran et al., 2018). This is now less strictly enforced, and farmers are allowed to switch from rice to, for example, annual crops without punishment. However, only a few farmers are willing to take the initiative to make this change independently. When farmers change practices without following government guidance and fail, there is a possibility that they might receive no financial support. In contrast, those who did follow government instructions and failed have a higher chance of receiving support (V. Sharma, personal communication, March 2025).

In addition to the government, the Communist Party plays a powerful role and ultimately decides what needs to be done. According to an interview with Thanh Tran, the Hội Nông dân Việt Nam (Viet Nam Farmers’ Union) is particularly influential. This is the group that visits villages and informs farmers about the agricultural calendar for the upcoming year (personal communication, April 2025). However, all interviewees have mentioned that not all villages are reached and there is no guarantee that these visits occur annually. In addition, it was mentioned that there are commercial seed traders in the agricultural business sector who sell seeds and fertilizers to farmers. These traders also provide instructions on how to use the seeds and how to achieve the highest possible yield (L. Hermans, personal communication, March 2025).

2.4. Migrations

The VMD is the region from which most people migrate, often moving to the nearest major city (Ho Chi Minh City), or the provinces above (Binh Duong and Dong Nai). Between 2005 and 2017, the out-migration rates in some provinces were almost ten percent (Nguyen et al., 2021). There are two main types of migration among those leaving the region: young individuals who no longer wish to live in the VMD, and entire households that cannot sustain themselves financially. It should be noted that there is also a third type: seasonal migration. These are individuals who are still considered part of their household, but temporarily move to work in other areas. This often happens during the dry season (de Brauw & Harigaya, 2007; Ngoc, 2022).

2.4.1. Youth migration

These are individuals between approximately 15 and 35 years old who leave the VMD. Research by UNDP (n.d.) shows that in certain areas, for example, the Bao Thao Commune, up to 80% of the youth labor force has migrated. They also found that migration is more common among people in poorer areas, which often includes members of the Khmer ethnic group (UNDP, n.d.). According to internal documents from Deltares, there are various reasons for leaving. Many cite a ”lack of opportunity” in their hometowns or state that life in the countryside was depressing. Moreover, they were unable to earn a stable income, and some were entirely without work. The step to migrate was easier if they already had contacts in the city. Migrants mention that city life is more exciting, allows them to save money, and provides a more reliable income (Deltares, internal document, 2025).

However, these migrants often leave their children behind in the countryside, and grandparents or other relatives will take care of them. Approximately half of youth migrants can send remittances home (UNDP, n.d.). These remittances are usually small and are mostly used to cover children’s education costs. According to an interview with a Vietnamese student, this group is the most likely to return to the VMD after a few years. Unpublished data from Deltares shows that 3.9 percent of total migrants have returned to their hometowns. Reasons for returning include feeling obligated to take care of elderly parents or to take over the family business as parents grow older. Others hope to start a small business at home, or simply want to escape the high cost of living in the city (Deltares, internal document, 2025).

2.4.2. Household migration

The second group of migrating inhabitants is the whole of households. There are multiple reasons, but the main one is environmental changes. Unpublished data from Deltares showed that people leave because the land has become too saline and dry, extreme weather conditions have damaged the trees, and there has been a decline in the catch of wild seafood due to increased levels of pesticides in the water (Deltares, internal document, 2025). In addition, small farms are particularly vulnerable to the rising costs of inputs such as seeds and fertilizer, and cannot negotiate seed prices (van Aalst et al., 2023). According to the interview with the Vietnamese student, this is the group of people who do not return to the VMD but instead stay in the higher regions of Vietnam (Tran, personal communication, April 2025). A research by Trinh and Munro (2023) found that crop-restrictive regulations were required to prevent further migration in the future.

Nonetheless, life in the city is not always better. Unpublished data from Deltares indicates that only a portion of migrants receive support, despite the claims of the mass media that support programs exist for them. Furthermore, they are often unable to enroll their children in school, it is difficult to obtain temporary residence, working conditions are poor, and there is a lack of social cohesion (Deltares, internal document, 2025).

An ABM considering out-migration is created by Nguyen et al. (2019a). They combined this model with the Theory of Planned Behavior, and found in some provinces an out-migration of around 10 percent.

3 Modeling approaches

A model is a simplification of reality, and there are static and dynamic models. Static models focus on the state at a specific point in time. An example used in Deltares is RIBASIM, which uses hydrological water inputs to determine, for example, the flow of the river at a given moment ("Ribasim", n.d.). Dynamic models, on the other hand, represent the state of a system, in this case, the VMD, over time. The focus of this thesis will be on three types of dynamic models: System Dynamics (SD), Agent-Based Modeling (ABM), and Discrete-Event Simulation (DES).

First, a requirements table was developed in collaboration with Deltares to identify the essential criteria for the model. Then, the three model types are compared based on these requirements, and the most promising techniques are identified.

3.1. Requirements

Together with colleagues at Deltares, requirements were established for what the final model should be able to do. The MoSCoW framework was used for this, which means that the requirements fall into four categories (Eduardo, n.d.):

- Must have = essential, must be included
- Should have = important, but considerable
- Could have = ideally included if resources allow
- Won't have = out of scope/unfeasible

Table 3.1 gives an overview of the requirements. It is important for the model to be easily adjustable (for example, the composition and number of people), to run quickly without an internet connection, and to allow the implementation of scenarios and Excel data. Additionally, it should be easy to connect to the data files and produce a clear and easy-to-understand output that is dynamic. Dynamic output means that there are, for example, sliders that one can use to change the input variables, and the graphics will change automatically.

3.2. Model comparison

3.2.1. System Dynamics

SD was developed in the 1950s by Forrester (Forrester, 2007). The dynamics of the system is, according to Howick et al. (2024), based on two factors: feedback loops and the fact that the structure of the system determines the behavior of the system. SD is a continuous simulation technique, and the structure of the system is created by combining stocks, flows, feedback loops, and delays. Most SD models are deterministic. Differential equations are used for the system specifications (Howick et al., 2024).

The SD aggregation level is macro-level, making it possible to simulate large populations efficiently (Maidstone, 2012). However, a disadvantage is that the model can quickly become complex and difficult

Table 3.1: Requirements defined with M. van Aalst, based on MoSCoW Framework

Requirements	Must have	Should have	Could have	Won't have
Functional requirements				
Easily change the composition of people	X			
Simulate scenarios	X			
Short runtime	X			
Parallel computing possible			X	
Distributed computing possible			X	
Import data from excel/csv	X			
Implement assumptions/use raw data		X		
Possible to model different types of inhabitants	X			
Possibility for exploratory modelling				X
Compatible with GIS		X		
Model human behavior/interactions	X			
Non-functional requirements				
Dynamic output	X			
Use big datasets		X		
Open source		X		
Accessible		X		
Good documentation		X		
No connectivity to internet required	X			
Clear and easy understandable output	X			
Modularly built	X			
Easy to connect to other models	X			

to manage when trying to include many different subgroups. All subgroups should have different stocks, and in this case, all stocks and flows should be connected to each other. The advantages of SD are its fast runtime and the fact that the models are easy to understand (Brito et al., 2011). This makes SD accessible, and the output is typically straightforward and interpretable. There are SD software tools, for example Stella, that allow dynamic outputs. Using sliders, the input variables can be adjusted, and in seconds, the updated output is shown in graphs (ISEE systems, n.d.).

A big disadvantage of SD is that it is not a behavioral model. It is not possible to simulate interactions between individual inhabitants of the VMD, as SD works on an aggregated level (Maidstone, 2012). Furthermore, SD can in some cases be integrated with GIS or other models, which is an important requirement as well. This integration could be achieved by developing the SD model in a platform like Python and subsequently connecting it to spatial data.

3.2.2. Agent-Based Modeling

ABM is a bottom-up approach (Maidstone, 2012), and the outcomes of the high-level system are determined by the lower-level behaviors. These behaviors are determined by entities called agents. The environment in which the agents occur has an impact on the agents, but the agents can also influence the environment. ABMs are stochastic models, and the model should be run multiple times to get a representative result (Howick et al., 2024). In most ABM approaches, there are discrete time steps, and each agent wakes up every day to see if they can do something or not. This makes ABM slower than other approaches (Caro et al., 2016; Railsback et al., 2017).

The advantage of ABM is that it can be used as a behavioral model. Through the use of agents, individual behavior can be simulated and agents can interact with each other (Maidstone, 2012). This leads to emergent behavior. Additionally, ABM can be linked to GIS, making it possible to include spatial aspects in the model. Lastly, by creating multiple classes of agents, it is easy to differentiate between the different types of inhabitants within the VMD.

The downside of ABM is that it does not typically offer dynamic output and is not very accessible. Based on discussions at Deltares and Maidstone (2012), it appears that ABMs are generally more difficult to understand and develop. However, the final model must be understandable for a broad audience. Furthermore, developing an ABM often requires a large amount of data, or else many assumptions must be made. It can also be challenging to calibrate the model to accurately reflect real-world behavior. This can be addressed by modeling, for example, the past ten years, and calibrating the variables to improve accuracy.

3.2.3. Discrete Event simulation

DES was also developed in the 1950s. One of the key characteristics of DES is that dynamic changes within a system are divided into discrete events, and during simulation, each event is executed in the correct chronological order. Between events, the state of the system remains constant. This makes the method very fast (Collins et al., 2023). In most cases, DES is a stochastic model, which includes randomness and requires multiple runs. This makes it hard to address stability in a system (Brito et al., 2011).

The advantages of DES are its speed and effectiveness when there are clearly defined events. However, it is more difficult to capture emergent behavior in DES compared to ABM. In DES, the model is determined by the system, while in ABM, the agents have their behavior (Maidstone, 2012). Furthermore, according to Brito et al. (2011), the user does not understand the underlying mechanics within a DES.

3.2.4. Hybrid model

Brito et al. (2011) and Howick et al. (2024) described multiple hybrid models: ABM combined with DES and DES combined with SD. An ABM is often combined with an SD model to simulate individual behavior using agents, while SD is used to summarize the data and apply it in a broader system context (Wu et al., 2019). A DES can be combined with an SD model, where SD simulates feedback loops and DES represents the remaining processes (Xu et al., 2018).

Another option is to combine DES and ABM. MESA 3 currently supports combining these two approaches (Ter Hoeven et al., 2025). The advantage of this is that agents no longer wake up at every time tick, but only when a specific event needs to occur. This significantly increases the speed of the model.

It is also possible to combine ABM, DES, and SD into one model; this can be done using AnyLogic. Another advantage of AnyLogic is its accessibility, as it requires little coding to build complex models. However, the downside of AnyLogic is the high cost of the license (Howick et al., 2024).

3.3. Model choice and packages

When looking at the requirements for the different modeling approaches, there are some conflicting factors. Dynamic output is only possible in Stella and Vensim, which are SD software. However, that means that it will not be possible to be a behavioral model, and it is also not possible to model all the different types of inhabitants. This is unfortunate since these are must-have requirements. However, SD ensures accessibility and provides an easily understandable output, and Deltares already has experience with this method. In addition, there is not one requirement that cannot be achieved by SD or ABM, while many requirements cannot be achieved by DES (for example, the modeling of human behavior and the dynamic output).

Based on the requirements and advantages/disadvantages of each modeling approach, several promising options became clear. These are outlined below, along with the reasons why they will or will not be created:

When looking at the functional needs of the model, a combination of SD, ABM, and DES would be ideal. This would allow for modeling different population groups in a fast and structured way, while also enabling quick visualization. All of this is possible using AnyLogic software (Anylogic, n.d.). However, Deltares currently does not hold an AnyLogic license, and obtaining one would be very expensive. Therefore, this option has been discarded.

Another option that came up during an interview with J. Kucharski was asked to build an SD model, convert it to Python, and connect it to a DES/ABM model. The output of the ABM/DES model would be aggregated per time step and used as input for the SD model. It is possible to build the SD model in Vensim or Stella and then convert it to Python using PySD. However, it cannot be converted back. This means that the interactive dashboard with sliders in Stella is no longer available (J. Kucharski, personal communication, March 2025).

MESA 3.0 also offers a combination of two of the three techniques. This version incorporates the DES features within ABM (Ter Hoeven et al., 2025). This makes it possible to assign actions to specific agents during the model's step function using a "do" function. As a result, only selected agents are activated, increasing the speed of the model compared to previous versions of MESA. The downside is that it still runs slower than an SD model and, due to the stochastic nature, multiple runs are required to obtain reliable results.

Another option is to build a standard SD model in Vensim or Stella. Stella is more dynamic, allowing for the creation of a dashboard with sliders to observe how the model responds to different input parameters. However, this is also possible to create in Vensim. Vensim was chosen for the familiarity, but it is possible to convert a model between Vensim and Stella. However, the downside is that the model can become very large very quickly, especially when trying to model all the different types of inhabitants (for example, low-skilled wage workers, agricultural households) as separate stocks (J. Kucharski, personal communication, May 2025).

All in all, it was decided to develop an ABM in MESA 3 and an SD model in Vensim. MESA 3 allows the addition of DES elements, which increases the model's performance. Moreover, this approach allows for simulating emergent behavior and building it around the different types of inhabitants. The disadvantage is the longer runtime, and that many assumptions have to be made. This is not the case for the SD model, but it quickly becomes complex and cluttered when modeling all types of inhabitants in separate stocks. Furthermore, the SD model is not a behavioral model. It is a continuity model that shows changes in the system over time (Brito et al., 2011).

Both of the models are created, and their output is compared to create advice for which modeling approach is most suitable.

3.4. Data analysis

To create the ABM and SD model, data was analyzed first. There were various datasets available from Deltares to analyze. The first is the Pop Housing Census, which provides information on household members' age, education, occupation, and housing situation. It is available for the years 2009, 2014, and 2019. The datasets from 2009 and 2019 contain panel data, in which the same individuals were surveyed, allowing for direct comparison over time. However, only the first half of the questions of the 2009 data were about the VMD; in the remainder of the questions, the region was taken out. As a result, questions about births, deceased members, and homes could not be used from the 2009 data. Looking at the 2014 data, there is only a province and hoso column, but no district level is available. Therefore, it was not possible to create a household ID and say something about the characteristics within a household. In addition, the occupation and sector codes of the 2014 data were not available, so it was not possible to determine what occupation people had. Therefore, it was decided not to include any of the 2014 data. For data that was not available from 2009, the 2019 dataset was used.

The second dataset available is the VHLSS. This set is available for 2010, 2014, 2016, 2018, and 2020. Besides age, this data also provides insights into income and expenses, and for example, yields from farmers' crops. The disadvantage of this data is that it is very raw and contains many outliers. Moreover, the weight of each respondent is unclear, making it difficult to look at as a representative dataset. It was therefore decided to focus only on the VMD as a whole, and not per district, for this dataset.

An overview of the data sources and their corresponding datasets is provided in the Appendix B.

4

Agent-Based Model conceptualization

Creating socioeconomic ABMs is a relatively new concept for the department "Climate Adaptation and Disaster Risk Management" at Deltares. Therefore, this chapter attempts to explain all the steps and considerations made during the conceptualization phase of the ABM. First, it is tried to define the agent classes by looking at some way to classify the households in groups. Then, all household member agents and household agents are explained together with their functions. The environment is created in the model class, and all these come together in the conceptual models. The steps taken for the initialization of the model are also demonstrated, together with the limitations and assumptions that were made.

4.1. Agent types

There are different ways to categorize households in the VMD. Deltares previously distributed households based on the dominant income source or on which occupation the household spent the most time. This resulted in seven household categories: low-skilled wage household, non-farm low-skilled wage households, agri crop household, aquaculture household, other agriculture household, business, of non-labour household. Table 2.1 describes these occupations.

In addition, Pham et al. (2022) categorized the VMD households based on their success rate. In their research, there were proponents, opponents, fragile, and unaffected farmers. Fragile farmers were, for instance, farmers with freshwater crops in a saltwater zone. However, not all household types would be represented in each district. Furthermore, this classification does not provide insight into the size of the farm or the type of crops cultivated.

It was tried to do a cluster analysis, based on the VHLSS data, to identify household types. However, data analysis shows that many households have multiple sources of income. When household income is divided into three categories (wage, self-employed agriculture, and self-employed non-agriculture), only 43% of households earn income from a single category, which means that there are 57% of "diverse" households. As a result, a cluster analysis is not able to generate representable clusters.

Another option is to define a dominant income, which is based on the main income source if more than 60% of the household income comes from that source. However, still 35% of the households remain "diverse" using this method. A second issue with this approach is that it overlooks the remaining income sources. For example, if a household is classified as a "wage" household but 40% of their income comes from rice cultivation, and the rice yield fails, that 40% income loss is ignored in the model.

All in all, there are many different options, but all have their disadvantages. Therefore, it was decided not to classify households by type. Instead, a simple distinction is made between households with land and without land. If they own land, they are further classified into three groups:

1. Small (0.3-0.5 ha)
2. Medium (0.5–2 ha)
3. Large (2-5 ha)

If a household does not have land, it falls into the class of landless households.

Each household also consists of household members. Each member has an occupation, according to the categories listed in Table 2.1, as well as an employment type: family worker, self-employed, or employee. This structure allows households to generate income from various sectors.

4.2. Household agents

The two main types of households (land and landless) have different activities. Both types have yearly activities, such as receiving interest on savings, and they may choose to migrate. In addition, land households are responsible for harvesting crops and paying wage workers. They can also switch crops, a decision that is determined based on social theories. These different functions are elaborated below.

4.2.1. Yearly activities

Each household has annual activities. First, it is determined whether a child is born in the household, based on the Pop Housing Census 2019. From an interview with a sociologist in Vietnam, it became clear that there are high interest rates on savings (5%) and loans (10%) (personal communication, April 2025). These are received or paid accordingly, and land-owning households with loans also pay off their debts.

In addition, there is a probability that a household has contacts in the city. This probability is equal to the ratio of households that have already migrated. Thus, if more people have migrated in the model, the chance that a household has contacts increases. The same logic applies to the facilities in the neighborhood: the current number of service workers is divided by the initial number of service workers. The more service workers migrate, the fewer local facilities remain.

Finally, for land households, it is determined whether they attended an information meeting that year. These are meetings organized by, for example, commercial companies or the Hội Nông dân Việt Nam (Vietnam Farmers' Union). If the household is a member of the association, it is assumed that they attended the meeting.

4.2.2. Cultivation of crops

Land households can cultivate crops. Within each sector (rice, annual crops, perennial crops, and aquaculture), there are many possible crop types, but data is not available for all of them.

First, an interview was conducted with N. Mulder, who developed a serious game about the VMD for Deltares. He selected crops based on diversity. Some of their crops were salt-tolerant, others provided a high income, and others had high water demands. However, since the focus of this model is salinity, not all those crops had clear data on how they perform under varying salinity conditions (N. Mulder, personal communication, April 2025).

Therefore, it was decided to use FAO data (Blom-Zandstra et al., 2017). For each category, it was looked at which crops were stated as "promising" and which had salinity-related data available. For annual crops, maize was selected, and for perennial crops, coconut. For aquaculture, research by Joffre et al. (2015a) was used. They identified three types of shrimp farming (extensive, intensive, and mangrove-shrimp), and found that extensive was implemented in 78% of the farms. Therefore, this type was selected for the model.

The first step is to calculate the yield, based on the type of crop, the size of the land, if a shock has occurred, and the human livelihood (this is explained in Section 4.2.3). For the yield per ha, FAO data were used (Blom-Zandstra et al., 2017). The impact of salinity calculated using the salinity curve: $Yield = 100-(slope*(salinity-threshold))/100$ (Tanji & Kielen, 2002). The **slope** is the percentage per dS/m, and means that when the salinity reaches this level, all yields for this crop will fail. The **threshold** is in dS/m and is the salinity level at which the crops behave perfectly. **Salinity** is the current salinity level. An example: for rice, the threshold is 3 and the slope is 12. When there is a salinity level of 5, the farmer will have a rice yield of 76%.

A disadvantage of this approach is that this formula should use soil salinity, but in this model, only water salinity is currently available for the VMD.

Talking to N. Mulder, it became clear that it is very hard to determine how effective certain measures are in preventing salinity shocks (N. Mulder, personal communication, April 2025). This has been simplified by using knowledge and experience as a proxy. When these are high enough, the household is considered better prepared and will be less impacted by salinity.

If a household cultivates shrimp, the model checks whether a disease outbreak occurs. The probability of this is based on Joffre and Bosma (2009). In the case of a disease, the household can choose whether or not to use antibiotics, which currently depends on their knowledge, experience, and financial situation. The benefit of using antibiotics is that the shrimp yield for that year is not reduced. However, this comes at the cost of antibiotic accumulation in the soil. According to conversations with N. Mulder and L. Hermans, after a few years of continuous antibiotic use, the concentration becomes so high that it starts to affect water quality, which in turn impacts shrimp yield. This can be seen as a lock-in effect: initially, yields remain high, but they drop quickly over time. Eventually, the household is forced to abandon the farm due to severe soil contamination (personal communication, March & April 2025).

The second step is to calculate the total costs, which are linear to land size. However, there is limited data available on this. The VHLSS data were not used, as they contained many outliers, and the costs were aggregated for all annual crops, rather than separated by crop (for example, maize). For rice costs, data were used from Pedroso et al. (2017) and Tong (2017). For maize, research of Nassirou Ba (2017), Nguyen and Luxner (2024), and Pedroso et al. (2017) was combined. The shrimp data was based on Joffre et al. (2015b) and Khai et al. (2018), and coconut from Nguyễn (2024) and Yeswanth et al. (2024). An overview of all values in literature is provided in Figure B.3 in Appendix B.

Within the total costs, the wage costs are determined. These costs are based on four factors: the number of man-days required per hectare per crop, the number of household members acting as family workers, whether or not farm machines are used, and the salinity level. The assumption was made that crops are supposed to be planted within 14 days. Rice is harvested within 7 days, while maize and shrimp are harvested within 14 days. Furthermore, approximately 1/3 of the man-days are needed for planting, and 2/3 for cultivation.

The model checks how many people are available as family workers. If more labor is needed during planting and cultivation, external wage workers are hired. If the household uses machines, the assumption was made that only half of the man-days are required during harvesting. If there has been a salinity shock, for example, rice yield is only 75% instead of 100 percent, then only 75% of the man-days during cultivation are needed, because there is less rice to harvest. Farm workers earn an average wage of 200,000 VND per day (Pedroso et al., 2017). In the model, a distinction is made between low-skilled (190,000 VND) and high-skilled (210,000 VND) wage workers.

In the case of maize, the total cost turned out to be less than the wages of the workers. This is because the number of man-days per hectare for maize is quite high, 106 per ha per growth cycle. (Pedroso et al., 2017), The total cost per hectare is relatively low (6.8 million VND). Compared with rice: rice has a cost of 16.5 million VND/ha and only requires 48 man-days/ha (Pedroso et al., 2017; Tong, 2017). Since this was a big difference, it was decided to use fixed costs for maize and add the wage worker costs on top. Otherwise, all households would immediately abandon maize farming due to its very low profitability.

After harvesting, the total household income is calculated for each household. This is based on the harvesting of crops if the households have land, and the income from wage working or working in the non-agricultural sector. The expenditure of the past time frame is calculated and subtracted from the savings. To calculate expenditure, VHLSS2014 is used, including expenditures on food, non-food, and housing. Then, the quartiles were calculated. For children, the 25th percentile value was used as their estimated expenditure.

4.2.3. Sustainable livelihood theory

To check how land households are doing after receiving income, the Sustainable Livelihood Theory was used. According to this theory, the well-being of a household is determined by five types of capital: natural capital, physical capital, human capital, social capital, and financial capital (McLeod, 2001). Each of these factors is assigned a score between 0 and 1, and then the average livelihood score is calculated as the mean of these factor scores.

This theory has been applied before in the VMD. For example, Tran et al. (2020) applied a variation of this theory, the livelihood vulnerability, to three districts in An Giang province. The main difference

Table 4.1: Factors on which the livelihood factors are based

Livelihood factor	Variables
Human livelihood	Education level
	Attended information meeting
	Experience level
	Dissabilities within the household
Social livelihood	Social situation
	Member of a farmer association
Financial livelihood	Savings
	Debt
Physical livelihood	Land size
	House quality
Natural livelihood	Salinity level

compared to the Sustainable Livelihood Theory is that this version also includes a livelihood strategy and a natural disaster and climate change factor, and focuses on how vulnerable people are, rather than how well they are doing. Based on their research, relevant variables used to determine the livelihood scores were chosen, and these were later validated by a Vietnamese student (T. Tran, personal communication, April 2025).

Table 4.1 shows an overview of the variables on which the livelihood factors are based. First, there is the **human livelihood**. When looking at *education*, the average level of education of all household members above 15 years of age is used. If someone has "below primary education", they receive a score of 0. "Primary education" is scored as 0.5, and, for example, secondary education is scored as 1.

If a farmer has cultivated the same crop for more than three years, the household has an *experience* score of 1. When this is not the case, they do not have much experience, and their experience score is 0. This three-year threshold is based on the Pop Housing Census 2019, which also uses three years as a benchmark. In addition, it is checked whether the household uses *machines*. If at least one household member uses machines, this variable is scored as 1; otherwise, it is 0. These values are also based on the Pop Housing Census 2019.

Finally, disabilities within the household are taken into account. This is based on difficulties in hearing, seeing, walking, and remembering, taken from the Pop Housing Census 2009. The dataset includes a 5-point scale of disability severity. A household member with "some difficulty" scores 0.5. When there is "a lot of difficulty", there is a score of 0.75, and "unable to do" scores 1. Then, the total level of disability of the household is calculated. All individual scores a summed, and a total score of 1 gives a disability score of 1 for the household. This means that a minimum of 1 household member is unable to do something, or two or more household members have some difficulties.

The **social livelihood** is based on the social situation of the household, and if someone in the household is a member of an association. The *social situation* is calculated by dividing the current number of households by the total number of households at the start of the model. The more households migrate, the lower the social situation. The household is *member of an association* if one or more members of the household are members, and this is based on the probabilities in the VHLSS2014 data.

The **financial livelihood** is calculated based on the savings and debt of the household. When the *savings* are higher than 0, this score is 1. For *debt*, the ratio between the current debt and the maximum allowed debt is used. The maximum value of debt is based on the value of the assets of the households. These are defined by the land size and value of the house.

The **physical livelihood** is based on the size of the land and the quality of the house. For *land size*, it was checked within each category how large the land is. For example, a medium-sized farmer has land between 0.5 and 2 ha. If someone has a land of 1.8 ha, the factor will be 0.86. *house quality* is defined using the Pop Housing Census 2019 and taking into account the main construction, roof, and outer walls.

For the **natural livelihood**, the *salinity level* is taken concerning the crops cultivated by the household. If the salinity level is below the crop's threshold, the salinity suitability is set to 1. If the salinity results in a yield of 75% or higher, the suitability is 0.5. For rice, this corresponds to a salinity level between 3 and 6 dS/m, and for maize, between 1.7 and 4.2 dS/m. If the salinity level leads to even lower yields, the suitability is 0, and as a result, the natural livelihood score is also 0.

4.2.4. MOTA framework

To determine whether land households are changing their crops or not, the Motivation and Ability framework is used. This framework is based on actor analysis methods and also includes behavioral insights (Pham et al., 2022). The framework starts with a trigger, which is, in this case, that the income is lower than the expenditure. There are perceived threats and opportunities, and based on those, the farmer has a motivation. On the other hand, the farmer also has abilities. These are categorized into technical ability, financial ability, and institutional ability. Motivation and ability are scored on a scale of 0 to 1. An action is defined by multiplying the motivation by the ability score. Figure 4.1 shows an overview of this framework, applied to farmers in the VMD.

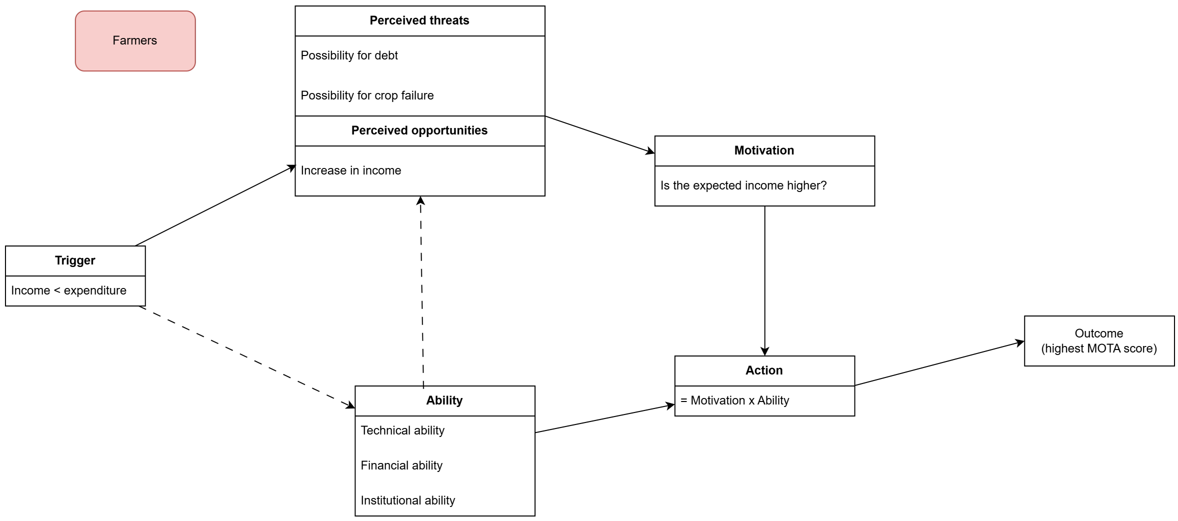


Figure 4.1: MOTA framework used for the farmers in the VMD

The MOTA framework has already been implemented for the VMD. For example, Korbee et al. (2019), Nguyen et al. (2019a), and Pham et al. (2022) both focused on the Ben Tre province, and Nguyen et al. (2019a) even on changing cropping systems. Based on their variables and the available data, this framework is applied in the ABM.

Before this is implemented, it must be determined which crops households can switch to. If a household has attended the information meeting or is a member of an association, it has received all the relevant information about which crops are recommended based on their salinity levels. Furthermore, all households can observe their neighbors: What kinds of crops are they cultivating? All of these crops are collected into a list called "possible next crops".

The VHLSS 2020 data was analyzed to determine how many people switch crops and what the average switching costs are. However, it also became clear that some crop switches were not made at all, meaning that no cost data were available for them. An example might be that people are not switching from shrimp to another crop, due to the lock-in effect.

Per crop, abilities and motivation scores are calculated. Ability scores are based on the abilities in Table 4.2. Each variable will receive a score between 0 and 1. This will be averaged per factor, and then the average of the three factors is calculated.

Financial ability checks if the household has enough *savings* to cover the costs of switching to the new crop. If the household has sufficient savings, the financial ability is set to 1. If not, the model checks how much the household could potentially borrow. If the expected profit over five years from the new crop is greater than twice the loan amount (which ensures that other expenses can still be covered),

Table 4.2: Variables required to determine ability

Ability factor	Variables
Financial ability	Switching price
	Current debt
	Savings
Institutional ability	Human livelihood
	Required knowledge for switching
Technical ability	Salinity level
	Machines

the household can take the loan, and the financial ability is set to 0.5. If the household cannot afford the switch, the financial ability is set to 0.

Institutional ability is determined by the household's *human livelihood*, which includes education level, whether someone attended the information meeting, experience level, and disabilities within the household. This human livelihood score is compared to the level of knowledge required to make the switch, which is based on assumptions. For example, switching to shrimp is considered more difficult than switching to coconut because shrimp farming requires precise antibiotic use; otherwise, the shrimp farm will be unsuccessful.

Technical ability depends on the salinity level. If the ideal salinity level of the new crop is lower than the current salinity level of the household, the technical ability is 1. However, for maize, there is an additional requirement: production costs increase significantly when the land size is larger than 1 ha, and the household does not use machinery. This is because maize requires 103 man-days per hectare per cycle, which requires the hiring of many wage workers. If the household lacks machinery to compensate for the man-days, the technical ability is set to 0.

The **average ability** is calculated by taking the mean of the three abilities. However, if either the financial or technical ability is equal to 0, then the average ability is set to 0 as well, since this means that the farmer is not capable of switching to this crop.

In addition to abilities, there are also **motivations**. This motivation is based on future income. If your expected income over five years is higher than your current annual income multiplied by five, and you have a financial ability of 1, then your motivation is 1. This means that you can afford the switch to your savings and you will become wealthier as a result. If you can only afford it by taking a loan, but your income would still increase, your motivation is 0.5.

In the MOTA framework, the current crop of the household is also taken into account. If the annual income from this crop is higher than your required income (that would happen, for example, in normal scenarios, and not during a salinity shock), the household receives a motivation of 1. Otherwise, the motivation is set to 0.2. This is based on an assumption, but it was decided not to assign a value of 0, since the household is already familiar with how the crop works and avoids the hassle of switching.

The final **MOTA scores** are calculated for each crop. The crop with the highest MOTA score will be implemented. When two crops have the same MOTA scores, a random choice is made between those two crops. Furthermore, a threshold is set to 0.2; if the highest score is below the threshold, no change will be implemented. This prevents farmers from switching to crops that are not suitable. However, 0.2 is an assumption.

Once the new crop is selected and differs from the current crop, a change should be implemented. First, it is checked whether a loan needs to be taken out and the savings of the household are reduced by (the remaining part of) the switching cost. The agent then changes sectors, based on the new crop. Lastly, the household's "crops and land" variable is updated. If the switch takes place in July, it is not possible to harvest the new crop as early as August, so a waiting period must be implemented. This waiting time is six months. When these are finished, it is possible to harvest a new crop (at the correct time of year).

There is an exception for coconuts, they take about five years to grow in the VMD. However, according to (Blom-Zandstra et al., 2017), it is possible to intercrop with rice or maize in the meantime. The trees are not yet fully grown, allowing rice or maize to be cultivated between them. Therefore, the crops and land variable will include rice and coconut or maize and coconut. Rice or maize will then occupy only half of the land, as the other half is used for coconut cultivation. The waiting time for coconuts is set to 60 months (5 years). After these 5 years, the household fully transitions to coconut farming, and rice or maize is no longer cultivated.

4.2.5. Switch occupation

When wage workers are paid, the landless household calculates their total household income and compares it to their expenditure. If the income is not sufficient to cover their expenses, they might switch occupations instead of crops. The MOTA framework is not applied in this case.

Not all occupation switches are possible: Low-skilled agents can only switch to other low-skilled jobs, and High-skilled agents can only switch to high-skilled jobs. If another household member is already employed in a different occupation, they will check if switching would be financially beneficial. If this comparison cannot be made, the household switches randomly. In this case, there is a chance that income improves, but also a chance that it worsens. When that happens, they might switch back.

4.2.6. Migration

When income is too low and there are no savings left, or if too many antibiotics have been used on the shrimp farm, a household will migrate. A Migrated Household agent is created, and each household member becomes a Migrated Household Member agent.

If the household owns land that is still in good condition (which means that there is no antibiotic surplus in the soil), neighbors have the opportunity to take over the land. Among neighbors, the one with the highest financial livelihood is considered first. Then, it is checked whether this neighbor can afford the new land. If so, the land is added to their land size. This may allow the neighbor to expand, for example, from a small farm to a medium-sized farm. The neighbor also takes over the type of land. For example, if the land was previously used for rice cultivation, the neighbor cannot immediately switch it to aquaculture without incurring switching costs. The decision to switch will be made later using the MOTA framework.

In addition to the entire household, it is also possible for individual household members to migrate. This occurs among people between 15 and 35 years of age. At each step, there is a fixed probability that they will migrate. This probability increases if the household has contacts in the city or if they have seen a job advertisement about the city. The migrating household members are then removed from the household and the model, and new migrated household member agents are created for them.

4.3. Household members

The individual household members also have a few functions. Each year, they become one year older, and there is a chance they might die based on their death age. When this happens, the household member is removed from both the household and the model. It is also checked whether they are older than 59 and eligible for retirement. If so, they become a Non-labourer agent.

Besides the retired household members, there are many children in the model who fall under the Non-labourer category. These children attend school, which increases their level of education. When a child turns 15, the probability that they will continue their studies and complete higher secondary education is assessed, based on data from the Pop Housing Census 2009.

If the child starts working, probabilities determine whether they will work in the agricultural or non-agricultural sector. If the child is part of a land household and enters the agricultural sector, they work on the land as an agricultural worker. If the household has no land, the child becomes an agricultural wage worker. In the non-agricultural sector, the child can become either a manual worker or a skilled service worker, with data showing approximately the same probabilities. The child is then determined whether it becomes self-employed or an employee, based on data from the Pop Housing Census 2019.

If the child continues their education, there is still a high chance they will start working by age 17. The same sector and employment status probabilities as for 15-year-olds are then used.

4.4. Model Class

All of the above functions are controlled from the model class. But before this happens, first the total number of households that have not migrated yet is calculated, and the proportion of remaining households is calculated. Second, it is checked if a shock has occurred. If that happened, the salinity level of every land household would be multiplied by 1.5. Thirdly, the waiting time per crop for the land households is reduced, allowing for, for example, harvesting coconuts. Fourth, the annual activities of all agents should be carried out. This means that they get older, a child might be born, or some will die. Lastly, based on the agricultural calendar, it is checked which crops can be harvested. An overview of when each crop can be harvested is shown in Table 4.3.

Table 4.3: Overview of crop types to harvest in each month

Month	**Crop**
February	Rice
	Coconut
April	Maize
	Shrimp
	Coconut
June	Coconut
August	Rice
	Maize
	Coconut
October	Shrimp
	Coconut
November	Rice
December	Coconut

After harvesting the crops, it is important to pay the wage workers. For each agent who has just harvested, the number of man-days of wage workers required is calculated. An interview with P. Jansson revealed that the specific agricultural sector in which wage workers are employed is likely not to matter. It is possible that they harvest rice one season and coconuts the next. It depends on where the work is (p. Jansson, personal communication, May 2025).

Then, the number of low- and high-skilled agents is calculated. An assumption is made that they work an equal number of hours. Each wage worker is paid based on the total number of man-days needed and the number of workers available. Low-skilled wage workers receive 190,000 VND per man-day, and high-skilled wage workers receive 210,000 VND per man-day.

Every month, non-agricultural workers are also paid. For low-skilled non-agricultural workers, the model calculates how many of them are still working, compared to the start of the model in this occupation. When more low-skilled non-agricultural workers have migrated, there is more work and higher wages for those who remain. The same applies to manual workers and those in the ”other occupation” category.

For service workers, wages are influenced both by reduced competition (due to out-migration of others in the same role) and by demand. If many people have migrated in general, the demand for their services decreases, which can reduce the income of service workers.

Once everyone has received income, the model checks the household income levels and may trigger changes if income is too low. This includes land-owning households going through the MOTA framework, and landless households potentially switching occupations. At this stage, migration decisions are also made.

4.5. Conceptual models

All functions of the household agents and the agents of the household members are combined in the ABM. Figure 4.3 presents a conceptualization of the land households, showing how these functions are interconnected. On the left side, in blue, are the yearly activities shown. Green represents the harvesting process of the crops, and yellow represents the process of calculating income and paying the wage workers. Following that, orange is the livelihood assessment process, the MOTA framework, and the possibility of migration.

Figure 4.2 conceptualizes the process for landless households. The yearly activities are shown in blue, and the yellow boxes represent the process of receiving income. The orange part shows the possibility for migration and the changes in occupation. Lastly, the red boxes mean that the agent becomes a migrated agent.

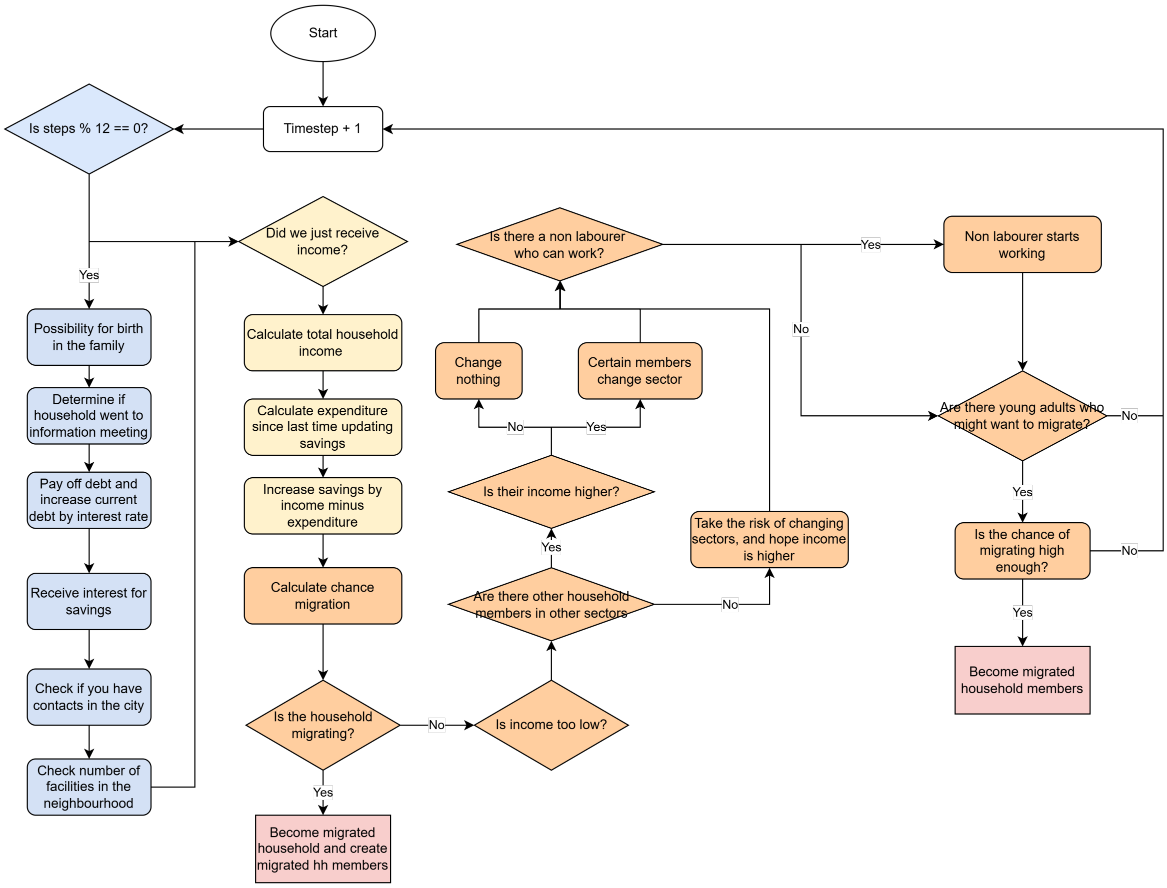


Figure 4.2: Conceptualization of the landless households in ABM

The conceptual models for individual households can be found in Appendix C.

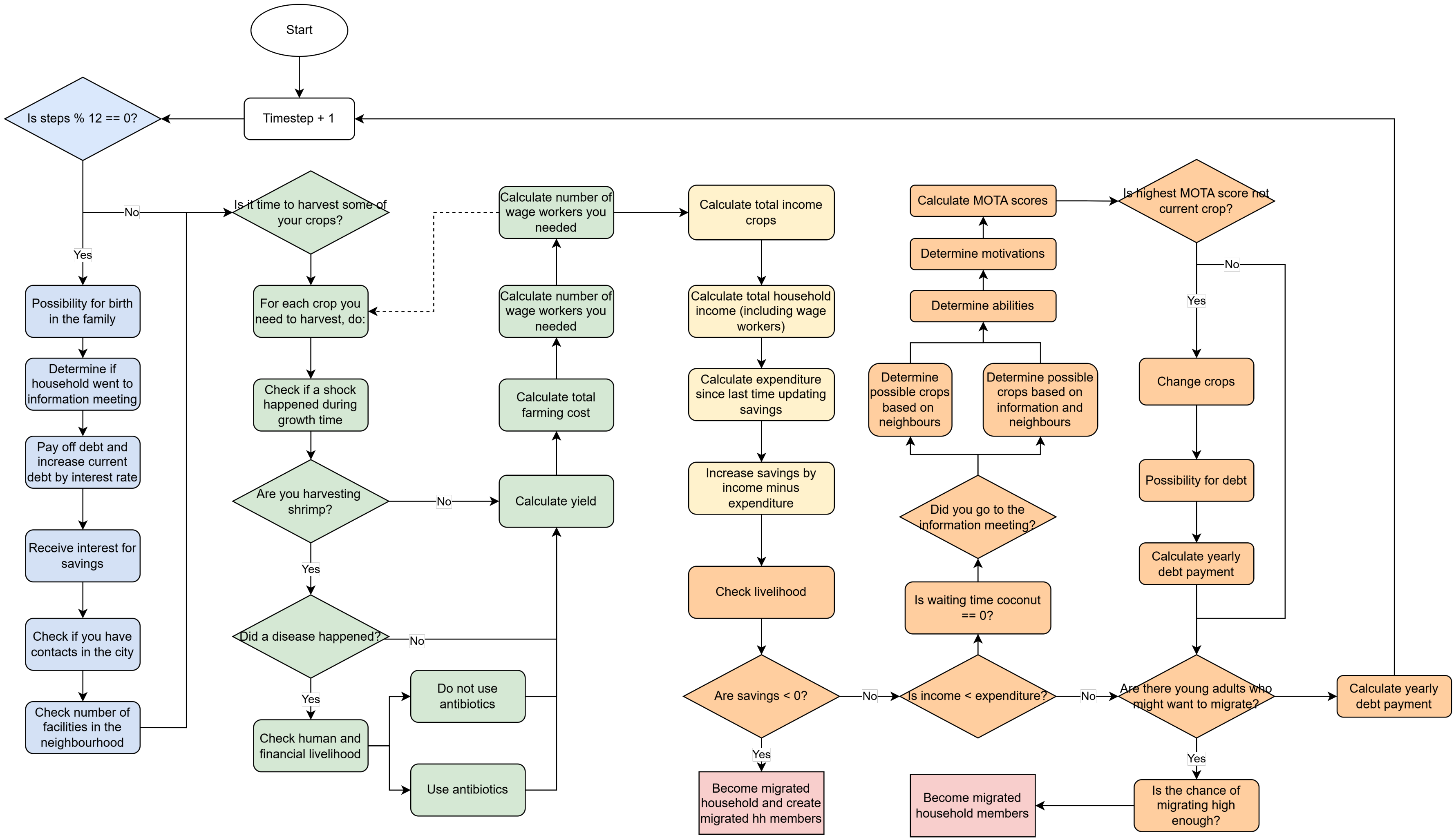


Figure 4.3: Conceptualization of the land households in ABM

4.6. Model initialization

The first step is to create individual members of the household. These are then assigned to a household, and then the land households are placed on a map. An Excel file of the data analysis is used as input for the initialization. An overview of the entire initialization process is shown in Figure 4.4.

At the start of the model class, the number of agents is defined: this is the number of household members that will be created. First, all agents are assigned an *age*, based on the Pop Housing Census 2009. Based on their age, it is determined whether the agent is *working* or not. If they do not work, they are placed in the Non-labourer class. Otherwise, a *sector, occupation, and employment type* are assigned. This is done based on the Pop Housing Census 2019. For each sector, there is a probability that an agent will have a certain occupation. In the aquacultural sector in the district Gò Công Đông, there is, for example, a chance of 62% that someone will work as a low-skilled agri worker. Furthermore, the household member can be a family worker, employee, or self-employed. This distribution is created within the sector and occupation distribution. For example, a low-skilled agri worker within the aquacultural sector has a probability of 64% of being an employee, 18% of being a family worker, and 18% of being self employed.

Based on their occupation, household member agents will be added to a **Class**.

When all household members are created, it is time to create households. First, **land households** are created, and this is based on the number of household members who are self-employed and work in the agricultural sector. These agents are the "owners of the farm". Based on the Pop Housing Census 2009 data, a *Household size* is defined, and the *main crop* is determined based on their sector. Furthermore, land households have a *land category* (small, medium, large), and *land size* (for example, 0.6 ha). Lastly, a *housing quality* is defined based on VHLSS 2014.

Then, it is time to add *household members* to the land household. Based on the VHLSS 2014, a distribution of household members within a certain type of household is calculated. For example, in a small aquacultural household, there are on average 0.64 persons working in "wage", 2.34 persons working in "self agri", and 0.23 persons working in "self non-agri". When the randomly generated probabilities are high enough, someone in these types of work is added to the household. When the household is not full yet, non-labourers are added.

De household agents are added to the model, and their agent class is based on their land size: small, medium or large.

When all land households are created, it is time to create **landless households**. It is required that each household has 1 adult, and when the adults are all assigned to a household, no new households are created. Each household has a *household size*, based on the Pop Housing Census 2009, and the household members are randomly added until the household is full.

After the creation of households, the land households are placed on a **map**. This map is created by taking salinity point data from Deltares, which is transformed to a raster file using QGIS. The disadvantage of this data is that this is water salinity, ad not soil salinity. This means that these data are not the correct salinity for which the crops are impacted, but it is the only available data. There are different formulas to transform water salinity to soil salinity, but all of these need other environmental factors, for instance, temperature, and will not make it more reliable. An expert should investigate this.

The raster file is combined with district shapefiles of 2015 (Hijmans, 2015). This process can be seen in the *"Create land for agents.ipynb" file.*

When entering the correct district, the data is imported in the function *gather shapefiles* in the model class. For each land household, the main crop is checked and a point is searched on the map that matches this salinity level. When all agents are assigned, the three nearest nodes are defined as "neighbors".

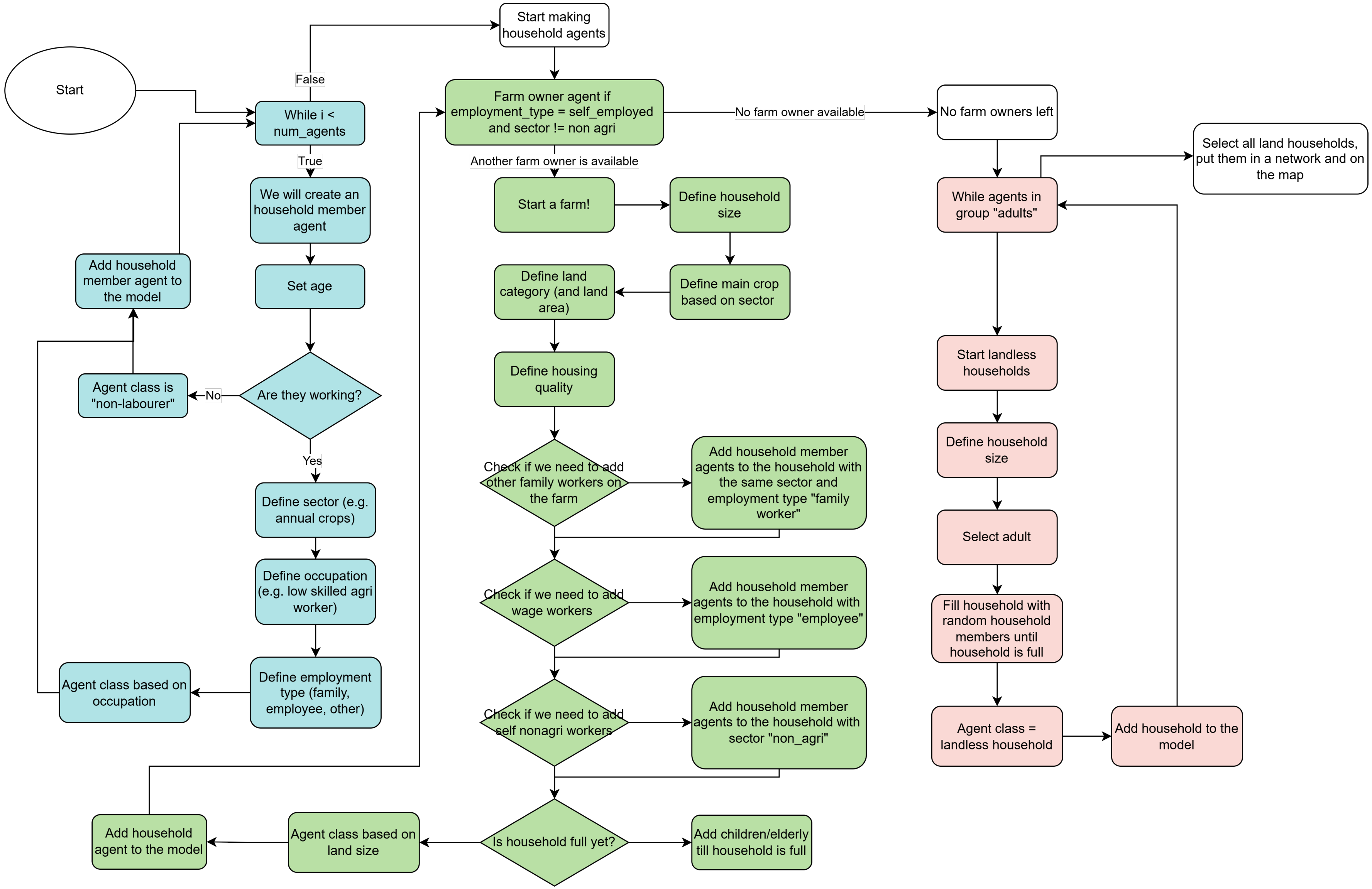


Figure 4.4: Initialization to create household member agents (blue), land households (green) and landless households (pink)

4.7. Assumptions and simplifications

During the formalization of the model, some assumptions and simplifications have been made. Most of them are already mentioned above, but this section gives a complete overview.

4.7.1. Assumptions

- The probability of households and household members migrating. It is difficult to estimate how high the probability is each year and how much this changes when people have, for example, contacts in the city. It was tried to tweak this to match past data from Deltares.
- Household members can easily switch jobs in the model, and if there is less work available, their income will be lower. It is not clear whether this easy switch is possible in each province.
- During the crop switching process, it is checked if a crop switch is financially feasible based on the condition that the profit over five years must be at least twice as the loan they take to pay the switch. This is to prevent land households from making switches that they cannot pay. However, it is not clear how this check is done in reality.
- The MOTA framework is used to check if agents are switching or not. However, this makes it seem as if the crop changes are a rational decision, and the residents really check beforehand if the crop change is a good idea or not. It is not known how rationally they actually think, and if they know about their abilities.
- When looking at crop changes, a motivation score of 0.2 is assigned to an agent's current crop when their income is lower than their expenditure. This is because switching would be more of a hassle. The 0.2 can also be, for example, 0.1 or 0.2, and is an assumption that might also differ per land household.
- The smarter individuals are less impacted by salinity because they are "smart enough" to take appropriate measures. In the ABM, this is determined by having a human livelihood of 0.5.
- Land agents want to plant their crops within two weeks, and harvest within one or two weeks. Additionally, one-third of the wage workers are required during planting, and two-thirds during harvesting. If machines are available, only half the number of wage workers is required during harvesting.
- The price to buy land from a migrating agent is 78 million VND / ha. This is a bit more than 2500 euros. A house costs between 1750 and 2600 euros.
- Each time a land household experiences a shock, its salt experience will increase by 0.2.
- Land households start with 20 million VND savings, and landless households 10 million VND.
- People retire at 59 years of age. However, if the household income is low, someone may continue to work until they are 75 years old. The minimum age to work in times of need is 11 years old.
- When farmers switch to, for example coconuts, the assumption is made that there is a market for coconuts and that they can sell their coconuts without issues.

4.7.2. Simplifications

- It was decided to model only one crop per sector. There is, for example, only triple rice available in the rice sector, no double rice or salt-tolerant rice.
- Except for the coconut/maize and coconut/rice combination, it is possible to grow only one crop at a time. It is not possible to combine, for example, shrimp and rice, to keep the model manageable. In addition, forestry and livestock are left out.
- It is not possible to sell only a part of your land. The only option for land households is to migrate and sell everything.

- Migrated agents do not have a function in the model. In reality, there is a chance that they send remittances back home or that households make decisions involving the migrated agents. However, including this would require a complete sub-model for migrated agents, which was beyond the scope.
- The probability that someone is migrating also depends on how far they live from a major city. This factor was not included.
- Only salinity was considered, not other environmental factors, such as available water, although they are correlated.
- Non-agricultural workers have a fixed income in this model, which is not the case for all household members in reality. However, the extent of income variation is unknown.

5

Agent-Based Model results

First, the model design is explained. It is explained what the scope of the model is and how many runs are done. Furthermore, the model is verified by looking at the map placement, household composition, and land area. Validation is done by face validation, historical data, and extreme conditions. The model output will be shown for three key performance indicators, and sensitive factors for migration are studied. The complete ABM can be found on GitHub: https://github.com/Juliettevanalst/Thesis

5.1. Model Design

5.1.1. Scope

The focus is on the rural areas of VMD, and therefore, people living in urban areas are not included in the model. In addition, farmers and wage workers are taken into account. There is a group of people in the VMD whose main income is of forestry or livestock, and these are not included.

The VMD has a population of 18 million inhabitants, with large differences in salinity levels and land use across the area. Therefore, it was decided to perform the analysis at the district level. On average, a district contains about 200,000 people. At the top of the model class, a district can be selected by entering the name and number of the district. In the file *Complete data analysis for districts.ipynb*, a district number can be selected, and the file will automatically generate an Excel file and load the correct data.

To get a representative view of the different areas, three districts have been selected. District 894, which is Thoai Son, is located in the northwest of the VMD and is not directly adjacent to the river. This district has low salinity levels and is mainly focused on rice cultivation. They are not used to high salinity, and therefore they should be impacted more by the shock. The second district is number 908: An Biên. This is a coastal area in the western part of the VMD, and the main focus is aquaculture. The third district number 824: Gò Công Đông. This district is located in the Tiền Giang province, which is in the northeastern part of the VMD. It is a coastal district, and the bottom of the district connects to a branch of the Mekong River. This district is interesting, since the salinity levels are high, while the main crop is rice according to the Pop Housing Census 2019. The farmers in this district will be more used to rice than the Thoai Son farmers. Figure E.1 in Appendix E shows these districts on the map. The experiments and sensitivity analysis in this document will be based on district 824: Gò Công Đông.

The model will run each time for 300 steps, which represent 25 years. The start year is 2014, to make it possible to compare the outcomes with historical data, and use the correct input data. The model creates 1000 household member agents, which leads to approximately 250 households.

5.1.2. Number of runs

ABM is a stochastic modeling approach, which means that each run will lead to a different result. Therefore, the model should run multiple time with different seeds to get a representative result. The appropriate number of run is calculated using a convergence test. The data is collected at the last step, and the expanding mean is calculated and standardized. It should be noted that the input variables stay the same during these runs, but the randomly generated numbers and probabilities will differ. When the convergence is between [-1, 1], the model can be seen as stable. Figure 5.1 shows the convergence for the number of annual crop agents and migrated households. It has been decided to run the model 150 times, since the running mean is around zero for both variables.

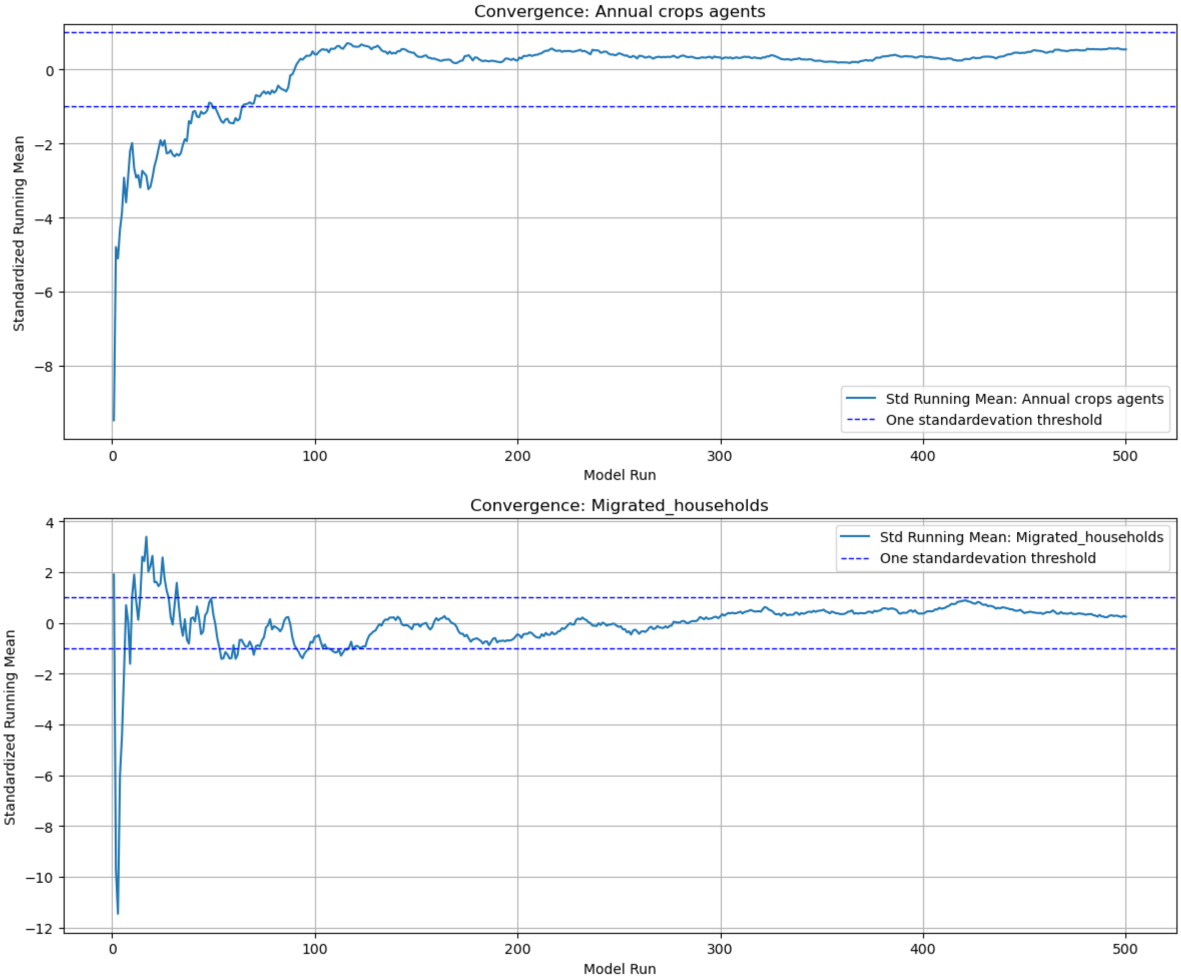


Figure 5.1: Convergence for annual crop agents (top) and migrated (bottom)

5.2. Verification

Verification is the process of checking whether the computational model matches the way it was intended to be constructed. The following three factors are taken into account: the placement of agents on the map, the composition of households with occupations, and the land area.

5.2.1. Map placement

The land agents are placed on the map of the district. The main problem was that there is only a small part of land suitable for rice and annual crops, while the data showed that the main crops were rice and annual crops in this area. Therefore, it has been decided to create an algorithm that finds a low-salinity place for these farmers. Figure 5.2 shows the salinity levels, and the placement of the agents on the district. There are 9 agents placed incorrectly. However, there are 105 agents, and the incorrect agents are less than 10%. Furthermore, in reality, there is a chance that there are indeed farmers in the saline area, due to the changing environment.

5.2.2. Household composition

Figure 5.3 shows the household composition for landless households, and large, medium and small households.

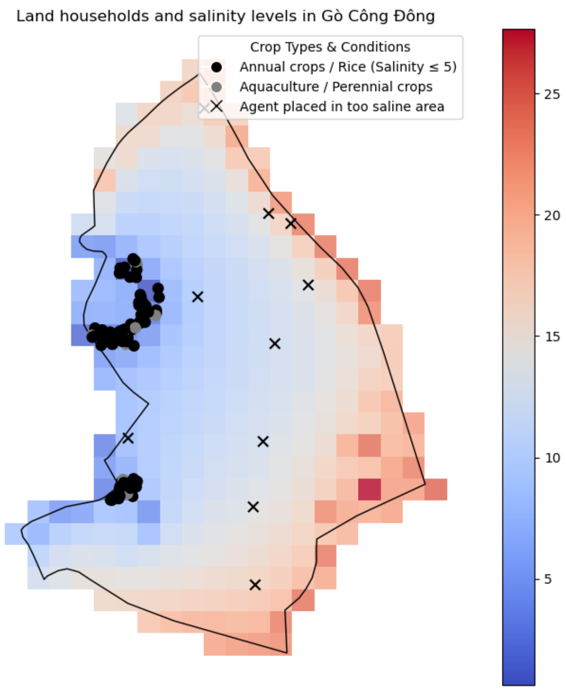


Figure 5.2: Agent placement on the district, based on salinity levels

The results of the land households are also in line with the expectations. When looking at the data of district 824, it can be seen that in all land households, the percentage of non-agri workers is 0. The only exception is the percentage of occupation in aquaculture, where 1.34% is a service worker. However, the data also shows that 1% of the households are in aquaculture, and therefore this is not shown in Figure 5.3.

The landless households are the "rest group". In the model, the land households are created, and when no farm-owners are left, the other adults can start a household and fill this until the household is full. This has no rules, and can therefore lead to chaotic results. When comparing this with the labor data for landless households in district 824, 13. 5% is an agri worker, 64% a manual worker (this is low-skilled non-agri, manual worker, and other combined) and 34% a skilled service worker. The skilled service workers are a bit low, but this can happen due to the randomly generated numbers.

5.2.3. Land area

The land households have three land categories: small, middle, and large. Small is supposed to be between 0.3 and 0.5 ha, middle between 0.5 and 2 ha, and large between 2 and 5 ha. Figure 5.4 shows the distribution of land size per category. It can be seen that there are a few outliers, but the rest of the land sizes are distributed perfectly. The landless households have no land, which is also in line with the expectations.

5.3. Validation

The model is validated by looking at historical data and comparing this together with experts. Furthermore, extreme conditions are tested.

5.3.1. Face validation

In Figure **??**, it can be seen that the model reacts strongly in the first few years. Many rice and annual crop farmers switch professions and then hardly respond anymore to salinity shocks. However, in reality, it is likely that they would continue to react. This is because the input data comes from many different sources, and the expenditures are higher than the savings in the beginning. Afterward, people have switched to their correct state and gradually become wealthier. All farms with too low an income have already left, and the remaining farms can withstand the salinity shocks. However, L. Hermans said

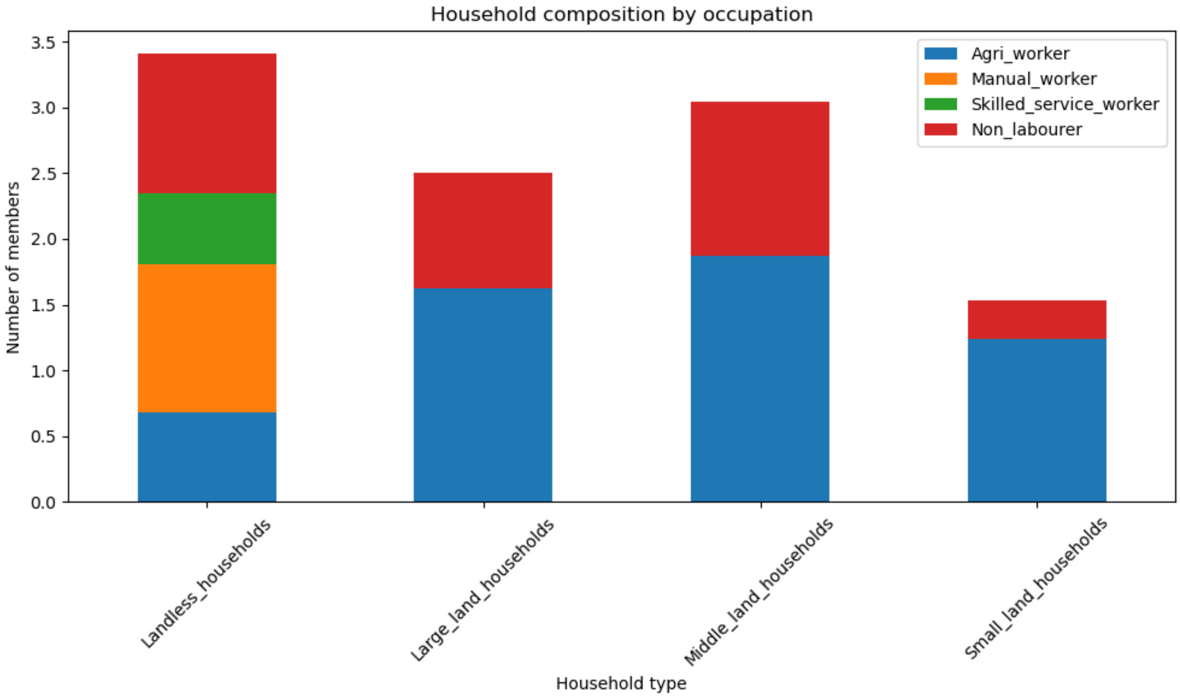


Figure 5.3: Household composition per occupation and household type

in a conversation that this is not so strange at all: the initial switches may be enthusiastic, but beyond that, it is quite logical model behavior (personal communication, May 2025). Additionally, unpublished data analyses of Deltares show that a significant portion of people migrated in the VMD after the first salt shock (Deltares, internal document, 2025).

From the interviews with M. van Aalst, L. Hermans, and P. Jansson, it appears that the speed of the switches may be due to one of the following factors:

1. The costs and revenues of the farmers is from different sources, different years, and sometimes even different areas.

2. Nothing like a conservatism factor or similar was included. As a result, people switch immediately, without considering whether they have been doing it for decades or perhaps lack the knowledge entirely. The way the MOTA framework is implemented assumes that people can rationally reflect on their choices, but this is not always the case.

3. Even before 2014, the farmers in the VMD were struggling. It is possible that they were already nearing their limits, and the 2016 shock was the final push to trigger change. This is also supported by the unpublished migration data from Deltares, where a lot of people are changing after the 2016 shock.

To see how the model reacts, it was decided to run the model in two alternative ways: first, when the household's expenditure equals its savings and second, when it is not possible to switch crops. When crop switching is not allowed, several farmers still leave in the first few years. This is shown in Figure E.6 in Appendix E. When switching is allowed but savings equal expenditure, many more agents migrate, and the initial switches are also higher. This can be seen in Figure E.7 in Appendix E.

5.3.2. Historical data

The model outcomes are compared with historical data from 2014-2018, to see how people behaved during and after the first salinity shock in 2016. Based on unpublished data by Deltares, it can be seen that only 62% of the agri farmer households of 2016 were still agri farmer households in 2018. 2% of them switched to aquaculture, and the rest started non-agri work or migrated (Deltares, internal

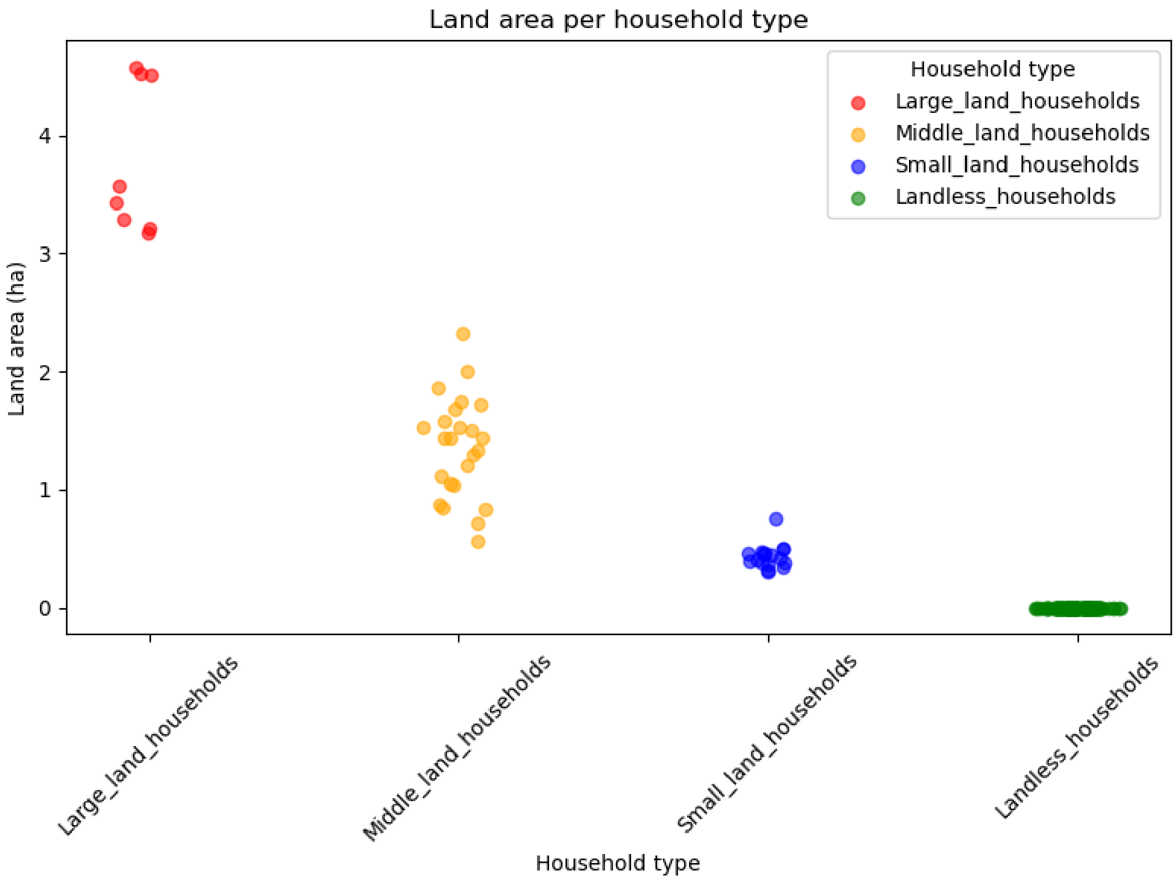


Figure 5.4: Distribution of land size per household type

document, 2025). These numbers are based on another region in the VMD, but show that a lot of people stopped farming after the first shock. This trend is also happening in Figure 5.6.

5.3.3. Extreme conditions

Extreme conditions were used to test if the model would "break" somewhere, and if unexpected behavior would arise. For ten variables, the variable is halved or almost set to zero, and set two times as high as normal. An overview of these variables and the system behavior per variable is given in Appendix F. Table 5.1 gives an overview of the expectations and whether they are reached.

Almost all expectations were met, and the model never broke down. The only outstanding factor was the possibility of debt. When there is no possibility of debt, the number of annual crop and aquaculture farmers is higher. When there is a higher possibility, the number of rice farmers is a bit higher. After a bad year, when a salinity shock has occurred, the farmer tries to switch crops immediately in the ABM to receive more income. This results in switching costs, and when one does not have the money, they will try to get a loan. Before, it was expected that when there was no debt, more people would migrate. But as one can see in Figure 5.5, at the start of the model, a lot of farmers are switching between crops, causing debts, which need to be paid of later. When there is no debt possibility, farmers who do have savings will not switch, or switch only one time instead of going back and forth, since they cannot pay for another switch. That declares that there are fewer rice farmers and more maize farmers and aquaculture farmers in the situation without debt possibility.

Table 5.1: Expected behavior and outcomes of extreme conditions test of ABM

What was changed?	What were the expectations?	What happened in the ABM?	Expected ABM behaviour?
Overall salinity level	The higher the salinity level, the more farmers will stop farming or change to aquaculture/perennial crops	With higher salinity levels, 20% more households migrated, with lower salinity this was 10% less. More people are switching to aquaculture and perennial crops since they can tolerate high salinity levels.	Yes
Frequency of salinity shocks	More shocks will lead to more migrations, and more farmers will change to aquaculture/perennial crops	The distribution of people migrating is larger, the effects are less intense than when increasing the intensity of the shocks. Without shocks, more people stay in annual crops, and with more shocks, more land households change to aquaculture or perennial crops. This impact is less shown when looking at rice.	Yes
Production costs	Higher production costs will lead to more people migrating. When there are no production costs, they will stay in their current profession	When production costs are twice as high, over 50% more households migrate. When there are low production costs, a lot of households have perennial crops and rice. Higher costs lead to a decrease in annual crops, perennial crops, and rice	Yes
Salary of wage workers	An increase will lead to more households with an income too low, and more people working.	When a wage worker's salary is halved, 250% of the landless households have an “income too low”, which means their expenditure is higher than their income. With a lower wage, 10-25% more wage workers are working	Yes
Number of required wage workers	With a lower required number, more households would stay in annual crops (they require the most wage workers), and fewer people would be working	When twice as many wage workers are required, the number of wage workers is more than 250% compared to the normal amount. This is due to fewer farmers stopping farming. A lot of farmers started perennial crops and stopped rice and annual crops, while during the low required wage workers scenario, almost 250% of the farmers did annual crops compared to the normal scenario.	Yes
Accessibility to the information meeting	When more people have access, more switches will be made, and livelihoods will be higher	Livelihood is higher during high attendance, but between nobody attends and the current attendance (10%) is no difference. High attendance leads to more perennial crops and aquaculture. However, low attendance also leads to higher aquaculture (the information meeting tells you to only switch if you are smart enough for aquaculture)	Yes
Contacts in city	There will be more individual youth migration when there are more contacts in the city	Higher contacts lead to 15-35% more migration, while no contacts lead to a decrease of approximately 50%.	Yes
Possibility for debt	When it is not possible to get a loan, more people are migrating and fewer people are switching to aquaculture or perennial crops. The livelihood will be lower	Without a possibility for debt, more people are migrating. Without debt, people have a higher livelihood, and more land households have annual crops and aquaculture. With a higher debt possibility, the number of rice farmers is a bit higher.	Partly
Probability of migration	An increased probability will lead to more people migrating	A 50% decrease in migration chance has a smaller effect (only 15% fewer migrations) than increasing the migration chance by 50% (20-30% more migrations). The same effect is seen by looking at the individuals	Yes
Facilities in the neighbourhood	More facilities will lead to fewer households migrating	Lower facilities will lead to more migrations, but higher facilities have no effect on the number of migrated households.	Yes

5.4. Model output

The ABM has three main outputs: the number of farmers over time in each crop category and land size, the savings of these farmers, and the number of migrations.

5.4.1. Number of farmers

Looking at the number of small farmers over time in Figure 5.5, there is an interesting change in the first few years, even before the 2016 salinity shock. For many farmers, their income is not enough to cover their expenditure. At that moment, no salinity shock has occurred yet, and most farmers are switching between rice and maize (salt-sensitive crops). Then in 2016, the salinity shock occurred: some farmers switched back to rice, but many farmers are migrating. They do not have sufficient savings to survive the shock and leave their land. Maize is even more sensitive to salinity than rice, and therefore, some farmers switch back to rice. There is a very small increase in coconut farmers in 2016, but the number remains low. This is because there are in some model runs 0 coconut farmers in the beginning, and if farmers do not go to the information meeting, or do not see their neighbors have a farm, they do not have information or an example on how to start the coconut farm. The same is for shrimp farming. During the next shock, in 2020, the model has reached the ”steady state”, where farmers with too low income have already migrated, and farmers have created enough savings to survive the shock.

The decrease and switches of farmers are less intense in farmers with medium land size. There are a few switches at the start of the model and the number of maize farmers decreases after the 2016 shock. A few farmers decided to start a coconut farm in the first few years; however, the trees need to grow for five years. During the 2016 shock, the farmers had a debt, and half their income from rice/maize, and baby coconut trees. The shock decreased their savings, and this could not be fixed by the half land full of maize or rice. As a result, they are also migrating after a few years.

Farmers with large land sizes are doing slightly better. Some farmers managed to buy land from migrating farmers and have become large farmers. This happened after the 2016 shock, when all farmers migrated. The maize farmers decrease slightly over time, and coconut and aquaculture increase slightly. But overall, they have reached their steady state after the 2016 shock, for the same reasons the small and medium farmers have reached that.

5.4.2. Migrations

In the ABM, there are two different types of migrations: households and individual members, especially young adults between 15-35 years old. Figure 5.6 provides an overview of these migrations over time.

The highest migration rate is after the first salinity shock in 2016, where almost 20% of all households migrated. In the next 23 years, this is increased by 10%, which is in line with the number of farmers seen in Figure 5.5. The number of migrated individuals is increasing slightly over time, but only starts after the 2016 shock, when households started migrating. This is because these migrations are influenced by the migration rate.

5.4.3. Savings

Migrations are based on the savings of farmers and are visualized in Figure 5.7. It should be noted that the savings are in VND. Small rice farmers have saved in 25 years 800.000.000 VND, which is a bit higher than €25,000.- For small farmers, rice farmers are the richest, followed by maize, shrimp, and coconut. This is logical, coconut farmers have had a ”start-up period” in which the coconuts grew, and their income was lower for five years. It can be seen that in 2016, some coconut farmers had negative savings, but took a loan.

For medium farmers, shrimp farmers are the richest. There are only a few shrimp farmers in the model, but they have been able to not pollute their land and receive a decent amount of income each step. This also shows that when correct measures are taken, shrimp farming can be successful. The maize farmers are the poorest in this category, due to the really high required man days/ha, which leads to high wage worker costs.

The same trends per crop type can be seen for the large farmers; however, their savings are higher. A medium rice farmer has almost €80,000.- savings, while large rice farmers have approximately €200,000.- savings.

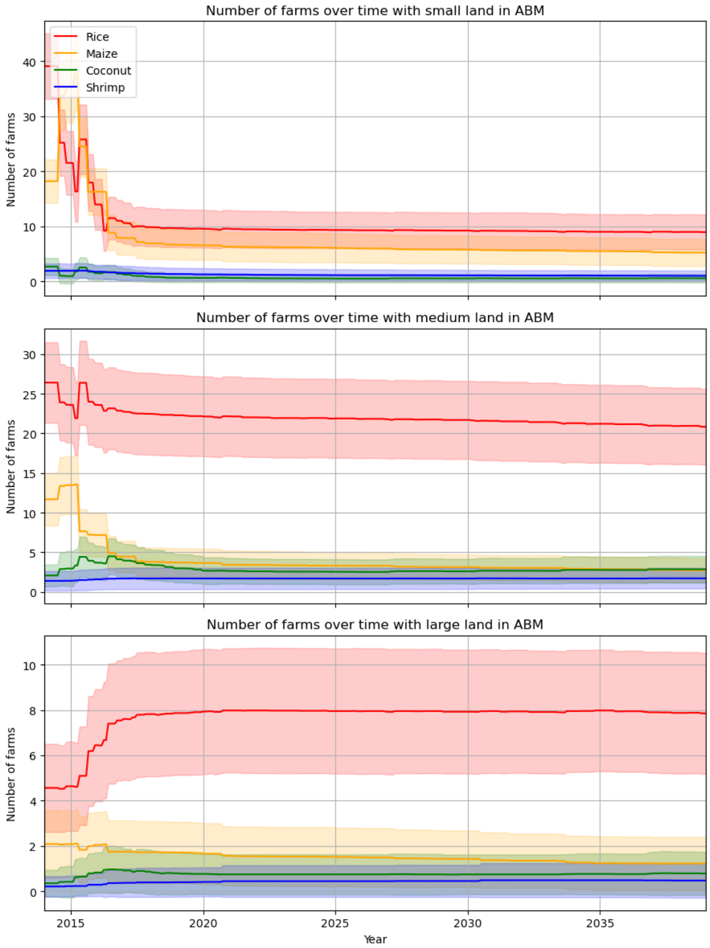


Figure 5.5: Number of farmers per land size and crop type over time in ABM

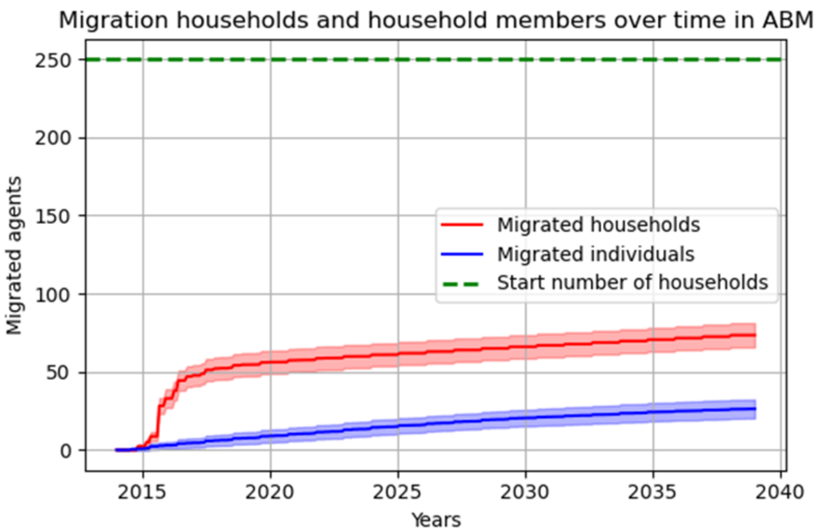


Figure 5.6: Number of migrating households and household members over time in ABM

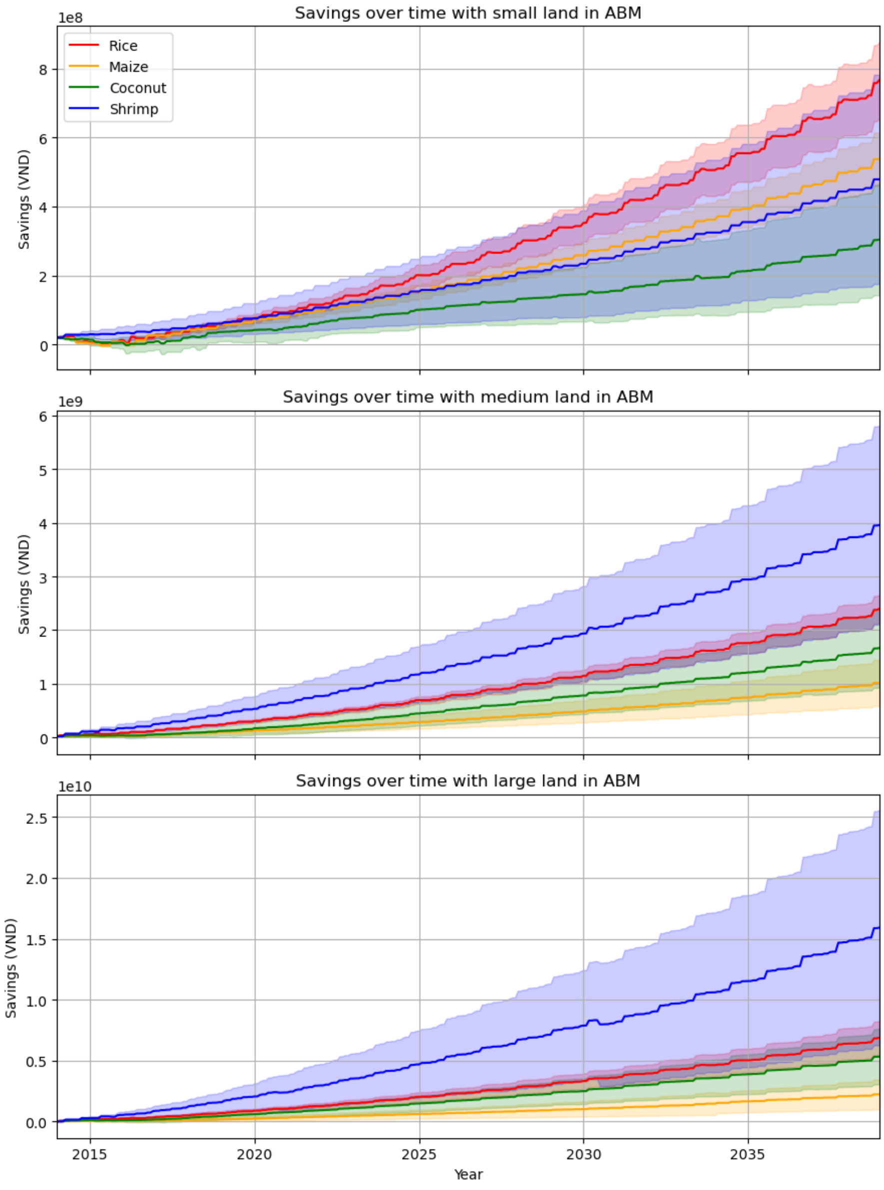


Figure 5.7: Savings per crop type and land size over time in ABM

5.5. Experiments

Experiments were conducted to study how migration levels change in response to potential government interventions. These experiments also provide insights into the model's sensitivity to key variables. A total of 100 runs were performed for each of the seven variables. In each case, the selected variable was varied across a range from 0 to twice its baseline value, while all other variables and the random seed were held constant. At the end of the 25-year simulation period, the analysis focused on identifying which households remained and which had migrated. Based on these outcomes, along with the results of the extreme value tests, several conclusions were drawn.

5.5.1. Sensitive factors for migration

For each of the seven factors below, the number of household migrations after 25 years is studied under different parameter values. The red lines represent the base value in the ABM. In addition, the LOWESS line is visualized as well, to get a clear overview of the trend in the scatterplot. Migrations are chosen as a performance indicator since they are based on savings and influenced by all of the factors below. In addition, it would be nice if there are still households left in 2040, and focusing on migration is therefore important.

Machines: Only 10% of the people in the VMD know how to use machines. Machines lead to a lower required man days/ha, which leads to less work for wage workers, and therefore less wage worker income. This decreases the savings and increases the percentage of migrations.

Figure 5.8 shows the results. It is interesting to see that when nobody uses machines, compared to the current 10%, the number of migrations is higher. This is due to the number of man days/ha for maize. Especially maize farmers have machines to prevent the high wage worker costs on a farm. Without a machine, maize farming is not sustainable in the long term in the ABM. The maize farmers are migrating when there are no machines, which is the peak at the start of the figure. Around 50%, there is a switch, where the number of migrations is increasing again. This is the point where farmers use fewer wage workers, and slightly more people are migrating.

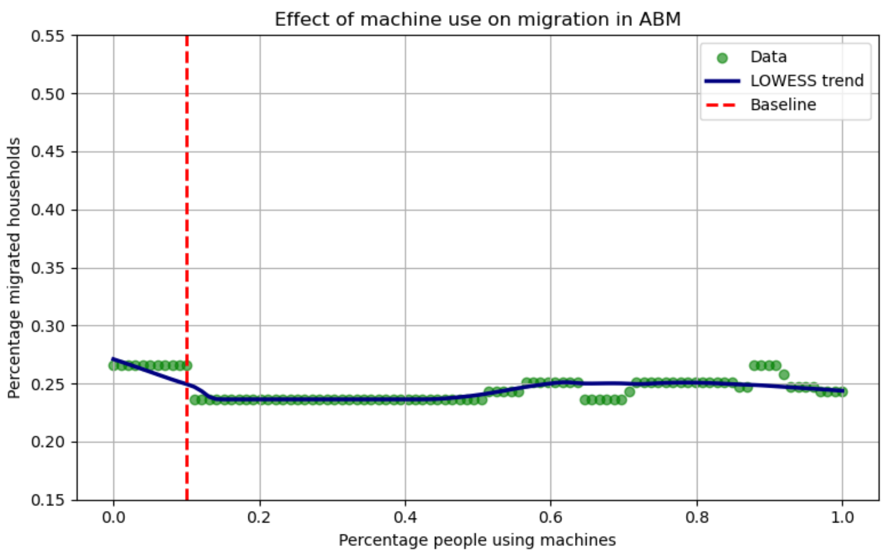


Figure 5.8: Effect of machine use in the ABM on migration of households

Education level: When the education level increases, farmers are less impacted by the salinity shock. This is happening when the education level is higher than 0.5, which means that the farmers have an average household education higher than primary school. This effect is visualized in Figure 5.9. When the education level reaches 0.5, the percentage of migrated households decreases slightly.

Wage worker salary: The current wage worker salary per day is set to the minimum wage. When the salary increases, farmers have more costs and there is a possibility they will have to migrate.

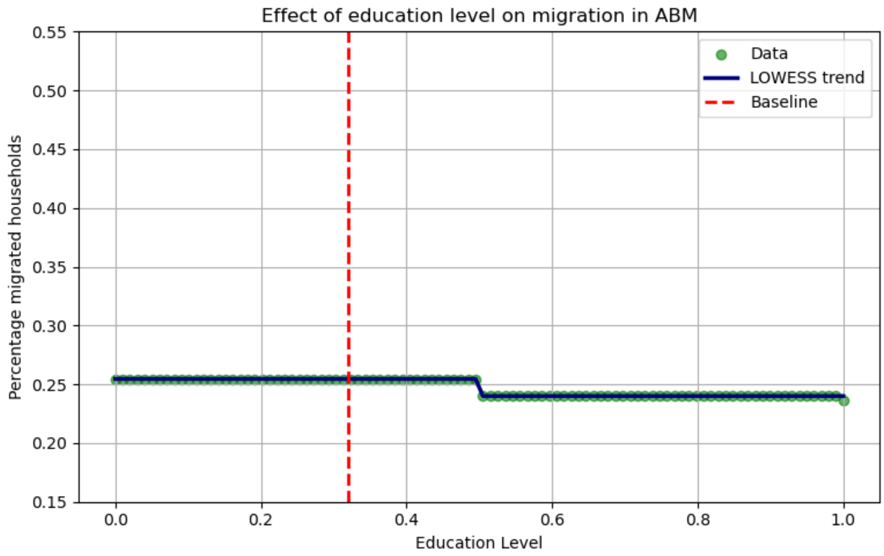


Figure 5.9: Effect of education level in the ABM om migration of households

However, when the salary decreases, landless households do not have a sufficient amount of income anymore, and will start migrating as well. This trend is also shown in the ABM, in Figure 5.10. It is interesting to see that at the end, when the wage worker salary is really high, the number of migrating households is decreasing again. The salary is so high that the wage worker's income from household members working on other farms compensates the wage worker costs per farm.

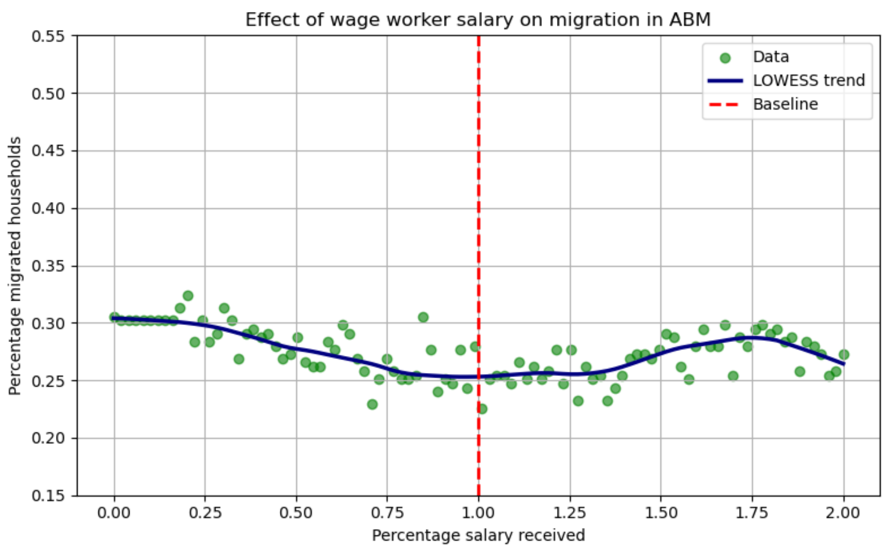


Figure 5.10: Effect of changing the wage worker salary in the ABM on the migration of households

Production costs: The fixed production costs differ for rice, maize, coconut and shrimp. Lower production costs will lead to more savings, and therefore less migrations. Figure 5.11 gives an overview of the effect of changing the production costs per crop type.

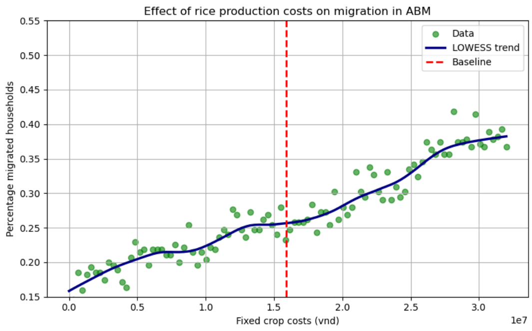
Most of the farmers in the model are *rice* farmers, and the majority of migration is driven by this group. When rice production costs are zero, these farmers accumulate sufficient savings and income, resulting in a very low migration rate. Increasing costs also lead to the expected increase in migrations. Figure 5.11a provides a graph of this effect.

In contrast, changes in *maize* production costs have no significant effect on migration, as seen in

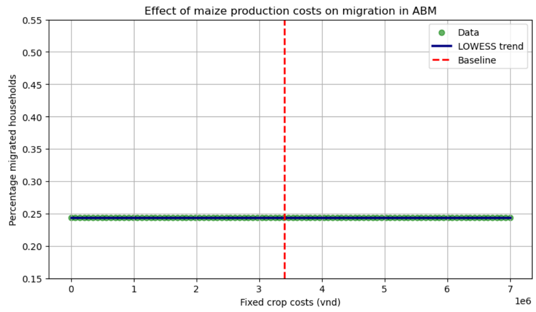
Figure 5.11b. This is due to maize having fixed production costs of 3.4 million VND per hectare, in addition to variable wage worker costs of around 13 million VND for a medium-sized farm. Adjusting the fixed costs, therefore, has minimal impact, particularly if the harvest has already failed.

For *coconut* farming, a fluctuating pattern in migration can be observed in Figure 5.11c. As wage worker costs increase, migration initially rises, but then declines again. In the model, agents switch crops when projected income exceeds expenses, and they migrate once their savings are depleted. When coconut production costs are very high, farmers immediately recognize the lack of profitability and switch to alternative crops. These alternatives do not have such high production costs, reducing the need to migrate. Lower production costs allow more coconut farms to remain operational. However, if production costs are reduced to zero, coconut farming becomes profitable, and fewer people migrate. Still, coconut farms require fewer wage workers compared to other crops, which results in a higher migration rate among landless households, who generally have a lower income.

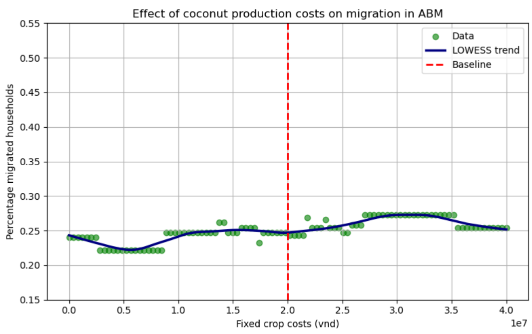
Shrimp farmers are the wealthiest group in the model, as shown in Figure 5.7, but there are also only a few shrimp farmers in the model. Consequently, they do not face the issue of decreased savings and rarely migrate. Changing the production costs has zero effect on the migration rate, as visualized in Figure 5.11d.



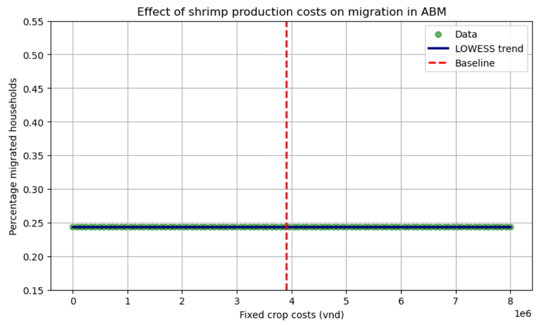
(a) Effect of changing rice production cost in the ABM on migration



(b) Effect of changing maize production cost in ABM on migration



(c) Effect of changing coconut production cost in ABM on migration



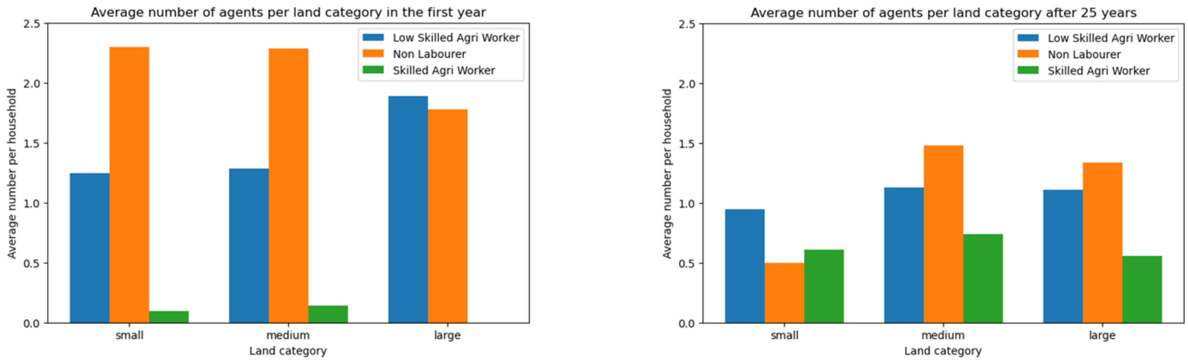
(d) Effect of changing shrimp production cost in ABM on migration

Figure 5.11: Effects of production cost changes on household migration in the ABM

5.5.2. Difference in characteristics after 25 years

Only a part of the households stayed in the VMD, and these households have no debt. The question is: what is different about these households compared to the ones the model started with? What characteristics do they have that prevent them from migrating? The household composition and crop type per land category are studied.

When looking at household composition, Figure 5.12b shows that the remaining households have significantly more high-skilled workers than the average household at the start of the model in Figure 5.12a. These individuals earn more income, which contributes to the household's financial stability. Additionally, the number of non-labourers in these households is considerably lower. Non-labourers only generate costs and do not contribute to household income, so logically, the surviving households have fewer non-labourers.

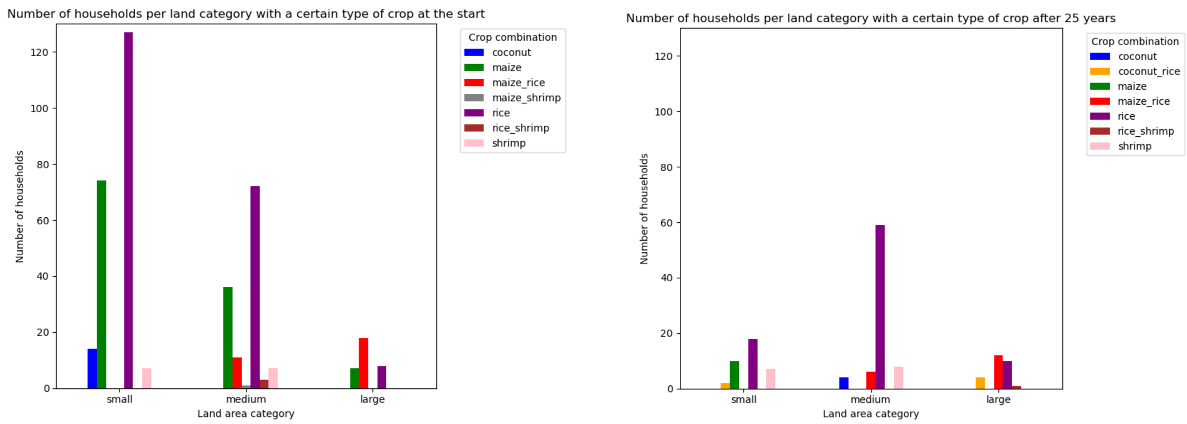


(a) Average number of agents per land category in the first year

(b) Average number of agents per land category after 25 years

Figure 5.12: Average number of agents per land category within a household

In addition, crop types were analyzed. At the beginning of the model, most farms were growing maize and rice, as seen on the left side of Figure 5.13. After 25 years, only medium-sized rice farms have remained, with almost no maize farms and very few small rice farms. Many crop combinations have emerged, due to farmers buying up land from others. As a result, combinations like maize-rice, rice-shrimp, and coconut-rice have developed.



(a) In the first year

(b) After 25 years

Figure 5.13: Number of households per crop type

The size of the households was also studied, but no significant differences were found, taking into account the fact that members could migrate as well.

6

System Dynamics

In addition to the ABM, a System Dynamics (SD) model was also developed. The SD model is created with the ABM in mind and has almost the same factors as the ABM. In Appendix G, another SD model can be found. This model is created together with Deltares, but has other factors as the ABM.

6.1. Conceptualization

The SD model contains four sub-models, which are explained below.

6.1.1. Households and occupations

There are four types of farmers: rice farmers, shrimp farmers, coconut farmers, and maize farmers. Subscripts are used to differentiate between small, middle, and large land sizes. Small is 0.4 ha, medium is 1.4 ha, and large is 2.5 ha. When the net income of farmers is too low, they will try to switch crops. To prevent the model from becoming too chaotic, a few crop switches are possible: a rice farmer can switch to coconut, maize, or shrimp, and a maize farmer can switch to coconut, shrimp, or rice. However, shrimp farmers can only stop farming since their land will be too polluted to switch to another crop. This happens after five years of antibiotic use, and therefore, a delay is implemented. Furthermore, the assumption is made that coconut farmers (with a salt-tolerant crop) will not switch back to salt-sensitive crops such as maize and rice. When farmers stop farming, they are migrating to the city. In that case, it is possible that others take over their land, and the number of large farmers is increasing.

In addition to farmers, there are also landless households. These are divided into three groups: non agri, agri wage, and service worker. Within the agri wage stock, it is possible to be low-skilled or high-skilled, using subscripts. Low-skilled agri workers receive less wage (190.000 VND/day compared to 210.000 VND/day), and the distribution is based on education level. To avoid a mess between the different households, it is not possible for landless households to switch between professions. They can only migrate; this is happening when their savings are too low.

A conceptual overview of these groups is given in Figure 6.1.

6.1.2. Crop yield and crop farmers' income

To calculate the crop yield for maize, rice, and coconut farmers, the same sub-model is used. This model also differentiates between the three types of land size, using double subscripts. Figure 6.2 visualizes the model in a causal loop diagram.

The higher the salinity level, the higher the yield loss ratio will be. This ratio is based on the formula by Tanji and Kielen (2002): $Yield = 100 - (slope * (salinity - threshold))/100$. The slope is the percentage per dS/m, and means that when salinity reaches this level, all yields for this crop will fail. The threshold is in dS / m and is the salinity level at which the crops behave perfectly. Salinity is the current salinity level. The yield loss ratio can be lower when the education level is higher than 0.5, which means that the average education is higher than primary education. It is decided not to implement measures to prevent farmers from using salinity, since it is not known how effective they are (N. Mulder, personal communication, April 2025).

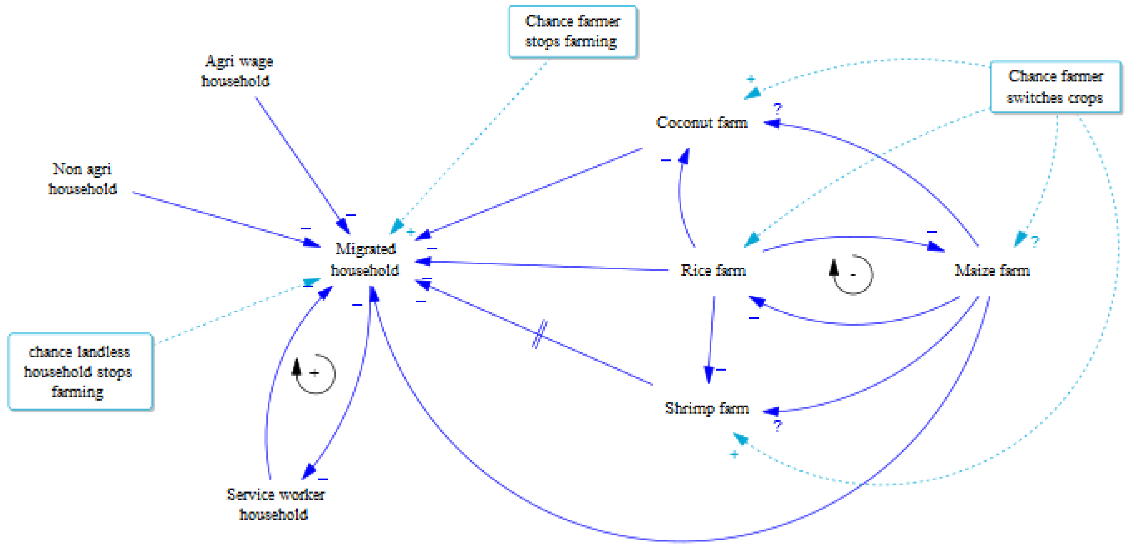


Figure 6.1: Conceptual overview of occupations in the SD model

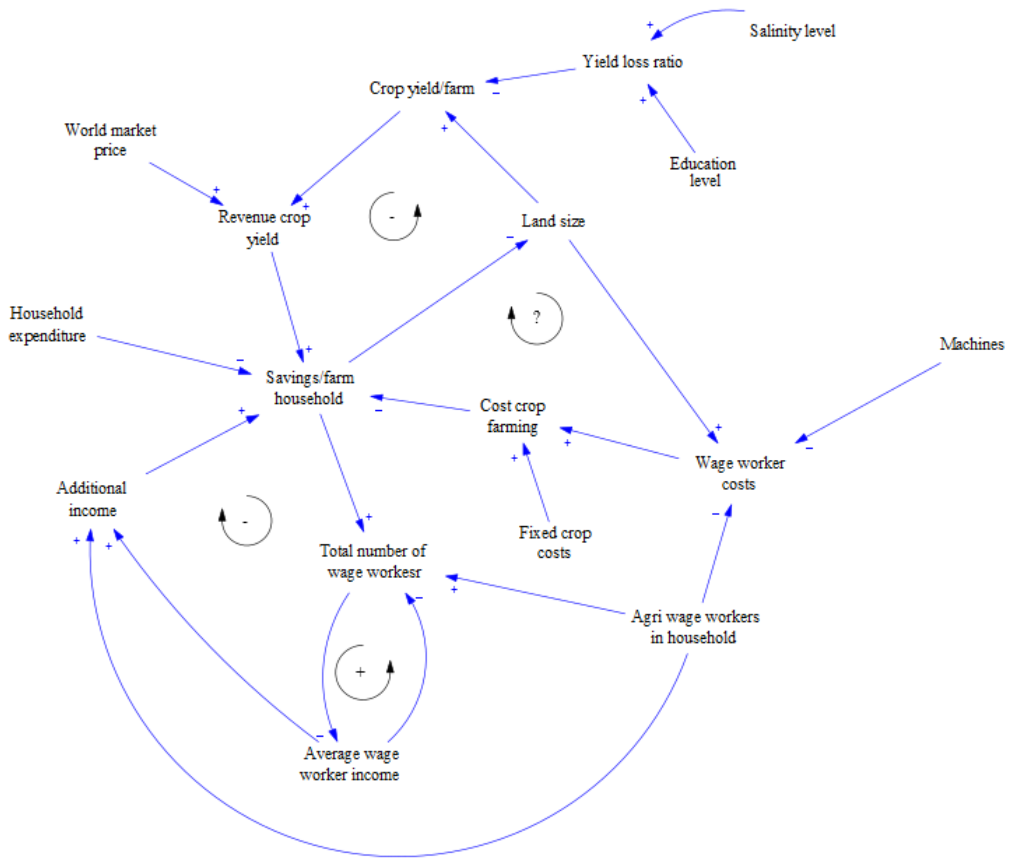


Figure 6.2: Conceptual overview of crop yield and crop farmers' income in SD model

Based on the yield loss ratio, land size and yield/ha, the yield/household is calculated Blom-Zandstra et al. (2017). Revenue is calculated on the basis of the market price and fixed costs are subtracted. Based on this yield and the fixed costs based on land size, the household makes a profit. The fixed costs represent the wage worker costs, and for example costs for seeds and pesticides. However, the assumption is made that these costs stay the same each year. When a salinity shock occurs, the number of wage workers is lower and the wages of the workers are reduced. But at the same time, the farmer has more costs to prepare the land for the next crop season, which will increase the costs (M. van Aalst, personal communication, May 2025). An exception is made for maize: When looking at the literature, the fixed costs of maize were lower than the costs of wage workers (Pedroso et al., 2017). Therefore, the costs of maize farming are the sum of fixed costs / ha and wage workers' costs.

The wage worker costs for a farmer are based on the required number of man days per farm type and the daily salary per wage worker. The farmer may also have family members working on the farm. This decreases the required number of man days. When farmers have machines (in this case that is set to True when more than 50% of the farmers have machines), they only need 2/3 of the man days. It is assumed that each farm has the average distribution of low and high-skilled wage workers; in case of Gò Công Đông this is 85% low-skilled, and 15% high-skilled wage workers.

Farmers also have additional income. Based on their crop type and land size, they have 0-3 people working outside of the farm, working in non agri wage, or in the service sector. This data is based on VHLSS2014 and work 20 days a month. In addition, it is possible for the agri wage workers to work on other farms as well, to earn some extra money.

The agri wage stock number is multiplied by the average number of wage workers within an agri wage household, and added to the total number of wage workers of the farm households. Based on the total available number of wage workers, and the required number of man days, each wage worker has a number of work days, and a salary. This salary is added to the savings of the household.

Lastly, each household has an expenditure, based on the VHLSS2014 data.

6.1.3. Shrimp farmers

Within the shrimp farmers stock, the distinction is made between farmers with disease and those without disease, in combination with the small, medium, and large land size. This is done using double-subscripts. For simplification and lack of data, shrimp farms are not impacted by salinity levels, and whether the shrimp has a disease or not is determined by a fixed, predefined chance. In reality, salinity levels can have an impact on water quality, and water quality itself has an impact on the chance that a farm is infected or not (S. Eslami, personal communication, March 2025).

In addition, when there is a disease, it is possible to use antibiotics and have approximately the same yield as a noninfected farm. However, it is not possible to distinguish in the model between the farmers who buy antibiotics or not and those who stay infected. Therefore, it has been decided to let every farm without disease pay for antibiotics; these are fixed costs/ha and are an assumption.

Based on the yield/ha and land size of the house, the different types of shrimp farmers have a yield/household (Joffre et al., 2015a). The farming costs are calculated in the same way as for the other crop farmers. Shrimp farmers also have wage worker costs, other household income based on wage workers, and expenditure based on VHLSS2014. Figure 6.3 provides an overview of the conceptualization using a causal loop diagram.

6.1.4. Landless households

The agri-wage, non-agri and service worker households also have a sub-model. Service workers receive income based on the overall migration rate of all types of households. When, for example, 20% of the households have migrated, service workers have an income of 80%. However, their income can also increase when more service workers migrate, and they have less competition. This last method is also used for the income of non agri households. When more non agri households are migrating, there is more work, and income will increase. The assumption is made that there is no stop to this, since, for example, a factory will always have work to do. All service workers and non-agri-homeworkers work 20 days a month, and the working force within a landless household averages 2.

The agri-wage household earns money based on the average wage worker income, which is influenced by the number of farmers and the number of available wage workers.

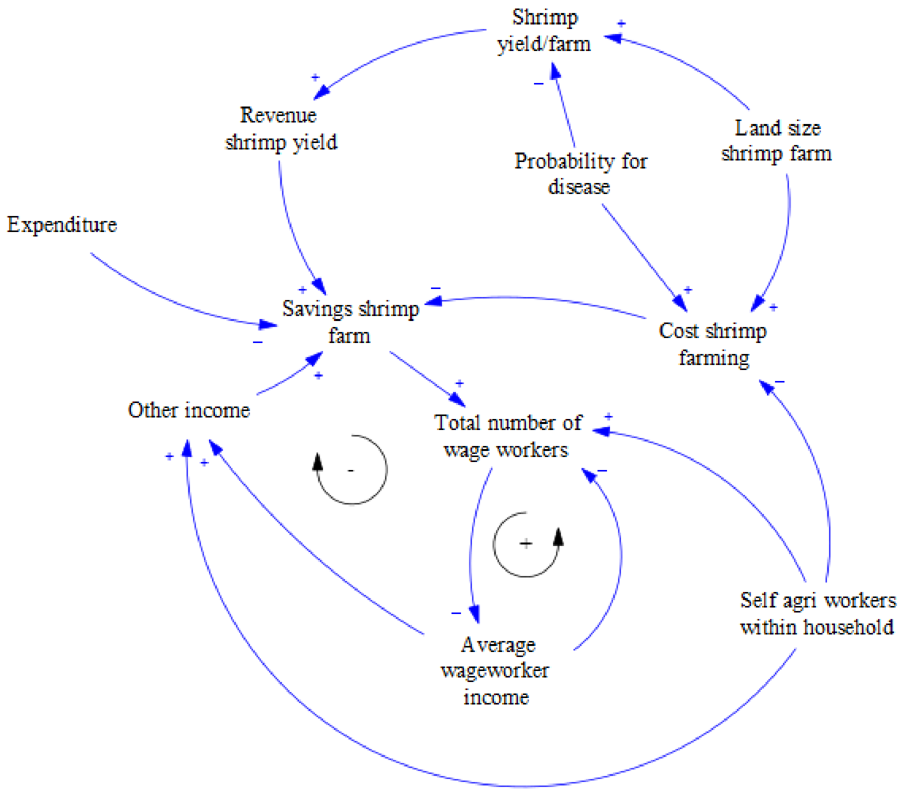


Figure 6.3: Conceptual model of the shrimp farmers and their processes in the SD model

7
System Dynamics Results

Data from district 824, Gò Công Đông, was used as input data for the SD model. In addition, trends of the ABM were implemented when the input data was insufficient. The SD model is deterministic, and therefore, one single run is sufficient. The model runs for 25 years, starting in 2014. The time step is set to 0.5 using Euler, to get the most realistic results. The model is verified by looking at three factors: crop yield, Wage workers and wage worker income, and the possibility of switching crops. Extreme value validation has been conducted as well, and the model outputs will be presented. Lastly, the sensitivity is checked for five variables. The complete SD model can be found on GitHub: https://github.com/Juliettevanalst/Thesis

7.1. Verification

Verification is the process of checking whether the computational model matches the way it was intended to be constructed. The following three factors are studied: whether the crop yield is really impacted by the salinity levels, if wage workers have higher income when more people are migrating, and whether farmers switch crops.

7.1.1. Crop yield

The crop yield is expected to be lower during salinity shocks. This effect is also shown in Figure 7.1. In the years 2016,2020, 2026, 2029, 2032, 2035, and 2038 is a salinity shock where the salinity level reaches 5 instead of 3. That shock will lead to a yield loss ratio of 24% for rice, and this is in line with the decrease in rice yield in Figure 7.1. In addition, the small land households have a land of 0.45 ha, while medium land is 1.4ha, and large land is 3ha. The small land size yield should be 6.6 times lower than the large land size yield. For rice, 17500/6.6=2625, and this is the value shown for small rice farmers in Figure 7.1.

7.1.2. Wage workers and wage worker income

Over time, the number of land households is decreasing and the number of wage workers should also decrease. This is in line with Figure 7.2, which visualizes the number of wage workers on the left, and the average wage worker income on the right. The number of wage workers is decreasing since more farmers are migrating. Looking at the income on the right, the overall income is also slightly decreasing. This is due to the high migration rate of farmers, which leads to less man days/ha required. The decrease is not of the same magnitude as the number of wage workers is decreasing, since income is also increasing when there are fewer wage workers available.

In addition, income is decreasing during salinity shocks because less wage workers are required during a shock.

It should be noted that this income is really low and that wage workers only work approximately 20 days a year. Therefore, wage workers are also working on their own farm, and there is income from non agri workers and service workers in the family.

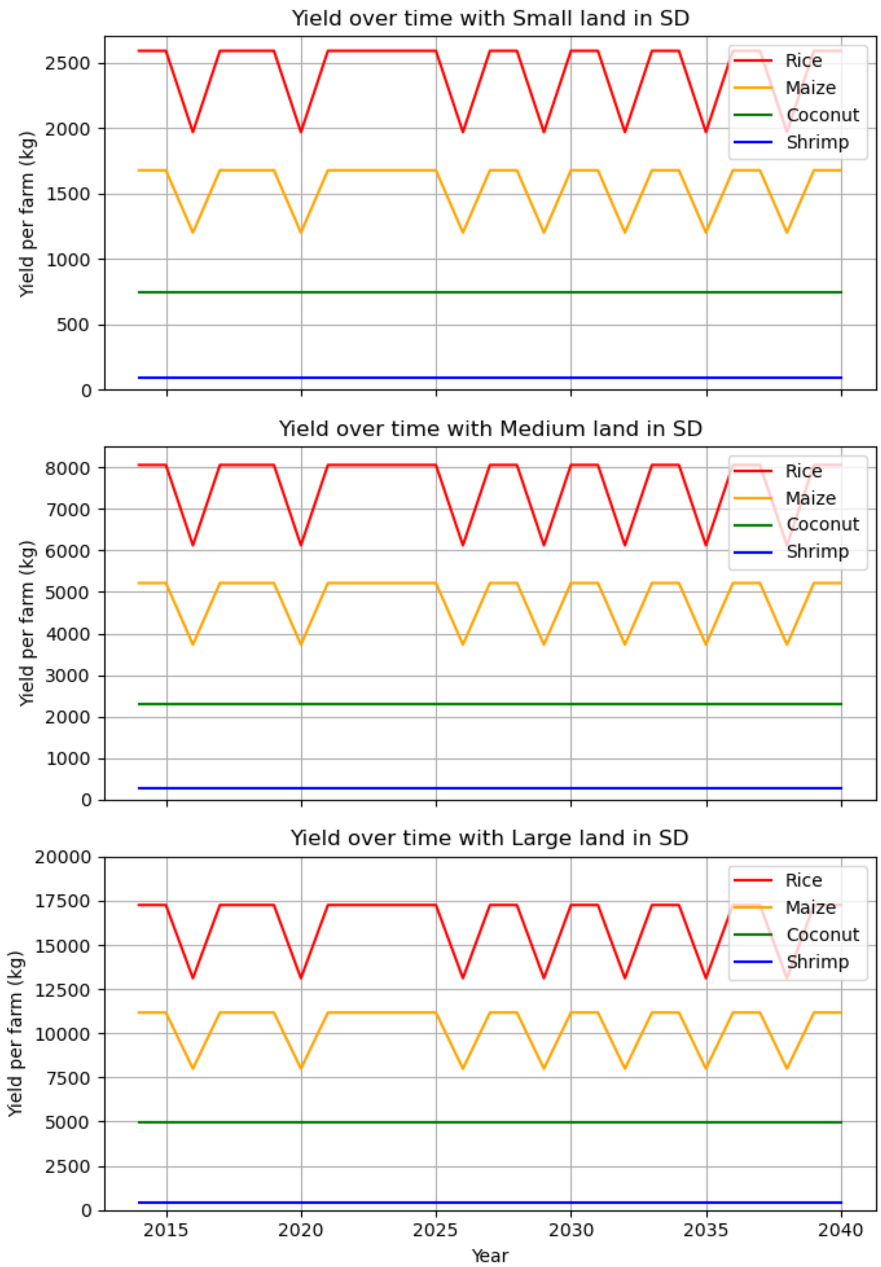
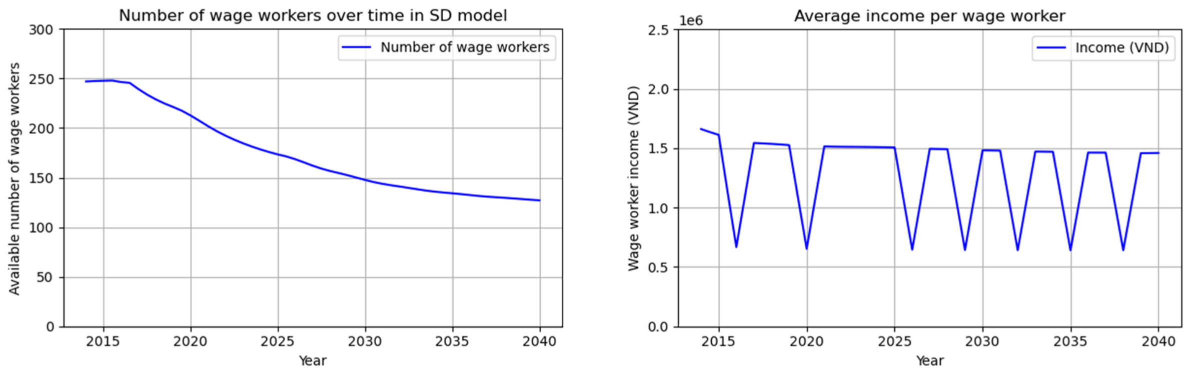


Figure 7.1: Crop yield over time with different land types over time in SD model



(a) Number of wage workers over time in the SD model

(b) Average wage worker income in the SD model

Figure 7.2: Wage worker dynamics in the SD model

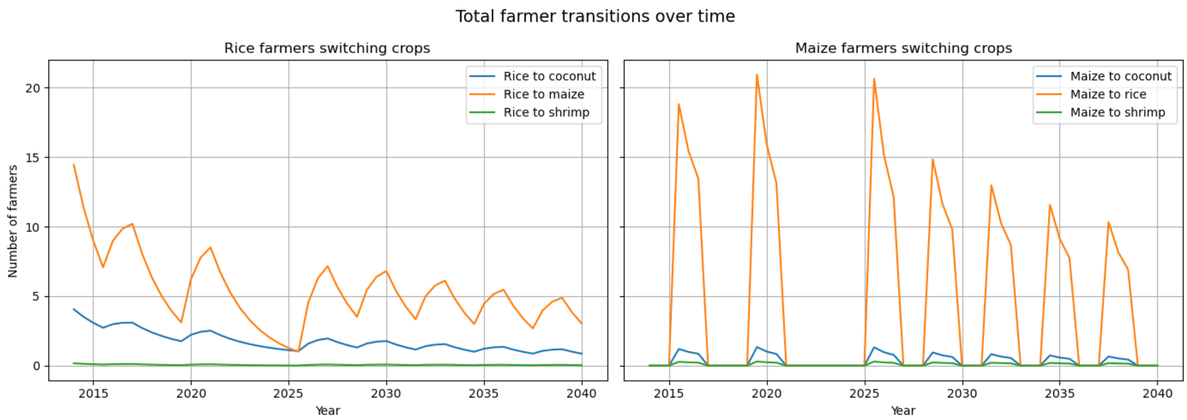


Figure 7.3: Crop switches over time in SD model

7.1.3. Switching crops

There is no social theory or behavioral model in the SD model. However, farmers still need to be able to switch between crop types. These switches are based on the net income of farmers. When these are too low, the ABM showed that 42% of the farmers will switch from crop to crop. It is checked if this is happening, and Figure 7.3 shows the results. After each shock, the net income is too low, and farmers are switching. From rice, the ABM trends showed that 86% switches to maize, 14% to coconut, and almost none to aquaculture. This is in line with the left graph in Figure 7.3. For maize, 94% should switch back to rice, only 5.5% to coconut, and 0.5% to shrimp. This is also shown in the right part of Figure 7.3.

7.2. Extreme value validation

The model is validated by testing extreme values based on ten variables. These variables are either halved/set to zero or doubled to observe whether the model breaks at any point. Table 7.1 provides an overview of these tests. The model never broke. However, it did not always show the expected behavior. This is in part due to thresholds in certain variables, such as contacts in the city or facilities in the neighborhood, which only have an effect once a threshold of 0.5 is crossed. For instance, if the model already has a value of 0.8 and this increases to 1, this has no impact on migration, even though it realistically should.

Table 7.1: Extreme value validation in SD model

What was changed?	What were the expectations?	What happened in the SD model?	Expected SD behaviour?
Overall salinity level	The higher the salinity level, the more farmers will stop farming or change to aquaculture/perennial crops. Lowering the salinity level will lead to less crop switches and migrations.	When the salinity level is doubled, almost half of the population is migrating, and the number of rice and maize farmers is decreasing fast for all land sizes. But they are not switching more to aquaculture or perennial crops. When there is no salinity, farmers are not switching anymore, and there are less migrations.	Partly
Frequency of salinity shocks	More shocks will lead to more migrations	More shocks are not leading to more migrations, but when there are no shocks there are less migrations.	Partly
Production costs	Higher production costs will lead to more people migrating. When there are no production costs, they will stay in their current profession	When there are no production costs, the migrations are really low for rice and coconut farmers, while they have no impact on the shrimp farmers. Increasing the costs increases the migrations in all categories, except for shrimp. Nobody switches anymore, except for maize farmers and a few rice farmers.	Partly
Salary of wage workers	An increase in salary will lead to less migrations and more savings, and this also works the other way around.	When wage workers have no salary at all, the number of migrations is increasing, but only with 33%. When salary increases, savings are increasing, and the migrations are decreasing slightly.	Yes
Number of required wage workers	With a lower required number, more households would stay in annual crops (they require the most wage workers)	When the required number of wage workers is set to zero, maize and rice farmers are not switching to other crops any more. However, there is less work for the agri wage workers, and this leads to less savings and more people migrating. With high required number of wage workers, the migrations are also increasing, since more maize farmers are migrating.	Yes
Contacts in city	There will be more migration when there are more contacts in the city	There is no difference in the number of migrations. Only landless households are impacted by the number of contacts in the city, but these are rich enough to stay in their current profession. And migration is based on savings.	No
Probability of migration	An increased probability will lead to more people migrating	When the chance is set to zero, nobody is migrating anymore. Doubling the probability is indeed increasing the number of migrations, but less than expected (this is due to the fact that migrations are only based on savings, and when savings are above 0, they are not migrating). Only the number of coconut farmers is decreasing fast.	Partly
Facilities in the neighbourhood	More facilities will lead to fewer households migrating, and the other way around	When there are no facilities, this leads to 33% more migrations. The current level of facilities in the SD level is already high (0.8). The migrations will start to increase when facilities are lower than 0.5.Therefore, when the level of facilities is set to 1, the migrations are not changing.	Partly

Additionally, when switching crops, the model does not take salinity levels into account. It bases decisions purely on probabilities. As a result, increasing salinity does not necessarily lead to more people switching to coconut or shrimp farming, even though that would be the most logical behavior.

Moreover, over time, people in the model accumulate so much savings that they are able to absorb additional salinity shocks. This means that these shocks no longer lead to increased migration, which may not reflect real-world dynamics accurately.

Finally, one would expect that if the migration probability increases, more people would migrate. However, this probability is based on savings, and if savings do not drop below zero for a certain group, those individuals will not migrate, regardless of how high the probability is set.

7.3. Model output

There are three main model outputs in the SD model: the number of farmers over time, the number of migrations, and the savings per crop type and land size over time.

7.3.1. Number of farmers

The total number of farmers with small land decreases over time in the SD model, as visualized in Figure 7.4. However, there are many switches between maize farmers and rice farmers. After each salinity shock, these farmers tend to switch again to the other crop because their income remains too low. The number of coconut farmers increases slightly with each salinity shock over time, but eventually declines again, as small-scale coconut farming does not generate enough income. Shrimp farming is the least common; the number of shrimp farms declines from 2020 onward due to increasingly polluted land. While households are switching to coconut after each shock, they are not switching to shrimp.

Medium-land size farmers experience no switches at all, as their net income appears to be high enough across all crop types. However, the number of shrimp farmers decreases after 2020, due to the soil polluted by antibiotics after five years.

A similar effect is seen among farms with a large land size. The net income is sufficient to live from, even during salinity shocks, and nobody is switching crops. There is one large shrimp farmer in the model, and this one appears to be healthy. Otherwise, the number of shrimp farmers would also decrease.

7.3.2. Migrations

Figure 7.5 provided an overview of the migrations over time in the SD model. Only households can migrate as a whole in the SD model. After the first shock in 2016, the first households started to migrate. The number of migrations increases steadily afterwards and is not influenced by the other salinity shocks. Each timestep, there is a fixed probability a household will migrate, based on their savings. Due to the level of aggregration and the fact that every household within a corp type and land size has the same savings, each timestep a fixed number of people will migrate. This declares the smoothness of the line.

7.3.3. Savings

The savings of the farms in the SD model are interesting, as shown in Figure 7.6. Starting with small farmers: rice farmers are the wealthiest; their savings increase over time. The savings of the maize farmers gradually decrease, but remain positive. It is also visible that savings are impacted by salinity shocks, which makes sense since farm profits are lower during these periods. Coconut farming is not profitable at all for small landholders, as their savings drop immediately and continue to decline further. The most interesting case is shrimp farming: there is a decline in savings from 2023 to 2032, after which savings begin to rise again. Shrimp farmer savings are calculated as the average of diseased and disease-free farms. The number of diseased farms increases between 2023 and 2032, and then decreases again. This explains the sudden decrease in savings followed by a recovery.

For medium-sized farmers, shrimp farms show the same trend: a sharp decline as more farms become diseased, followed by an increase in average savings once these farms migrate. Maize farmers are significantly poorer than rice farmers, while coconut farmers have experienced a turnaround: they are now among the wealthiest farmers, while they were the poorest in the small land category. Medium coconut farms have nearly twice as many non-agricultural wage workers compared to small ones. Furthermore, a medium coconut farm has 25% more self-employed agricultural workers, who also

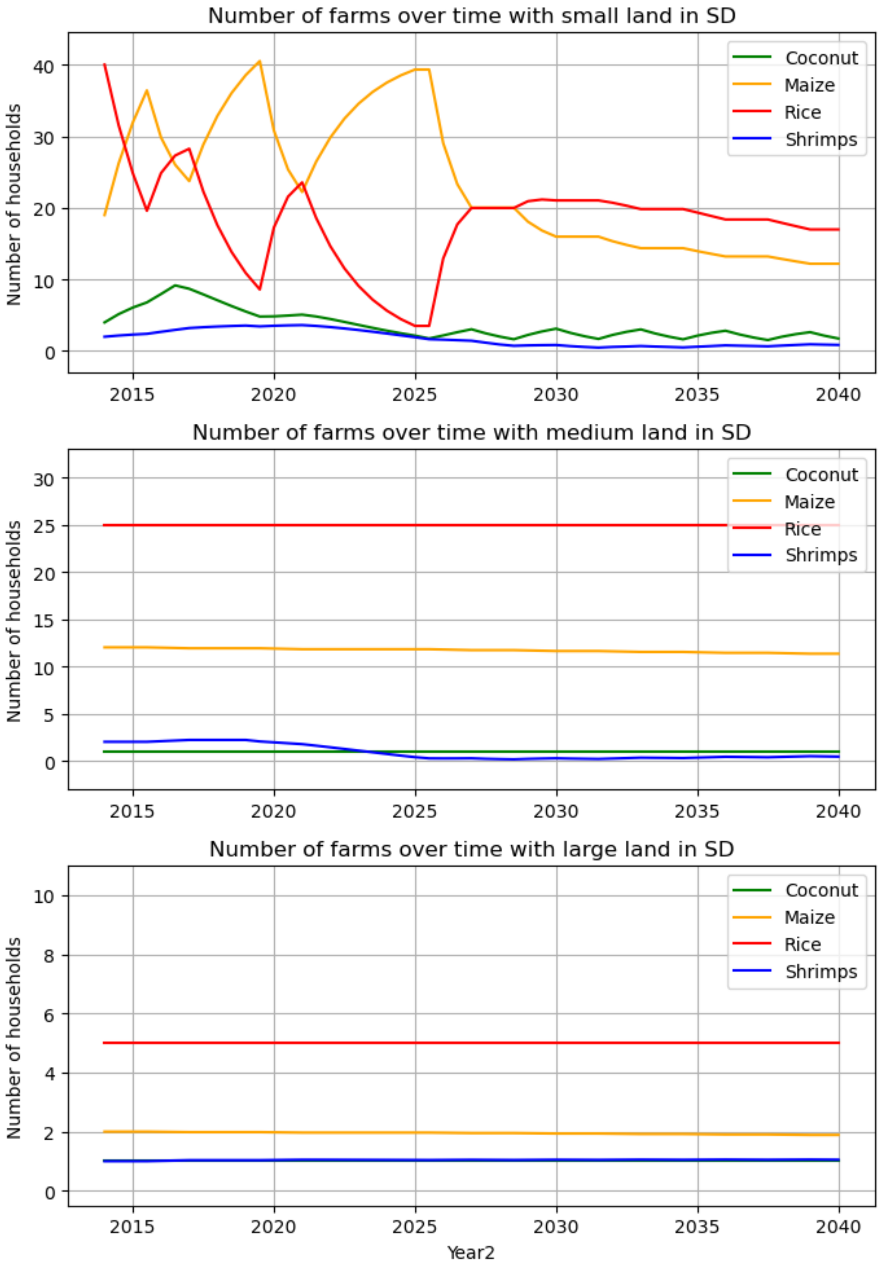


Figure 7.4: Number of farmers per crop type and land size in SD

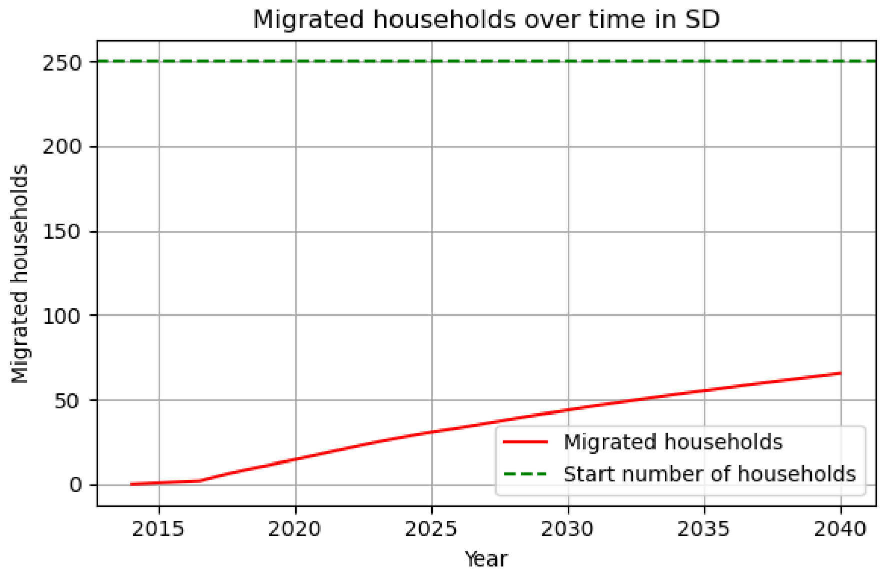


Figure 7.5: Number of migrated households over time in the SD model

contribute to income.

The sharp decline in shrimp farming among small and medium farms is not seen in the large land category. This is because there is only one shrimp farm in this category, and it is disease-free. As a result, diseased farms do not decrease the average savings. Quite surprisingly, this farm is the wealthiest of all. Maize, rice and coconut follow the same trend as observed in the medium land category.

7.4. Experiments

Experiments were conducted to study how migration levels change if potential government interventions were implemented. These experiments also provide insight into the model's sensitivity to these variables. In the SD model, migration is influenced by savings, making it a strong key indicator.

For each variable, 100 iterations were run, while all other variables were kept constant. The variable in question was tested over a range from 0 to 2 times its original value, without accounting for interaction effects. In each plot, the red line represents the baseline, which corresponds to the current value used in the SD model.

7.4.1. Sensitive factors for migration

Machines: In the SD model, it is not possible to state that some people have machines and some do not. Therefore, when the variable machine is greater than 0.5, the assumption is made that everyone has machines and less wage workers are required during harvest time. The income of wage workers decreases and farmers do not have enough money to stay. This is visualized in Figure 7.7.

Education level: When the education level is higher, farmers are less impacted by salinity shocks and therefore the yield will be more stable. This leads to more savings and less migrations. But the same problem is here: all farmers have the same education level in the SD model. When the level of education is higher than 0.5, it is assumed that all farmers are educated enough and are less affected by salinity. This effect is shown in Figure 7.8, where migrations decrease when the level of education reaches 0.5.

Wage worker salary: A higher salary leads to higher additional incomes in the SD model. The line in Figure 7.9 is decreasing in steps. When there is almost no salary, the migrations are the highest, which is a logical relation. But then there is a small stagnation around 0.25-0.50% of the current salary: for most of the farmers, this income is sufficient to live from. These are farmers with a low number of

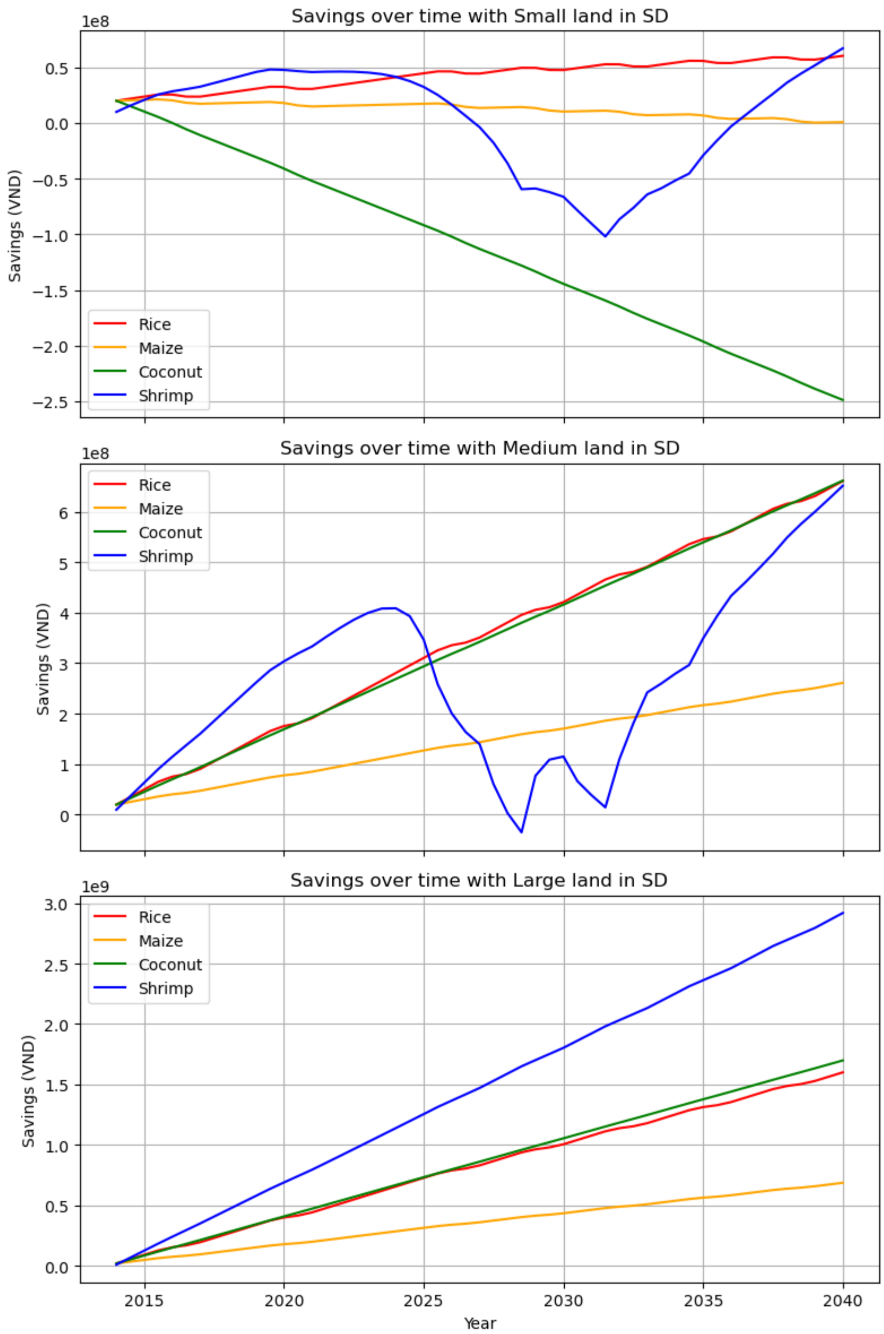


Figure 7.6: Savings per crop type and farm size in the SD model

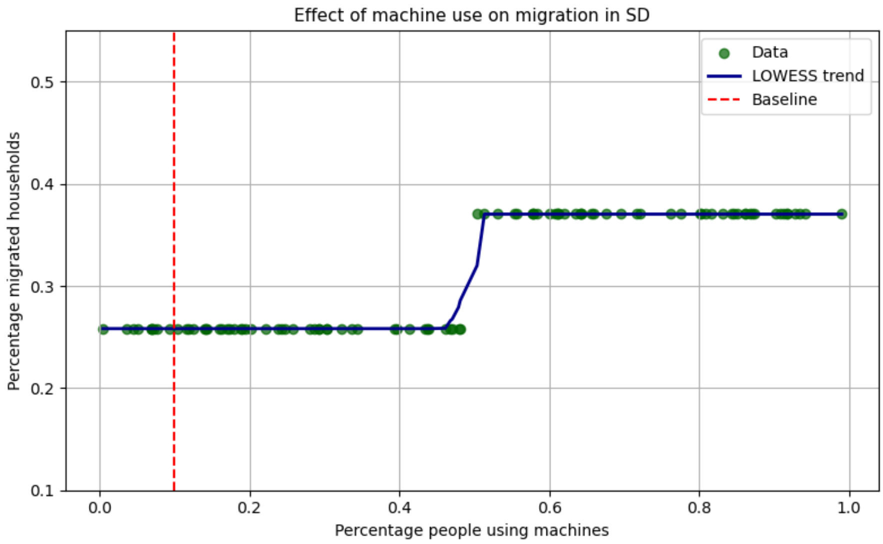


Figure 7.7: The effect of machine use on migration in the SD model

agri-workers in the family and a high number of non-agri-workers. This group exists for example out of small rice farmers, they have the lowest number of agri workers, but their additional income is one of the highest. However, large rice farmers have an average of 2.6 agri workers, and one of the lowest non agri workers. They are really impacted by the changes in wage worker salary.

After another stagnation between 0.75-1.1 due to the same phenomenon, the number of migrations is decreasing slightly.

Production costs: All farmers have fixed production costs, while for maize, production costs also depend on the wage worker costs. Changing *rice* production costs has the greatest effect on migration. When the production costs are doubled, migration rates more than double as seen in Figure 7.10a. The rice farmers are leaving, but this means less work for wage workers. They receive less income and other farms with a lot of agri-wage workers are also impacted.

For *maize*, decreasing the production costs has no impact. This is due to the fact that maize farmers have relative low fixed costs, and maize is the only crop for which wage worker costs are added separately. Maize still has high costs when fixed production costs are set to zero, and therefore, this has no effect. Increasing the costs gives the expected result, as seen in Figure 7.10b, since more farmers are migrating.

Coconut: Small coconut farms have the lowest savings, as can be seen in Figure 7.6. They are really impacted when production costs are set to zero, and this can also be seen in Figure 7.10c. There is a large switch when the costs are around 1.25e7 VND. The medium sized farmers have a positive net income in this scenario, while it is negative during the normal coconut production costs. This is the sudden increase in the graph. The same is for the small coconut farms when the costs reach around 2.4e7 VND.

Savings have zero effect on whether shrimp farmers are migrating or not in the SD model. Shrimp farming migrations are purely based on if the farm has a disease or not. Therefore, changing shrimp production costs has no impact, as seen in Figure 7.10d.

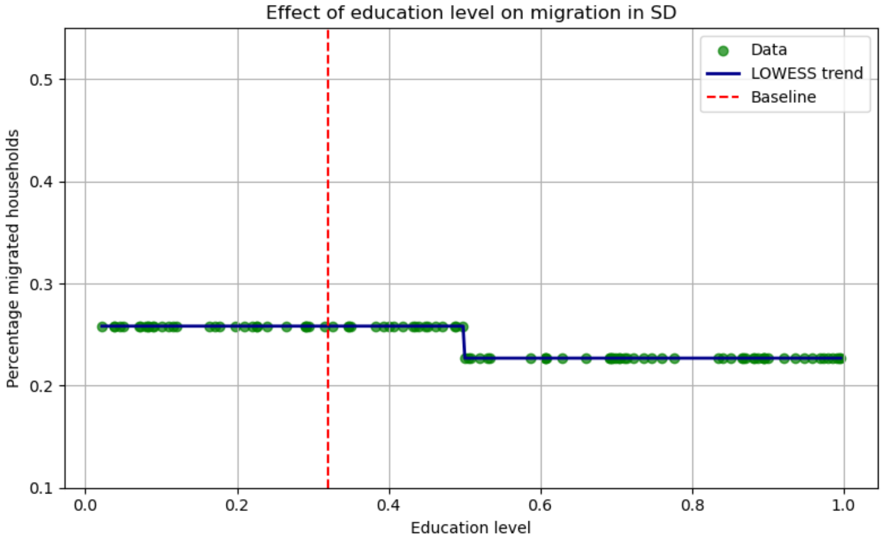


Figure 7.8: Effect of education level on the number of migrations in SD

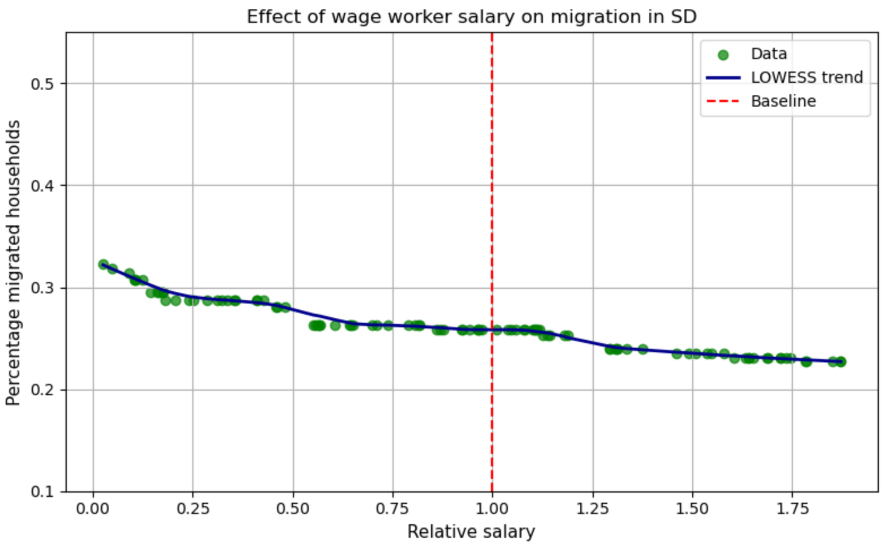
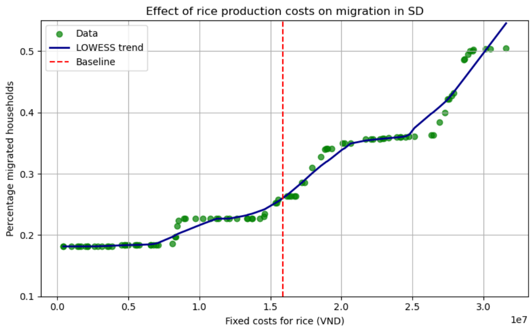
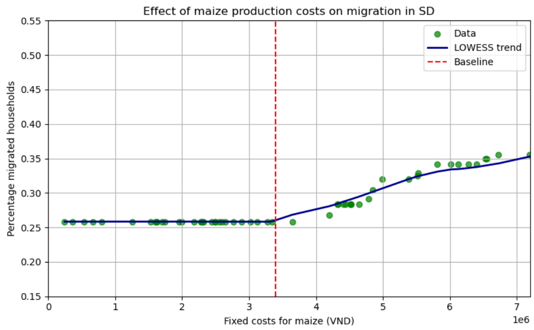


Figure 7.9: Effect of changes in wage worker salary on the number of migrations in the SD model

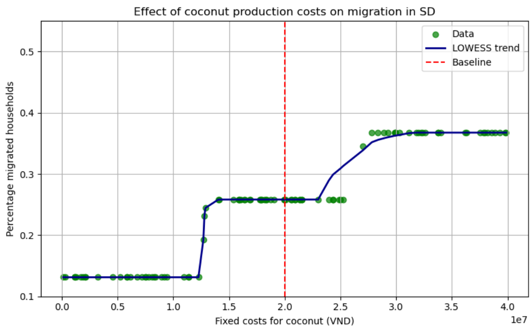
Effects of production cost changes on household migration in the SD model



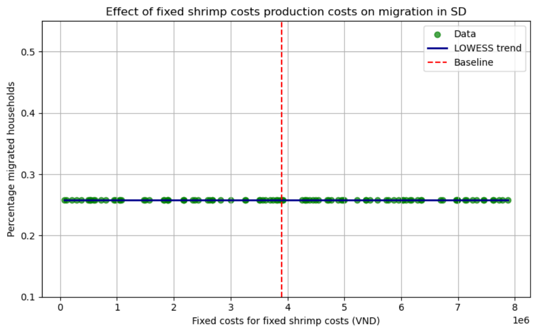
(a) Effect of changing production costs for rice



(b) Effect of changing production costs for maize



(c) Effect of changing production costs for coconut



(d) Effect of changing production costs for shrimp

Figure 7.10: Effects of production cost changes on household migration in the SD model

8

Comparison ABM and SD model

An attempt was made to create both an ABM and an SD model using the same functions and input variables. This section will discuss three points: What are the conceptual differences between the ABM and the SD model, what are the differences in results, and what are the differences in sensitivity? Furthermore, literature is used to see if the missing values in the SD model are crucial, and the differences in the modeling process are studied.

8.1. Conceptual differences

Due to the differences in the modeling approaches, there are a few factors included in the ABM that could not be implemented in the SD model. These are detailed below:

Crop switches: In the ABM, agents switch crops when income exceeds expenses. It is checked whether people attended the information meeting, where they received a recommended crop based on salinity levels and education. The agents then consider what their neighboring farmers are doing and apply the MOTA framework to determine the most suitable crop for the farmer. In the SD model, no crop recommendation is given during the information meeting, as it is not possible to make household-level recommendations. The model also does not take into account neighbors' behavior or apply the MOTA framework. Instead, it considers trends observed in the ABM: when people switch crops, to which crop do they switch? The vast majority switch to maize, and this percentage is then incorporated into the SD model as a "chance of switching to maize." Based on income levels, there is a probability that farmers will switch crops, which is then multiplied by this chance.

In addition, when a farmer switches to coconut in the ABM, there is an initial growth period of five years. During this time, the farmer cultivates maize or rice on half of their land, which still generates some income. However, this is not possible in the SD model: although it is possible to implement a delay, these farmers would still need to generate income during that period. This might have been possible by introducing an additional intermediate stock, but doing so would significantly reduce the clarity and simplicity of the model.

Furthermore, in the ABM, farmers must pay switching costs when changing from one crop to another, since the land needs to be prepared. In the SD model, this is not possible: farmers do not have individual savings. All farmers in the same stock have the same savings based on averages. It is therefore impossible to say "one new farmer has joined, now all farmers in this stock must pay a certain amount of VND in switching costs."

Debt: In the ABM, it is possible to take out a loan when switching crops or when the savings of a farmer are depleted. This debt is then repaid in subsequent years. However, the same limitation applies in the SD model as with switching costs: since everything is aggregated, all farmers in a stock would effectively have to repay the same debt. For this reason, debt was not included in the SD model.

Household composition: In the ABM, households consist of individual members, each with their own occupation. These are combined to form the household, resulting in multiple professions and income sources within a single household. In the SD model, this is approximated for farm households: for each crop type and land size, a fixed number of household members is assigned to work in a given sector. This distribution is based on district-level data analysis, which shows how many people work as wage laborers or as self-employed non-agricultural workers. Wage workers are assumed to be non-agri wage workers (otherwise they would be classified as self-agri), and self non-agri workers are service workers. Thus, each household of a certain crop type and land size has the same composition of household members.

For service worker households, non-agri wage households, and agri wage households, this level of detail was not applied in the SD model. It is assumed that everyone in a service worker household works as a service worker, and everyone in an agri wage household works as an agri wage laborer. Although the total number of workers per category is still representative, the composition of the household differs.

Wage workers: In both the ABM and SD model, farmers employ wage workers. However, in the ABM, agents can change roles: if total household income is too low, an agent may start manual work if this yields more income. Agents can also switch back. These transitions are not possible in the SD model, since all households within a stock earn the same income and have the same number of workers in certain categories. When changing occupations, everyone in the stock would have to switch at the same time, which is not realistic.

Youth migration: In the ABM, youth aged 15 to 35 years can migrate. This is not possible in the SD model because households do not consist of individual members, and thus have no age structure. It is impossible to determine whether a household has children who want to migrate. It would have been possible to let a certain percentage migrate over time based on ABM trends. However, this would require reducing the number of wage workers in those households while keeping the number constant in others. Due to the level of aggregation in the SD model, this was not feasible and therefore not included.

Salinity levels: In the ABM, each agent is placed on a spatial map and has a unique salinity level. Some agents are therefore more affected by salinity shocks than others. In the SD model, everyone has a fixed salinity level of three, which increases from three to five during salinity shocks.

Machines, experience and education level: In the ABM, each household has an experience level per crop, can own harvesting machines, and has an individual education level. In the SD model, it is not possible to differentiate between households. As a result, either all or none of the households have machines based on averages, and a single average education level is used. This yields benefits if the level is greater than zero point five. The level of experience per crop is not included at all in the SD model.

Household attributes: In the ABM, a household agent could have sixty-four million VND in savings, two agricultural workers, one non-agricultural worker, and cultivate rice. If that household switches to coconut farming, it retains those characteristics, becoming a coconut farmer with the same savings and workers. This is not the case in the SD model: if a small rice farmer switches to a small coconut farmer, they immediately adopt the savings, wage worker numbers, and household composition of a typical coconut farmer.

Lastly, all of the factors above influence the *livelihood* indicator in the ABM. This is a measure of agent well-being. This factor was not included in the SD model because it would be the same for all households. Due to the many assumptions required, the livelihood indicator was not further used in the SD model.

8.2. Differences in results

Based on the conceptual differences, there are differences in the outcomes. The same variables were used as model outputs for both models: number of farmers, migrations, and savings. To check for any modeling errors, other variables were also compared, such as yield over time per crop type and land size, profit from farming, wage worker costs per farm, and the total number of wage workers.

8.2.1. Number of farmers

In both models, a farmer can switch crops if the net income is less than 0. The percentage of times this switch occurs in the ABM was counted, as well as how often people continue with the same crop. The switching percentage was 42% for rice and 55% for maize.

Figure 8.1 gives an overview of the number of farmers in the SD model and the ABM. For the *small farmers*, there are significant differences: in the ABM, farmers switch crops at the beginning, reach a steady state, and then stop switching. The ”strong farmers” remain and have found their optimal crop category, meaning their income will always be sufficient. In the SD model, shown on the left side of Figure 8.1, completely different behavior is shown: after each shock, the income of farmers is too low, causing them to switch between maize and rice. The SD model does not differentiate over time between ”stronger” farmers who can handle shocks and the ”weaker” farmers, as everyone in the SD model has the same characteristics. This differentiation occurs in the ABM, which is why the switching peaks are absent after the first few years. It is also noticeable that many more rice and maize farmers remain in the SD model than in the ABM. In the SD model, the land size is fixed at 0.45, while in the ABM, the land size for small farmers ranges from 0.3 to 0.5. This results in more small farmers dropping out of the ABM for this category.

Furthermore, there are a large number of coconut farmers at the start of the model in the SD version, whereas this peak is much smaller in the ABM. In the ABM, the next crop is determined by the neighbors and the information meeting. If there is no salinity shock (such as in 2015), and none of the neighbors grow coconuts, the farmer is unaware that coconut is an option. This leads to fewer small coconut farmers in the ABM than in the SD model.

However, the opposite difference is observed for medium and large land size farmers: in the SD model, there are hardly any medium and large coconut farmers, while they are present in the ABM. This is because all medium land size farms in the SD model have an insufficient net income, as the model uses averages. In the ABM, some ”weaker” farms do not earn enough income and must switch, but there are also richer farms that can stay. This phenomenon also explains why there are switches in the medium ABM graph, but not in the SD graph.

The number of large rice farmers in the ABM is increasing: These are farmers who take over land from smaller rice farmers who quit. However, fewer small rice farmers quit the SD model, which means that no land is taken over, even though this option was taken into account in the SD model.

It was possible to use a lookup table for the probability that a household switches crops over time, which aligned the model results. However, this lookup table would not have been created if the ABM had not been developed. In addition, the lookup was not implemented to highlight the difference between the ABM and the SD model when exactly the same numerical values were used.

8.2.2. Migrations

Figure 8.2 shows the difference in the number of migrations between the ABM and SD models. In the ABM, the number of migrations increases significantly from 2016 onward, as income and savings have decreased during the first shock. After that, the number continues to rise slowly.

In the SD model, these migrations occur somewhat more slowly: small farmers are still actively switching crops instead of migrating in 2016. However, the migration rate rises almost linearly, and after 25 years, approximately the same number of households have migrated. In addition, there are no migrated individuals in the SD model, as this is not possible within its structure.

8.2.3. Savings

The biggest difference between the models lies in the savings. In the ABM, each agent has their savings, earns their own income, and carries their savings when switching. The ”poorer” agents migrate to the city, and the wealthier agents remain. This does not happen in the SD model, which uses averages. When the ”poor” agents leave, the average savings do not suddenly increase, since there are no poor or rich agents represented individually. As a result, average savings are much lower in the SD model than in the ABM.

There is also something interesting visible in the average shrimp farmer’s savings. The peak seen in the shrimp farmers’ savings in the SD model (due to an increase in sick shrimp farmers) is not present in the ABM: in the ABM, a shrimp farmer may be sick one year and healthy the next, so there are no consistent savings drops among a few agents that pull down the average every year.

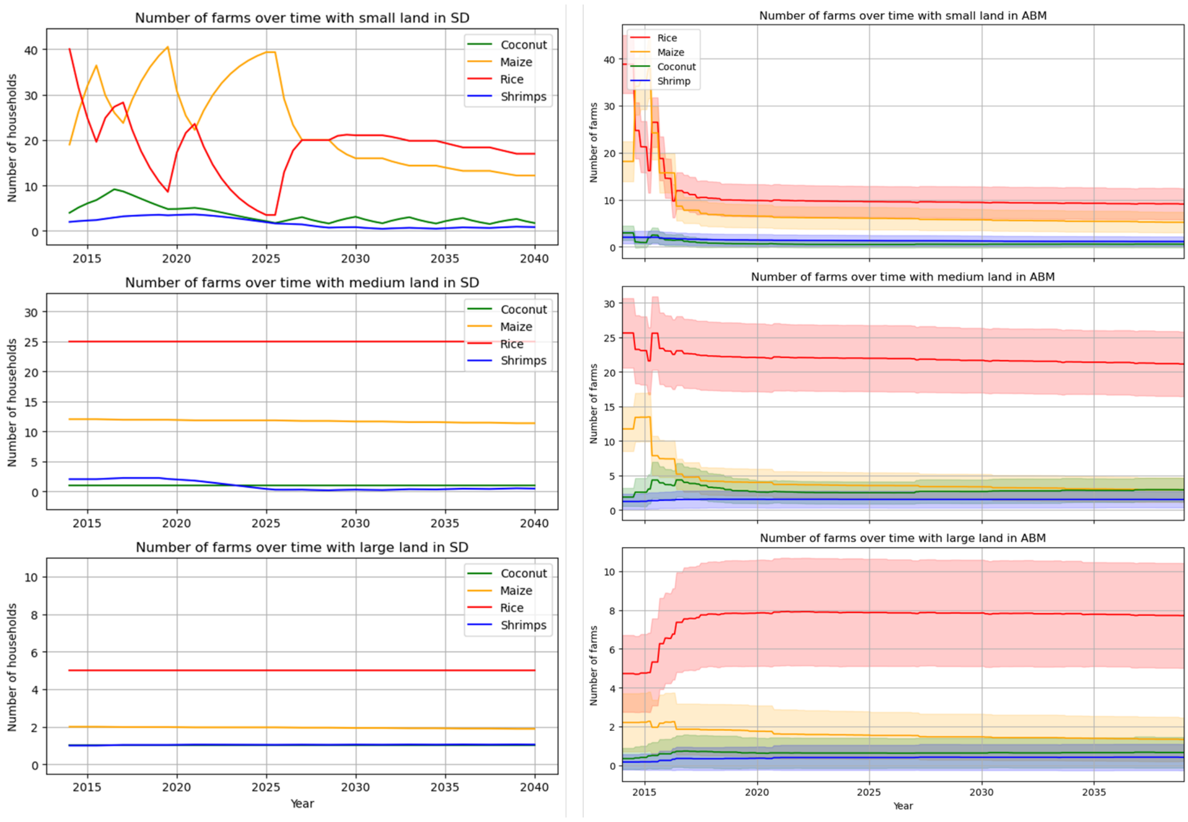


Figure 8.1: The number of farmers per crop type and land size over time in the SD model (left) and ABM (right)

The same effect can also be seen in the savings of the landless households in Figure H.4 in Appendix H. The savings in the SD model are much lower than the savings in the ABM.

8.2.4. Comparison other variables

In addition to the three main outputs, other variables were also compared to observe differences. The graphs for visualization can be found in Appendix H.

When looking at the *yield per farm over time*, there are no large differences. However, the yield/household decreases faster in the SD model during a shock, while the decrease is much smaller in the ABM. This is because in the ABM, each agent has a different salinity level, and the "stronger" agents with favorable salinity levels remain. These agents are less affected by shocks. At the start of the ABM, the impact of the shock is also more intense than in the later years.

It is also visible that the yield of large farms is slightly higher in the ABM than in the SD model. This is due to some outliers in farm size for large farmers in the ABM, which are defined between 2 and 5 ha, raising the average. In the SD model, farm size is a fixed value, set at 3. This is also reflected in the profit per farm in Figure H.2.

The average wage worker costs per farm are also slightly different in the ABM and SD models. The average values were used in the SD model, which results in the wage worker costs being zero for small farmers. However, in the ABM, some small farmers do require wage workers, so there are indeed costs for the small farmers. There is also a small difference in large farmers, which is again caused by the outliers in land size in the ABM.

8.3. Differences in uncertainty

In addition to differences in model output, the sensitivity of both models was compared by studying how changes in five variables affected the number of migrations.

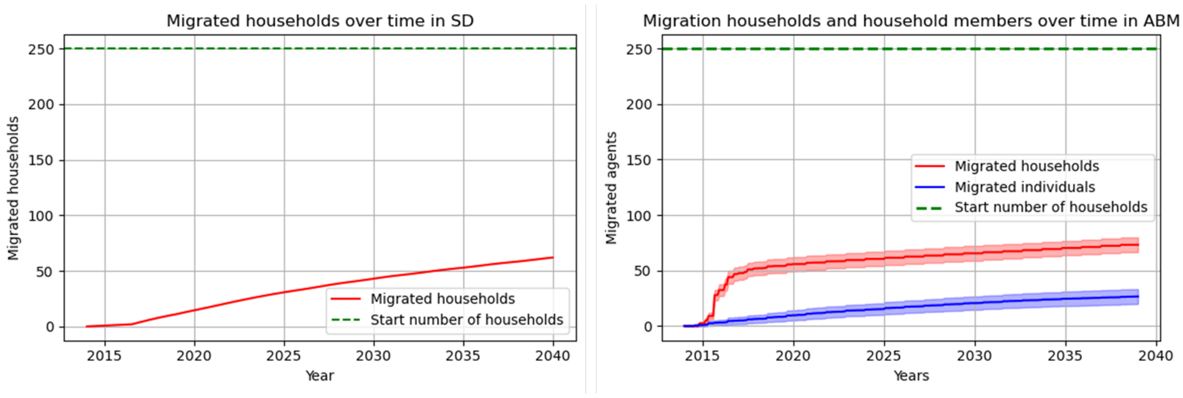


Figure 8.2: Number of migrated households over time in the SD Model (left) and ABM (right)

8.3.1. Machines

There is a clear difference in sensitivity between the ABM and SD models when looking at the number of people using machines. In the SD model, there is a peak at 0.5: this is the threshold that was set, and when more than 50% of the farmers use machines, everyone immediately adopts them. In the ABM, this threshold was not needed, and if the value is 50%, then indeed only 50% of farmers have a machine.

However, the SD model is much more sensitive: each farm has a fixed number of wage workers, and this income decreases when everyone uses machines (since there is less work to do). The wage workers cannot switch to, for example, manual labor; the household income drops, and subsequently, the households are forced to migrate. In the ABM, wage workers can become manual workers when less work is available, and still earn approximately the same income. Therefore, people do not migrate, and the ABM is much less sensitive.

8.3.2. Education level

Both models show the same trend, as seen in Figure 8.5. There is a threshold at 0.5: if the education level is higher than this, the impact of salinity is reduced, leading to higher yield, more savings, and fewer migrations. In the SD model, the education level directly affects the reduction of salinity level during a shock, and thus also the yield loss and income. In the ABM, the human livelihood variable is used, which includes the level of education, but also whether someone attended the information meeting, their experience, and the level of disability. This explains why the ABM reacts slightly less strongly than the SD model.

8.3.3. Wage worker salary

Both models also show approximately the same trend, as seen in Figure 8.6. However, there is a small peak around 1.75 in the ABM that does not appear in the SD model. In the ABM, small farms also have wage worker costs, while in the SD model, small farmers do not have those, as shown in Figure H.3. For maize farmers, wage worker costs directly impact total costs. So if wage worker costs rise, there is less budget available, and farmers may need to migrate. Maize farmers in the SD model do not experience this, which explains why there is no migration peak there.

8.3.4. Crop production costs

As shown in the comparison for savings in Figure 8.3, households are much wealthier in the ABM, making them more resilient to changes. In the SD model, for rice, maize, and coconut, it is seen that the higher the costs, the more migrations occur. For coconut and rice, this trend is less intense than in the ABM, but still present, while for maize, it has no effect at all. For shrimp, there is no difference in either model.

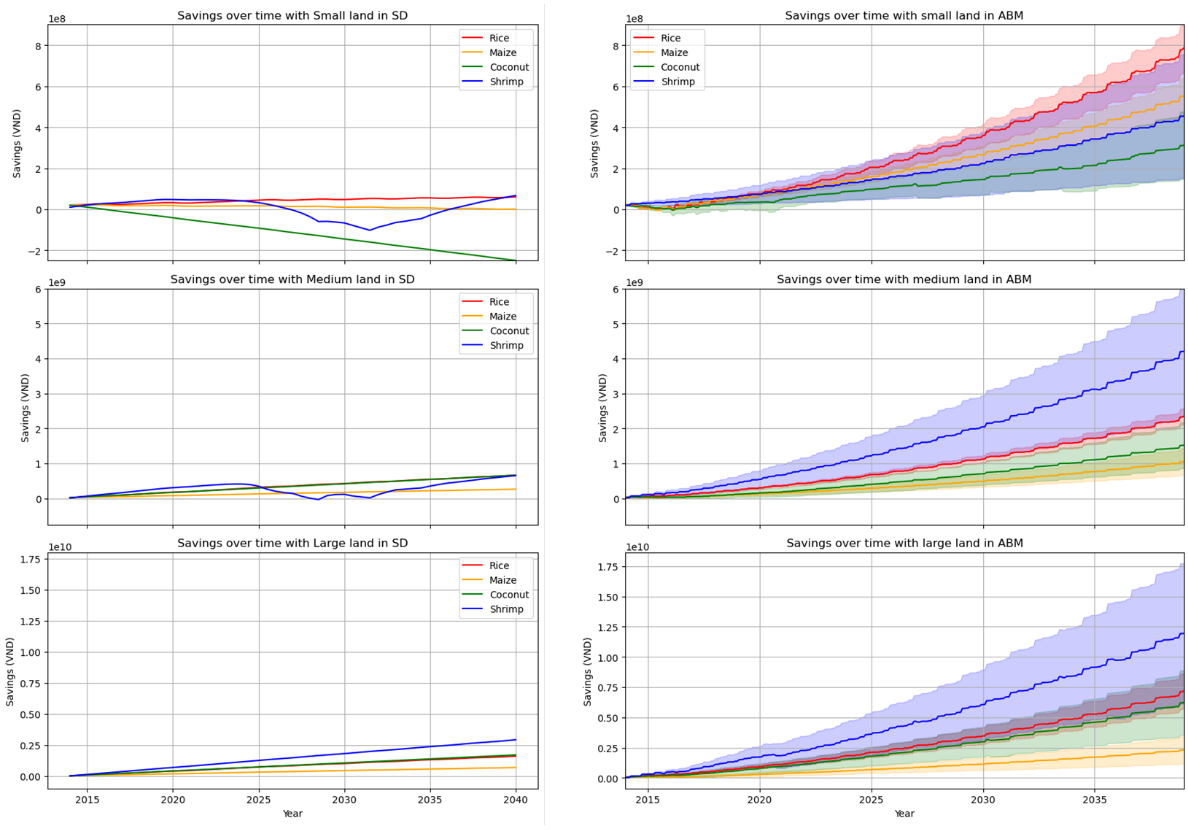


Figure 8.3: Savings over time in the SD model (left) and ABM (right)

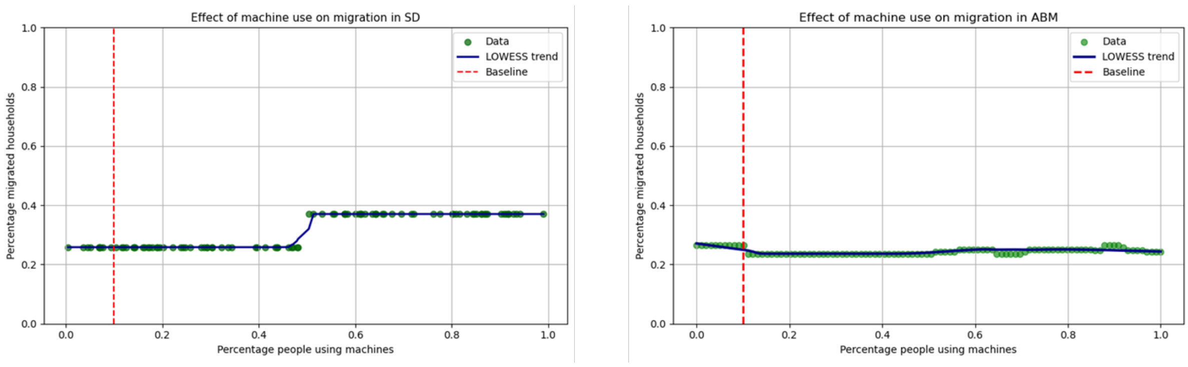


Figure 8.4: Effect of machine use on the percentage of migrated households in the SD model (left) and ABM (right)

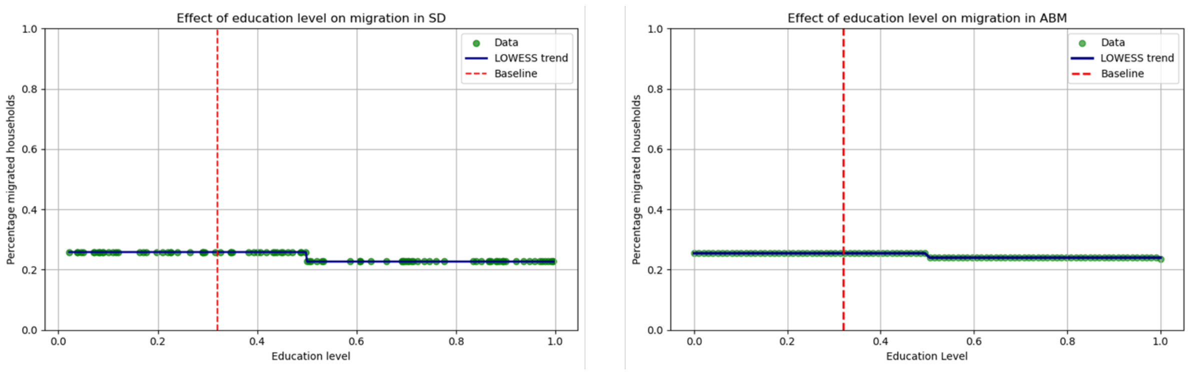


Figure 8.5: Effect of education level on the number of migrations over time in the SD model (left) and ABM (right)

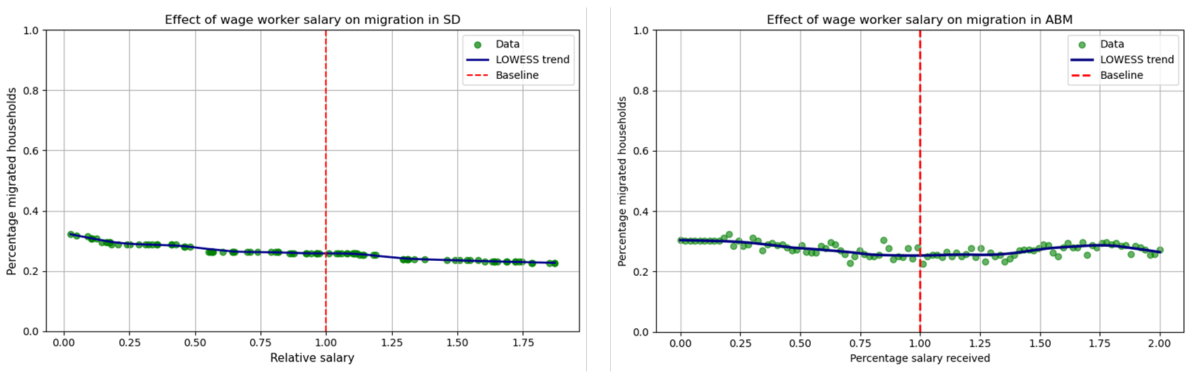
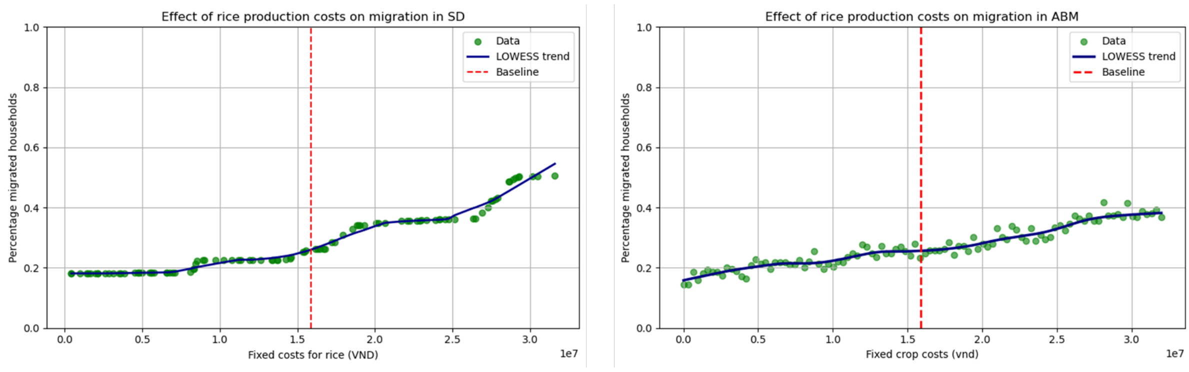
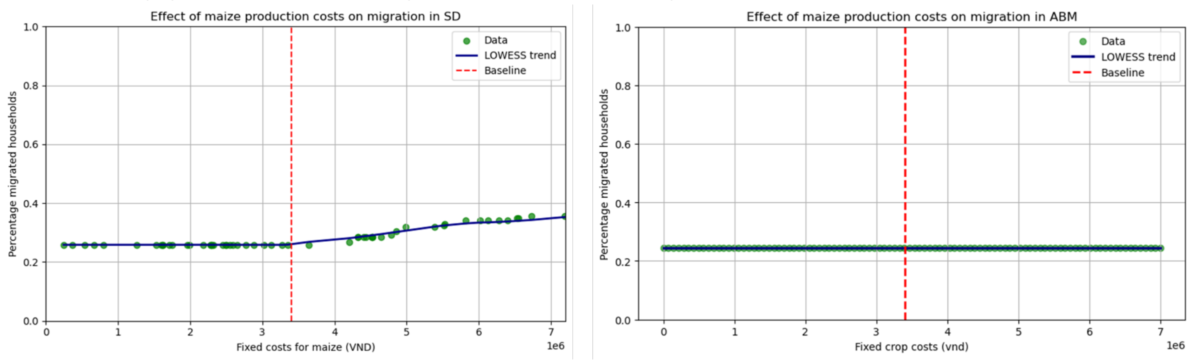


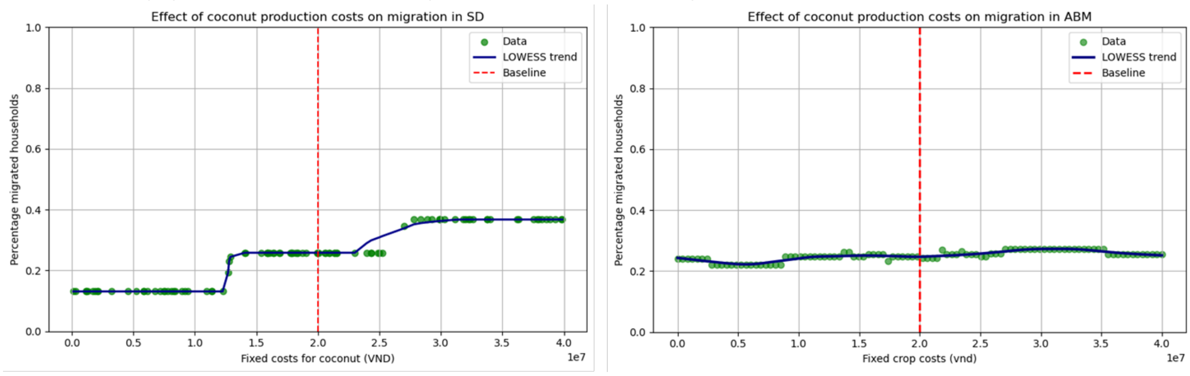
Figure 8.6: Effect of changing the wage worker salary on the number of migrations, in the SD model (left) and ABM (right)



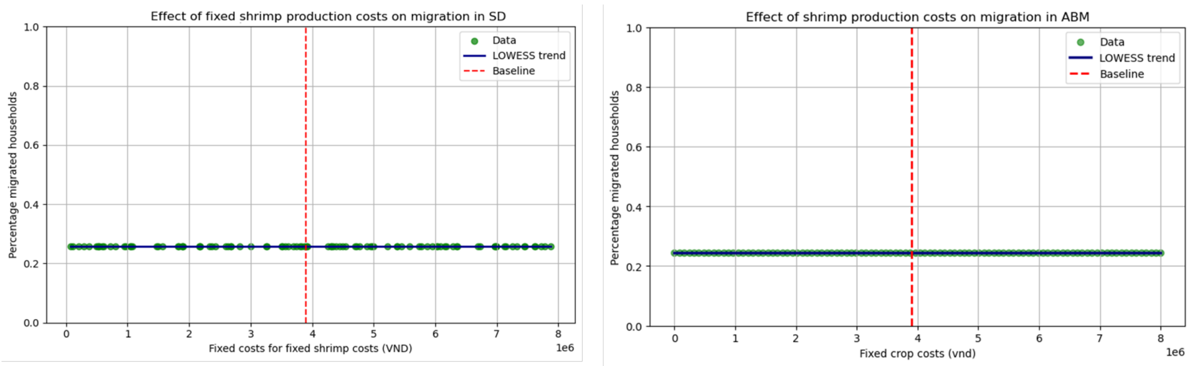
(a) Effect of changing rice production costs on migrations in SD (left) and ABM (right)



(b) Effect of changing maize production costs on migrations in SD (left) and ABM (right)



(c) Effect of changing coconut production costs on migrations in SD (left) and ABM (right)



(d) Effect of changing shrimp production costs on migration in SD (left) and ABM (right

Figure 8.7: Overview of migration effects from changing crop production costs

8.4. Implications of the absence of certain factors in the SD model

When looking at the factors that could not be included in the current version of the SD model (since it was constructed to have the same structure and input variables as the ABM), it is important to consider what effect the absence has on the results. This is done by checking if these factors are considered important in the literature. Furthermore, it is studied whether these factors could still be implemented in some way within the SD model. Table 9.2 provides an overview.

From this analysis, it becomes clear that the absence of the MOTA framework in the SD model does not influence the high-level outcome. But, should the dynamics change in the future, these percentages will remain fixed. This can be a problem, given that the literature still debates whether farmers will switch to certain crops or not (Kaveney et al., 2023).

In contrast, the absence of crop switching costs, growth period, debt, occupational changes, youth migration, spatial positioning on the map, and heterogeneity in machine use, experience, and education level is more problematic. Literature identifies these as important factors that shape behavior and crop decisions. In the current SD model, most of these variables have been incorporated via trend inputs derived from the ABM, sometimes resulting in similar model behavior. Without the ABM, these trends could not have been used as input, and the SD model would have required assumptions instead. An example of this is the education level and machine use: by using averages, the SD model shows the behavior of an average farmer. However, in reality, farmers have different characteristics, leading to different individual behaviors, which then aggregate into a group average. Modeling only the average skips over this individual variability.

Some of these features can technically be added to the SD model, in an attempt to replicate the exact ABM behavior in the SD model. However, this often requires lookup functions based on ABM trends. Without the ABM, it is unclear what impact these features would have or how strong their influence would be. For example, the ABM MOTA framework showed that, on average, 42% of rice farmers switch crops when income is too low. It showed that not all farmers can afford the switching costs or have knowledge of alternatives. Without this insight, the SD model might have assumed: "If income is too low, everyone will switch.", and there would be fixed assumptions. Should other variables change, these fixed assumptions would need to change as well. This can be done by either using new lookups or by re-running the ABM to obtain updated trends.

The last issue is the lack of household attributes in the SD model, since this gives an unrepresentative view of reality. In the VMD case, many farmers switch between stocks, and each stock has different attributes. When a switch occurs, it makes sense for a farmer to retain these attributes. For example, if someone switched from rice to coconut, it would be strange if they suddenly had two fewer self-agricultural workers. In the ABM, this does not happen, which allows one to observe what happens to these agents over time and whether they perhaps perform better than the original farmers.

Table 8.1: Implications of the absence of certain factors in the SD model, related to literature and how these could possibly be implemented.

Missing feature in the SD model	Implication of absence	Is the feature important according to literature?	Can this somehow be implemented in the model?
MOTA framework for crop switches	SD uses statis switching probabilities, failing to reflect dynamic adaptation to increasing salinity. Switching to salt sensitive crops, e.g. rice and maize, will still occur in high saline areas, while shrimp or coconut would be more suitable. Furthermore, the motivation and ability of the farmers is not taken into account, and therefore it is unclear what the motives behind the crop switches are.	Partly, it is aimed to have 450,000 ha of fruit trees, vegetables and shrimp in salt saline areas of the VMD in 2030 to be more salt tolerant, and farmers in these areas should switch to these crops (Wilbers et al., 2025). However, researchers are still searching for promising alternatives who will indeed be adopted by farmers (Kaveney et al., 2023).	Partly, a lookup could be implemented based on salinity levels and the probability of someone switching crops. However, these would be assumptions or would have to be based on trends from the ABM. It would still not be possible to verify whether farmers are truly capable, motivated, and have the necessary resources to make these switches.
Crop switching costs	Each time step, a fixed percentage of farmers is allowed to switch, while in reality a large share of farmers cannot afford to make this switch at all. In addition, the savings in the SD model turn out more favourable than they would in reality due to the lack of switching costs.	Yes, research shows that for many farmers in the VMD, production costs are already very high, and investing in switches is challenging (D. D. Tran et al., 2018).	No, it is not possible to assign individual costs to farmers in an SD model, as everything is aggregated. Everyone within the same crop category would have to bear the same costs if someone switches, which would be highly unrealistic. However, the SD model does account for the fact that only 42% of farmers make the switch during periods of reduced income, since they cannot pay the switching costs. This is based on ABM trends. However, when factors change, this switching probability should also change.
Growth period	Due to the growth period of for instance coconut trees, farmers experience reduced income for several years. This cannot be incorporated into the SD model, which leads to a distorted representation of savings and, consequently, the number of migrations	Yes, research shows that perennial crops are currently not very popular because they produce low yields in the initial years. Not everyone can afford this lack of income (E. A. Chapman et al., 2022).	Partly, it is possible to implement a delay and allow farmers to enter the coconut stock only after 5 years. However, the impact on savings and income for these individual farmers, which is the important part since some are not being able to afford them, cannot be modelled.
Debt	In the SD model, it is not possible to take out a loan, which means that if farmers have no savings, they must migrate immediately instead of being given another opportunity. In addition, debt is used in the ABM when switching crops, but it has no impact in the SD model because there are no switching costs.	Yes, the possibility for a loan has a large impact on the livelihood of a farmer. For example shrimp farmers in the VMD who have access to loans, have an average increase in income of 35% (Ly & Nguyen, 2020).	No, this is not possible due to the aggregation level. It would be unrealistic if all households need to pay back loan, if only one household has debt.
Household composition	In the SD model, every household has the same composition, which gives a misleading picture of the heterogeneity in society and how different types of households behave.	Yes, household composition does have impact on the income of households. For instance land households in the VMD with a higher dependency ratio (meaning they have more children or elderly members) had higher	No, this is not possible due to the level of aggregation.

Missing feature in the SD model	Implication of absence	Is the feature important according to literature?	Can this somehow be implemented in the model?
		agricultural incomes and fewer off-farm incomes (Ho et al., 2024).	
Change occupation	In the SD model, it is not possible to switch occupations when salary for wage workers decrease. This leads to lower income, less savings, and more migrations, especially for the landless households.	Yes, due to environmental changes in recent years, more people are switching jobs and occupations, and they are trying to find employment with higher income (Thi Quyen, 2022).	Yes, this is possible. However, all households within a stock have the same household composition and same income. Therefore, when income is not high enough for this household category, this is the case for all households in that category. These households all need to switch their occupations, which might become chaotic.
Youth migration	The youth migration will change household compositions, e.g. the land household will have less self agri workers, and therefore change the income of the household. Furthermore, it is possible that there are deficits in sectors, e.g. the number of facilities is decreasing due to their migrations, which is not taken into account in the SD model.	Yes, research from Ethiopia shows that youth migration in general has led to a labor shortage in the rural agricultural sector, causing a decline in local productivity (Dadi, 2021). Migration has also changed the structure of households in the VMD, resulting in fewer people available to care for children and the elderly (Quach & Vo, 2023)	Partly, it is possible by implementing a fixed percentage of youth migration, based on the trends of the ABM. However, it is not possible to decrease the number of e.g. self agri workers for 1 household. Then all the households should have less self agri workers, which is unrealistic, since not every household has youth migration.
Map placement and salinity level	Because the SD model does not differentiate between salinity levels, everyone is equally affected by rising salinity. In reality, there are rice farmers living in more favorable areas where salinity levels are lower, and they are less severely impacted	Yes, higher salinity levels lead to lower crop productivity, causing these farmers to be more severely affected and possibly migrate or switch crops more quickly (Thach et al., 2023).	No, is not possible to place the households on a map in SD, since everything is aggregated. In addition, all households have the same salinity level each step.
Machines, experience and education level	Since it is not possible to account for heterogeneity in the SD model, everyone has the same education level, experience level, and either all have or all lack machinery. As a result, the entire population will respond in the same way, whereas in reality, some farmers perform better than others	Yes, for example households with higher education levels have more efficiency and higher yields in the VMD (Ninh, 2020; D. B. Tran et al., 2023). In addition, due to farming techniques and experience, some farmers were better able to cope with environmental changes (Brown et al., 2018).	No, due to the level of aggregation, all households should have the same characteristics, based on averages.

8.5. Comparison of modeling process

Several differences emerged during the development of both models, which are explained below.

First of all, SD models are easier to explain. In ABM, individual behaviors can lead to emergent patterns at the aggregate level. For instance, a farmer might attend an informational meeting and learn that perennial crops are a good idea. A neighbor might then see the coconut trees growing and think, “That looks promising, I want to try that too,” and begin growing coconuts as well. Agents can decide whether to develop themselves or not, based on probabilities, which can sometimes appear like a ”black box” of code. This level of detail cannot be modeled in SD. Instead, SD would model this as: ”X percent of the group transitions to perennial farming,” without incorporating the decision-making rules behind individual behavior. In ABM, the behavior is modeled as: ”Each agent has a different probability X of doing this, based on their factors Y and Z.” These variables X, Y, and Z can vary for each agent.

Besides explainability, SD models are also easier to build and interpret. In SD, one works with stocks and flows. Adding a new stock can be done by simply clicking a button in Vensim. In ABM, adding such a feature might require hundreds of lines of code. For outsiders, ABMs are harder to interpret. There is no visual overview; it is just thousands of lines of code. Interviews with Deltares colleagues revealed that the ABM was often vague and difficult to understand, which complicated communication. The SD model, by contrast, offered a clear and intuitive overview right away, allowing colleagues to quickly provide useful suggestions for improvement.

The output of an SD model in Vensim or Stella is also more interactive for Deltares (M. van Aalst, Personal communication, May 2025). Dashboards can be created with sliders and graphs that update instantly when a slider is moved. ABMs are stochastic and require many simulation runs to produce reliable results. Furthermore, in ABM, model code must be modified to make changes since there are no interactive sliders available.

However, one advantage of ABM is its flexibility in terms of visualization. SD models typically produce only line graphs, and customizing these is often not possible. For example, when plotting multiple variables, Vensim frequently assigns inconsistent axes, making the interpretation difficult. To address this, the SD output was exported as CSV files and visualized in Python. ABM is already built in Python, where tools like Seaborn and Matplotlib allow much more refined and aesthetic visualizations than Vensim’s default line graphs. If there is limited Python knowledge, this can be a disadvantage of SD.

9 Conclusion and discussion

The purpose of this research was to explore the advantages and disadvantages of different modeling approaches to study the distributed and disaggregated impacts on different types of inhabitants in the Vietnamese Mekong Delta. To reach this goal, several sub-questions were answered. After answering the research question, Deltares will receive recommendations, followed by a description of the strengths and weaknesses, as well as the practical and theoretical implications. Finally, recommendations for further research are presented.

9.1. Answers to research questions

First, all sub-questions will be answered. Based on these answers, the main research question will be addressed.

Sub-question 1: *What are promising different modeling tools and approaches for Deltares to model the disaggregated and distributional impacts?*
Three modeling approaches were considered: Discrete-Event Simulation (DES), Agent-Based Modeling (ABM), and System Dynamics (SD). DES was found to offer no advantages for this case that could not also be achieved with ABM or SD, and therefore, DES was excluded. Although DES can focus on the micro level, ABM can do this as well (Maidstone, 2012). DES is faster than ABM (Railsback et al., 2017), but nowadays, DES characteristics can be modelled in MESA 3 (Ter Hoeven et al., 2025), and SD is even faster than DES (Caro et al., 2016).

Furthermore, a set of requirements was defined to assess whether the model would fit the needs of Deltares. This resulted in 12 ”must-haves”, and Table 9.1 provides an overview of these factors, and whether these can be fulfilled by SD and ABM.

This table shows that SD fails to meet two requirements: easily changing the composition of people and modeling human behavior/interactions. This aligns with the SD model created by Yuan et al. (2011), who concluded that SD is unable to capture microscopic individual behavior due to the lack

Table 9.1: Overview of the “must have” requirements and whether they can be met by SD and ABM

“Must have” requirement	Possible in SD	Possible in ABM
Easily change the composition of people	No	Yes
Simulate scenarios	Yes	Yes
Short runtime	Yes	No
Import data from excel/csv	Yes	Yes
Possible to model different types of inhabitants	Semi	Yes
Model human behavior/interactions	No	Yes
Dynamic output	Yes	No
No connectivity to internet required	Yes	Yes
Clear and understandable output	Yes	Yes
Modularly built	Yes	Yes
Easy to connect to other models	Semi	Yes

of heterogeneity. Also, agents in SD cannot communicate with each other, preventing the emergence of macro-level behavior. Modeling different types of inhabitants is only partially possible: the model includes small, medium, and large farmers, but true individual variation with unique characteristics cannot be represented. In an SD model developed by Chapman and Darby (2016) about farmers, there were also only three fixed land sizes, and no further differentiation in farmer composition. This limitation was also observed by Von Loeper et al. (2016), who noted in interviews that certain individuals exhibited a different behavior from the population, but this could not be modeled in SD.

ABM also fails to meet two requirements: short runtime and dynamic output. Due to the stochastic nature of ABM, it takes longer to run (Chopra et al., 2023), and this also makes it impossible to build interactive dashboards with sliders for instant feedback, which is possible in SD.

Both models can potentially be connected to other models. For instance, ABM or SD outputs could be used as inputs for other models. However, attention must be paid to the abstraction level. SD operates at a macro level, making it harder to connect to other models (Ding et al., 2018). The ABM is built in Python, and due to fixed time ticks, it connects more easily to other models. According to Macharis (2000), SD models in Vensim can also be linked to other models, but this requires additional software to connect Vensim to, for instance, MCDA. This software might not be available for all model types. An alternative is to export the output from Vensim and import it into another model (Macharis, 2000).

Sub-question 2: *How can these promising approaches be conceptualized, combined with their data requirements?*
The conceptual models can be found in Figures **??**. Several factors cannot be modeled in SD but are included in the ABM:

1. **Crop switching costs:** When farmers switch crops, costs are incurred to prepare the land. In the SD model, these costs would apply to all farmers in a stock, rather than only those switching.

2. **Growth period:** When switching to coconut, it takes around five years for the trees to mature. Meanwhile, farmers can grow maize or rice, but with lower yields, which affects their savings. A delay can be added to the SD model, but the savings impact cannot be properly captured without affecting everyone.

3. **Debt:** Due to the level of aggregation, it is not possible to assign individual debts. It would be unfair to apply debt equally to all.

4. **Youth migration:** Youth migration alters the composition of the household, which cannot be modeled at the individual level in SD.

5. **Map placement:** In the ABM, agents are placed on a spatial map with their salinity level. In SD, all farmers share the same salinity level.

However, these are important factors that significantly influence system behavior (Chapman et al., 2022; Ly & Nguyen, 2020; Quach & Vo, 2023; Thi Quyen, 2022; Tran et al., 2018), and it is therefore interesting to see how this causes differences between SD and ABM results.

Moreover, several factors were aggregated or simplified in the SD model. For example, there is no MOTA framework in the SD model to determine crop switching. Instead, predefined percentages are used. The household composition is identical for everyone, and all households have the same education level, and either all use machines or none do. While household members have occupations, they cannot switch between them, unlike in the ABM. This aligns with the findings of Schieritz and Mulling (2003), who developed the same model in both ABM and SD for trees. They concluded that the SD model felt like modeling the forest, while the ABM felt like modeling the trees. This is similar to how households and members are modeled in the ABM, whereas SD only includes household types. They also noted that the SD model lacked features such as neighborhood effects and spatial elements and instead relied on fixed proportions of the stock performing actions, rather than behavior driven by individual characteristics (Schieritz & Mulling, 2003).

The ABM was developed using VHLSS, Population and Housing Census data, and literature. It relied on percentages and standard deviations to generate input distributions for the different agents. For the SD model, certain input variables were unclear, such as "chance rice farmer switches to coconut".

This variable was not needed in ABM, as it was calculated using the MOTA framework and various factors such as salinity, education level, and savings. Therefore, ABM trends were used as input for the SD model. This is a technique commonly used, such as in the hybrid simulation framework by Nguyen and Megiddo (2021). The data difference is consistent with the findings of Schieritz and Mulling (2003) and Van Dyke Parunak et al. (1998), who compared ABM and SD by building two models. In the SD model, population sizes and fixed probabilities were used, whereas ABM incorporated the identities of the agents themselves.

Sub-question 3: *How do the ABM and SD model differ in representing disaggregated impacts across farmer subgroups under environmental changes*

In ABM, heterogeneity allows for all different compositions and characteristics to be modeled. It showed that households with high-skilled wage workers were more likely to remain in the system after 25 years. Farmers who took over land from migrating neighbors also did well, having multiple income sources and sufficient savings. In contrast, SD focuses on averages, making it impossible to identify which household characteristics lead to the most migrations.

A key benefit of ABM's heterogeneity is that when an agent migrates, their attributes are removed from the system. If poor farmers migrate and wealthy ones remain, the average savings will increase over time. This dynamic cannot be captured in SD: everyone within a crop type and land size category has the same income, and overall savings remain low even after migration. As a result, SD trends are lower, whereas ABM provides more realistic results. The same applies to salinity. In ABM, each household has a different salinity level, so some farmers are affected more than others. Those in high-salinity areas can switch crops or migrate, reducing overall yield loss. In SD, everyone is affected equally, since the salinity level is the same for all, resulting in a higher intensity of impact. This can be seen in Figure H.1. This also leads to the biggest difference between the models: after each shock, nearly half of the small farmers in the SD model switch between rice and maize, whereas in ABM, agents reach a steady state after a few years, become wealthy and stop switching. Those who could not handle the shocks have already migrated, but in SD, their characteristics are still included, leading to unrealistic switching patterns.

This is a well-known phenomenon in the literature, for instance in Borschchev and Filippov (2004). According to Van Dyke Parunak et al. (1998), this difference arises because SD assumes homogeneity, whereas real systems are heterogeneous. To align ABM and SD results, lookup tables can be implemented (Wilson, 1998), which corresponds to Table 8.1.

Both models capture the impacts of changes well: they show similar patterns in terms of migration. Likewise, sensitivity to migration produces comparable trends. However, only the ABM can model youth migration, which is impossible in SD model.

Main research question: *What are the advantages and disadvantages of different socioeconomic response modeling techniques in assessing the disaggregated or distributional impacts for different subgroups in light of environmental change now and in future scenarios, tested on the Vietnamese Mekong Delta?*

Based on the model results and the modeling process, advantages and disadvantages have been identified for both an SD model and an ABM.

The biggest disadvantage of SD is the aggregated nature of the model. As shown in sub-question 2, this leads to the exclusion of many important features. Moreover, it results in distorted model outputs: for example, if poor people leave the model, the average savings should increase. However, in SD, everyone is equally wealthy, so savings do not increase when people leave. Furthermore, it would make sense that if a rice farming household (e.g., with many self-agricultural workers) switches to coconut farming, it would still have the same number of self-agricultural workers. But suddenly, in the SD model, household members are lost because the rice farm is now classified as a coconut farm and thus acquires characteristics of the coconut farm.

Table 9.2: Advantages and disadvantages of SD and ABM

Category	(Dis)advantage	SD	ABM
Modeling disaggregated or distributional impacts	Advantage	Clear visual structure in the stock-flow system allows overview of which variables impact farmer groups.	Agents can learn over time; the MOTA framework simulates rational behavior in response to shocks such as low yields due to salinity.
	Disadvantage	Unable to model specific behavioral mechanisms such as youth migration, occupational switching, or credit access at household level.	–
Modeling different subgroups	Advantage	Subscripts allow modeling of subgroups like small, medium, and large farmers and different crop types.	Allows detailed tracking of individual household compositions, behavior, and outcomes over time.
	Disadvantage	Aggregated structure leads to uniform behavior: all households have the same composition; individual loans or migration can't be modeled.	Wide variety of occupations and household types risks overfitting, especially when empirical data is limited.
Modeling environmental change	Advantage	Enables rapid simulation of salinity levels over time and their impact on yield across the region.	Agents have spatial positions (via GIS) and react differently depending on their local salinity level.
	Disadvantage	Unrealistic uniform salinity assumption across entire districts; doesn't account for local variation in environmental stress.	GIS slows down initialization; placing agents in appropriate zones during initialization (e.g. rice farmers avoiding saline zones) is computationally expensive.
Data requirements	Advantage	Does not require detailed distribution data for individual households or agents.	Most input values can be derived directly from datasets and literature, allowing modeling across VMD districts.
	Disadvantage	Depends on ABM-derived switching rates due to lack of empirical data, e.g. post-2016 crop transitions.	Requires complex calibration; relies on assumptions where data are unavailable (e.g. youth migration probabilities).
Must-have requirements	Disadvantage	Cannot represent dynamic household composition or interactions; no behavioral adaptation modeled.	High computational cost; stochastic outcomes require many simulation runs for robustness.
Modeling process	Advantage	Easy to develop: adding stocks and flows is straightforward; runs very fast.	BatchRunner allows for automated sensitivity analyses; flexible and detailed behavioral logic possible.
	Disadvantage	Largely deterministic behavior; difficult to trace input-output pathways without manual inspection of all model elements.	Can function as a black box; code is complex and functions can require hundreds of lines (e.g., one logic function = 300 lines).

When looking at the modeling process itself, SD is much easier for Deltares to develop. They already have experience with SD, and the Python code and emergent behavior of ABM can be seen as a black box. Stocks in SD can be created with the click of a button, whereas in ABM this might take hundreds of lines of code. Additionally, in SD the structure is immediately visible through the stocks and flows, and it is instantly clear which variables influence what. The dashboard with sliders also makes it much easier to communicate the model to outsiders. These points are consistent with the findings of Nugroho and Uehara (2023), which show that SD is more transparent and accessible for communication.

9.1.1. Recommendations

Based on the advantages and disadvantages of both methods, the model results, and all discussions over the past five months, two recommendations have been formulated:

1. Develop an ABM. When examining the differences in results, it becomes clear that the SD model (due to its high level of aggregation and use of averages) provides less valid results. For example, if poor farmers leave, the average savings should increase more significantly. If a farmer switches crops, they should retain the same household composition. It is unrealistic that nearly half of the small farmers switch crops after each salinity shock—after some time, farmers would have found their optimal crop. These kinds of small inconsistencies lead to different behavior. Moreover, there are many factors that cannot be included in the SD model, while literature shows that these are important, as found in Table 8.1. Currently, trends from the ABM are used as input, but if the ABM had not existed, there would not have been input data for the SD model. For example, there are no district-level data available on how many people switch crops or the exact percentage switching to specific crops after a shock.

   If developing a full ABM is considered too big a step or if its output is deemed too unclear, it is recommended to develop a NetLogo model. This is an ABM platform that includes sliders and graphs, allowing for clear visualization of what is happening. It also allows the modeled behavior to be more realistic. The downside is the programming language—it is written in Scala (CCL, 2023), which would need to be learned.

2. Regardless of the method chosen, it is recommended to collect more data. There are many different types of groups in the VMD, and an effort was made to distinguish between them. However, no data are available for all these different group types, which creates a risk of overfitting to the limited data that do exist. Fieldwork with the local population is recommended. First, determine which decision rules are needed—for example, who makes decisions within a household, how conservative people are, and what would be the final trigger for them to migrate. Additionally, it is very important to obtain a realistic overview of the costs and revenues of farming different crops. Based on this, specific questions can be formulated. If this is done in a specific region through interviews and monitored annually over a five-year period, it will result in specific data that can be used as model input. This would make the models much more reliable and realistic, reducing the number of runs needed to address the wide range of uncertainties.

9.2. Discussion

When looking at other studies that have developed SD and ABM models and their model choices, similar patterns emerge. In healthcare, for example, SD is mainly used for hospital waste and LTC services, while ABM is used to model individual behavior, such as insurance decisions (Cassidy et al., 2019). The same trend can be seen in the VMD: one study attempted to create an SD model for farmers but encountered similar issues as noted in Table 9.2 (Chapman & Darby, 2016). SD is also used mainly for rice production (Nguyen Thanh et al., 2020; Tuu et al., 2020), while ABMs are used to model individual behavior related to migration (Nguyen et al., 2021, 2019b), farmer behavior in land use (Truong et al., 2016), and crop choice (Le et al., 2024).

Across all these models, when individual behavior is involved, ABM is generally preferred. The exception is Von Loeper et al. (2016), who found that heterogeneity is poorly represented in SD compared to reality, leading to more unrealistic model behavior.

It is important to keep in mind that in this study, the ABM was developed first, followed by the SD model, using ABM input. The SD model was thus developed with an ABM mindset, taking a bottom-up perspective. If this were not the case and an entirely separate SD model were developed by someone else, a different model with different functions might emerge, perhaps even a better one. If an SD model is built from scratch, the aggregation level makes it essential to be aware of the oversimplification of complex interactions (Nugroho & Uehara, 2023).

9.2.1. Strengths and weaknesses

To my knowledge, there are very few studies that have developed both an SD and an ABM and directly compared the results. By using the same input variables and avoiding tweaking or using lookup tables, a pure comparison of the models was made possible. This also provides Deltares with insight into what happens when one method or the other is used.

Another strength is that the model can run for all districts in the VMD. There are large differences between districts, as shown in the land use maps in Figure 2.3. A Jupyter notebook analyzes all data per district; the data is collected in an Excel file that can be used as input for the ABM.

The biggest weakness was the availability of data. Although a lot of data was available, it was often raw and sometimes incomplete. As a result, a wide range of sources from the period 2009 to 2020 were used, introducing a great deal of variability. Furthermore, a salinity shock occurred in 2016, during which many residents migrated, making the combination of 2009 and 2020 data as input within a single model not representative.

The second weakness is that several factors were not included, although they could influence the system. Examples include sluices, dikes, and pesticides. These were not included due to a lack of data and because adding assumptions would further risk overfitting the model. Furthermore, no adaptation strategies or policies were implemented. It would be interesting to explore how, for example, equipment might better protect farmers. However, this current study can be seen as a first step toward modeling the distributional impacts on different types of inhabitants in the VMD. It is important that these models are improved and that subsequent research investigates the impact of these strategies and policies, which could then be implemented.

The third weakness is that, aside from the modularity of the VMD, no consideration was given to other river deltas. As a result, the models may need adjustments if applied to another riverdelta, such as Bangladesh.

9.2.2. Practical and theoretical implications

Many studies compare the pros and cons of ABMs and SD models (Howick et al., 2024; Maidstone, 2012), but only a few have developed the same model using both methods and then compared the results. These have been done for forests and trees (Schieritz & Mulling, 2003) and population models (Wilson, 1998). These papers are over 20 years old, and no newer papers were found that used the same variables for both modeling methods. This paper contributes by using identical variables and comparing the model outputs.

Comparison papers often discuss general differences such as runtime and heterogeneity (Brito et al., 2011; Maidstone, 2012), but they rarely clarify how the actual application of the models reveals specific advantages and disadvantages for a certain case. By comparing results and closely looking at the system behavior, it becomes possible to identify pros and cons based on system components.

This is the first SD model on farmer behavior in the VMD. Although ABMs have been developed for the VMD, each focused on a specific aspect, such as migration or rice farmers (Le et al., 2024; Truong et al., 2023). This study attempted to include yield, crop switches, and migration, as well as landless households. It also draws a conclusion about which farmers will remain in the region after 25 years, something that has never been done before.

For Deltares, this study provides insight into how they can proceed in developing socioeconomic models for the inhabitants of the VMD and potentially for other river deltas in the future. Very few ABMs had been developed within the department before this. It is hoped that this paper will guide to development of such models. By building both methods, comparing them, and presenting an overview of their advantages and disadvantages, this paper aims to serve as an example for Deltares in deciding which model is best suited for the VMD, as well as for other river deltas and scenarios.

9.2.3. Further research

This study can be seen as the starting point for Deltares in developing socioeconomic behavioral models for river deltas. Based on this analysis, Deltares can assess which method they could use. First of all, more data must be collected. It might be a good idea to start with a conceptual model, what is wanted, and then decide which data will be collected. For example, data on the number of man-days required, the effect of machines, the farming costs, and income/kg can be useful. When this data is collected over a few years, the conceptual model can be formalized, and a computational model can run.

In addition, more research should be conducted into the impact of water supply, pesticide use, sluices, and the acquisition of protective equipment. These are also factors influencing the yield and salinity levels. Based on this, a more comprehensive model can be developed in the future that incorporates all system elements.

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A

Interviews

Name	Function	Date
Sepehr Eslami	Coastal engineer	February 25, 2025 & April 7, 2025
Vrinda Sharma	Ph.D. candidate in Climate Change and Economics of Water	February 25, 2025 & March 6, 2025
Peter Jansson	Expert in Water Management and Climate Adaptation	Multiple casual meetings between February – June 2025
John Kucharski	Senior Expert Advisor, Climate Adaptation and Disaster Risk Management	Multiple casual meetings between February – June 2025
Leon Hermans	Associate Professor in Environmental Planning and Management	March 13, 2025 & May 23, 2025
Niels Mulder	Hydrologist	April 4, 2025
Thanh Tran	Vietnamese exchange student in The Netherlands	April 22, 2025
Vietnamese colleague		April 4, 2025
Vietnamese sociologist		April 4, 2025

Table A.1: Overview of people that were interviewed

B

Overview variables data analysis

Table B.1: Variable overview for data analysis for VHLSS2020

Dataset	Column	Question in questionaire	Description
Ho1.xlsx	m2vtn + m2xtn	-	Received subsidies/scholarships education (vnd)
Ho1.xlsx	m2xct + m2vct + m2dct	-	Expenditure education (vnd)
Ho2.xlsx	m4atn	-	Income from salaries, wages, pensions, allowances (vnd)
muc4b11.xlsx	m4b11c3	Question 3 4b1	Rice land area (m2)
muc4b11.xlsx	m4b11c4	Question 4 4b1	Rice harvest (kg)
muc4b11.xlsx	m4b11c8	Question 8 4b1	Rice value last 12 monts (vnd)
muc4b12.xlsx	m4b12c3	Question 3 4b12	Food crops and annual crops land area (m2)
muc4b12.xlsx	m4b12c4	Question 4 4b12	Food crops and annual crops harvest (kg)
muc4b12.xlsx	m4b12c7	Question 7 4b12	Food crops and annual crops value of harvest products (vnd)
muc4b13.xlsx	m4b13c3a when m4b13c3b == M2	Question 3 4b13 code 1	Annual and perennial industrical crops land (m2)
muc4b13.xlsx	m4b13c4	Question 4 4b13	Annual and perennial industrical crops harvest (kg)
muc4b13.xlsx	m4b13c7	Question 7 4b13	Annual and perennial industrical crops value of harvest (vnd)
muc4b14.xlsx	m4b14c3a als m4b14c3b == M2	Question 3 4b14 code 1	Fruit trees area (m2)
muc4b14.xlsx	m4b14c4	Question 4 4b14	Fruit trees kg harvest (kg)
muc4b14.xlsx	m4b14c7	Question 7 4b14	Fruit trees harvest (vnd)
muc4b15.xlsx	m4b15c5	Question 5 in 4b15	Revenues from byproducts
muc4b16.xlsx	m4b16c2a	Question 2a in 4b16	Cost rice
muc4b16.xlsx	m4b16c2b	Question 2b in 4b16	Cost food crops
muc4b16.xlsx	m4b16c2c	Question 2c in 4b16	Cost industrial crops
muc4b16.xlsx	m4b16c2d	Question 2d in 4b16	Cost fruit trees
muc4b21.xlsx	m4b21c5	Question 5 4b21	Value of products by husbandry, hunting etc
muc4b22.xlsx	m4b22c19	Question 19 in 4b23	Costs by husbandry, hunting etc
	-	Question 1a in 4b31 (1 = yes, 2=no)	Do you own machines, equipment and tools?
muc4b31.xlsx	m4b31c5	Question 5 in 4b31	Revenue by these machines
muc4b32.xlsx	m4b32c17	Question 17 in 4b32	Costs of agricultural services

Dataset	Column	Question in questionaire	Description
muc4b41.xlsx	m4b41c3f	Question 3f in 4b41	Revenues from foresty
muc4b42a.xlsx	m4b42c14	Question 14 in 4b42	Costs foresty
muc4b51.xlsx	m4b51c5	Question 5 4b51	Value of products aqua
muc4b52.xlsx	m4b52c19	Question 19 in 4b52	Costs of aqua in
muc4c1.xlsx	m4c1c18	Question 18 in 4c1	Revenue processing agri aqua en foresty
muc4c2.xlsx	m4c2c33	Question 33 in 4c2	Costs for processing agri aqua en foresty
muc4d.xlsx	m4dc2	Question 2 in 4d	Other revenues (e.g. wedding gifts)
Ho4.xlsx	m5a2ct		Yearly expenditure on food
Ho4.xlsx	m5b2ct		Yearly expenditure on non food
muc7.xlsx	m7c27	Question 27 in 7	Expenditure on housing/electricity etc
muc1a.xlsx	m1ama	-	Household member id

Table B.2: Variable overview for data analysis Pop Housing Census

Dataset	Question	Description
Census2009_MDMigration_Q1Q34	C5	Age
	C11A	Hearing
	C11B	Seeing
	C11C	Walking
	C11D	Remembering
	C12	Education level
	C20	Working or not
Sample Census 2019 (Q01-Q41)	C27C	Sectors of agents
	C26C	Occupations
	C30	Employment_type
	C28	Did you follow training?
	C29A	Do you have 3+ years of experience?
	C29B	Do you use machines or equipment?
	C40A	Total boys born this year in the household
	C40B	Total girls born this year in the household
Sample Census 2019 (Q42-Q49)	C47	Age a household member died
Sample Census 2019 (Q50-Q65)	C55	Main construction of the house
	C56	Quality of roof on the house
	C57	Quality of the outer walls of the house
	C59	Who is the owner of the house?

Table B.3: Different data sources used to calculate farming costs and revenues

Crop	**Variable**	**Value** in literature	**Source**
Rice	Man days / ha	48	(Pedroso et al., 2017)
	Yield / ha / harvest	5753 kg	(FAO, 2025)
	Farming costs / ha / harvest	16.9 miljoen vnd	(Tong, 2017)
	Income / kg	5373 vnd	(Tong, 2017)
Maize	Man days / ha	106	(Pedroso et al., 2017)
	Yield / ha / harvest	4414 kg	(FAO, 2025)
	Farming costs / ha/ harvest	6800000 vnd	(Nassirou Ba, 2017)
	Income / kg	6900 vnd	(Nguyen & Luxner, 2024)
Coconut	Man days / ha	8	(FAO, n.d.)
	Yield / ha / harvest	1645 kg	(FAO, 2025)
	Farming costs / ha/ harvest	20000000 vnd	(Yeswanth et al., 2024)
	Income / kg	17500 vnd	(Nguyễn, 2024)
Shrimp	Man days / ha	33	(Khai et al., 2018)
	Yield / ha / harvest	140 kg when there is no disease 37 kg when there is a disease	(Joffre et al., 2015)
	Farming costs / ha/ harvest	3800000 vnd	(Joffre et al., 2015)
	Income / kg	42838 vnd	(Khai et al., 2018)

C

Conceptual models ABM

Chapter 4 showed the conceptual models for the land households and landless households. In Figure C.2 and Figure C.1, the conceptual models for the individual household members are shown. All these members only have yearly activities.

Figure C.3 shows the overall process what happens within the model. At each step, it checks whether a salinity shock has occurred. Then, the waiting time of the land agents is decreased, and it is determined whether it is time for the yearly activities of all agents. After that, based on the crop calendar in Table 4.3, the model checks if certain crops need to be harvested, and the land agents will pay the wage workers. Next, land agents update their savings, and the model checks whether they may need to switch crops. When all other household members are paid, by for example doing manual work, the landless households will check their income.

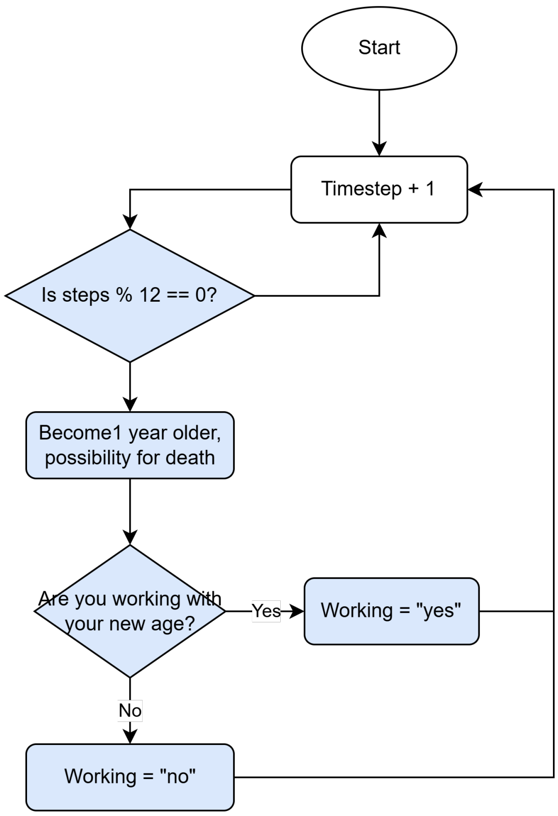

Figure C.1: Conceptualization of the working household members in the ABM

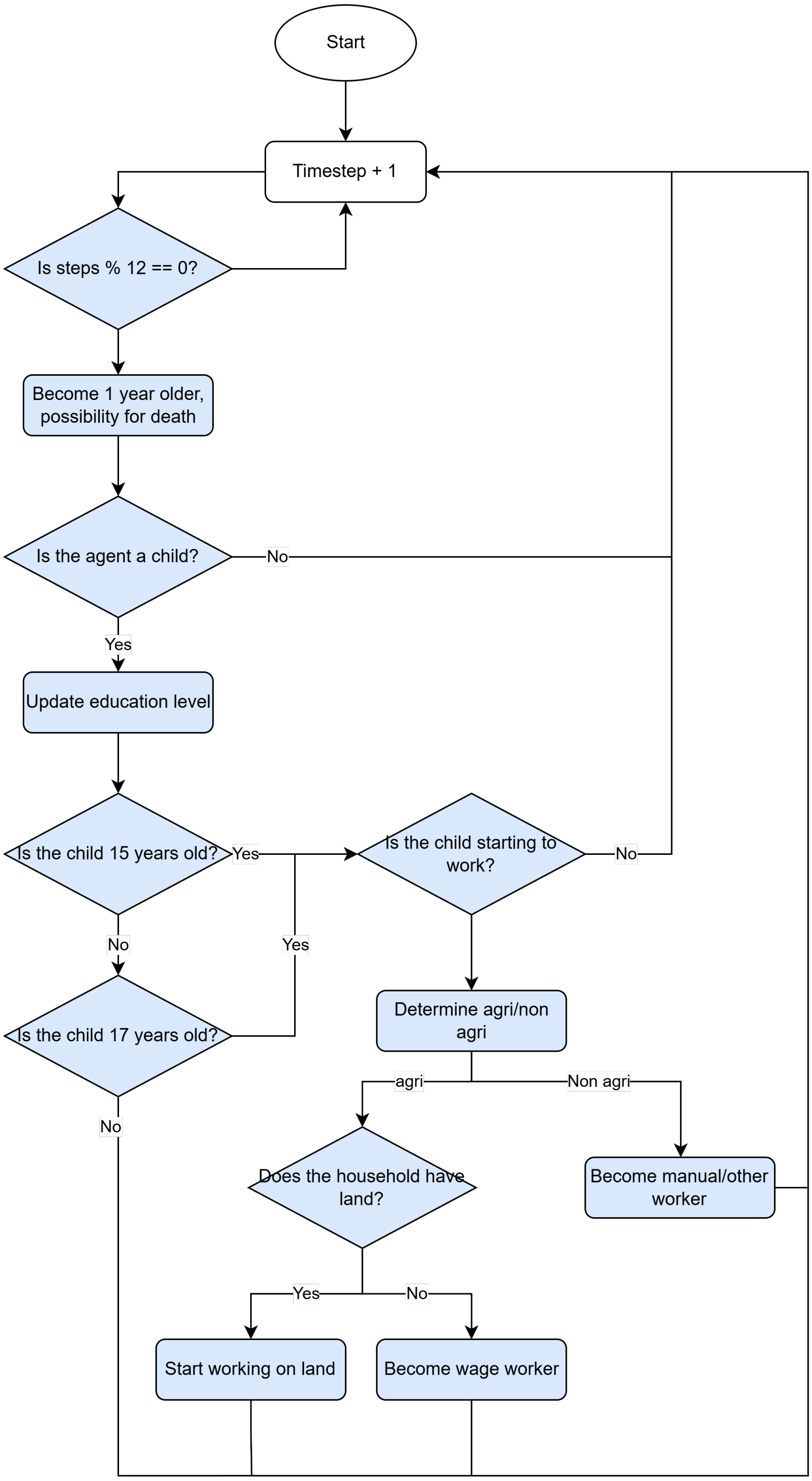

Figure C.2: Conceptualization of the non laborers in the ABM

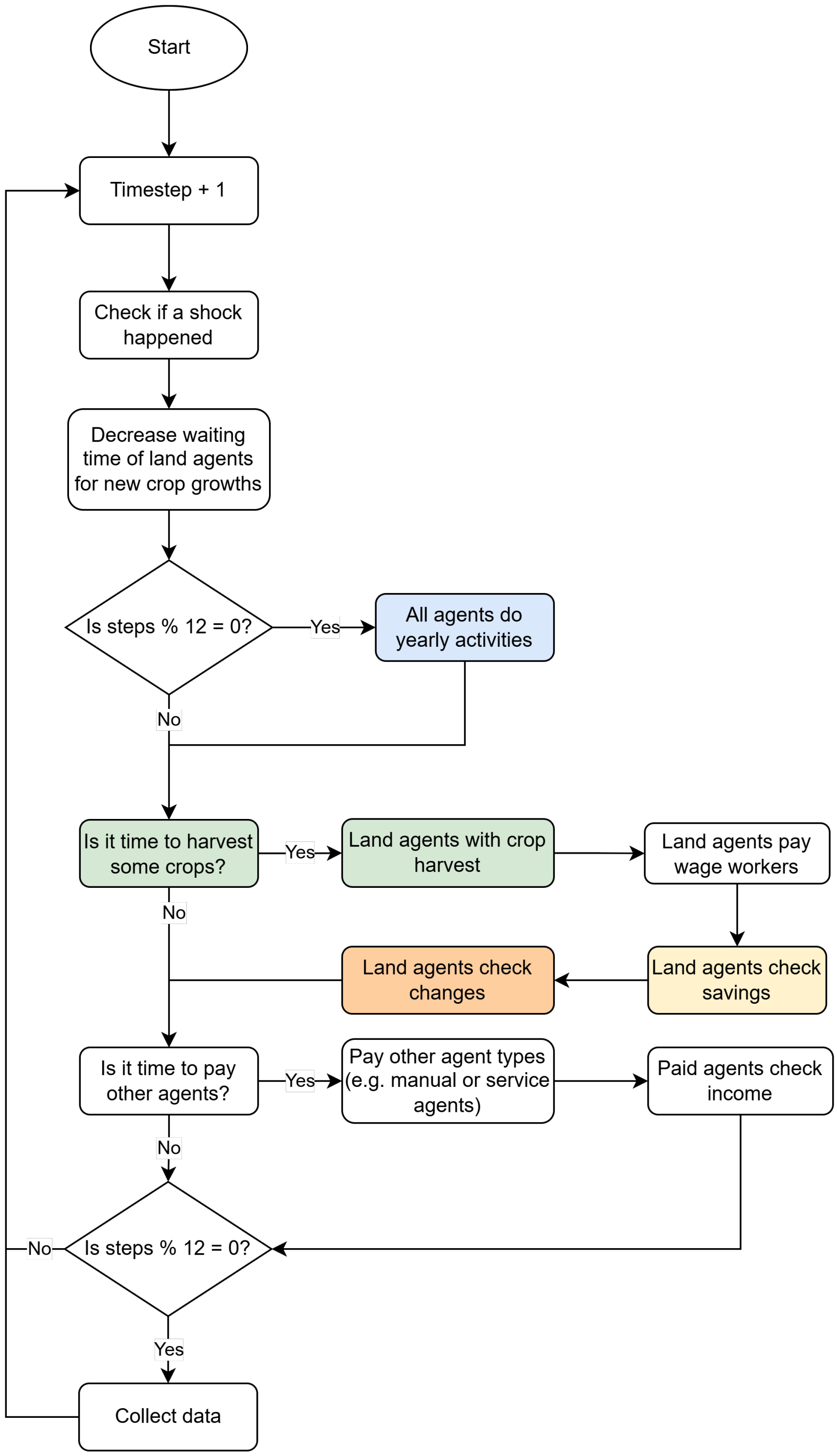

Figure C.3: Conceptualization model class in the ABM

D
Variable overview ABM

Table D.1: Attribute table individual agents ABM

Variable	Description	Possible values
Agent_type	The type of agent. In this case the agent is a household member	“Household_member”
Age	Age of the agent	Real: [0,∞]
Agent_sector	Sector in which the agent is working	[Non agri, rice, annual crops, perennial crops, aquaculture]
Agent_occupation	Occupation of the household member	[Low_skilled_agri_worker, Low_skilled_nonAgri, Manual_worker, Skilled_agri_worker, Skilled_service_worker, Other, Non_labourer]
Assigned	If the household member is assigned to a household or not	{True, False}
Works	If the agent is working or not	{True, False}
Education	The education level of the agent	[Higher_secondary, lower_secondary, primary_education, below_primary, no_schooling]
Death_age	The age the agent will die	Real: [0, 110]
Income	The income the agent receives by doing the work of their occupation	Real: [0,∞]
Experience	If the agent has 3+ years experience in its occupation	{True, False}
Machines	If the agent is used to using machines	{True, False}
Disabilities	The level of disabilities an agent has. This is based on hearing, walking, seeing and remembering	Real: [0, 1]
Time_since_last_ savings_check	The time since the last time the agent got paid. Based on this, the expenditure is calculated	Real: [0,12]
Household	The household that the agent is connected to	Household object

Table D.2: Attribute table households ABM

Variable	Description	Possible values
Agent_type	Type of agent	Household
Household_size	Size of the household (number of members)	Real: [0,10]
Household_members	The individual agents who are part of the household	Household member objects
Land_category	Category of land size	[small, medium, large]
Land_area	Land size	Real: [0.3, ∞]
House_quality	Vulnerability of the house	Real: [0,1]
Salinity_during_shock	Salinity level during a shock	Real: [0, ∞]
Possible_next_crops	List of crops the household can switch to	[Aquaculture, Perennial crops, annual crops, rice]
New_crop	The crop the household will cultivate next year (highest MOTA score)	Rice, Maize, Coconut, Shrimp
House_price	Price of the house	Real: [0, ∞]
Value_of_assets	Total value of assets (land + house)	Real: [0, ∞]
Maximum_debt	Maximum loan a household can take	Real: [0, ∞]
Debt	Current household debt	Real: [0, ∞]
Yearly_loan_payment	Annual payment needed to become debt free	Real: [0, ∞]
Wage_worker_payment	Indicates if wage workers were paid	Real: [0, 1]
Savings	Household savings	Real: [0, ∞]
Total_cost_farming	Total seasonal farming costs per crop (e.g., rice)	Real: [0, ∞]
Wage_costs	Total costs the farm spends on wage worker costs	Real: [0, ∞]
Total_income	Dictionary with the seasonal income per crop (Total_income_rice, total_income_maize, total_income_shrimp, total_income_coconut)	Real: [0, ∞]
Yearly_income	Annualized version of recent income	Real: [0, ∞]
Percentage_yield_	Yield per crop as percentage (e.g., percentage_yield_rice = 0.8)	0–1
Expenditure	Total household expenditures	Real: [0, ∞]
Required_income	Income required to cover expenditures	Equal to expenditure
Information_meeting	Did the household attend the information meeting?	Real: [0, 1]
Association	Is one of the household members member of a farmer association?	Real: [0, 1]
MOTA_scores	Dictionary with MOTA score per possible crop	[0, 1]
Waiting_time	Time before harvesting a new crop (e.g., 5 years for coconut)	Real: [0, ∞]
Livelihood	Dictionary: human, social, financial, physical, natural	Real: [0, 1] per factor
Use_antibiotics	Use of antibiotics in shrimp farming	Real: [0, 1]
Farming_time_left	Time left until shrimp farming becomes unviable due to pollution	Real: [0, 5]

Table D.3: Attribute table households ABM part 2

Variable	Description	Possible values
Crop_history	Dictionary of crops with years of experience per crop	Real: [0, ∞]
Machines	Does someone in the household know how to use machines?	Real: [0, 1]
Average_hh_experience	Combined factor of the experience of the household members, and if some of them uses machines or not.	Real: [0, 1]
Saw_advertisement	Did they see city-life advertisement (which will increase the motivation to migrate)?	Real: [0, 1]
Contacts_in_city	Does the household have city contacts?	Real: [0, 1]
Facilities_in_neighbourhood	Quality of local facilities (decreases if service workers leave)	Real: [0, ∞]
Migrating	This is true when the household is leaving, otherwise false	{ True, False}

Table D.4: Attribute table model class ABM

Variable	Description	Possible values
District	Chosen district to run the model with	Gò Công Đông (and all the other districts in VMD)
Excel_path	Path to the correct excel file	\\Data\\model_input _data_824.xlsx
Salinity_shock_per_ step	The steps in which a salinity shock occurs	Real: [0, ∞]
Excel_data	Dictionary with all excel sheets and their data	Dictionary
Num_agents	Number of agents in the model	Real: [0, ∞]
Data_salinity	Dataset with salinity shapefiles is saved in this variable	Shapefile
Polygon_districts	Dataset with the district boundaries is saved in this variable	Shapefile
Households_which_ need_a_node	Land households that are supposed to be placed on a map	list
Salinity_shock_step	The steps a salinity shock might happen	Real: [0, ∞]
Salinity_shock	If a salinity shock is currently happening	{True, False}
Time_since_shock	The time since the last salinity shock happened. This determines which crops are impacted by the shock during growth time	Real: [0, ∞]
Chance_info_ meeting	The probability a land household will go to the information meeting	Real: [0, ∞]
Chance_diseases	The probability a shrimp farm will get a disease	Real: [0, 1]
Maize_fixed_costs	The fixed costs of mais per ha	Real: [0, ∞]
Land_price_per_ha	The price a land household needs to pay per ha when they want to buy land from other land agents who are migrating	Real: [0, ∞]
Chances_migration	List of the chances that a landless household is migrating, depending on their circumstances	Real: [0, 1]
Chance_leaving_ household	Probability the young adults (15-35 years olds) are migrating without the rest of the household	Real: [0, 1]
Increased_chance_ migration_ familiarity	Increase in the chance of migration when young adults saw an advertisement and have contacts in the city	Real: [0, 1]
Possible_to_change	If it is possible for land agents to change. This is nt possible during the first year	Real: [0, ∞]
Interest_rate_loans	The interest rate land households need to pay each year for their debt	Real: [0, 1]
Interest_rate_saving s	The interest rate all households receive on their savings	Real: [0, 1]
Man_days_prep	The percentage of man-days which is required during planting the crops	Real: [0, 1]
payment_low_skille d	The daily wage of low_skilled agents	Real: [0, ∞]
Payment_high_skille d	The daily wage of high skilled agents	Real: [0, ∞]
Distribution_high_lo w_skilled	Percentage of high skilled agents compared to the total number of agents	Real: [0, 1]
Deceased_ households	The number of households of which all the household members are migrated or death	Real: [0, ∞]
death_agents	The individual agents who died	Real: [0, ∞]

Table D.5: Attribute table model class ABM part 2

Variable	Description	Possible values
Child_births	The number of children which are born in the model	Real: [0, ∞]
Number_of_ households	Total number of current households in the model	Real: [0, ∞]
Start_households	The number of households during initialization	Real: [0, ∞]
Current_hh_left	Percentage of households which is not migrated yet	Real: [0, ∞]
Start_total_low_non _agri	The number of total low wage non agri workers after the initialization of the model	Real: [0, ∞]
Start_manual_servic e_workers	The number of manual workers after the initialization of the model	Real: [0, ∞]
Start_service_ workers	The number of service workers after the initialization of the model	Real: [0, ∞]
Current_service_ workers	The current number of service workers in the model	Real: [0, ∞]
Work_days_per_ month	The total number of days working agents are working each month	Real: [0, ∞]

E

Model output Agent-Based Model

The land households are placed on a map. The chosen district was Gò Công Đông, Figure E.2 shows the land agents on the map in this district at the start of the model, and after 25 years. The same is done for An Bien and Thoai Son, these results can be seen in Figure E.3 and Figure E.4.

What happens when it is not possible to switch crops for land households is shown in Figure E.6. What happens when it is possible to switch crops for land households, but their savings are equal to their expenditure, is shown in figure E.7

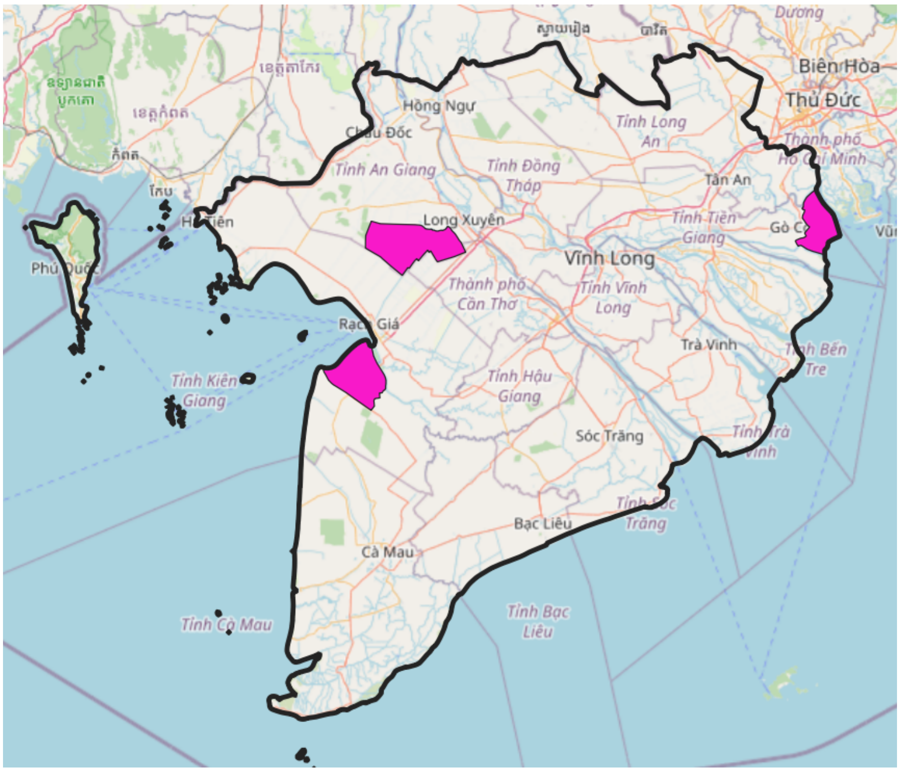

Figure E.1: Three chosen districts in the VMD. Top right is Gò Công Đông, coastal left is An Biên and in the middle is Thoai Son

Figure E.2: Land agents placed on the map in Gò Công Đông

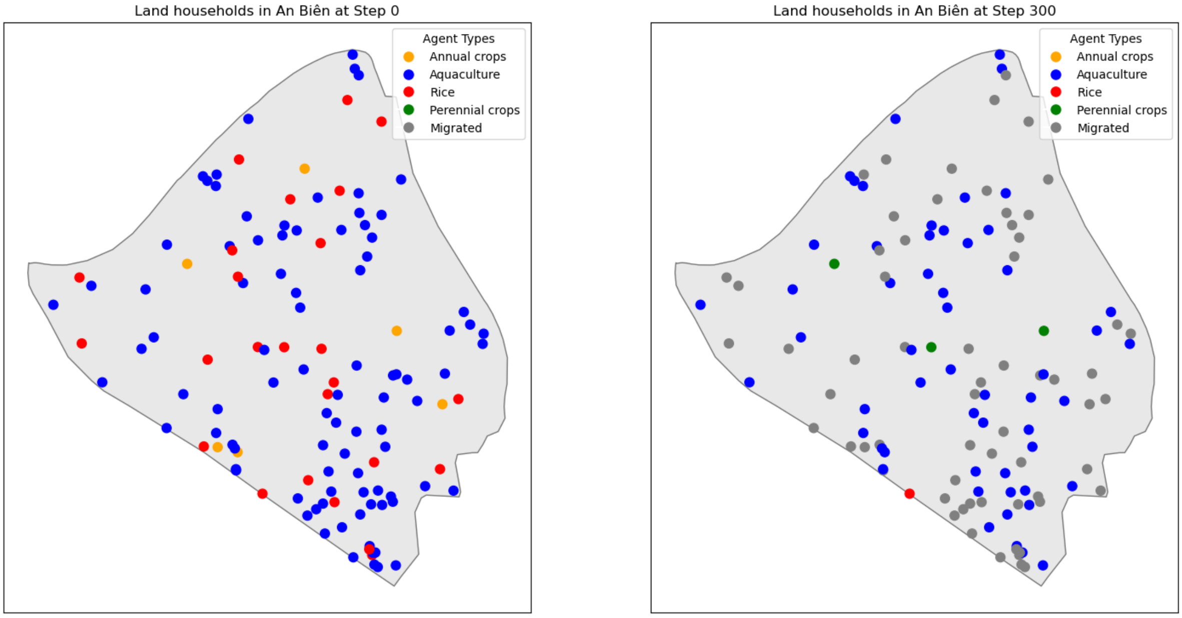

Figure E.3: Land agents placed on the map in An Biên

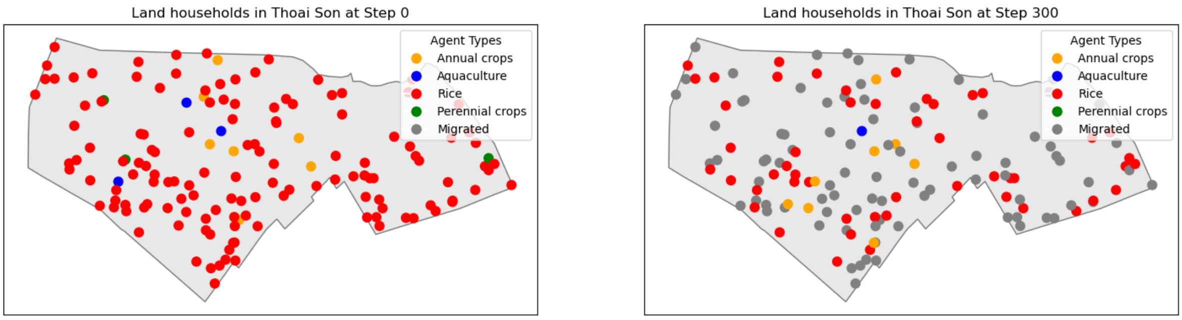

Figure E.4: Land agents placed on the map in Thoai Son

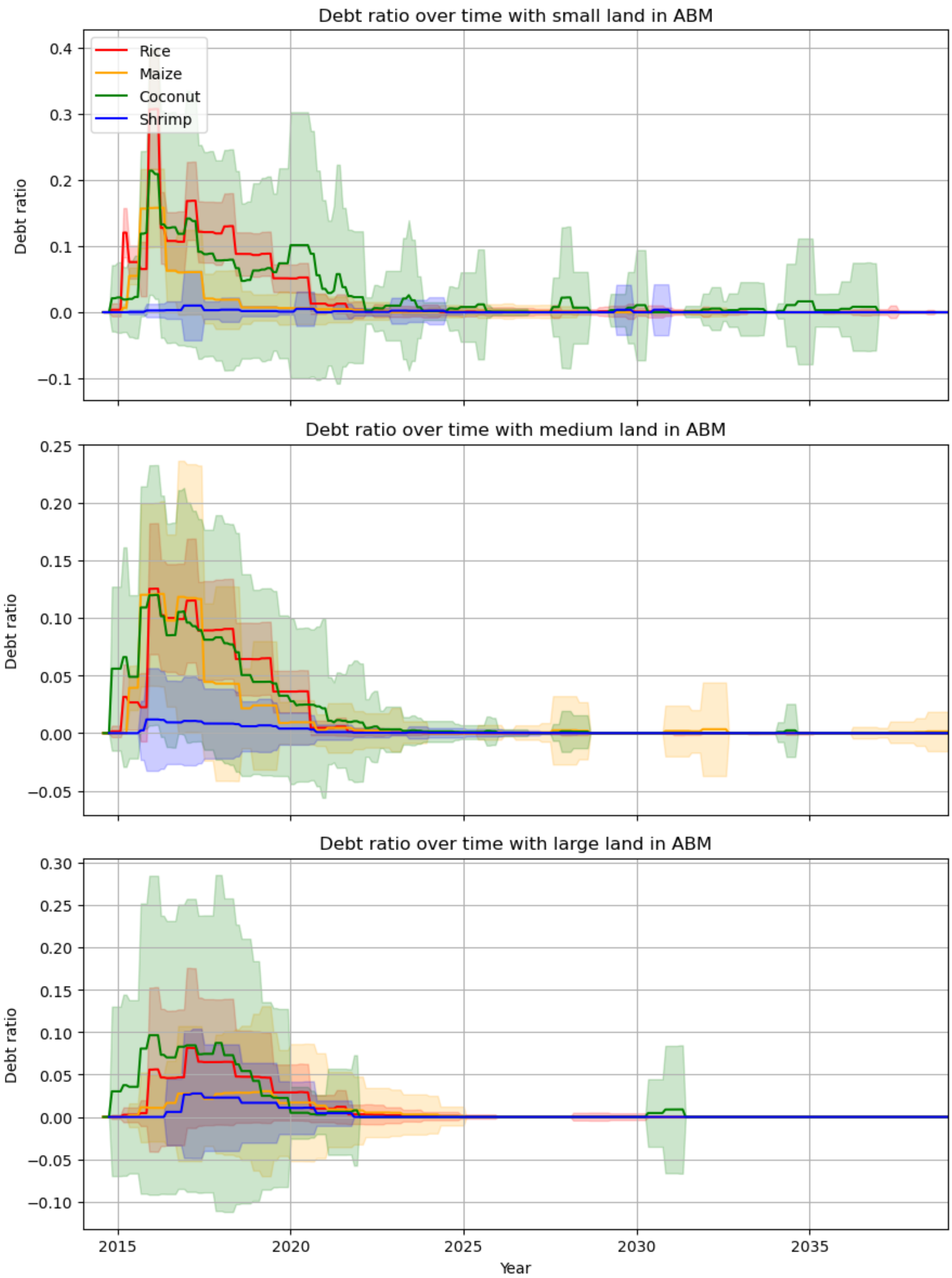

Figure E.5: Debt ratio of land households over time in ABM

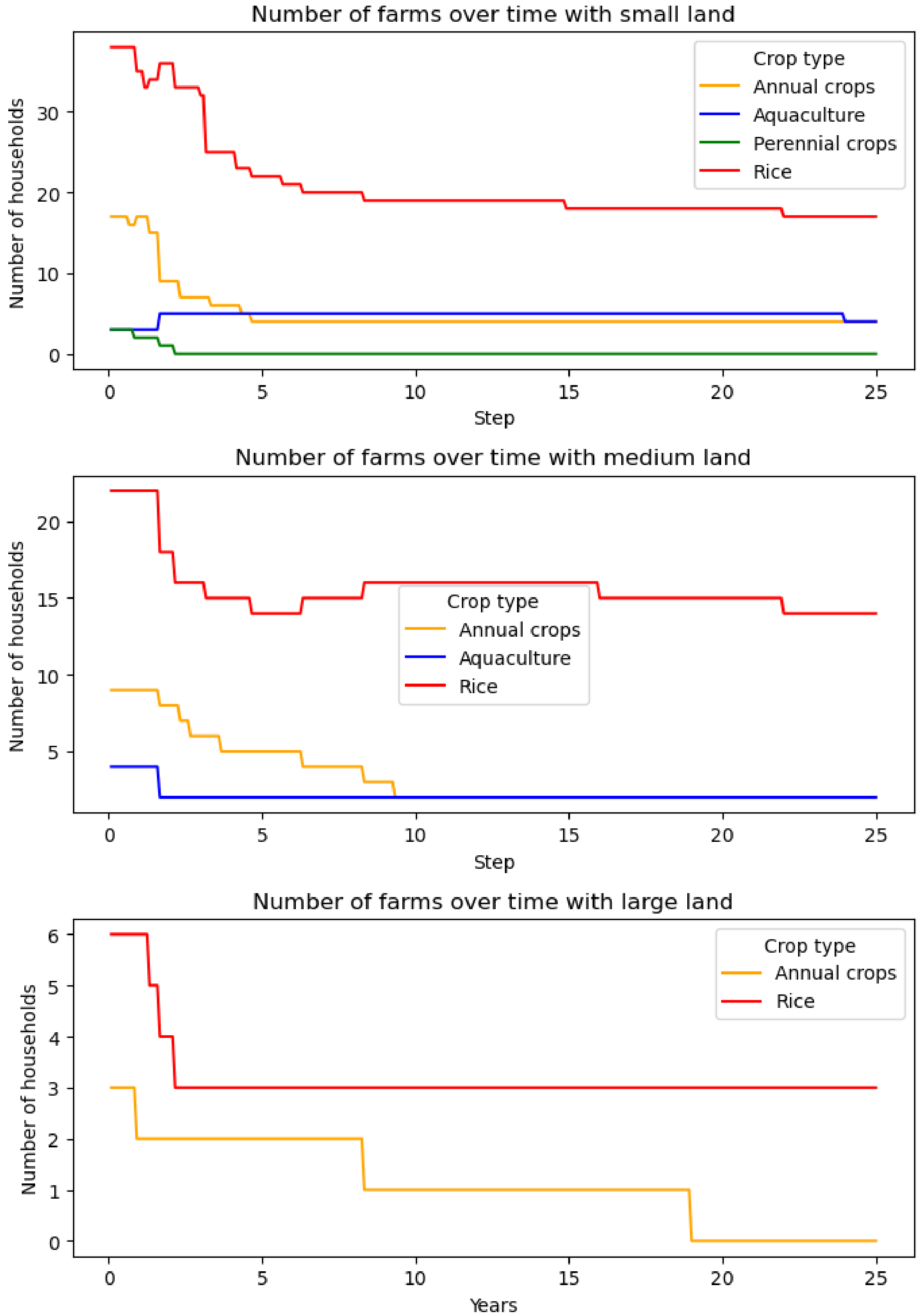

Figure E.6: ABM run without the possibility for land agents to switch crop categories

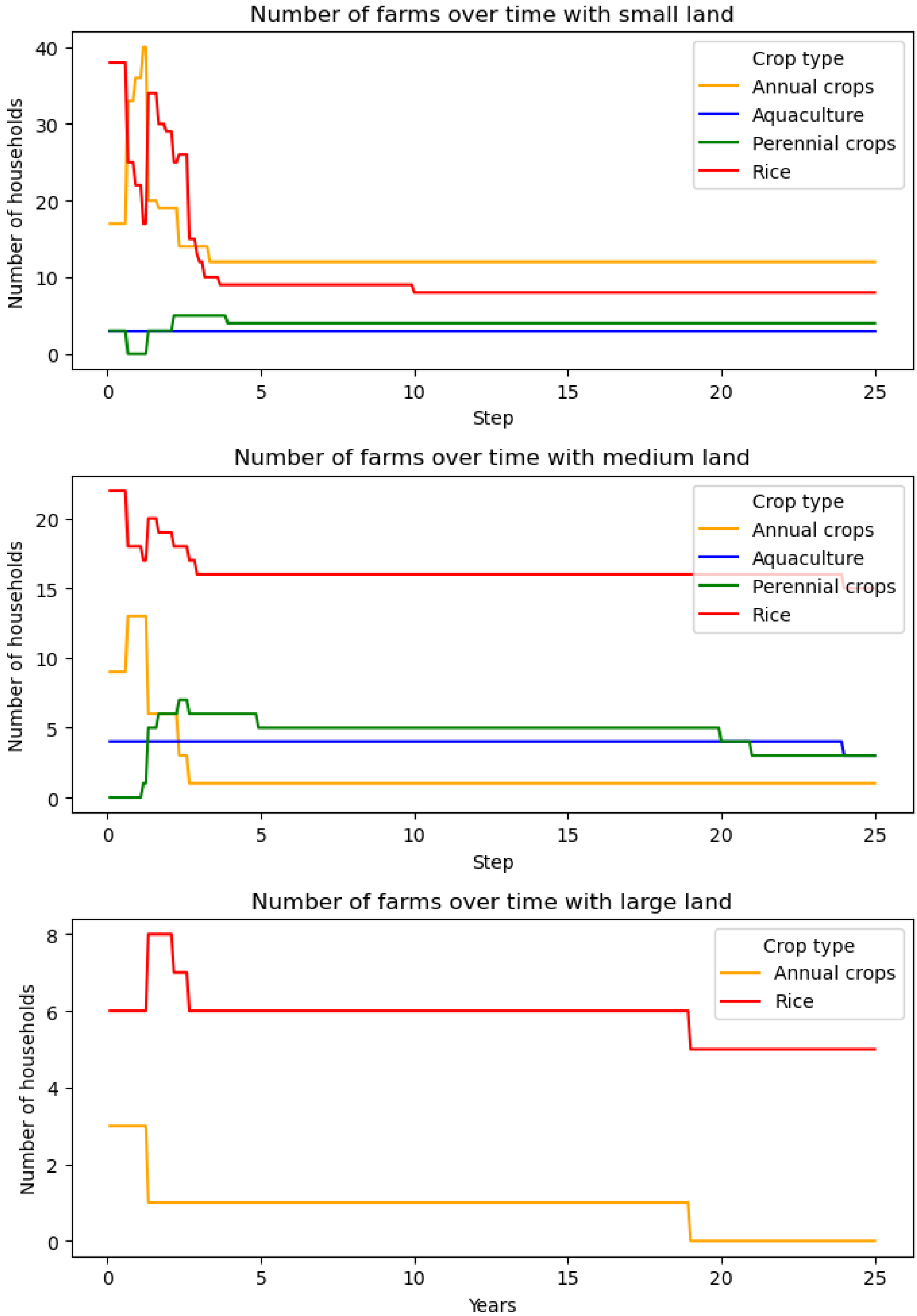

Figure E.7: ABM run while expenditure was equal to income for land households

F Extreme value validation ABM

For 10 variables in the ABM, the values have been decreased and increased, to see if the model would respond correctly. In this appendix, for each variable, de increase/decrease is given, together with the expected behavior, a box-plot of what happened after 25 years and an explanation.

F.1. Salinity level

Question: What would happen if there is 0 salinity for all farmers, or if their salinity is twice as high all the time?

Expected behavior: The higher the salinity level, more farmers will stop farming or change to aquaculture/perennial crops, since these are salt tolerance crops. When there is no salinity, it is expected that more farmers would stay in rice, but that there is not much of an impact for annual crops, since they already have high costs and are switching because of that.

Results: The number of farmers per crop is shown in Figure F.1. When there is no salinity at all, more farmers are staying in annual crops, and slightly more farmers in rice. Less farmers are switching to perennial crops, and no farmers are switching to aquaculture. When the salinity levels are twice as high, the number of rice and annual crop farmers is significantly lower. This is since the crops will fail almost completely during the high salinity levels. The farmers have no time to save money, since they crops are failing constantly instead of only during a salinity shock, so they are migrating.

The number of household migrations is also shown in Figure F.2: When the salinity level is twice as high, approximately 20 percent more households are migrating. When there is no salinity at all, there are only 10 percent less household migrations, compared to the normal salinity levels.

All in all, the results are in line with the expected behavior.

F.2. Salinity shocks

Question: What would happen if there are no salinity shocks at all, or when there are twice as many shocks than initially modeled?

Expected behavior: When there are more shocks, it is expected that there will be more migrations, since more crops are damaged. Furthermore, it is expected that more farmers will switch to perennial crops or aquaculture. However, the expected effect is minimal, since there are currently not much reactions in the model during the base case. When there are no shocks at all, there are probably less people migrating, but still a lot due to the high farming costs.

Results: As expected, twice as many shocks does not have a big difference in the number of migrations. However, when there are no shocks at all, the number of migrated households decreases slightly (between 0-10 percent). This effect is shown in Figure F.4.

Annual crops are even less salt tolerant than rice. Therefore, when there are no salinity shocks at all, more farmers are doing annual crops. This is shown in figure F.3. The number of rice farmers is

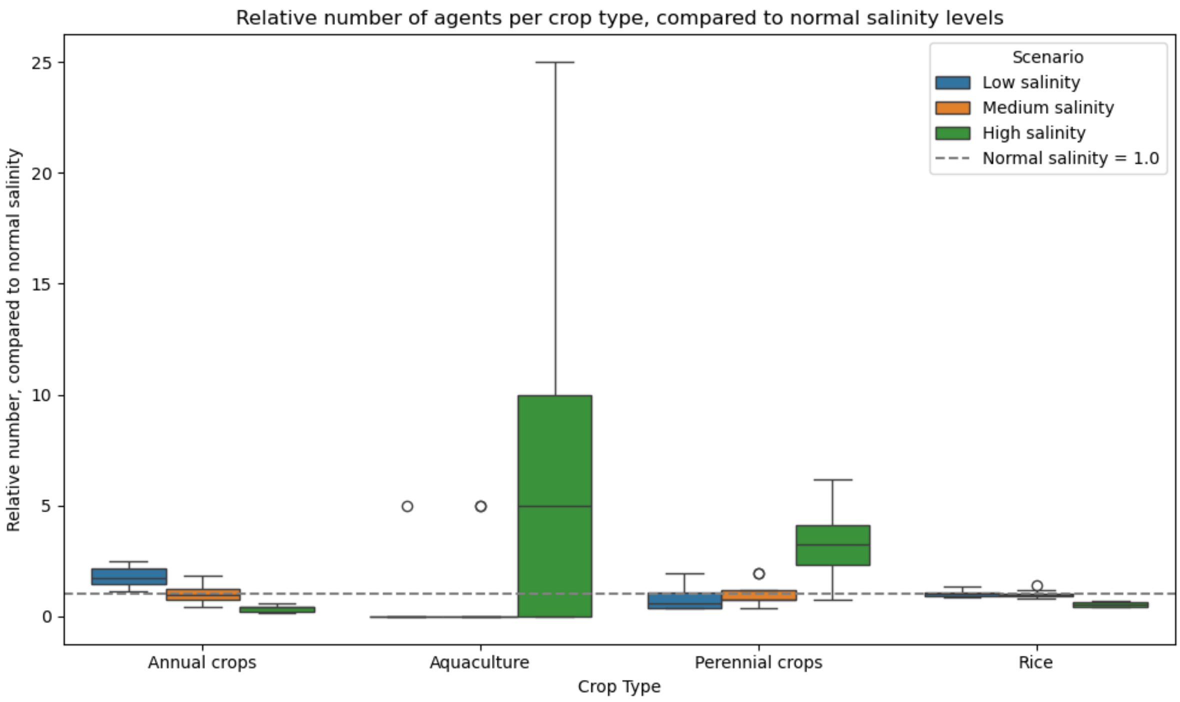

Figure F.1: Number of agents per crop type, when the salinity levels are zero, normal, or twice as high

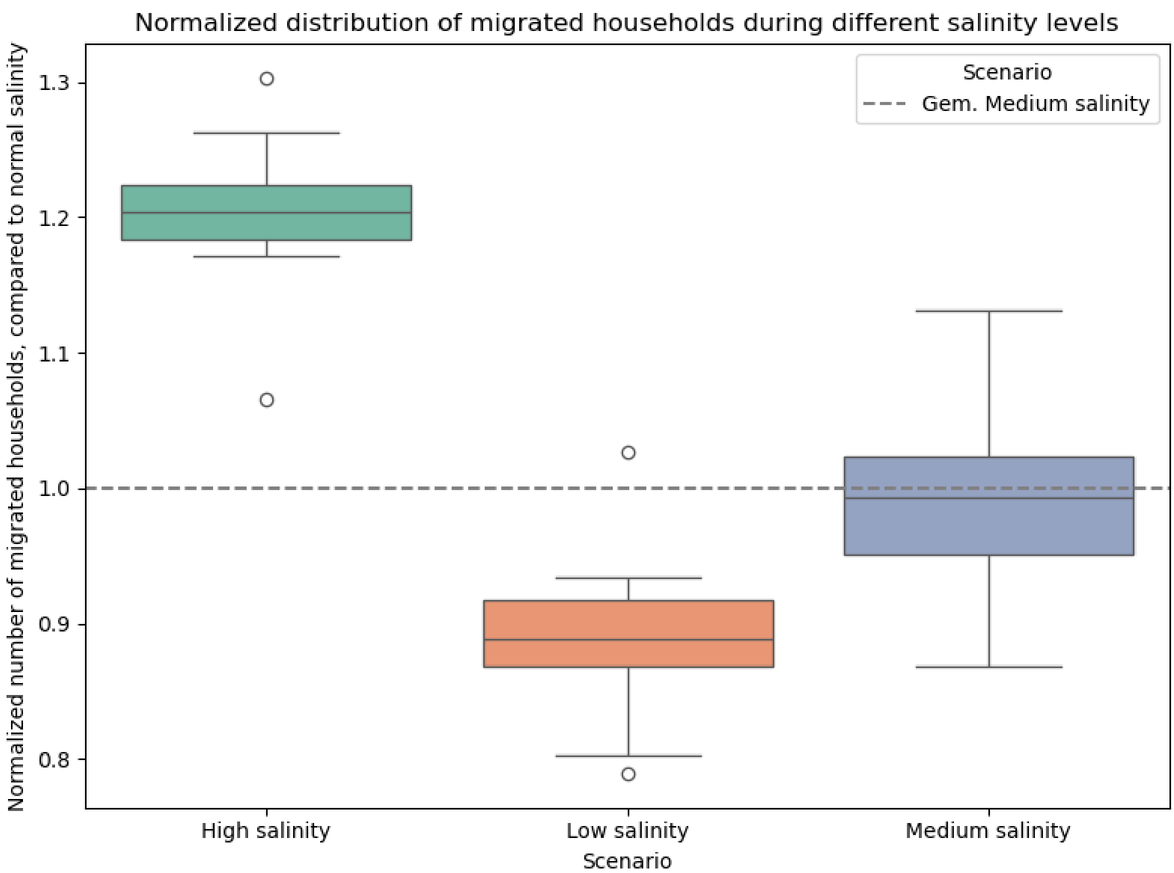

Figure F.2: Number of migrated households during different levels of salinity

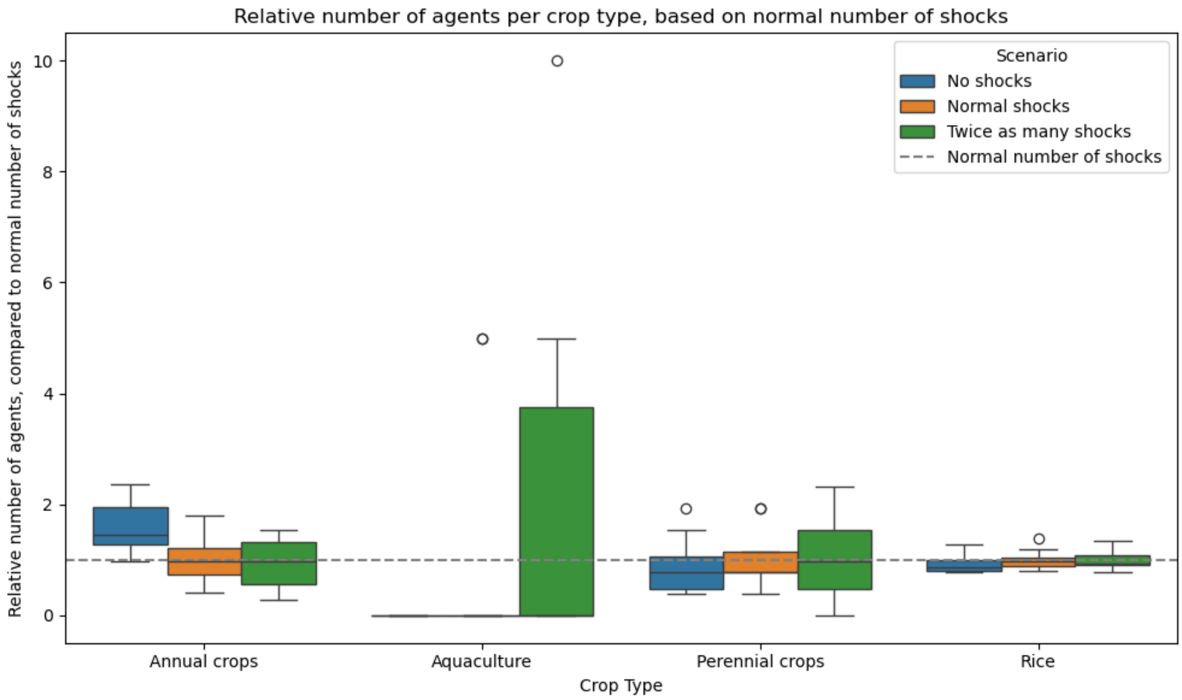

Figure F.3: Number of agents per crop type, when changing the frequency of salinity shocks

doing some interesting things: when there are no shocks, less people are doing rice. This is because they have all transferred to annual crops during the first few steps. In the normal shock scenario, a lot of farmers switch in the beginning, due to the input values, and then reach their steady state. Now, they also do this switch, but they are not impacted by salinity anymore, so they stay in annual crops instead of switching back during the first shock in 2016.

The number of perennial crops and aqua-cultural farmers is higher during the twice as much shocks scenario, since these are salt tolerant.

All in all, the model results are in line with the expectations. It was only not expected that the number of rice farmers would decrease when there are no shocks, but this effect can still be declared.

F.3. Production costs

Question: What would happen when the production costs for farmers where set to zero, or when they are twice as high than during the normal scenario?

Expected behavior: Higher production costs will lead to more migrating households. Furthermore, the number of farmers per crop can go both ways: higher production costs lead to lower revenues, and therefore more switches. However, it is also possible that there is no money for these switches, and they will stay in their current profession. The same is when there are lower production costs: do they finally have the money to change, or is their current income enough and will they stay in their current crops?

Results: When looking at the number of farmers per crop type, there are more people in rice, perennial crops and sometimes also in annual crops. This can be declared by the fact that less people are migrating, as shown in Figure F.6. When the production costs are twice as high, the number of migrating households is significantly higher. This effect is also seen in Figure F.5: there are almost no rice farmers, perennial crops farmers left, and also the number of annual crop farmers is decreased.

All in all was it partly line with the options given in the expectations: higher costs indeed lead to more migrating households, but this effect is so strong that the number of rice, perennial crop and annual farmers are all low. This did not lead to more switches, they just migrated. The low production costs did lead to more switches, but also overall more people in all professions.

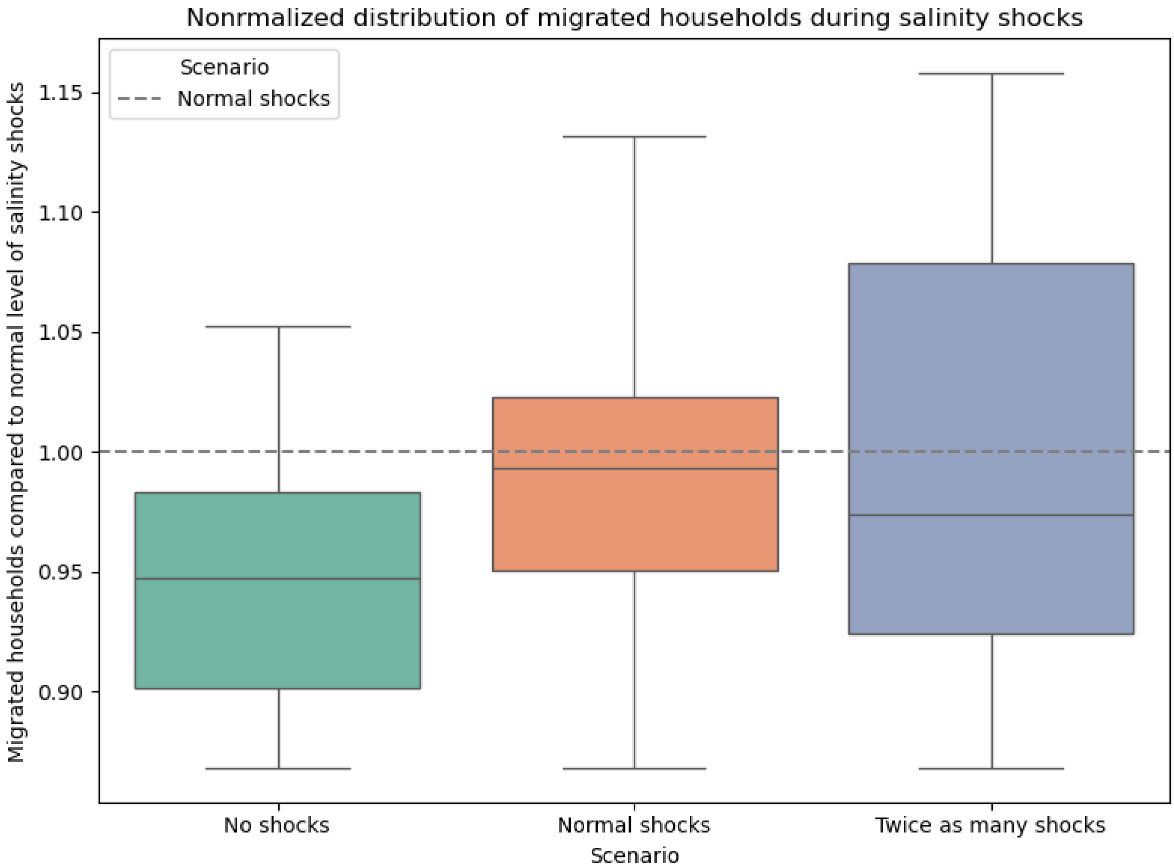

Figure F.4: Number of migrated households during different frequencies of salinity shocks

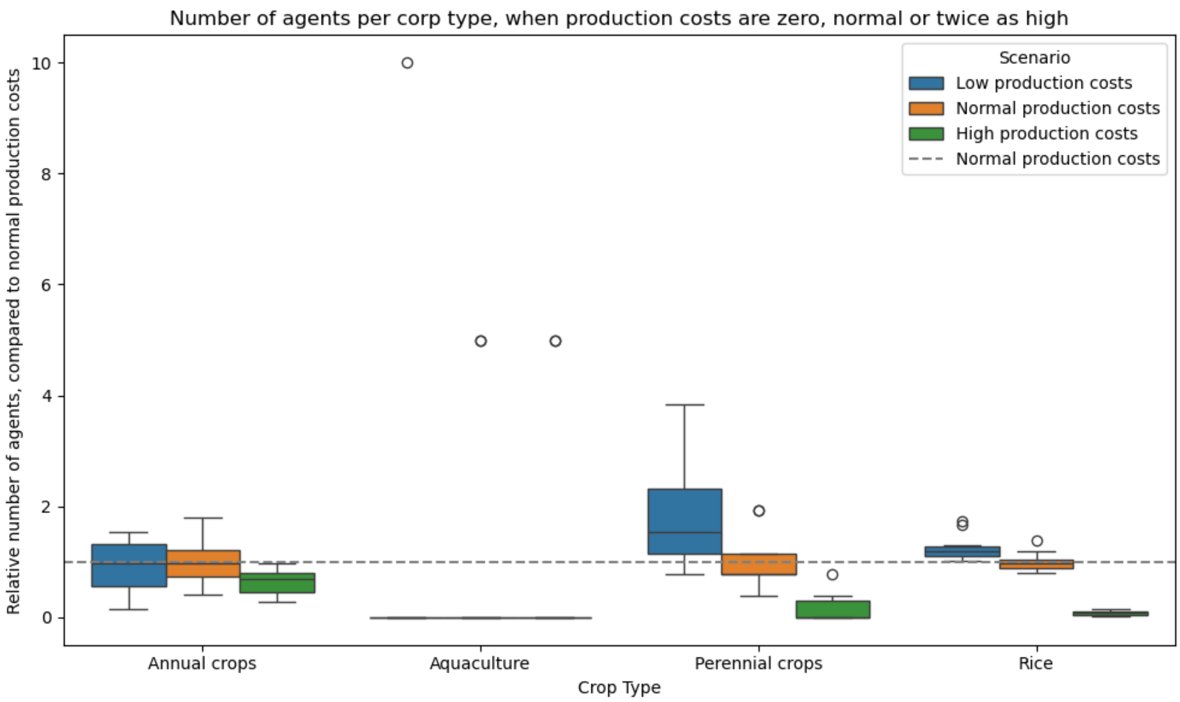

Figure F.5: The number of farmers per crop type, when there are high production costs, normal, or zero costs

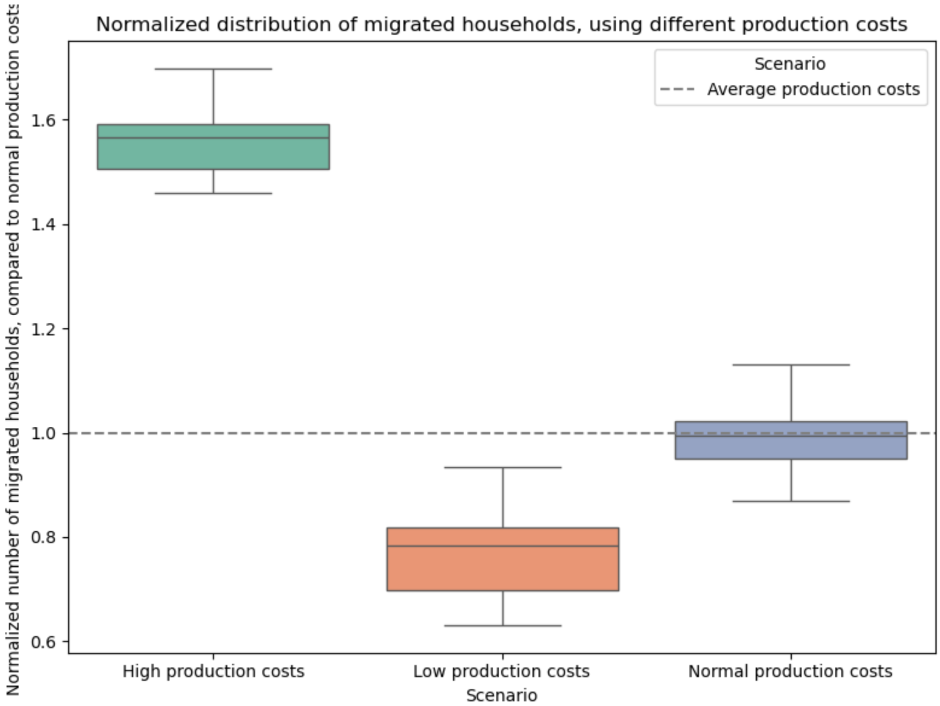

Figure F.6: Normalized number of migrated households when there are no production costs, or twice as high

F.4. Wage worker salary

Question: What would happen when the salary of the wage workers is halved, or is twice as high compared to the current salary of wage workers?

Expected behavior: Lower salary will lead to more farmers with an ”income too low”. When the salary is twice as high, most of the farmers should have a sufficient amount of income. Furthermore, when there is lower salary, people are working more to earn a sufficient amount of income, and therefore the number of wage workers will be higher. This can maybe also be declared by the fact that the farmers have less costs, and are therefore less migrating/switching crops, and more wage workers can work. The same effect would happen when the salary is twice as high: farmers are migrating more, and less people can work. But also less people have to work, since they already have enough income.

Results: The results are in line with the expectations. When the salary is halved, the number of wage workers is more than 2.5 times as high as in the normal scenario. This may be declared due to the interaction effect between the farmers having more money to pay, and more people working due to the low salary. When the salary of wage workers is high, the number of wage workers has decreased drastically. These effects are visualized in Figure F.7.

When salary is low, more households have a ”too low income”. When the salary is higher, this is the other way around, which was expected. Figure F.8 shows these impacts.

F.5. Required number of wage workers

Question: What would happen when the required number of wage workers for farmers would be halved or twice as much, compared to the normal number of man-days/ha?

Expected behavior: When there is a high number of wage workers required, more people are working in wage working. Furthermore, less people would do annual crops, since the number of wage workers in that sector is already high compared to the other sectors. When there is a low number of wage workers, more people would work in annual crops. Maybe the same effect would happen as what happened during the frequency of salinity shocks scenario: people first switch from rice to annual

Figure F.7: Normalized number of wage workers when salary is halved, normal, or twice as high

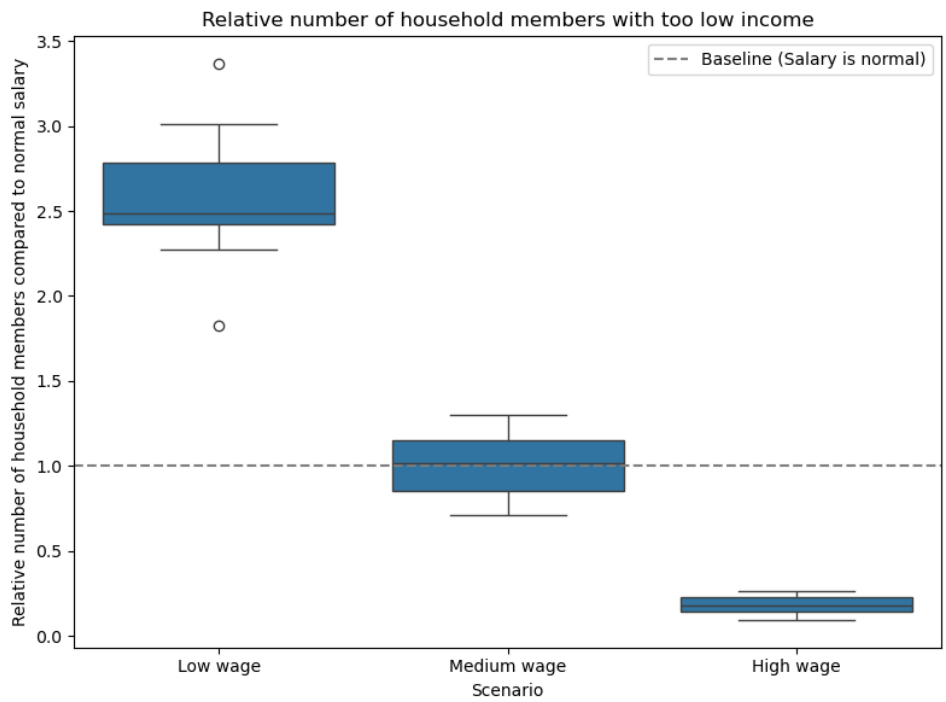

Figure F.8: Normalized number of households with a too low income, when salary is halved, normal or twice as high

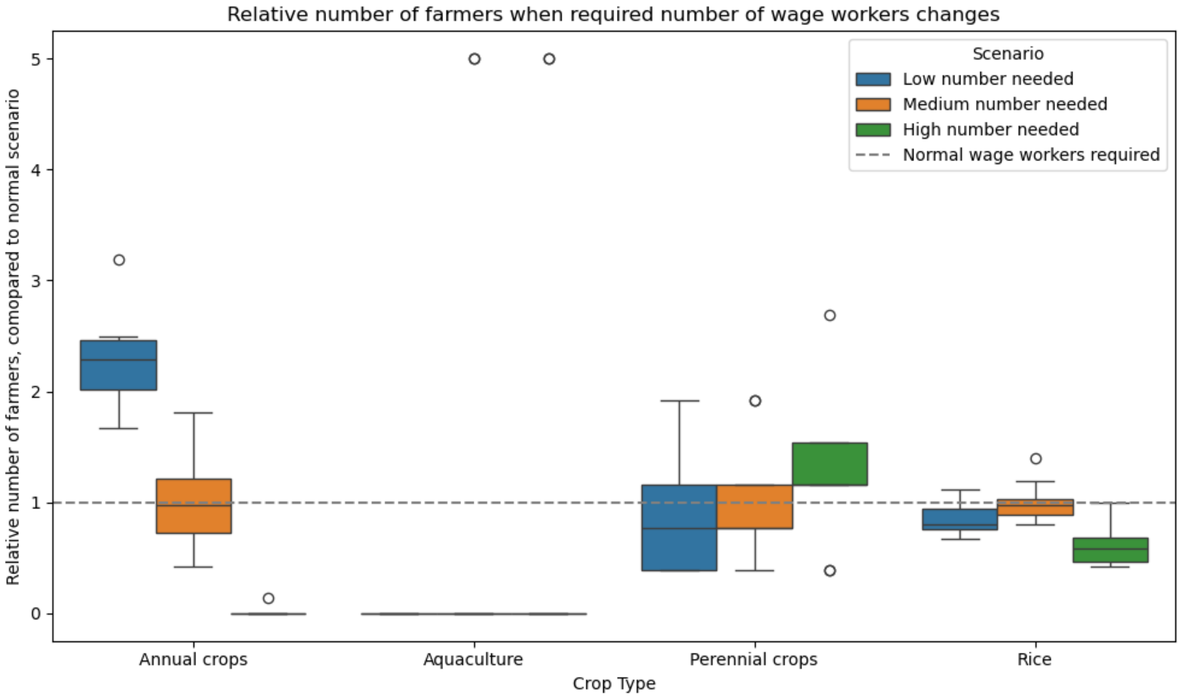

Figure F.9: Number of farmers in each crop type, when the required number of wage workers changes

crops due to the incorrect start data, and than stay there.

Results: The results are perfectly in line with the expectations. When there are less wage workers needed, the number of wage workers is really low. When there are much wage workers are needed, the number of wage workers is really high. This effect is shown in Figure F.10.

When looking at the crops, the same happened as in Figure F.3: the number of annual crops increased during the low wage worker scenario, while the number of rice farmers decreased. This was also expected to happen. Interesting to see is that the number of annual crop farms is zero, and some of them switched to perennial crop farms. The number of rice farms is also lower when more wage workers are required, but not as low as the annual crops, since rice needs less wage workers overall (Pedroso et al., 2017). Figure F.9 visualizes the effects.

F.6. Access to information meeting

Question: What would happen when all land household households have access to the information meeting?

Expected behavior: It is expected that when more people have access, more switches will be made to perennial crops and aquaculture. Furthermore, the livelihood would be higher, since their crop matches with their salinity levels. When no one has access, there livelihood would be lower, but people still switch based on their neighbors.

Results: Figure F.11 shows the number of households doing crops under the different scenarios. There is not much of a difference between attending the information meeting for the number of annual crop farmers and rice farmers. However, when more people attend, more farmers have annual crops and aquaculture. At first, it seems strange that the number of aqua-cultural farmers is high when nobody attends the meeting. But during the meeting, it is told to only do aquaculture if you are smart enough, otherwise you will fail due to antibiotic use. These people during the nobody attends scenario just started since they saw there neighbors doing it. However, it is strange that this is effect is so large, and nobody is doing agriculture in the normal attendance scenario.

As seen in Figure F.12, there is not much of a in livelihood difference between the nobody attends

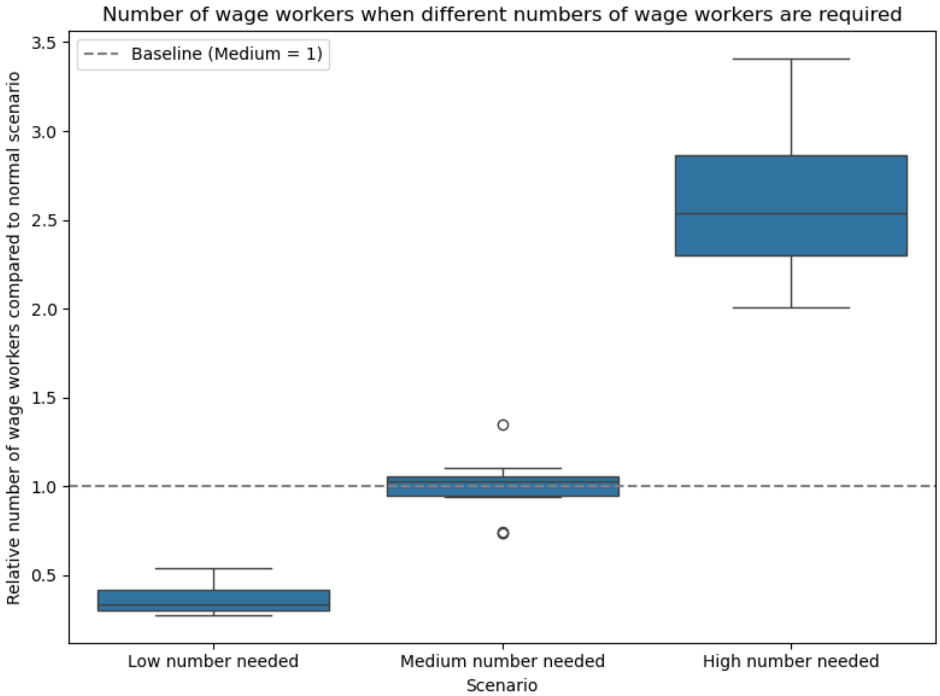

Figure F.10: Number of wage workers, when the required number differs

and normal attendance scenario. This can be declared by the fact that now only 10 percent attends the meeting. During the high attendance scenario, the livelihood increased slightly, which was expected.

Overall, the model behaves as expected, except the aquaculture farmers when there is no attendance to the information meeting. But this can be declared.

F.7. Contacts in the city

Question: What would happen when all individual household members have contacts in the city, or no contacts at all in the city?

Expected behavior: It is expected the number of migrated household members increases significantly when the number of contacts in the city increases. The opposite effect is expected when the contact in city probability decreases.

Results: The expected behavior is visualized in Figure F.13. When everybody has contacts, the migrations increase with approximately 15-35 percent, while the number of migrated individuals decreases with almost 50 percent when there are no contacts. This is in line with the expectation.

F.8. Debt

Question: What would happen when it is not possible to have debt as all, or to have twice as much debt as the current debt?

Expected behavior: It is expected that when it is not possible to have debt, less people would switch crops. Furthermore, it would be logical if more people migrated, since they do not have money. The impact on savings can go both ways: when there is more debt, people make more investments and need to pay more, but might also have more income. The other way around, peoples income is not increasing as much as the annual loan payments, and savings are decreasing. This might depend on the crop switches too.

When more debt is possible, there might nog be a large change. When looking at the debt ratio in Figure E.5, almost all agents have a maximum debt ratio of 0.5. It is not as if their debt ratio is already

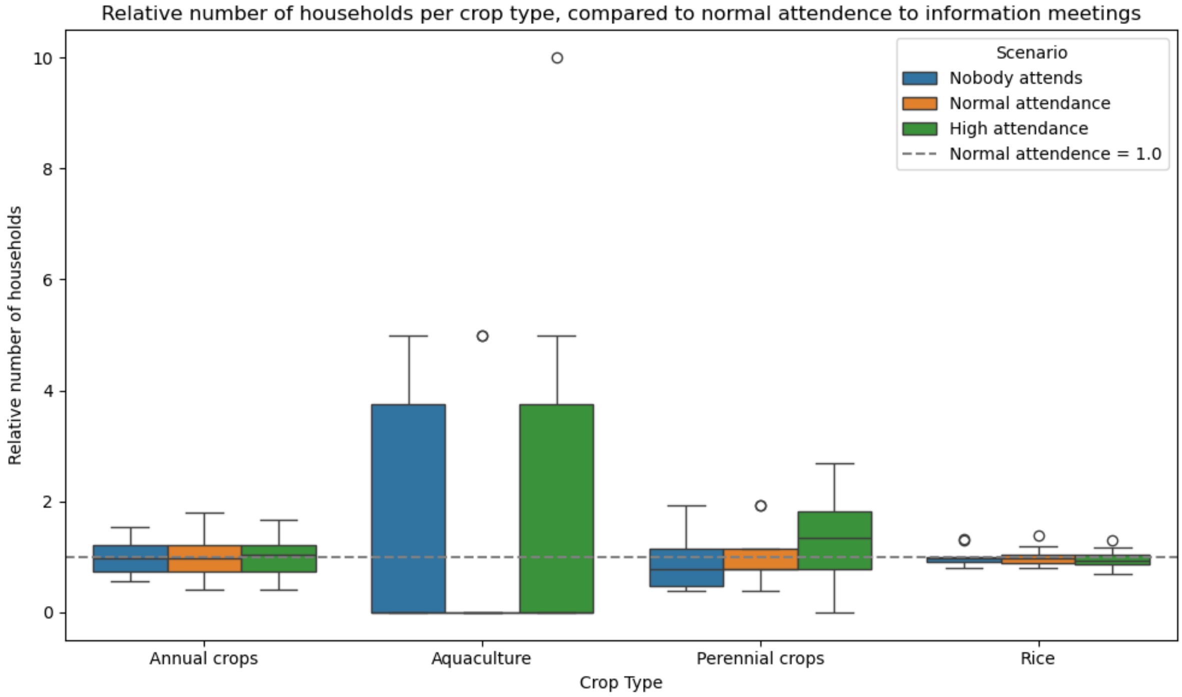

Figure F.11: Number of households doing certain crops, in different information meeting attendance scenarios

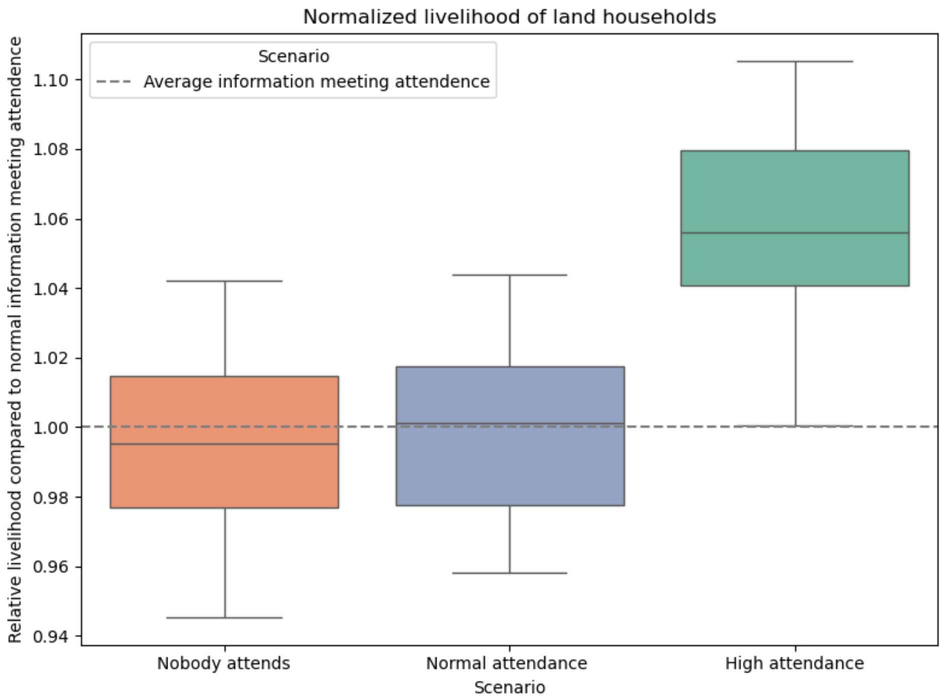

Figure F.12: Livelihood of land households during different information meeting attendance rates

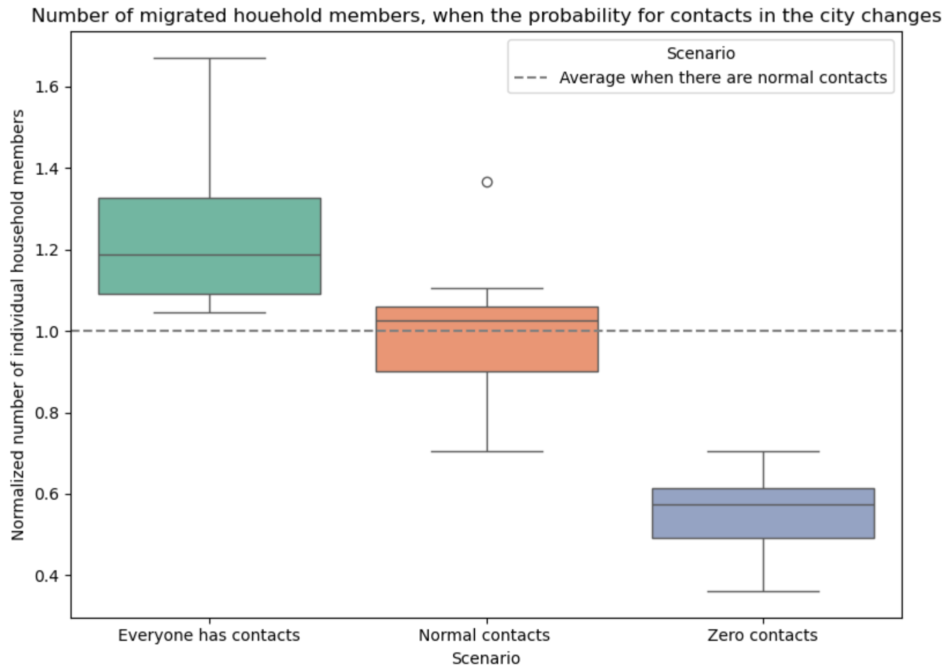

Figure F.13: Number of migrated individuals when the probability for contacts in the city changes

1, and they want more debt

Results: There is no difference in savings, maybe a combination of the two expected behaviors is happening. The livelihood during the no debt scenario is a bit higher, but there is no difference in the current debt or high debt scenario. However, during the no debt scenario, more households are migrating. This is logical: households do not have the ”last chance” of getting a loan when there savings are below zero, they just need to migrate. The migrations are shown in Figure F.14.

Furthermore, something strange happens with the farmers per crop type, but this can be declared. This distribution is shown in Figure F.15. At the start of the model, during normal scenarios, a lot of rice farmers are switching to annual crops. But then, their savings are emptied, and they cannot switch back to rice after the first shock in 2016: they stay in annual crops. That declares why the number of rice farmers is lower, and the number of annual crop farmers is higher when no debt is possible.

The other strange thing is the same peak as what happened in Figure F.11: The number of aquaculture farmers is high when no debt is possible. It is cheaper to switch from rice to shrimp than from rice to coconut. Maybe some rice farmers do not have the money to switch to perennial crops, and therefore switch to aquaculture.

F.9. Probability for migration

Question: What would happen the probability a household or household member is migrating is increased or decreased?

Expected behavior: It is expected that the number of migrations will increase, when the probability increases, and the other way around.

Results: The results are in line with the expectations, and visualized in Figure F.16 and Figure F.17. The effects are higher for the individual household members, than the complete migrating households.

F.10. Facilities in neighborhood

Question: What would happen when the facilities in the neighborhood stayed the same, instead of decreasing when service workers are leaving? Or what would happen if there were no facilities at all?

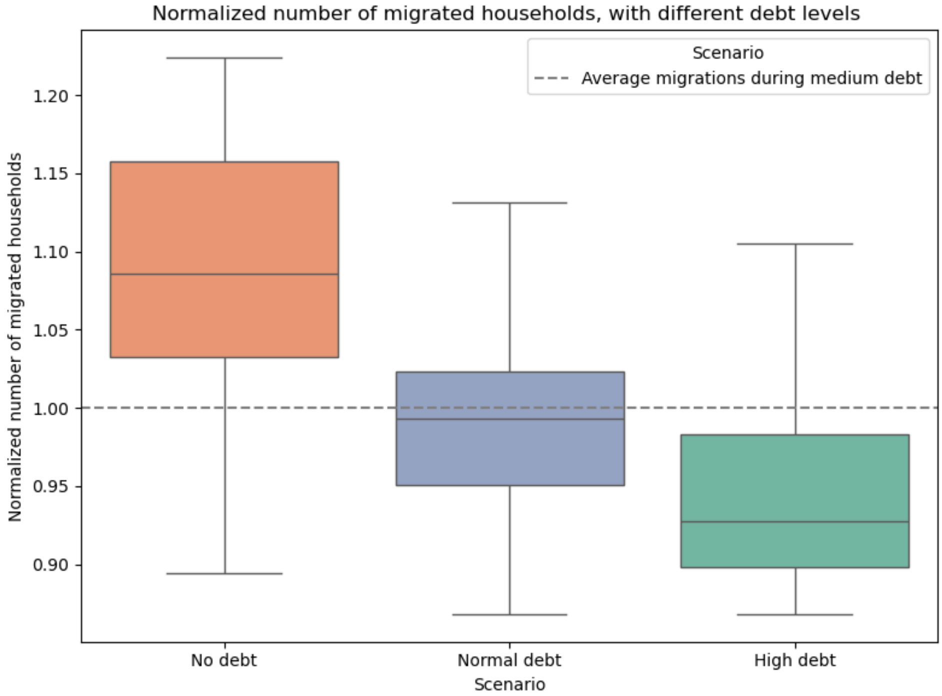

Figure F.14: Number of migrations during different maximum debt levels

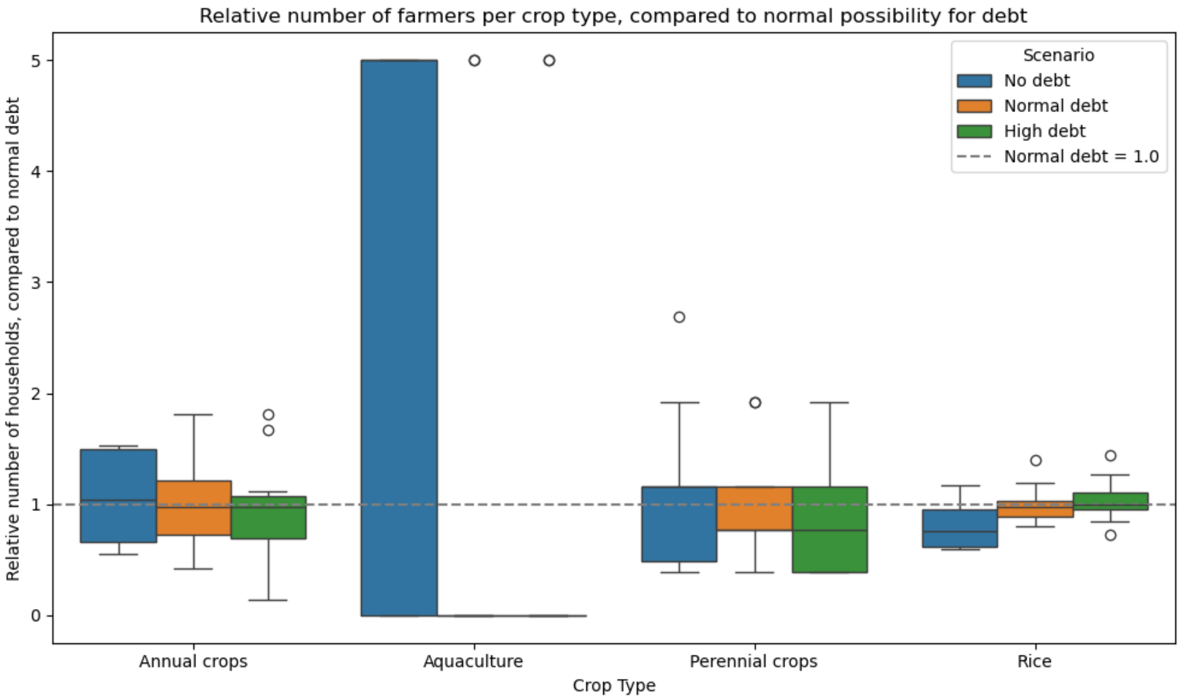

Figure F.15: Number of farmers per crop type, when differentiating between different levels of possible debt

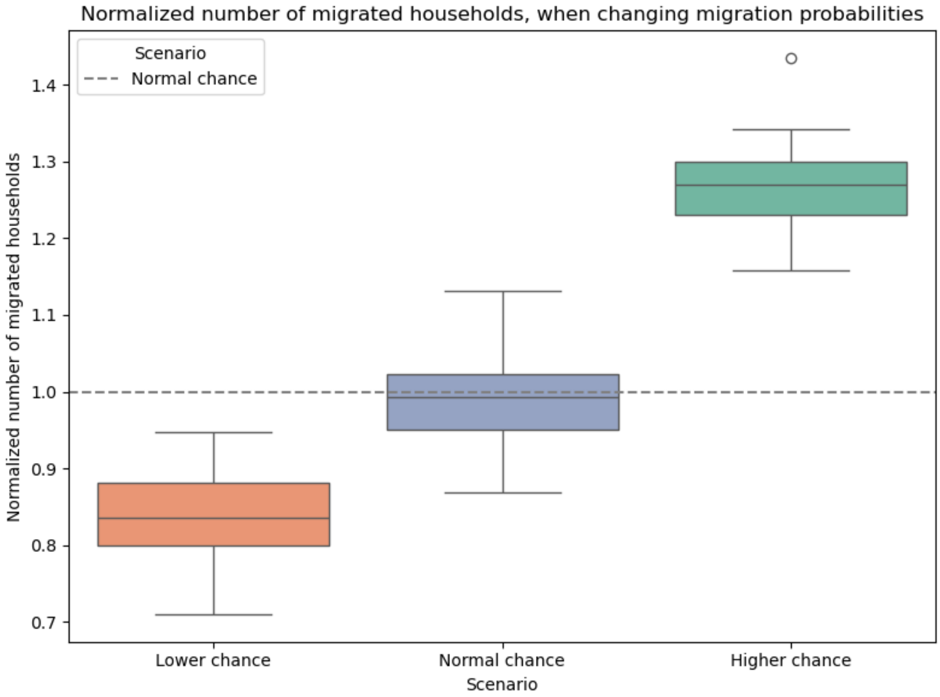

Figure F.16: Number of migrated households, when migration probabilities change

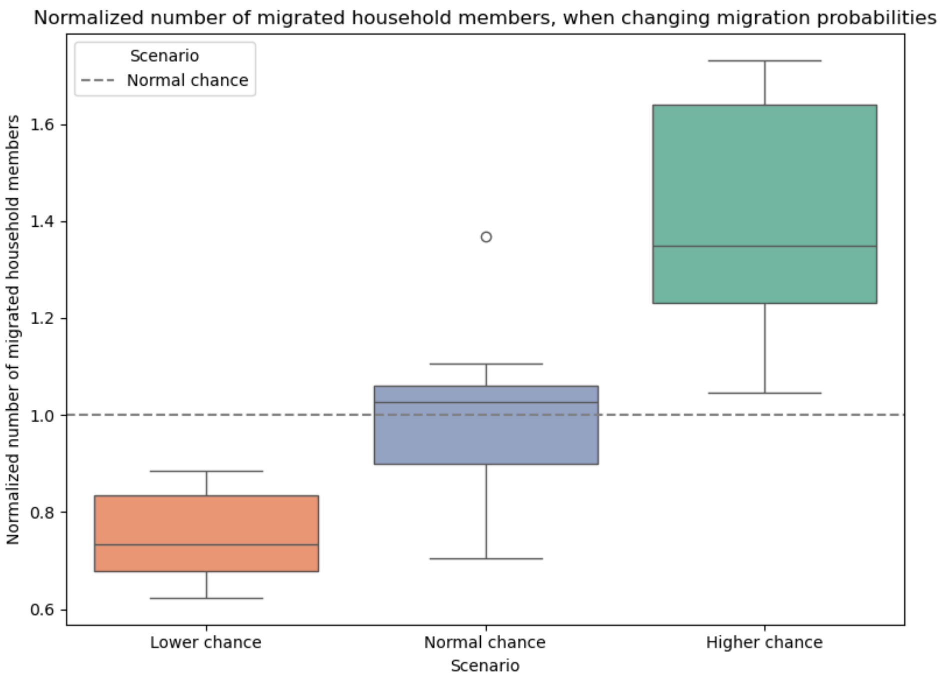

Figure F.17: Number of migrated household members, when migration probabilities change

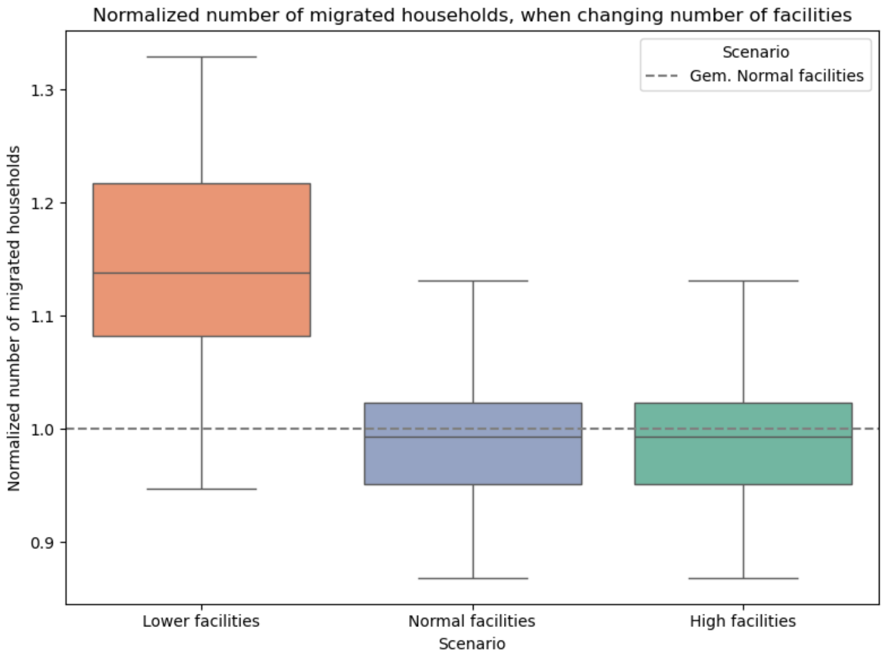

Figure F.18: Number of migrated households, when the number of facilities nearby changes

Expected behavior: The number of facilities in neighborhood influences the change households are migrating. Therefore, it is expected that more facilities in the neighborhood lead to less migrations, and the other way around.

Results: The number of migrating households is shown in Figure F.18. It is striking to see that there is no difference between the normal and high facilities scenario. This can be declared by the fact that almost none of the service workers are migrating in the base case,so the number of facilities stays high. When facilities are decreasing, the migrations are increased by 10-20 percent, which might be lower than expected. This is since migration is also dependent on a lot of other factors, for example income and savings. However, in the future this should be considered more, since when there are no facilities at all, most of the people are not staying, even when they have savings.

G

System Dynamics Model - Deltares Version

In addition to ABM, a basic System Dynamics (SD) model was also developed. This can later be expanded by Deltares with the desired factors. First, the model will be explained using causal loop diagrams. Then, the model output and validation will be shown.

G.1. Conceptualization

G.1.1. Groups of households

First, it was decided which groups of people would be modeled. A distinction is made between two types of farmers: shrimp and rice. In addition, a distinction is made between commercial farms and small family farms. In the Vensim model, this is indicated by color: purple represents commercial farms and light blue represents small family farms.

If the savings of the rice farmers are too low, there is a chance they will switch to shrimp farming, become landless agricultural wage workers, or become non-farm workers. These non-farm workers can either be low- or high-skilled, depending on how many people in the model have received training. There is also a chance that the shrimp farmers fail due to diseases. In that case, the affected households may return to rice farming, or become agricultural wage workers or non-farm workers. Figure G.1 shows an overview of the possible switches. Based on unpublished research by Deltars, the switch percentages are chosen (personal communication, May 2025).

G.1.2. Rice farmers

Two sub-models have been created for a small family rice farmer and a commercial rice farmer. They both have the same structure, which is visualized in the causal loop diagram in Figure G.2.

The higher the salinity level, the higher the rice yield loss ratio. However, this ratio can be reduced if farmers have received training or if their equipment level has increased. The rice yield loss ratio is based on Van Aalst et al. (2023). For small farmers, this ratio is $y = 0.11 + 0.57x$, and for medium farmers $y = 0.05 + 0.47x$, where x is the salinity level, and y the rice yield loss ratio. The slope coefficient of the formula decreases in this model when farmers have training or equipment. This means that there is less impact on salinity, as they are better prepared and their yields will be higher.

A higher rice yield loss ratio leads to a lower rice yield per household. The other factor influencing the rice yield is the land size of the households. The rice yield determines the revenue, along with the world market price of rice. This revenue is added to the savings per household.

Rice farmers also have farming costs, which are based on standard rice farming costs per ha. These include, for instance, wage worker costs and seed costs. Furthermore, when a salinity shock has occurred, the farming costs will increase next year, since the land needs to recover from the salt increase. The percentage increase in costs is in line to the rice yield loss ratio. These costs are deducted from the household's savings.

If household savings become too low, the farmer will stop farming. Other farms then take over their land, increasing their land size. This results in higher costs, but also in more yield, and therefore more

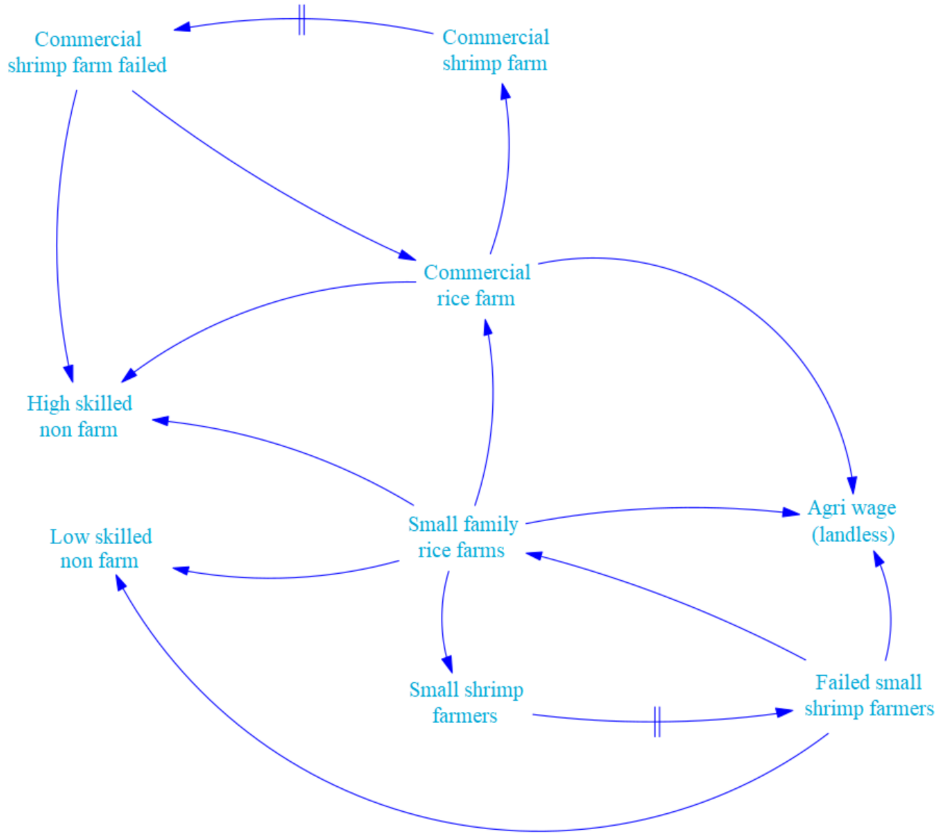

Figure G.1: Conceptual overview of the different types of groups modeled in the SD model

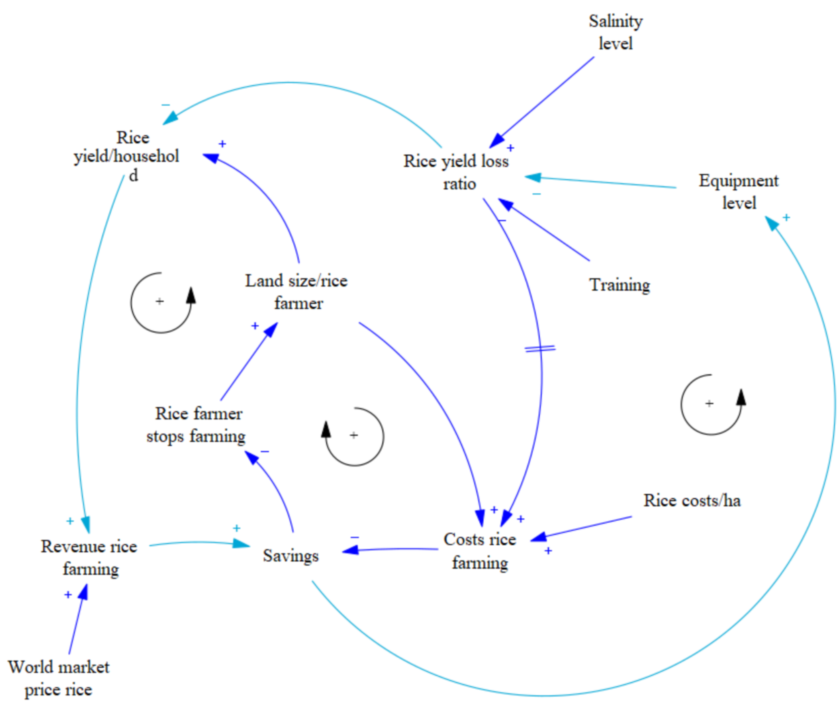

Figure G.2: Causal loop diagram of the rice farmers in the VMD

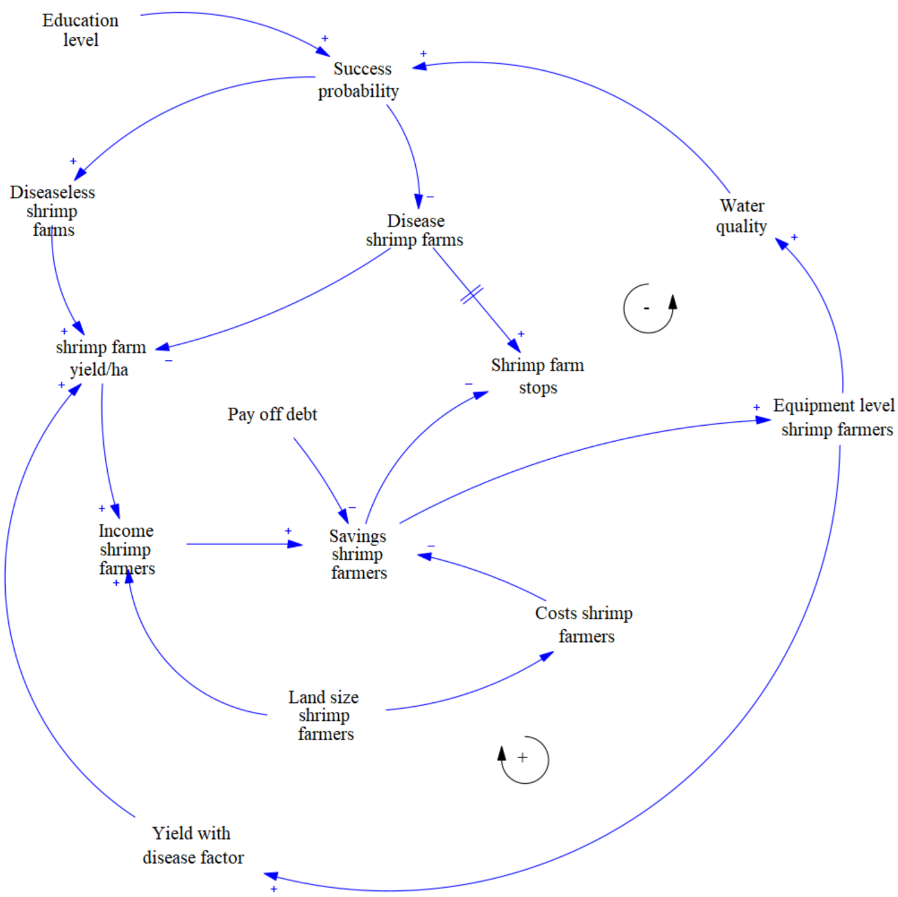

Figure G.3: Causal loop diagram for the shrimp farmers in the VMD

revenue. As a result, two feedback loops are created. Rice farming costs are lower than revenue, so farmers benefit from taking over land from others.

In addition, there is a reinforcing feedback loop between *savings – equipment level – rice yield loss ratio – rice farming costs – and savings*. The more savings a farmer has, the more they can invest in new equipment. This raises the level of equipment and lowers the rice yield loss ratio, as the farmer is better protected against salinity shocks. As a result, post-shock farming costs also decrease, allowing savings to remain higher. This is a reinforcing loop. However, the feedback can also follow a slightly different path (indicated in light blue in the diagram): the more savings a farmer has, the more they can invest in equipment to reduce the impact of salinity shocks. This lowers the rice yield loss ratio, increases the rice yield, and therefore results in more revenue.

G.1.3. Shrimp farmers

In this version of the model, shrimp farmers are not affected by salinity but by diseases. The success probability determines how many shrimp farms are affected by disease. This probability depends on the education level and water quality. The more farms affected by disease, the lower the average shrimp yield per hectare and, as a result, the lower the income of the farmers. This also depends on the land size of the farmers.

Farmers can protect themselves by investing in equipment, which creates two feedback loops. When savings increase, the level of the equipment also increases. This improves water quality, resulting in fewer shrimp farms becoming diseased. In addition, farms affected by disease are less affected when equipment levels are high, since the 'yield with disease' factor increases as equipment levels increase. Unfortunately, it is not included whether farmers choose to use antibiotics or not. The assumption is that all farmers whose farms are affected by disease use antibiotics and, after five years, must stop shrimp farming. Figure G.3 shows the causal loop diagram for shrimp farmers.

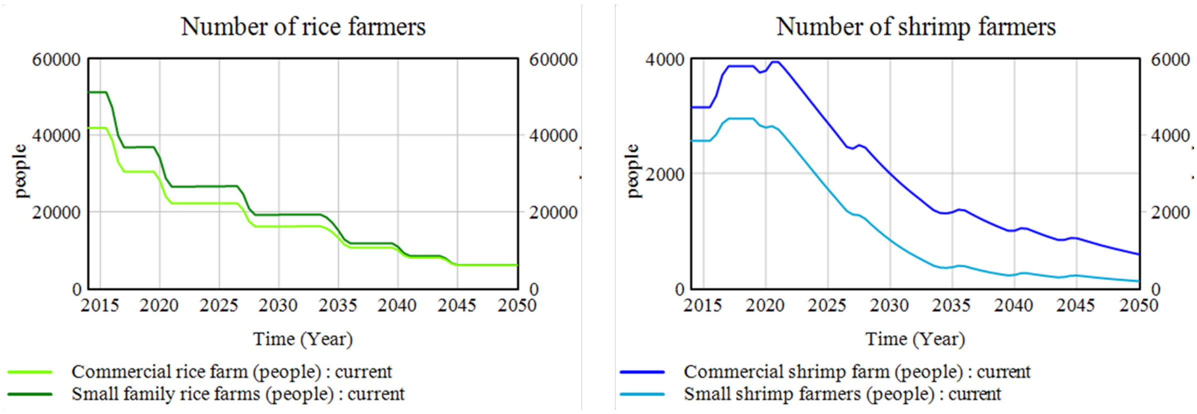

Figure G.4: Number of rice farmers (left) and shrimp farmers (right) over time in the SD model

In the formal model, a distinction is made between extensive and intensive shrimp farming among commercial shrimp farmers. Approximately three-quarters of the people in the VMD use extensive shrimp farming, but intensive farming is also practiced Joffre et al. (2015a). In the Vensim model, extensive shrimp farmers are shown in light blue, while intensive shrimp farms are shown in dark blue.

The total savings per type of shrimp farm (intensive and extensive) are calculated by taking into account the savings of diseased and disease-free shrimp farms, as well as the ratio between the number of diseased and disease-free farms. In the Vensim model, this is indicated in the pink section.

It is important to note that in this model, the disease farms and shrimp farms without disease are aggregated: When wealthier farmers invest in equipment, the disease-affected farms (which are often less wealthy) also benefit from this. This is because not every farm experiences disease every year. It is possible that a farm is affected one year and in the following years it may remain healthy. However, it was decided to let these shrimp farms fail after a 5-year delay. This is because, on average, there is a relatively constant number of shrimp farms affected by disease each year. And since this is an aggregated model, it is not possible to model individual outcomes such as 'you have disease this year, but not next year, and then again next year'.

G.2. Model output

The same data was used for the SD model as for the ABM model. However, these data were tweaked to better reflect reality and to ensure, for example, that savings do not immediately drop to zero. For intensive shrimp farming data from Joffre et al. (2015a) was used. However, the costs for intensive shrimp farming were set at 150 million VND instead of 200 million. In addition, fixed wage worker costs were used for rice farmers, while these costs were variable in the ABM model. Lastly, assumptions were made regarding the impact of training and equipment. From all interviews, it became clear that no one knew how effective these actually are. Furthermore, no one knew the exact cost of investing in equipment. Therefore, reasonable estimates were chosen.

Figure G.4 shows the number of farmers of rice and shrimp over time. It can be seen that when the rice farmers are decreasing at the start of the model (during the first shock in 2016), the number of shrimp farmers is increasing. The same happens in 2021. However, the first shrimp farmers who switched in 2016, fail due to antibiotics in 2021. That is the decrease seen in 2021. The little decrease in 2020 can be declared by the fact that those are the shrimp farmers who "started" in 2015 as shrimp farmer, when the model started.

In general, the number of rice farmers is decreasing really fast after each shock. This is due to the high migration rates, which are taken from the unpublished data analysis by Deltares (personal communication, May 2025).

In the current model version, small family rice farmers are too poor to invest in equipment. As a result, their rice yield remains the same, it only decreases during a salinity shock. Commercial rice farmers are wealthier because they own more land and therefore have the budget to invest in equipment. This happens in 2033 and 2047. As a result, the rice yield loss ratio decreases and is slightly less affected by salinity.

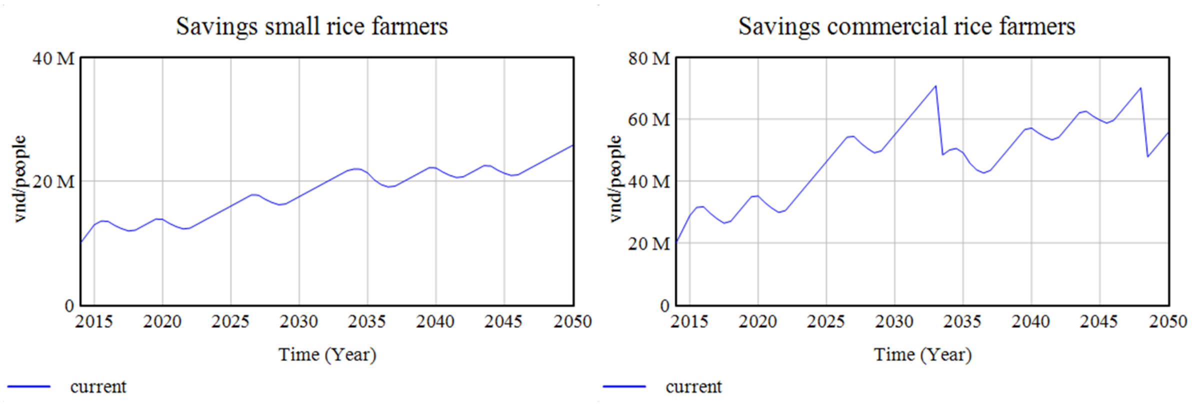

Figure G.5: Savings of the small rice farmers (left) and commercial rice farmers (right)

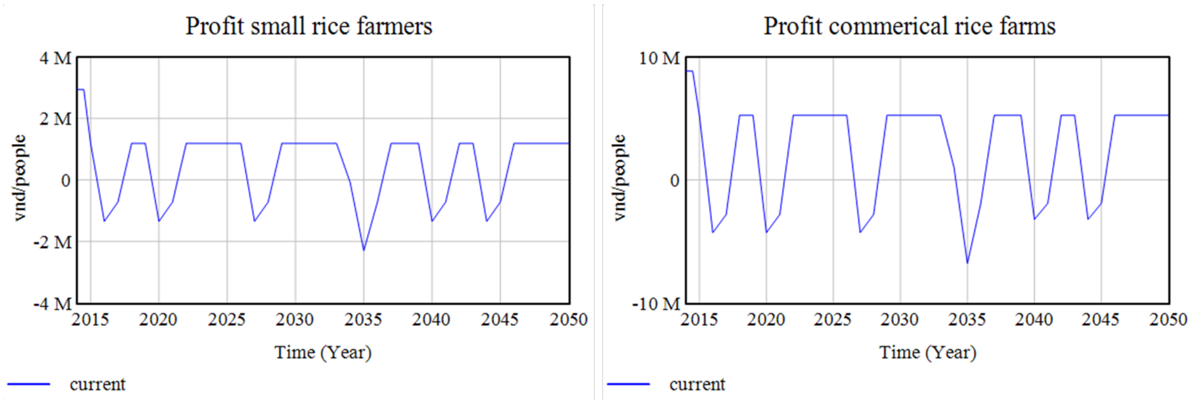

Figure G.6: Profits of small rice farmers (left) and commercial rice farmers (right)

Looking at the profits of rice farmers, the same pattern can be seen. For small family rice farmers, nothing changes and there is only a drop during a salinity shock. In the next step, there is still a slight decrease, as farmers need to spend money to repair the land after the shock. Commercial rice farmers show the same effect, but in the last 10 years, the decline in profits becomes slightly less severe. This is because the rice yield loss ratio has decreased due to investments in equipment.

The same effects are seen among shrimp farmers. Small family shrimp farmers can only invest slightly in equipment and the number of disease-free and disease-free farms remains almost constant. However, commercial farms invest in equipment and the success probability slightly increases. In addition, the shrimp yield per hectare of disease-affected farms increases over time due to equipment investments. The biggest impact is seen among the intensive shrimp farms, as their costs are significantly higher than those of extensive shrimp farms.

Figure G.5 shows the savings of the small family and commercial farmers over time. It can be seen that the commercial rice farms invested in equipment in 2033 and 2047. Furthermore, during the salinity shocks the savings are decreasing. This is in line with the profits, shown in figure G.6. The profit of small rice farmers is lower than the profits of the commercial rice farmers, but the impct of the salinity shock on their savings is also less intense. Furthermore, it can be seen in Figure G.6 that after the shock, there is a ”recovery year”, where the profits are still low due to repairing costs.

The savings of small shrimp farmers with and without disease are shown in Figure G.7. The small shrimp farms are able to buy equipment. However, the profit of the diseases shrimp farms is decreasing fast. It should be noted that this is an aggregated model, and shrimp farms can be have a disease one year, and have no disease the next year. Therefore, their savings will not be constantly low.

The savings of the commercial shrimp farmers without disease is shown in Figure G.9. The intensive shrimp farms are richer than the extensive shrimp, but they also have higher risk for diseases. They are both able to pay for the equipment. This is in line with the profit of the disease shrimp farms in Figure G.8: the profit is increasing slightly over time, due to the increase in equipment.

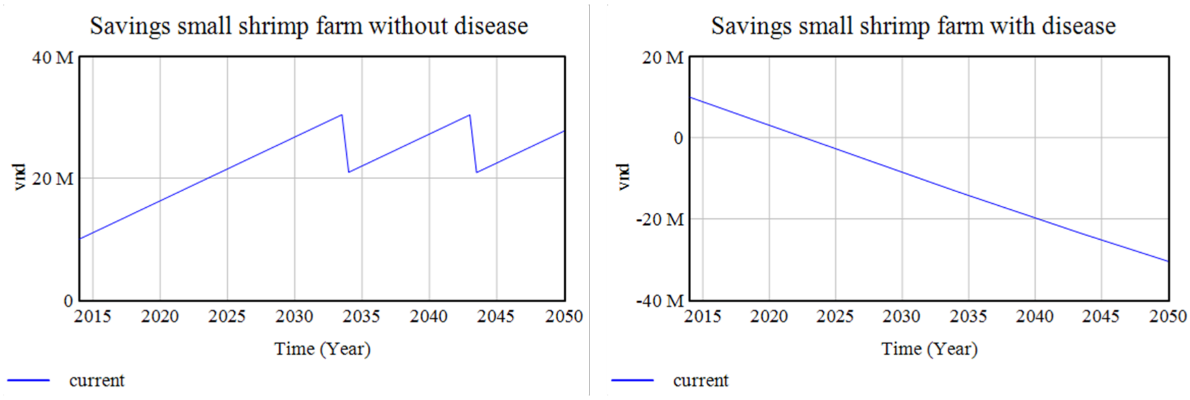

Figure G.7: Savings of small shrimp farmers without disease (left) and with disease (right)

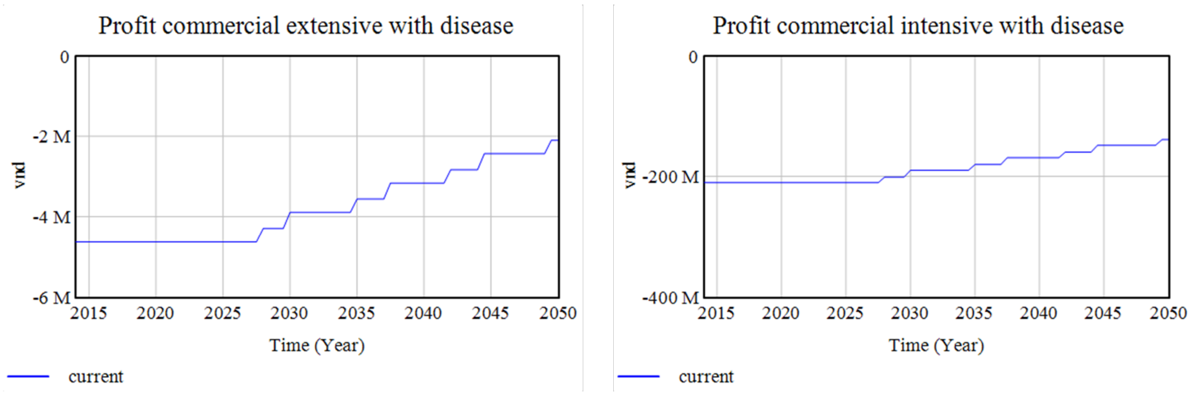

Figure G.8: Profits of commercial farms with disease (left) and without disease (right)

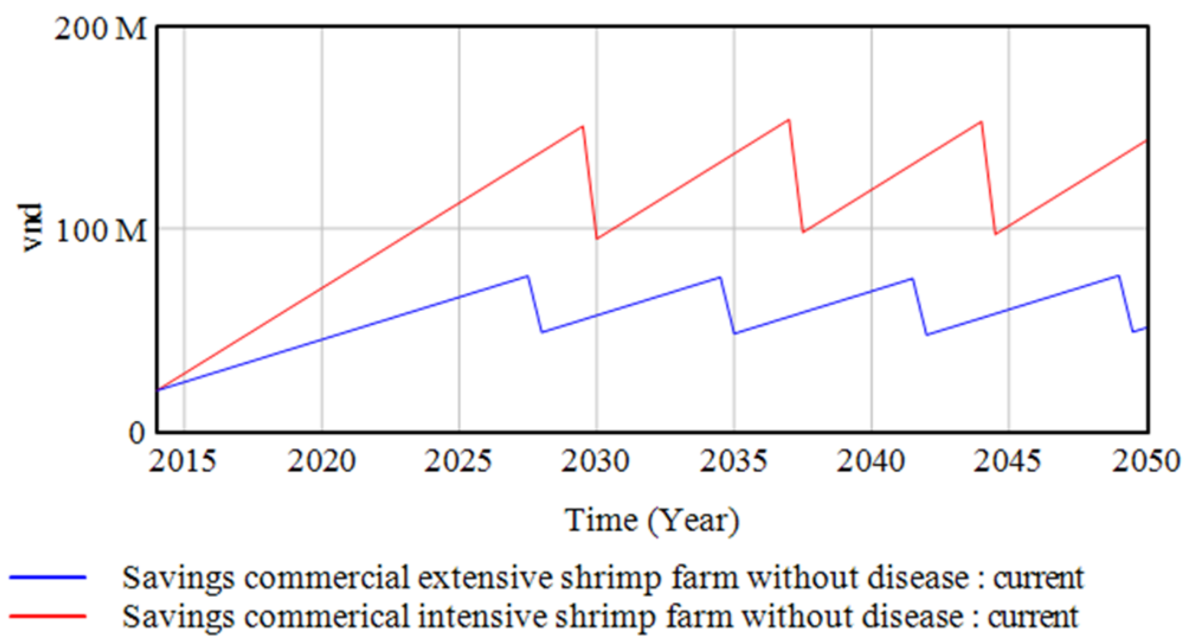

Figure G.9: Savings of commercial intensive and extensive shrimp farmers

G.3. Validation

Together with P. Jansson and M. van Aalst, the model was reviewed for validation and evaluated to see where it can be improved in the future. The model outcomes for the number of households align with expectations based on the unpublished data by Deltares (personal communication, May 2025). However, upon closer inspection, it appears that the switching probabilities are quite high and likely overestimated. When people own land, they tend to attach to it, and most rice farmers have worked in this sector for decades. The likelihood that they will all switch is simply not that high, there will always be some who stay behind.

In addition, the savings of all rice and shrimp farmers increase over time in the model, whereas in reality, there is not that much financial leeway, especially for small family farms. In real life, there are other types of expenditure: people need food, have to pay for car repairs, or buy new clothes. None of this is included in the model.

The reason for this is the same as in the ABM: the input data is not accurate. As a result, some tweaking was done to produce a somewhat reasonable outcome, but even this still does not fully reflect reality.

G.3.1. Extreme value validation

Extreme value validation has been conducted on the variables of table G.1. There are a few interesting things happening, these are explained below:

* When increasing the production costs rice, the number of small family rice farms is not changing. But when decreasing the production costs, it would be expected that more farmers kept farming. This is not the case, since the farmers started investing in equipment, and then their savings decreased, and then they became poor. This is happening since SD is not a behavioral model, and there is no think process "maybe a shock is happening, so I need to be prepared and not spend al my savings on equipment". The farmers just think "oh i have have, let's spend". This effect is also seen in the rice yield loss ratio, which is lower than during the normal or high scenario.

**Migration in this group is based purely on the success probability regarding disease, rather than savings. These effects may therefore need to be estimated as larger than they currently are.

*** Something interesting happens here. When more or fewer small farmers stop farming, the number of commercial rice farmers decreases as well. In the first few years, the number of commercial rice farmers is even higher when the chance of small rice farmers quitting is high. This is because the commercial farmers have taken over the land from the small ones. However, during the shock in 2034, this number drops drastically and becomes lower than in the normal and low chance scenarios. This is because from 2034 onward, almost no small rice farmers stop farming anymore in the high-risk scenario (so no new commercial farmers enter), while new commercial farmers still appear in the normal and low-risk scenarios. There is no inflow in the high chance case, while there is in the others, which causes the stock to decline and the total number of commercial farmers to fall below that in the normal scenario.

**** Skill level indeed increases, but this is later combined with training level, which minimizes the difference in rice yield loss ratio.

Table G.1: Sensitivity analysis conducted with SD variables

What was changed?	Variable	Low	Normal	High
Overall salinity level	Small family rice farms	6.60	0.00	-1.00
	Commercial rice farmers	5.73	0.00	-1.00
	Small shrimp farmers	-1.00	0.00	-1.00
	Commercial shrimp farmers	-0.83	0.00	-0.63
Frequency of salinity shocks	Small family rice farms	6.60	0.00	-0.81
	Commercial rice farmers	5.65	0.00	-0.80
	Small shrimp farmers	-1.00	0.00	-1.00
	Commercial shrimp farmers	-0.79	0.00	0.30
Production costs rice	Small family rice farms*	-0.69	0.00	0.00
	Commercial rice farmers	4.81	0.00	0.00
	Rice yield loss ratio during shocks	-0.52	0.00	0.00
Production costs shrimp	Small shrimp farmers**	1.05	0.00	-0.36
	Commercial shrimp farmers	1.13	0.00	-0.41
	Water quality small shrimp farmers	0.10	0.00	-0.05
	Water quality intensive shrimp farm	-0.43	0.00	0.14
	Water quality extensive shrimp farm	-0.17	0.00	0.04
Wage worker costs	Commercial rice farmers	0.75	0.00	0.00
Chance small rice farmer stops farming	Small family rice farms	1.71	0.00	-0.86
	Commercial rice farmers***	-0.05	0.00	-0.13
Chance commercial rice farmer stops farming	Commercial rice farmers	0.67	0.00	-0.80
Expected small shrimp farmers to fail	Small shrimp farmers	30.68	0.00	-1.00
Expected commercial shrimp farm failures	Commercial shrimp farmers	3.26	0.00	-1.00
Training	Rice yield loss ratio small farmers during peaks	0.53	0.00	-1.00
	Rice yield loss ratio commercial farmers	-0.29	0.00	0.14
	Succes probability small shrimp farm	0.63	0.00	-0.27
	Succes probability extensive commercial	-0.24	0.00	0.56
	Succes probability intensive commercial	-0.24	0.00	0.62
Price of equipment	Rice yield loss ratio small farmers during peaks	0.00	0.00	0.00
	Rice yield loss ratio commercial farmers during peaks ****	0.00	0.00	0.00
	Skill level commercial rice farmers	0.09	0.00	-0.17
	Water quality small shrimp	0.04	0.00	-0.02
	Water quality extensive commercial	0.02	0.00	-0.07
	Water quality intensive commercial	0.06	0.00	-0.17

H
Comparison SD and ABM

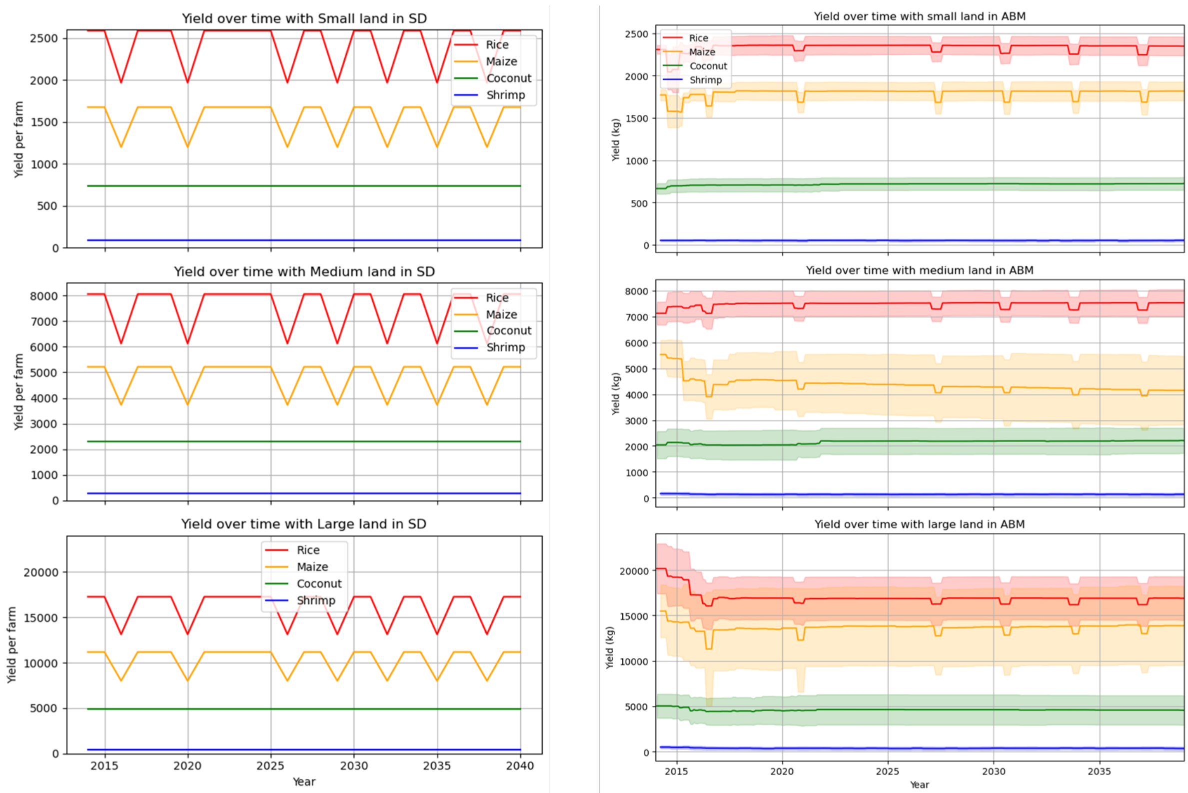

Figure H.1: Yield over time per farm in SD (left) and ABM (right

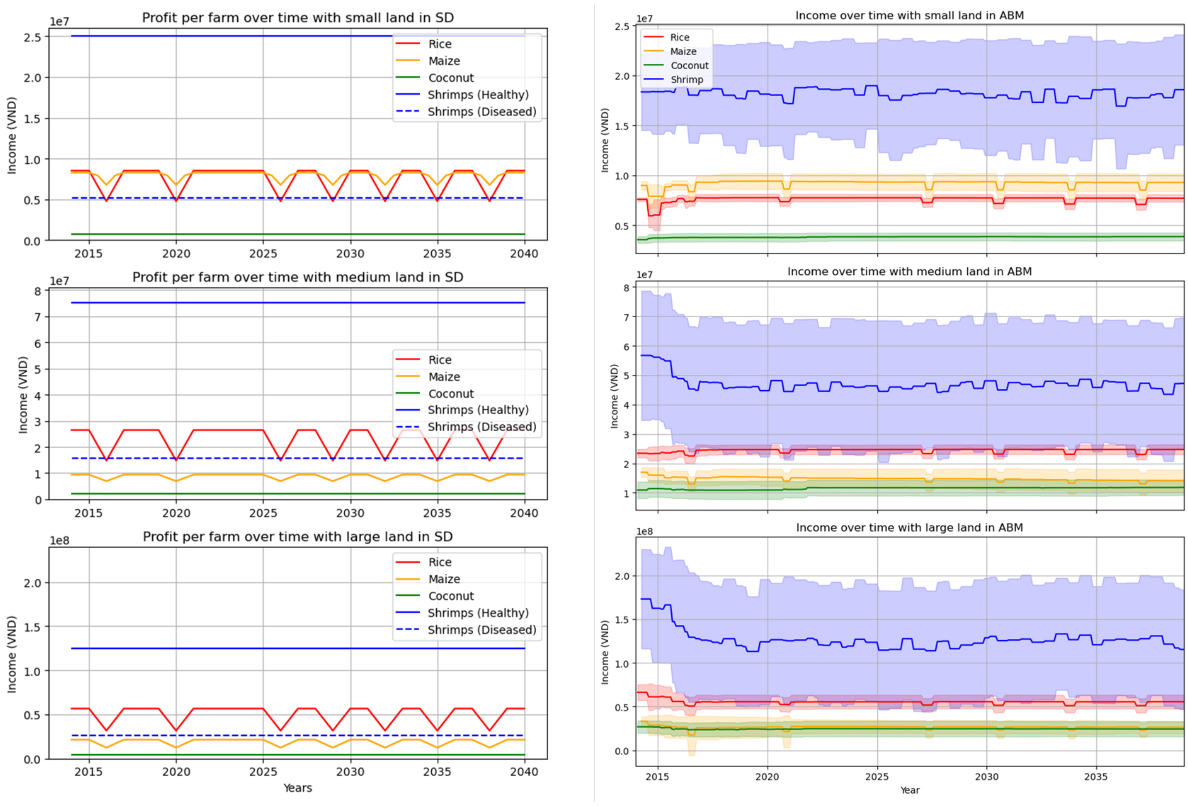

Figure H.2: Farming profit over time in SD (left) and ABM (right

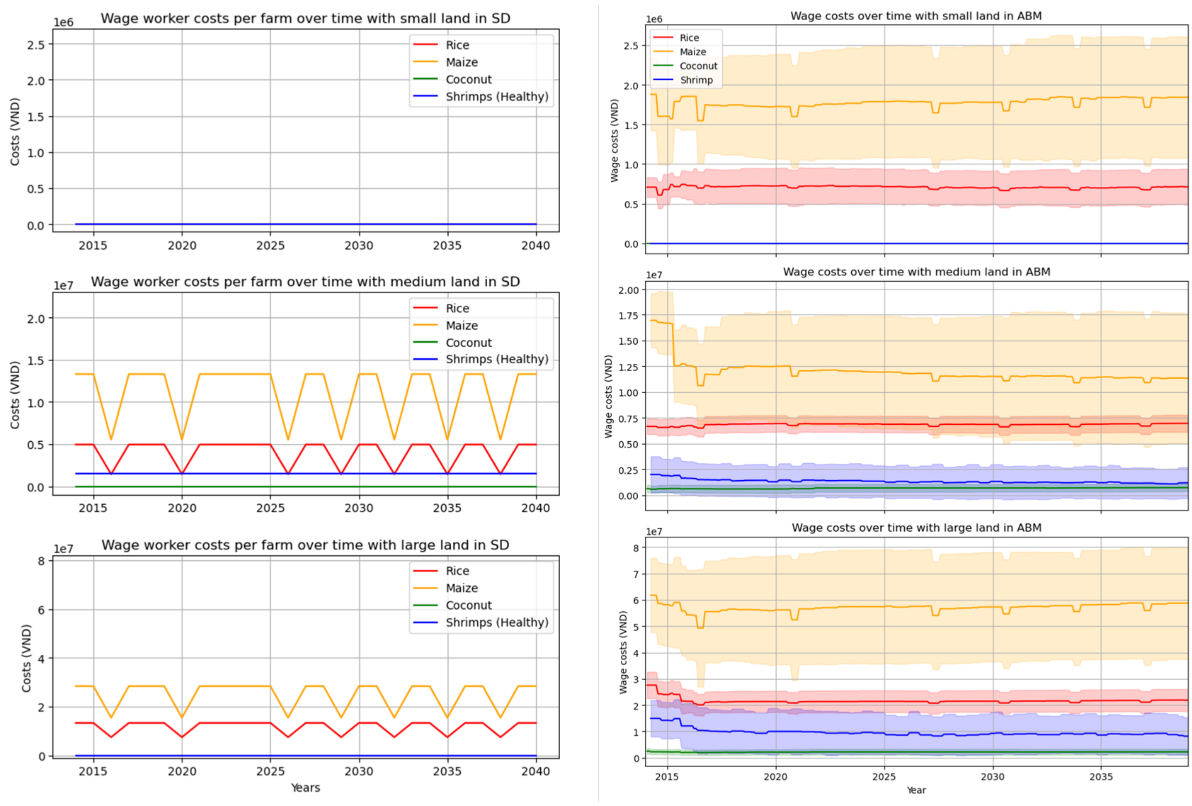

Figure H.3: Wage worker costs per farm over time in SD (left) and ABM (right)

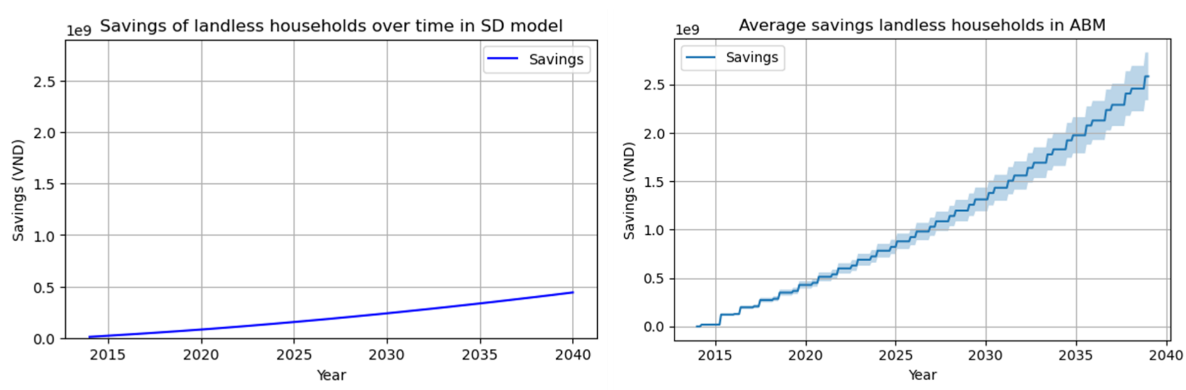

Figure H.4: Savings of landless households over time in SD (left) and ABM (right