THE EFFECTS OF CLIMATE CHANGE ON RURAL-URBAN MIGRATION IN THE MEKONG DELTA, VIETNAM

A Dissertation

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Abstract

In many parts of the world, climate change is increasingly impairing human livelihoods and well-being by escalating the intensity and frequency of natural hazards and climate variability. This may compel part of the population in high-risk areas to consider migration. The aim of this study is to examine whether climate change phenomena affect migration decisions, and if so, to investigate the mechanism of that effect (Chapter 2), and to predict the volume of future rural-urban migration out of the Mekong Delta of Vietnam in response to the impact of climate change (Chapter 3).

The consequences of climate change are expected to play a role in migration decisions. However, estimating the impact of climate change on migration is difficult, given the reliance on historical data and currently limited exposure to actual climate changes. Chapter 2 of this dissertation takes a different route by employing the choice experiment (CE) method to investigate intention to migrate among farmers living in the Vietnamese Mekong Delta (VMD), one of the areas in the world most significantly affected by climate change. This is the first study to use CE to examine the influence of climate change on rural-urban migration and in lowland areas. Based on prior literature and initial piloting, the CE is designed to ask the respondents to make a choice about migration for eight hypothetical scenarios constructed using six main attributes: drought intensity, flood frequency, income gain from migration, network at the potential destination, neighbors' choices, and crop choice restrictions. The results confirm that increasing intensity and frequency of climate change phenomena raise the likelihood of choosing to migrate, with severe drought standing out as the factor most strongly affecting people's choice. Second, people who are relatively young, poor, have small

household size, or have current migrant(s) in their families are more likely to choose to migrate. Third, we find that prior experiences of climate change significantly influence people's valuing of drought and flood attributes; and that contribution of network attributes is gendered and dependent on migration experiences. The findings of this model can be useful for projections of environmental-induced migration and could provide insights into the debate regarding climate change – migration nexus in developing and seriously affected countries/regions.

Huge future flows of migration due to the impacts of climate change are inevitable in some parts of the world, especially in the Vietnamese Mekong Delta (VMD). In Chapter 3 of this dissertation, we present a novel approach of integrating an agent-based model (ABM) with a choice experiment (CE) to simulate future migration out of the rural VMD in response to varying future climate scenarios and other migration stimuli. The ABM incorporates empirical measures through both agent behavior specification deriving from the CE model studied in Chapter 2 and population characteristics deriving from the census data using the Iterative Proportional Fitting (IPF) method. The model projects that by 2050 about 1.8 to 2 million people could migrate under the impact of climate change scenarios. The current crop choice restriction in the VMD may contribute to nearly 350,000 migrants out of the VMD coastal provinces under the severe climate change scenario by 2050. We also find large social feedback effects on migration for the case of VMD. This study contributes to the literature a flexible method for simulating environmentally induced migration and provides a good reference for the formulation of policy strategies related to climate change and migration in Vietnam.

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Chapter 1 Introduction

1.1 Introduction

People migrate for many reasons – economic, social, political, and environmental reasons. In recent times, climate change has emerged as a major driver of migration, propelling increasing numbers of people to move from vulnerable to more viable areas of their countries to build new lives (Rigaud et al., 2018). However, estimating the impact of climate change on migration is difficult, given the complex and multi-causal nature of the migration process and the requirement for intensive datasets on migration movement and climate variability. Standard approaches mainly rely on historical data to establish causality; however, in many cases, it can only capture a limited incidence of climate change phenomenon and migration experience and may not guarantee the temporal order to establish a causal relationship of environmental change on human mobility.

This thesis takes a different route by employing the choice experiment (CE) method and agent-based model (ABM) to investigate intention to migrate and predict migration flows induced by climate change among farmers living in the Mekong Delta, Vietnam. The CE approach can provide extensive data on environmental evolution and migration decisions and enable the investigation of environmental factors as an isolated driver of migration. The agent-based model (ABM) is a well-suited technique to model migration decision-making and simulate migration flow. The integration of the CE method into an ABM provides a well-established economic theory and empirical basis to foster the use of the ABM for predictive modeling. This is the first study to use CE to examine the influence of climate change on rural-urban migration and in low land areas. In addition, this is the first study to combine the ABM and CE method in the study of environment-migration nexus. The rationale of using the CE and ABM method will be discussed in detail in the following chapters.

The findings of this study suggest that increasing the intensity and frequency of drought and flood increase the likelihood of migration. While empirical evidence of the impact of slow-onset climate change phenomena on migration is limited in the literature, we find that drought and saline intrusion stands out as a dominant driver of decision to stay or leave for the case of the Vietnamese Mekong Delta (VMD). We also find considerable heterogeneity in migration behavior among individuals with different socio-geographic characteristics, previous experience of climate change, and migration experience. Our ABM model predicts a substantial migration flow out of the rural VMD in the next decades and that the negative impact of climate change is one of the most important reasons for migration. Although quite a few studies have raised the awareness of the mass migration induced by climate change in Vietnam and especially in the VMD, our research is the first study involving the quantification of future migration flows triggered by climate change impact. Our model projects that by 2050 about 1.8 to 2 million people in the rural VMD could migrate under the impact of climate change scenarios.

This first chapter provides the research background that motivates the investigation of migration behavior in response to climate change in the Mekong Delta. The research objectives, the significance of the research, and the structure of the thesis are presented afterward.

1.2 Research background

1.2.1 Definition of climate change and migration

Climate change is defined as a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer (IPCC 2014). Using this definition, the variation can be in the mean of climate variables or in the intensity and frequency of extreme weather events. In the survey, we provide a more specific and understandable definition of climate change to the respondents. As such, climate change refers to unusual changes in climate for an extended period such as decades. Climate change may take several forms such as unusual timing of seasons, changes in temperature and rainfall pattern, more frequent and severe extreme weather events (floods, droughts, storms, etc.), more frequent salinity intrusion, a rise in sea level compared with average sea level for several previous years. In the estimations of the thesis, we interpret climate change variables as the variation in drought severity and flood frequency.

There are different definitions of migration depending on the approach of measurement and objective of studies. The International Organization for Migration (IOM) defines migration as the movement of a person or a group of persons, either across an international border, or within a State. It is a population movement, encompassing any kind of movement of people, whatever its length, composition, and causes; it includes migration of refugees, displaced persons, economic migrants, and persons moving for other purposes, including family reunification (IOM 2011). The General Statistics Office (GSO) of Vietnam defines migration as those people who have moved from one district to another district for residence in the five years prior to its surveys. In this study, we collect migration data in the origin area and aim at collecting migration experience of respondents for a long period and even for those who have returned the origin. Therefore, we define migration as the movement since 2000 of any family member within the age of 15 and 59 at the time of moving to another district/province/city for living, working, or studying for at least six months in a year, or just moved recently but intend to stay for at least six months.

1.2.2 The link between climate change and migration

The migration–environment nexus is not a new issue; however, climate change significantly increases its current and future relevance. In 1990, in its First Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) posited that the greatest effects of climate change might be those on human migration (Houghton, Jenkins, & Ephraums, 1990). In its following assessment report, IPCC emphasizes population movement as a likely key consequence of climate change (Solomon et al., 2007). Since then, scientific arguments and evidence have drawn increasing attention to the influence of climate change on migration.

Over the last two decades, there are growing evidence and widespread debates on the correlation between climate change and migration across the academic world. The linkage between those two has been examined in two directions. Firstly, climatic stresses and variabilities as the consequences of climate change are increasingly recognized as one of the push drivers inducing migration. In particular, rapid-onset change such as flooding, typhoons, or land erosion is linked with environmentally induced displacement and relocation (Warner, Hamza, Oliver-Smith, Renaud, & Julca, 2010). Moreover, slow-onset climate change and variabilities such as sea-level rise, salinization, or droughts would affect individuals' drivers of migration (e.g., income level and income variability), and therefore contribute to the decision of migration (Lilleør & Van den Broeck, 2011; Warner et al., 2010). Secondly, migration in itself can be considered as a livelihood diversification and adaptation strategy to climate change. On the one hand, migration remittance would provide investment capital for households' production and financial support for implementing adaptive strategies in the original areas. On the other hand, experience and knowledge from migration could also provide flows of new livelihood, new ideas, and social practices to areas of origin (Raleigh, Jordan, & Salehyan, 2008). As a result, migration might enhance resilience and reduce the vulnerability of individuals and communities.

Empirical evidence for the impact of climate change on human migration remains inconclusive because the relationship is not straightforward and involves many complexities. In most cases, it is difficult to establish a simple and direct causal link between the movement of people and the environment since climate change is only one of the multiple intertwined factors involved in a decision to move. As a result, disaggregating the role of climate change from other economic and social factors is a challenging task (Brown, 2008). In addition, the relationship is unpredictable as the science of climate change and migration is itself complex. Climate change impact varies upon resources, capacity to adapt to external shocks, and the stage of environmental degradation (Brown, 2008). At the same time, migration can take many forms; and migration decisions are high contextual depending on migration history and the dynamics of all migration determinants (Cattaneo et al., 2019). Therefore, different types of climate change phenomena tend to produce different forms of migration.

Given the increasing severity of climate change impact over the last two decades, researchers have predicted mass climate migration in the upcoming decades (e.g. (Rigaud et al., 2018; Stern & Stern, 2007))[1]. However, future projections of climate migration reveal a lot of uncertainty and limitations (Brown, 2008; Cattaneo et al., 2019). Predicting future flows of climate migrants is complex because it depends on baseline data, distribution, and resilience to environmental pressures, future population growth, evolution of climate change, and future emissions (Brown, 2008). One reason limiting the prediction of climate migration is the lack of data analyzing the specific impacts of increases in frequency and intensity of natural disasters on migration. Therefore, research and data are needed to improve our understanding of the complex relationship between climate change and migration and the prediction of future environmentally induced migration.

1.2.3 Climate change in Vietnam and the Vietnamese Mekong Delta (VMD)

Vietnam is a long narrow country consisting of an extensive coastline (3,200 km long), two major river deltas (Red river and Mekong river), and mountainous areas on its eastern and northern borders (see *Appendix Figure 1* for lists of regions of Vietnam). Vietnam is one of the Southeast Asian countries most significantly impacted by climate change (Margulis et al., 2010). Due to the country's geographic location and diverse topography and climate,

[1] The most widely cited figure predicts 200 million people moving by 2050 due to environmental factors (Stern & Stern, 2007). Recently, Rigaud et al. (2018) conducted a state-of-the-art analysis and projected that there will be 143 million climate migrants by 2050 from regions and sub-regions including East Africa, South Asia, and Mexico and Central America.

different regions in Vietnam are likely to experience different climate change impacts. In particular, the Northern Mountains is at high risk of landslides; the Red River Delta is highly vulnerable to storms and flooding; the Central Coast is severely impacted by storms, flooding, and drought; the Central Highland is mostly affected by severe droughts; and the Vietnamese Mekong Delta (VMD) is heavily exposed to the risks of flooding, salinity, and sea-level rise (SLR).

According to the Ministry of Natural Resources and Environment (MoNRE), during the last 50 years, Viet Nam's annual average surface temperature has increased by approximately 0.5 - 0.7^{o}C, and the sea level along its coastline has risen by approximately 20 cm. Natural hazards have been observed to happen more frequently and/or be more severe. Specifically, the typhoon and flood seasons are getting longer; droughts in areas previously not vulnerable to aridity have been noted; and storms are tracking into new coastal areas (Carew-Reid, 2008). Worse still, the trend in the future seems to be more severe. Vietnam's official scenario for climate change conducted by the MoNRE shows that the dry seasons are projected to get drier, and the wet seasons are projected to get wetter, leading to the increase in frequency, intensity, and duration of floods and the exacerbation of drought problems. The sea level is projected to rise approximately 30 cm in 2050 and up to 75 cm in 2100 under the medium scenario.

The Vietnamese Mekong Delta (VMD) is a very low and flat topography located at the most downstream part of the Mekong River Basin. The region is mostly suffered from environmental degradation and the consequences of climate change in terms of both livelihood and human-related risks and losses in Vietnam. The main challenges of climate change impacts in the VMD include sea-level rise (SLR), increased number of extreme weather events such as unusually heavy rainfall, floods, droughts, rising average temperatures, and increasing salinity intrusion. The risk of flooding and storm is severe during the rainy season. Due to climate change impacts, rainfall has changed the pattern and increased in volume. As a result, flooding becomes more severe and unexpected, causing human losses and agricultural productivity reduction.

During the dry season, the VMD experiences increasing damage by saline intrusion and droughts. Indeed, during the dry season in 2016, the VMD experienced the most severe drought-salinity intrusion over the last 100 years. In the 2016 drought, saline intrusion peaked two months earlier, intruded further inland, and remained longer than previous years (Sebastian et al., 2016). Research Institute for Climate Change – Can Tho University (DRAGON Institute) reports that in 2016, seawater intrusion reached 90 km deep inland, affecting 300,000 ha of land. Salinity rate reached up to more than 20g/l at some main river estuaries, which much exceed 4g/l, the rate at which crops start to be damaged (see *Appendix Figure 2*). Consequently, rice yields were reduced by 50-100%, or total loss (Sebastian et al., 2016). In some provinces, salinity levels have reached too high for some species to tolerate, especially for catfish, one of the dominating species of VMD's aquaculture sector.

The VMD is particularly vulnerable to SLR. The sea level around the VMD has risen by 20 cm since 1901 (Sebastian et al., 2016). SLR not only causes salinity incursion severely in the VMD but also aggravates flooding in the delta by reducing the river's slope and decreasing its flow. This exerts considerable damage to agricultural production, especially water-grown rice crops, as well as put certain pressure on national food security. Additionally, in the future, the VMD may incur a great loss in residential and agricultural land. It is predicted that there would be migration flows of farmers from inundated land to sub-urban areas and cities in the northwest part of the region or Ho Chi Minh City, raising significant challenges in the fields of urban planning, urban environment, and social order in those urban centers (Le Quang Tri, 2016).

1.2.4 Current migration in Vietnam and the VMD

In 2019, 6.4 million Vietnamese people have migrated out of the population of 88.4 million people at the age of five or more. Table 1.1 presents internal migration of Vietnam over the period of 1999 to 2019. While the period of 1999 to 2009 experienced a significant increase in the number of emigrants, the period of 2009 to 2019 shows decreasing trends in both number of emigrants and the emigrant rate. In 2019, inter-district and inter-regional migration had been the most striking feature of flows in Vietnam, in which inter-district migration rate has accelerated over the past decade. According to GSO (2019), the Southeastern region continues to be the region with the highest in-migration rate, with 1.3 million immigrants. Economic reasons are the main factors influencing migration decisions (e.g., finding jobs/found jobs in new places), followed by factors relating to proximity to families.

Table 1.1. Number of emigrant and emigrant rate by type of migration in Vietnam (1999-2019)

Type of migration	1999		2009		2019	
	Number (1,000 persons)	Rate (%)	Number (1,000 persons)	Rate (%)	Number (1,000 persons)	Rate (%)
In district	1,343	1.9	1,618	2.0	2,419	2.7
In province	1,138	1.7	1,709	2.2	1,199	1.4
In region	2,001	2.9	3,398	4.3	2,816	3.2

Source: (GSO, 2019)

According to data from the GSO, the VMD has the lowest in-migration rate (3.64‰) and the highest out-migration rate (9.07‰) in Vietnam, with out-migration occurs mainly from rural areas[2]. Between 2004 and 2009, 714,000 people migrated from the VMD to the South-eastern region (the region around Ho Chi Minh City (HCMC)), which represents by far the largest migration corridor in Vietnam (Entzinger & Scholten, 2016). Over the last decade, the VMD experienced a huge volume of migration out of the region. Although migration decreased gradually in the period 2014-2017, it started to increase sharply again in 2018 (refer to *Appendix Figure 4* for the trend of migration in the VMD over time). It is estimated that nearly 1.1 million people, roughly equivalent to the population of one province in the region or about 6.4 percent of the current region population, left the region in the period 2009-2019 (V. T. T. Anh, Binh, Cuong, Du, & Giang, 2020). It should be noted that largescale rural-to-urban migration is a common feature of developing countries. This migration is expected to be particularly prevalent in countries and regions most affected by changing climate (Buhaug & Urdal, 2013).

[2] Data is over the period 2005-2019. Source: https://www.gso.gov.vn/default.aspx?tabid=714.

Table 1.2 summarizes the average migration rate in the VMD provinces and cities, with the average in-, out-, and net-migration rate (number of migrants per 1,000 population) in a period from 2005 to 2019. All provinces and cities in the VMD have a negative net migration rate, indicating that they are migrant-sending areas. Most of the inter-provincial out-migrants from the VMD are to the Southeast[3] (e.g., HCMC, Binh Duong). Some of them migrate to other provinces within the Mekong Delta (e.g., Can Tho city). Other regions do not attract many out-migrants from the Mekong Delta. Most of the inter-provincial in-migrants to the Mekong Delta are from other provinces within the region. Some of them are from the Southeast, and only a small number of migrants are from other regions.

Table 1.2. Average migration rates of cities and provinces in the VMD region from 2005 to 2019

Province	Net-migration	Out-migration	In-migration
Long An	-3.00	-7.50	4.51
Tien Giang	-1.19	-7.13	5.95
Ben Tre	-6.46	-9.88	3.42
Tra Vinh	-3.71	-8.11	4.39
Vinh Long	-4.23	-8.79	4.56
Dong Thap	-6.23	-8.81	2.59
An Giang	-7.84	-10.14	2.30
Kien Giang	-5.93	-9.39	3.45
Can Tho	-1.22	-8.14	6.92
Hau Giang	-5.71	-9.59	3.88
Soc Trang	-7.91	-9.99	2.08
Bac Lieu	-7.47	-9.13	1.66
Ca Mau	-9.61	-11.31	1.69

[3] Southeast region of Vietnam includes Ho Chi Minh city and five provinces (Dong Nai, Binh Duong, Ba Ria – Vung Tau, Binh Phuoc, Tay Ninh). This region is the most economically developed region in Vietnam.

1.3 Research objectives

This study aims to investigate migration behaviors of farmers in the Vietnamese Mekong Delta region in response to climate change. The specific objectives of the study are:

1. To examine the causal relationship between climate change and rural-urban migration, and the mechanism by which climate change influences migration decisions;
2. To investigate other significant factors influencing people's migration choice;
3. To predict migration outflows from the rural VMD under the impacts of future climate change scenarios;
4. To estimate the impacts of other migration determinants on future flows (e.g., migration network, crop choice restriction, and income gap).

1.4 Significance of the research

As discussed in previous sections, although the scientific basis for the impact of climate change on migration has been increasingly established, there are still significant gaps in our understanding of this complex relationship. Our research contributes to the literature a novel methodology and data collection approach for investigating the causal relationship between climate change and rural-urban migration and for predictive modeling of migration. The Vietnamese Mekong Delta region provides an appropriate case study for an investigation into the issue of environmentally induced migration because the region is heavily exposed to climate change and experiences high and increasing migration flows towards urban areas.

In this study, we conduct a choice experiment (CE) to examine intention to migrate among farmers in response to the impacts of climate change phenomena and other key migration drivers. This is the first research using CE to investigate climate change – migration nexus for low land areas and for Vietnam. In addition, this is one of the few studies investigating both slow-onset and sudden-onset climate change events. The findings of the CE model are significant to facilitate the prediction of environmentally induced migration.

This study also presents the development of an agent-based model (ABM) integrated with a choice experiment (CE) to simulate future migration out of the rural VMD in response to a variety of future climate scenarios and other migration stimuli. This integrated modeling framework is first developed on the topic of climate change and migration and provides a feasible alternative to improve the predictive modeling of climate migration. The projections of migration flow provide a reference for the formulation of adaptation strategies to climate change and a basis for good preparations for both migrants and people in the sending and receiving communities.

1.5 Thesis structure

The thesis is organized into four chapters.

Chapter 1 provides the research background, the research objectives, the significance of the research, and the structure of the thesis.

Chapter 2 discusses climate change and migration in the VMD, and by means of a CE, examines the extent to which climate change phenomena and other socioeconomic attributes influence intention to migrate. This chapter also justifies the use of CE, explains the process of data collection, and presents the implementation of the CE.

Chapter 3 develops an integrated modeling framework for simulating future migration outflow of 12 VMD provinces by 2050 in response to different climate scenarios and external stimuli. The discussion emphasizes the rationale for integrating ABM and CE, model design, and model evaluation.

Chapter 4 summarizes the outcomes of the research. Policy implications, limitations of the research, and future research are also presented.

Chapter 2 Climate change and migration in the Mekong River Delta of Vietnam – A choice experiment

2.1 Introduction

In many parts of the world, climate change is increasingly impairing human livelihoods and well-being by escalating the intensity and frequency of natural hazards and climate variability. This may compel part of the population in high-risk areas to consider migration. Farmers in poor and highly vulnerable regions tend to be the most affected group because their main livelihood is sensitive to climate conditions, and poverty can magnify the impact of climate change. Although migration induced by climate change impact was considered as a failure to adapt, evidence from recent studies characterizes migration as an adaptation to climate change (McLeman & Smit, 2006; Perch-Nielsen, Bättig, & Imboden, 2008; Tacoli, 2009; Warner & Afifi, 2014; Warner et al., 2012). Remittances, new resources, and networks from migrants can help to reduce vulnerability to environmental risks; diversify livelihoods and income; and build social resilience of both migrants and their families of migration origin (Scheffran, Marmer, & Sow, 2012; Tacoli, 2009). Therefore, migration can be a viable climate change adaptation strategy if managed carefully and supported by appropriate development policy and targeted investment (Rigaud et al., 2018).

Different types of climatic events can have different effects on migration decisions and types of movement. In particular, the literature shows that in most cases, displacements caused by sudden, short-term environmental events such as floods, storms, and hurricanes are likely to be temporary, over a short distance, and involuntary (Cattaneo et al., 2019; Koubi, Spilker, Schaffer, & Bernauer, 2016; Warner et al., 2012; Webber & Barnett, 2010). Moreover, such movements tend to occur in the aftermath of such natural disasters (Koubi et al., 2016). In contrast, migration decisions driven by slow onset and long-term environmental problems such as droughts, desertification, sea-level rise, and temperature increase are largely voluntary (Cattaneo et al., 2019; Webber & Barnett, 2010). Since slow-onset environmental hazards have a smaller intermediate impact on the wellbeing of individuals (Koubi et al., 2016) and are generally associated with gradual departures (Cattaneo et al., 2019), there is mixed evidence in the literature on the influence of these kinds of environmental changes on population mobility.

Most previous country-case studies analyzed historical data of climate change experiences and migration departures from surveys and/or environmental datasets to examine environmental influences on the decision to migrate (e.g. (Bhatta, Aggarwal, Poudel, & Belgrave, 2016; Jha, Gupta, Chattopadhyay, & Amarayil Sreeraman, 2018; Koubi et al., 2016; Murali & Afifi, 2014)). The use of historical data suffers from two major shortcomings. First, historical data capture a limited incidence of past climate change events, so researchers can only observe migration decisions in response to a specific event or phenomenon, but not behavior change under variabilities of frequency and intensity of climate change phenomena. In other words, a researcher can investigate the possible causal relationship between environmental changes and population movements, but they cannot observe the mechanism by which climate change influences migration decisions. This gives rise to considerable uncertainty concerning future migration flows in studies of climate change-migration nexus (Cattaneo et al., 2019); since inferences from limited and unvarying climate change events in the past cannot be extrapolated to the dynamics of environmental changes in the future. From the perspective of policymakers, projections of climate-induced migration are particularly important for the formulation of policy strategies to secure resilience and for the development prospects of both migrants and those in the sending and receiving communities (Rigaud et al., 2018).

Second, it is difficult to establish causation using historical data. An important criterion for establishing causality is that the cause must temporally precede the effect (i.e., in this case, an environmental event must precede a migration departure) (Fussell, Hunter, & Gray, 2014). In many cases, historical data for a sample during a period may not guarantee this temporal order because the timing of a migratory event varies across households, and climate change phenomena can take place in a more complicated manner than one single incident. It is especially challenging to establish causality when investigating the effects of multiple or slow-onset climate change events because their incidence lasts for a long time and their effect on the population is gradual. One possible solution is to use retrospective survey questions that specify the timing of migratory and climate change events. However, this method of collection may present problems of recall bias concerning details far from the past. Another solution is to employ a longitudinal data collection method, but, in many cases, this is not possible due to time and financial constraints. Those limitations could explain in part why current studies on climate change - migration nexus are rare and show mixed results for slow-onset and multiple climate change events.

In the migration literature, the drivers of migration have been characterized as complex, non-linear, multiple, multi-dimensional (i.e., both push and pull), and dynamic in nature (Oliver-

Smith & Shen, 2009). The causes of migration are highly dependent on the social and ecological context of the migration origin and the potential destination of migration, as well as on the socio-economic characters and demographic profiles of individuals (Oliver-Smith & Shen, 2009; Perch-Nielsen et al., 2008; Webber & Barnett, 2010). Given the multidimensionality of migration determinants, the complexity of climate change-migration relationships, and the aforementioned limitations of using historical data, there is a need for further solid evidence and methodology to confirm the isolated, causal impacts of environmental stresses on human mobility.

Instead of using historical data, this study employs the discrete choice experiment method to determine whether climate change phenomena affect migration decisions, and if so, to investigate the mechanism of that effect. Choice experiment (CE) methodology is useful in this context as it can address two of the shortcomings of the current methodology discussed above. CE design allows the construction of hypothetical scenarios to observe different migration responses in a diverse range of environmental exposures, even for people who have not been exposed to climate change and, hence, for whom no data is available. In a CE, the researcher has the flexibility to vary the severity and frequency of climate change-related events. Moreover, CE can be an effective method for examining the environment as an isolated driver of migration in a complex decision-making process. CE design guarantees temporal order between environmental factors and migration intention, and therefore, meets the criterion for establishing causality. The CE method and its advantages are discussed in detail in the following sections.

This chapter investigates migration preferences under different scenarios of climate change impact and other migration determinants. Climate change attributes contain both slow-onset and sudden-onset events in order to observe the effects of different types of environmental hazards on migration intention. We take into account personal and family socioeconomic factors and previous experience at origin to capture heterogeneity in behavior among individuals. We focus on the population at risk and consider migration as a strategy for adapting to climate change. This study contributes to the environmental migration literature, as it addresses some limitations of existing studies. In addition, this is one of the few studies to use the CE method to investigate the climate change-migration nexus, and is the first study to examine rural-urban migration and lowland areas.

Our focus on Vietnam, and more specifically on the VMD, is particularly relevant since we can observe both great vulnerabilities to climate change and an increase in rural-urban migration in this specific region. Vietnam is extremely vulnerable to weather variability and climate change since its economy is largely agricultural (more than 70 percent of the population is in rural areas); a high proportion of the population and economic assets are located in coastal lowlands and deltas; and the level of development in rural areas is relatively low (Margulis et al., 2010). The Mekong River delta is of particular interest, given its massive recurrent exposure to climate change phenomena. According to (World Bank, 2010b), if regional vulnerability to climate change can be assessed in terms of exposure and sensitivity indexes, the Mekong River delta is the only region in Vietnam for which both indexes are above average. This has drawn research attention to the effect of the great vulnerability of the Mekong River delta to climate change on migration flow from this region to industrial and commercial cities.

The chapter is organized as follows. Section 2 reviews the existing research on the correlation between climate change and migration and the few studies that examine that relationship using the choice experimental methodology. Section 3 provides information on the experimental design, while section 4 explains the data collection process. The results of the CE are reported in section 5, and section 6 draws conclusions and discusses the CE results.

2.2 Literature review

Out of the studies researching climate change and migration in Vietnam and its VMD (e.g., (Entzinger & Scholten, 2016), (Van Der Geest, Khoa, & Thao, 2014), (Koubi et al., 2016), (Dun, 2009), (Warner et al., 2010) and (O. L. T. Kim & Le Minh, 2017)), the majority rely on qualitative and descriptive analysis. Koubi et al. (2016), which used original survey data to quantitatively examine the impacts of environmental stressors on decisions of individuals to migrate or stay, is one of the exceptions. The study investigates the influence of both slow-onset and sudden-onset events on the decision of migrants and non-migrants, concluding that sudden and short-term environmental weather events significantly increase the migration probability whereas long-term environmental problem reduce the likelihood of migration. However, it cannot avoid the aforementioned drawbacks of using historical data. Moreover, the research does not consider people who had prior migration experiences as migrants, and therefore, neglects a potential group of migrants.

Trinh, Feeny, and Posso (2021) and Berlemann and Tran (2020) are the two recent studies that confirm the significant influence of climate-related hazards on migration in Vietnam. Trinh et al. (2021) employ household survey data from the Vietnam Household Living Standard Survey (VHLSS) for the period 2006-2008 to examine whether the severity of natural disasters is important for migration decisions in Vietnam. They find that more severe disasters are directly associated with a greater probability of migration. Berlemann and Tran (2020) make use of the Vietnam Access to Resources Household Survey (VARHS) commune-level data for the period 2012-2016 to investigate the effect of natural disasters on emigration decision. They find that episodic droughts and floods tend to cause higher emigration from the affected communes.

Baker et al. (2009) and L. Lu, Lu, and Rahman (2015) are two of the few studies investigating voluntary movements using the CE method[4]. Baker et al. (2009) evaluate the trade-off between the level of risks of hurricanes and income in moving and location choice intention of those who were displaced by Hurricane Katrina in New Orleans and other Gulf Coast areas in 2005. In particular, the respondents are asked to choose between two hypothetical locations, A and B, in which three main characteristics, including housing cost, monthly income, and risk of damage from a hurricane, are varied. The paper finds that people who have experienced and been severely affected by the hurricane have a high subjective perception of

[4] CE approaches addressing the general influence of environmental changes on population mobility are also relatively rare. (Kloos & Baumert, 2015; Vlaeminck et al., 2016) (for Egypt and Uganda) focus on involuntary settlement and find that prior experiences of climate change phenomena have impacts on the resettlement-related preference such as the probability of accepting a preventive resettlement program, or how people assess a resettlement program's criteria.

risks. Accordingly, their decisions of relocating are negatively and significantly influenced by levels of hurricane risks. However, the study does not account for the impacts of social characters such as network or neighbor on moving decision.

L. Lu et al. (2015) employs a stated preference questionnaire survey to investigate behaviors of residence and job location change under flooding and cyclone scenarios in urban Bangladesh. Specifically, respondents are asked to gives choices under four flooding and cyclone scenarios. The respondents have to choose one from six choice options, which are constructed from the joint choices of change residence, change job, and house reinforcement. The study shows that flooding and cyclone attributes such as frequency and intensity turn out to be the most significant factors affecting people's behavior, but because there is no income or other monetary variable in the list of attributes, valuation of options and scenarios is not possible.

Our paper includes a monetary dimension (difference income between origin and destination). More to the point, it focuses on migration out of an important agricultural region that is likely to see major changes induced by climate change. It also considers social elements such as network or choices of peers, which have not been paid much attention to in existing studies using the CE, as migration determinants to capture the social context of the migration decision-making process.

2.3 Methodology

2.3.1 Rationale for the CE method

The discrete choice experiment (DCE) is a stated preference method for eliciting individual preferences over sets of hypothetical scenarios. In a DCE, the respondents are presented with several scenarios, called choice sets, including one or more alternatives of a good or service, and asked to select the most preferred alternative. Each alternative in the choice set is defined as a combination of a set of attributes and their levels, i.e., any two alternatives have similar attributes, but the levels differ in at least one attribute. This design reveals (i) the implicit trade-offs between the levels of the attributes in different alternatives and (ii) the contribution of each attribute and its level to the choices made by the respondents. The study objects are hypothetical and are created by the researcher. The scenarios should resemble the actual choice situation as much as possible but should not create excessive cognitive load for the respondents with too much complexity. Mangham, Hanson, and McPake (2009) confirm that DCEs are reasonably straightforward and closely resemble real-world decisions.

The use of CE for estimating the climate change-migration relationship offers two major benefits. First, a big advantage of CEs is that they can provide extensive data for the investigation of the impact of climate change on migration. This extensive data is manifest in different types of climate change events (i.e., through attributes enriched with descriptions of climate changes), variations in the intensity and frequency of the events (i.e., through levels of climate change attributes), and abundant data for each subject (i.e., through the sequence of scenarios the respondent faces). The CE approach can address the fundamental shortcoming of methods in the current literature that use revealed and historical data, which is limited information in terms of environmental evolution and migration experience (Piguet, Pécoud, & De Guchteneire, 2011), especially for subjects who have limited exposure to climate change. The CE method can also compensate for the scarcity of studies examining the specific impact of an increase in the frequency of natural disasters and the way in which populations respond to the risk of cumulative shocks (Cattaneo et al., 2019).

Second, the CE method can enhance the validity of forecasts of future environmentally induced migration. More particularly, this experimental approach allows researcher to observe respondents' intentions to move because of changes not yet faced. Migration intention is crucial for studies on mobility and migration projections because migrant decision-making behavior is determined by the migrant's intentions (De Jong, 2000) and because behavioral intentions are good predictors of future migration (Van Dalen & Henkens, 2013). Mortreux and Barnett (2009) and Abu, Codjoe, and Sward (2014) are two of the few studies that examine migration intention by asking the respondents whether they intend to move from the current community in the next couple of years. However, these studies only explore respondents' perceptions of historical experiences; then seek information about their decisions under possible changes in the future. The CE experimental approach is novel in the sense that respondents are asked to declare their intentions in the context of possible future environmental changes as presented in different hypothetical, but realistic scenarios.

Despite the considerable benefits of the CE method, a major question concerning the validity of CEs is hypothetical bias, the deviation between stated and revealed preference evidence. That is, what people say they will do is not the same as what they will actually do (Train, 2009). There have been few approaches used to test for hypothetical bias in CE. If monetary costs are estimated in the CEs, a comparison of those costs with some sort of external monetary value of the same object can be a logic validation (Alriksson & Öberg, 2008). Another method for validating a stated preference is using a revealed preference study for comparison (Alriksson & Öberg, 2008). If revealed preference data are available, it is possible to validate by determining whether the preferences stated in the CE are in accordance with the actual behavior. However, without monetary values or revealed preference data, validating CE results is challenging. Therefore, the assessment of CE results depends heavily on how well the CE is designed and implemented.

2.3.2 Process of designing a CE

A number of key stages characterize the implementation of a CE.

Selection of attributes

That is the process of identifying relevant attributes of the choice of interest. Blamey et al. (2002) suggest that attributes that are demand-relevant, policy-relevant, and measurable should be used. Literature reviews and focus group can be used to select attributes that are relevant to people, while expert consultations help to identify the attributes that will be impacted by the policy (Hanley, Mourato, & Wright, 2001). A monetary cost is one typical attribute to allow estimation of Willingness-to-pay. How many attributes to use will vary with the subject being investigated. However, the number of attributes should be manageable since the number of combinations of choices expands quickly when attributes of the alternative are added (Baker et al., 2009). This is the trade-off between avoiding misspecification due to insufficient attributes and avoiding intractability due to too many attributes.

Assignment of levels

The attributes levels should be feasible, realistic, non-linearly spaced, and span the range of respondents' preference maps (Hanley et al., 2001). Focus groups, pre-tests, literature reviews, and expert consultations can be used to select proper attribute levels. A baseline 'status quo' level is usually included.

Choice of experiment design

Statistical design theory is used to combine the levels of the attributes into a number of alternative scenarios to be presented to the respondents (Hanley et al., 2001). A full factorial design that allows to estimate all the combinations of all attributes and levels can be used. However, there is an upper limit of how many alternatives a respondent can handle before a fatigue effect, a risk that the respondents weary of without completing the task in a preferred way due to too many alternatives, occurs (Alriksson & Öberg, 2008). In many cases, a full design would mean far too many evaluation situations for the respondents (Alriksson & Öberg, 2008). In such cases, a reduced design can be used.

Construction of choice sets

The profiles identified by the experimental design are then grouped into choice sets and presented to the respondents. Profiles can be presented individually, in pairs, or in groups (Hanley et al., 2001).

Estimation procedure

As the number of choices people face is limited (a discrete variable), the usual econometric approach involves the use of logit or probit models or their variants, depending on the type of CE conducted (Baker et al., 2009).

2.3.3 Identification of attributes and assignment of levels

This session explains the process of identifying CE attributes to present the main drivers of migration. In doing this, it is important to step back to consider major theories of migration. The two main theoretical perspectives that have come to dominate the theoretical understanding of migration are neoclassical and new economics. Lee (1966)'s 'push-pull' theory of migrant agency and Todaro (1969)'s 'behavioral model of rural-urban labor migration' are examples of the neoclassical perspective. Individualism, rationality, optimization, and economic aspects characterize the framework of the neoclassical theory of migration. This theory assumes that migration is an individual choice in which actors are purely rational and motivated to move to maximize their own personal gains in terms of monetary or human capital (Gubhaju & De Jong, 2009).

The new economics perspective, on the other hand, possesses characteristics that depart from the neoclassical theory. For example, the New Economics of Labor Migration is summarized under the following headings: i) the emphasis on relative deprivation as a determinant of migration; ii) the emphasis on the household as the relevant decision-making unit; iii) the emphasis on migration as a strategy to diversify risk and overcome market incompleteness; iv) the introduction of information-theoretical considerations in migration theory; and v) the interpretation of migration as a process of innovation adoption and diffusion (Stark & Bloom, 1985). Departing from the neoclassical theory, new economics theory incorporates the social dimension in the decision to migrate. Moreover, the shift from individual independence to mutual interdependence is particularly salient for developing countries (Gubhaju & De Jong, 2009). It is argued that within the context of poor families in developing countries, migration decision of one or more members is a decision of the whole family to guarantee family income and minimize risks associated with crop failure, falling prices, and unemployment (Massey et al., 1993).

At a more theoretical level, the role of social network has received the widest acceptance in the area of explanation of migration (Black, Adger, et al., 2011). The role of social network can also yield a self-perpetuating process known as cumulative causation (Massey, 1990). Once the number of network connections in origin reaches a critical level, migration becomes self-perpetuating because migration itself creates the social structure necessary to sustain it, especially in rural areas where social ties are strong (Flores-Yeffal, 2013; Massey, 2015).

In this study, I draw on elements of both perspectives. In particular, six attributes were selected to capture the key elements of the migration decision-making process under the impacts of climate change. The identification of these six attributes and their levels was derived from the literature on migration decisions and on historical events, real situations, and social norms in the research area. This section discusses the process of attribute selection. Detailed information about the attributes and their levels is presented in Table 2.1.

Two main attributes are drought and saline intrusion; and flood. These two attributes were selected because drought and flood are two common annual climatic phenomena in the VMD. Given geographical features of the coastal areas, drought and saline intrusion often occur concurrently in many regions of the VMD. Therefore, in this research, drought and saline intrusion were combined as one climate change phenomenon. Moreover, flood and drought are the variables most commonly used for the presentation of climate change impact in the climate change–migration literature (studies examine both stated preference and revealed preference). A flood is an example of a sudden, short-term environmental event, while a drought is an example of a slow-onset, long-term environmental event. In the literature, one of those two events (e.g., (Barrios, Bertinelli, & Strobl, 2006; Gray & Bilsborrow, 2013; C. Gray & V. Mueller, 2012)) or both (Koubi et al., 2016) are used as climate change variables. This study follows the latter genre, aiming to discover whether effects on migration differ among different types of climate change phenomena (Koubi et al., 2016). Drought and flood attributes have been assigned three levels of management reflecting three levels of damage, with the description of damage at each level based on historical events that happened in the VMD.

Table 2.1. Attributes and levels used in the CE

Attribute	Definition	Management Level
Drought and saline intrusion	This attribute refers to the intensity of the annual drought and saline intrusion in the community.	1- Mild: Drought and saline intrusion are under control, and thus do not affect crops and aquaculture. 2- Moderate: Moderate drought and saline intrusion occur, reducing crop and aquaculture yields by 30%. 3- Severe: Serious drought and saline intrusion occur, reducing crop and aquaculture yields by more than 70%.
Flood	This attribute refers to annual flood frequency. The major flood inundates crops, causing 50% yield loss. Furthermore, such flood damages the houses, compelling some reinforcements.	1- None: No major flood. 2- Once every two years 3- Once every year
Income	This attribute refers to the average monthly income gap between the potential destination and the original area (after living costs).	1- 1.000.000VND less 2- Same 3- 2.000.000VND more 4- 4.000.000VND more
Network	This attribute refers to whether the respondent has family members, relatives, or friends (e.g., previous neighbors) who are living and working at the potential destination. They may provide physical support (e.g., accommodation, accommodation finding, or job finding).	1- No 2- Yes
Neighbor	This attribute refers to whether many of the respondent's neighbors have moved to other locations for living and working or not.	1- Very few 2- Many
Crop choice restriction	This attribute refers to the existence of the crop choice restriction on the respondent's agricultural land.	1- None 2- Partial: Growing rice in some seasons. 3- Total: Growing rice in all seasons.

The third attribute is income, defined as the average income gap between the potential destination and the origin[5]. According to the theoretical framework for drivers of migration (Black, Adger, et al., 2011) and to studies on migration for a case study of Vietnam (Dun, 2009), economic factors are the primary drivers. While high income and earning potential at the destination encourage migration, high cost of living and rising housing costs can negate the attractiveness of a destination (Ewers & Shockley, 2018). In this study, the use of income gap (after living costs) was expected to capture the wage and living cost differentials between origin and destination and simplify the complexity of mobility decisions. Based on the statistics on income gaps in city and country, and the average income level in areas studied, four levels of income gap are identified: -1, 0, 2, and 4 (million Vietnam Dong)[6]. Here, income was coded as a continuous variable, allowing estimation of trade-offs or willingness to pay (WTP).

The next two attributes, network and neighbor, were selected to reflect the fact that migration decisions are taken in a broad socio-economic context[7]. Migration network has commonly been taken into account in migration studies (international cases: (Black, Adger, et al., 2011; Gray & Bilsborrow, 2013; C. Gray & V. Mueller, 2012; C. L. Gray & V. Mueller, 2012)).

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[5] This research studies rural areas and therefore, the main trend in this research sites would usually be rural-urban migration. As such, the income gap between destination and origin can be considered as the income gap between the city and the country.

[6] Monthly income per capita gap between city and country for the poorest quantile and the richest quantile are about 0.8 and 5 million Vietnam dongs, respectively.
Monthly income per capita in Kien Giang and Long An are about 2.8, and 3.2 million Vietnam dongs, respectively.
Statistics for 2016, source: GSO (https://www.gso.gov.vn/Default.aspx?tabid=217)

[7] The attitudes of urban residents towards migration may be one of the social factors affecting ability/willingness to migrate. However, Spilker, Nguyen, Koubi, and Böhmelt (2020) find no evidence of a specific resistance or a notion of deservingness to environmental migrants in their study of Vietnam. Therefore, those factors were not included in our CE.

Moreover, evidence from numerous studies of the case of Vietnam supports the notion that social networks play a significant role in migration decisions (see (Coxhead, Cuong, & Vu, 2015; Koubi et al., 2016; Winkels & Adger, 2002)). The existence of networks at the potential destination is expected to increase the likelihood of migration since such networks can provide information on job opportunities and life in the city, and thus reducing the costs and mitigating the risks associated with migration (Koubi et al., 2016).

Neighbor attribute illustrates subjective norms in the migration decision-making process. Conceptual models of migration adaptation to climate change point out that subjective norms such as peer choices or social norms are one component involved in individual cognition that shapes migration behavior (Kniveton, Smith, & Wood, 2011; C. Smith, Kniveton, Wood, & Black, 2011). In addition, the influences of neighbors on the decision-making process are a common factor in rural areas in general and in the VMD in particular. In rural areas and the VMD, people in a given community have close relationships, often exchange information, and learn from their neighbors. Therefore, the neighbor attribute, which shows neighbors' migration behaviors, may have a decisive influence on individual intentions to migrate.

The last attribute, crop choice restrictions, is specific to the case of Vietnam. Due to the process of industrialization and the change in the agricultural structure, paddy land area is shrinking in rural areas of Vietnam. In order to maintain the area of paddy land at a proper level, the Government imposed crop choice restrictions, which prohibit the conversion of paddy land to other purposes and mandate farmers to cultivate at least one rice crop during the year in some designated plots. According to the Vietnam Access to Resources Household Survey (VARHS), land restricted for rice production accounts for 68.3 percent of all land for agricultural crops in the VMD. The levels of this attribute reflex the practical content of the crop choice restrictions. The crop choice restriction attribute is expected to have mixed effects on the likelihood of migration and migration patterns. On the one hand, crop choice restriction can be an obstacle factor to migration intention. Because a land under crop restriction will be confiscated if it is not cultivated within 12 months, the restrictions can inhibit household members move out of their homes to other provinces/cities. This can also influence migration patterns in the sense that people are more likely to migrate individually and less likely to migrate as a whole household. On the other hand, the crop choice restriction can trigger a higher rate of rural-urban migration. Due to climate change-related hazards, rice yields may be much lower than yields of other crops or aquaculture. However, the restrictions prevent farmers from converting their rice fields to other crops or aquaculture, urging them to diversify their income by nonfarm activities in cities or other provinces.

2.3.4 Econometric specification and CE design

Discrete choice models have usually derived under an assumption of utility-maximizing behavior by the decision-maker (Train, 2009). As such, the models can be derived in a manner referred to as random utility models (RUMs) (Marschak, 1959; Train, 2009). Accordingly, the utility of choice consists of the deterministic component (V) and an error component (ε), which is independent of the deterministic part and follows a predetermined distribution, to yield

$$U_{ij} = V(x_{ij}) + \varepsilon_{ij},$$

where, U_{ij} represents the utility a respondent i derives from choosing alternative j on choice situation and X_{ij} is the vector of observed attributes contributing to migration intention.

According to the random utility maximization hypothesis, a decision-maker will select alternative j if and only if the utility provided by the alternative j is the largest utility, i.e., $U_{ij} > U_{ih}$ ($j \neq h$). In this study, the respondents are considering whether they will stay at the origin (i.e., country) or move to another place (i.e., city). In other words, a decision-maker will compare the utility at the origin (U_{io}) and at the destination (U_{ic}), and choose to move if the utility in the city is larger than the utility at origin, i.e., $U_{ic} - U_{io} > 0$. Because we consider both push factors from the origin (i.e., climate change phenomena, income, neighbor, and restriction) and pull factors from the destination (i.e., income and network), U_{ic} *and* U_{io} are asymmetric in terms of attributes:

$$U_o = \alpha_o + \beta_1 Drought + \beta_2 Flood + \beta_3 Incomeo + \beta_5 Neighbor + \beta_6 Restriction + \varepsilon_o \quad (2.1)$$

$$U_c = \alpha_c + \beta_3 Incomec + \beta_4 Network + \varepsilon_c \quad (2.2)$$

A more natural characterization of the decision process is to think of the respondent as having utility associated with both push and pull factors (i.e., $U_{ic} - U_{io}$)

$$U_c – U_o = (\alpha_c - \alpha_o) - \beta_1 Drought - \beta_2 Flood + \beta_3 (Income_c - Income_o) + \beta_4 Network - \beta_5 Neighbor - \beta_6 Restriction + (\varepsilon_c - \varepsilon_o)$$

or

$$U = \beta_0 - \beta_1 Drought - \beta_2 Flood + \beta_3 \Delta Income + \beta_4 Network - \beta_5 Neighbor - \beta_6 Restriction + \varepsilon \quad (2.3)$$

Therefore, in this study, the CE departs from the conventional CE design in the way that the choice set presented to the respondents shows only one alternative that contains conditions at both the origin and destination, and the respondents are asked to choose moving or staying. This design is more straightforward and easier for the respondents to grasp, especially for people in rural areas and who have relatively low educational attainment.

The use of one alternative in one choice set allows sociodemographic control variables to be included in the models without interacting with choice-specific attributes. This also allows interactions between CE attributes and sociodemographic variables to capture how different people value migration attributes differently. As a result, the reduced form of the model is:

Intention to migrate = *f* (CE attributes, individual characteristics,

CE attribute * individual characteristics)

From aforementioned numbers of attributes and levels (Table 2.1), full factorial design results in 432 unique combinations. Since not all 432 possible treatment combinations can be presented for practical reasons, it is possible for the analyst to use only a fraction of the treatment combinations (Hensher, Rose, & Greene, 2005). In this study, a D-efficient method was applied to draw a sample of 32 scenarios. The D-efficient is a statistically efficient choice design that minimizes the variance-covariance matrix of the parameter estimates. Four principles of efficient choice designs are orthogonality (i.e., the levels of each attribute vary independently of one another), level balance (i.e., the levels of each attribute appear with equal frequency), minimal overlap (i.e., the alternatives within each choice set have non-overlapping attribute levels, and utility balance (i.e., the utilities of alternatives within a choice set are the same) (Huber & Zwerina, 1996; Zwerina, Huber, & Kuhfeld, 1996). The D-efficient method does not necessarily satisfy all four principles, but it satisfies at least some principles depending on the choice design applications (e.g., zero priors, non-zero priors, interactions).

A set of priors for β was used to reflect the differences in preferences. Priors for β are used when the researcher has some information about the relative importance of attributes or the relative value of their levels (Huber & Zwerina, 1996). Huber and Zwerina (1996) prove that a prior estimate is required to generate utility-balanced designs. The sensitivity analysis also shows that using even distorted estimates of betas is better than assuming they are zero (Huber & Zwerina, 1996; Zwerina et al., 1996). In this study, coefficients of flood and network were inherited from (Koubi et al., 2016), whereas the rest was the analyst's initial expectations for β. In particular, since all the attributes were expected to have positive impacts on the probability of choosing to move, all priors were given positive values. The range of the priors is from 0.03 to 1.5. The highest levels of drought (i.e., severe drought) and income gap (i.e., 4 million Dong) were expected to have the largest influences on the likelihood of moving, and therefore, their priors were given the highest values. In contrast, partial crop restriction was expected to have a negligible and mixed effect on migration decision; therefore, its priors for β was not different from zero. Then with those priors, D-efficient design was generated in Stata, using the *dcreate* command (Hole, 2016).

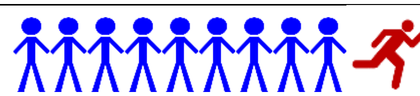
In order to avoid learning and fatigue effects, the sampled scenarios were randomly blocked to four different versions of eight questions. That is, four blocks of scenarios were constructed, and every respondent was asked to express his/her intention to migrate under each of the eight hypothetical scenarios.

A challenge in implementing repeat-response formats is the growing body of evidence for order effects; a term that embraces a variety of phenomena in which systematic changes in expressed preferences are observed along the sequence of valuation tasks (Bateman et al., 2008). Hensher et al. (2005) suggest that to overcome possible biases from order effects, the order of appearance of these choice sets can be randomized across questionnaires. Given the relatively small sample size here, this study created two versions of the questionnaire for each single choice experiment undertaken, with the aim of minimizing the occurrence of order effects. To that end, the order of the questions in each block was randomized to create a new version, in the end generating eight blocks of eight scenarios.

The flow of the DCE was designed to follow two stages. In the first stage, each respondent was randomly provided one block of eight hypothetical scenarios and asked whether they would choose definitely stay, probably stay, probably migrate, or definitely migrate for each scenario. The setting of more nuanced choices was aimed at providing more detailed information and arriving at a more comprehensive understanding of the formation of migration intentions. In the next stage, the respondents who decided to leave in at least one scenario were then asked follow-up questions about items such as potential destination and duration of stay. Before the experiment, respondents were fully instructed about the selected attributes and their levels, the experimental procedures, the number of scenarios, and the initial context. Special attention was paid to explaining the initial context and hypothetical scenarios to ensure that the respondents would make decisions based on the provided information rather than on their real experience. Additionally, colored pictograms and show cards were used to facilitate the comprehension of the introduction and of each scenario (see *Figure 2.1* for sample scenario).

Figure 2.1: Sample scenario

SUPPOSE that in the next six years, you face the situation as follows. Would you stay here, or would you/your family members move to another province/city for working and living?

Annual drought and saline intrusion	SEVERE 70% yield loss	
Major flood	ONCE EVERY YEAR 50% yield loss + house damaging	
Per capita monthly income in destination	4.000.000VND <u>more</u>	
Connections at destination	YES	 Information Housing Job finding
Neighbors	VERY FEW have moved	
Crop choice restriction	PARTIAL	Growing rice in <u>some</u> seasons
In this situation, what do you think you would do? *Please select one* 1= Definitely stay 2 = Probably stay 3 = Probably move 4 = Definitely move		

2.4 Data collection

2.4.1 The study area

The VMD is an agroecological region covering 13 provinces in the Southwest of Vietnam. It has a population of 17.3 million people, which accounts for 19% of the whole country's population (GSO, 2011). The natural area of the region is 39,734 km^2 (around 4 million ha), equivalent to 12% of the nation's area (GSO, 2011). This is a flat and low-elevation area with an average height of 1 to 2 meters above sea level. Because of being affected by the humid tropical climate with equatorial features, this land has an annual average temperature ranging from 24 to 27 Celsius degree and two seasons, the wet season, which lasts from May to November, and the dry season, which lasts from December to April.

Since the VMD region has been fertilized by the river's alluvial deposits, it has big advantages in agriculture and fruit growing. This land is famous for being the country's largest rice-growing area. The long coastline (around 700 km) also brings benefits to the region in the fields of aquaculture and fishery. The VMD contributes 30% of the agriculture production value, 57% of total rice production (accounting for 90% of Vietnam's exported rice production), 70% of total fruit production, and 41% of aquaculture production of the whole country (GSO, 2010).

Figure 2.2: Maps of the VMD and the two provinces in which the research was undertaken

Source: http://www.mdpi.com/2072-4292/5/2/687/htm

2.4.2 Interviewer recruitment and training

We collaborated with the Southern Institute of Social Sciences (SISS) to conduct the survey in Vietnam. In particular, SISS was in charge of contacting locals, recruiting enumerators, organizing the training sessions, implementing the survey and experiments, and inputting and cleaning data. Our researchers participated as trainers during training sessions and as supervisors during the pilot and survey period. Professor Munro joined the first training session and pilot. SISS was chosen since it is very experienced in survey work and has a good reputation in the research community for providing quality data. Moreover, it is located in the South of Vietnam, where the surveys were conducted, making it appropriate for being a research partner.

The enumerators were recruited from officials in the SISS and some collaborators who have had a long time working with SISS. Many of them are researchers who are eager to learn from and contribute to our research. As most of the enumerators have considerable experience of doing surveys in the VMD, they are familiar with the culture as well as local language in the research areas. The survey team includes eight enumerators, one supervisor, one coordinator from SISS, and our researchers.

The enumerators were involved in three intensive training sessions – one before the pre-test and two before the two surveys in Kien Giang and Long An. In the 3-day first training session, the enumerators were introduced to the research topic and their tasks in detail (e.g., conducting the interview, dealing with potential respondents, survey locations, time schedule, etc.). The content of the questionnaire was the focus of this session. Every single question and instruction in the questionnaire were explained to the enumerators, the supervisor, and the coordinator. The enumerators were encouraged to ask about anything they did not understand, felt ambiguous, or confused. Comments from the enumerators were noted and used to refine the questionnaire. After explaining all the questions in the questionnaire, enumerators had chances to observe interviewing demonstrations from random pairs in the team and then practiced in pairs.

The one-day second training session was conducted before the survey in Kien Giang. In this session, the enumerators were given the final version of the questionnaire, which had been refined after the pilot. The training manual, which covered specific reviews from the pilot and important issues of the survey, was issued to the enumerators. The three main objectives were to recall and master the questionnaire, to practice the interview, and to understand the logistical arrangement during the interview period. We reviewed every common mistake that happened in the pilot. The final version of the questionnaire was checked for a second time. All enumerators then took turns to practice in pairs. The enumerators were also provided with the detailed arrangements for the coming survey, including their travel, accommodation, local travel, local guides, and means of contact.

The one-day third training session was conducted before the survey in Long An. After roundly cleaning the data of the survey in Kien Giang, we found some common mistakes of the enumerators (e.g., recording answers, choosing proper codes, or inconsistent use of number units (meter or centimeter, Vietnamese dong or thousand Vietnamese Dong)). Moreover, some enumerators shared their experiences dealing with respondents who found difficulties in understanding the questions and required more time to explain. Therefore, we spent the first-half part of the training session reviewing all the common mistakes and suggested a good approach to explain abstract ideas to the respondents so that they can get the point precisely and quickly. Then, all enumerators took turn to practice with a partner in a role-playing game.

2.4.3 Questionnaire design

The questionnaire was developed on the basis of the research objectives, key concepts, conceptual framework, and past studies. In addition, the design of the questionnaire took into account the characteristics of the respondents. Targeted subjects are farmers living in the VMD who may not be familiar with the discussion topic (i.e., climate change and migration) and have limited educational levels. Therefore, the questionnaire design considered the following key issues. First, personal and face-to-face interviews were chosen. Given the fact that the topic may not be well understood by the majority of local farmers and that many questions ask about farmers' perception and behavior, a personal and face-to-face interview is absolutely necessary. By such a communication method, the enumerators can effectively explain any confusing point to the respondents and investigate personal thoughts without interference. Additionally, this approach encourages farmers to stay for a long interview, anticipated to take about one and a half hours. Therefore, the direct interactions between well-trained enumerators and farmers contribute significantly to the quality of the data and the success of the interviews.

Second, fixed-alternative questions were mostly used, and survey instruments were employed to facilitate the interviews. The use of fixed-alternative questions dominated in the questionnaire because they save time and are easier to answer. The 'other, specify' option was usually used to capture any point that was not anticipated by the researchers. In this study, different types of fixed-alternative questions were used, including 'yes/no' questions, multiple-choice questions, checklists, and scales. Moreover, survey instruments such as show cards with illustrated colored pictures were used as visual aids, especially in scale questions and choice experiment part.

Third, information and questions were kept simple, clear, and in familiar language to the farmers to avoid measurement errors. In particular, proper attention was paid to the use of local dialect and the consideration of local culture. For example, ‘cong’[8] was used instead of hectare to measure the amount of land in the research site. The question ‘when were you born (in the solar year)?’ was used rather than ‘how old are you?’ because of the fact that the rural people commonly use lunar instead of the solar calendar to calculate their age and that old people are more likely to overestimate their ages as a way to earn respect from the community. Questions investigating living standards (e.g., income, expenditure) can be sensitive in some contexts and easily over-/under-stated. Thus, in this study, both questions about income and expenditure, which were calculated by summing main categories, were used to control for measurement errors. Additionally, as the questionnaire refers to many events/decisions that have been lasted from/happened in the past, timelines were especially emphasized and clearly stated in the questions to avoid confusion.

Fourth, the order of the questions was carefully considered for engaging respondents' cooperation and confidence. Understanding that rural people are eager to share their experience in terms of farming activities and climatic events, questions asking that information were put in the first part after basic demographic questions. Then, our main research objectives, questions about migration experience and choice experiment of migration decision, followed as the central session. Finally, more difficult, sensitive, personal, and potentially embarrassing questions (e.g., income, expenditure, asset, land ownership, etc.) were put in the closing section.

[8] ‘cong’ is one area measurement unit in Vietnamese which is often mainly used by the local people in the research site. 1 ‘cong’ = 0.1 hectare.

Taking into account the above issues, the questionnaire was developed and finalized with five major sections: (i) Basic demographic; (ii) Experience of climate change; (iii) Experience of migration; (iv) Choice experiment of migration decision, (v) Others (i.e. demographic and household characteristics, wealth and income sources).

2.4.4 Sampling and survey implementation

This study was conducted in two provinces in the VMD, Kien Giang and Long An. Kien Giang province is highly drought and saline intrusion prone, whereas Long An province is flood-prone. In particular, Kien Giang has experienced drought and saline intrusion for many years, including the most recent and severe event recorded in the dry season of 2016. In contrast, Long An is located in Dong Thap Muoi region[9] and is subject to flooding during the wet season (refer to risk map in Appendix Figure 3).

In each province, two districts, which are comparative in terms of main livelihoods and income levels but represent different levels of climate change impacts, were chosen (see Table 2.2 for code and climate risks of each selected district). In each district, one commune was randomly selected (see Table 2.3 for more details of the main features of selected districts and communes). In each commune, three to four villages were selected to conduct the survey. The selection of villages follows the rules that the distances between villages are far enough to avoid spillover effects and that high population villages are prioritized to increase representative features. From each selected village, households were randomly selected using the sampling interval (i.e., the number of households in the population divided by the

[9] Dong Thap Muoi region (also known as the Plain of Reeds) is an inland wetland in Vietnam's Mekong Delta. Most of the wetlands are within Long An Province, Tien Giang province and Dong Thap Province.

number of households needed for the sample) (Lavrakas, 2008) [10]. When the targeted household was unavailable, the adjacent households were chosen as replacements.

Table 2.2: Survey areas

Provinces	Districts	Communes	Drought-salinity risk	Flood risk	Codes	Villages	Sample size
Kien Giang	Vinh Thuan	Vinh Binh Bac	Medium	Low	11	Hiep Hoa	75
						Tan Binh	
						Binh Minh	
	An Bien	Nam Yen	High	Low	12	Ba Bien A	75
						Bao Tram	
						Hai Bien	
Long An	Tan Hung	Vinh Chau B	Low	High	23	02	97
						01	
						04	
						05	
	Thanh Hoa	Thanh Phuoc	Low	Low	24	Ca Sau	103
						Da Bien	
						Thanh Trung	
							Total: 350

Finally, a total sample size of 350 households was collected from 2 provinces/4 districts/4 communes/13 villages (refer to Table 2.2). This study excludes outliers, including too-rich households and ones who do not involve in farming activities. The targeted respondents are household heads or their spouses or the one who decides most important decisions in the household.

[10] The sampling interval method is also referred to as 'nth selection'. That is we select every nth participant (sampling unit) in the list. This sampling interval produces a random selection from throughout the total population, provided the population is not ordered in groups of n or its multiples.

Table 2.3: Geographical characters of survey areas[11]

	Kien Giang, Vinh Thuan	Kien Giang, An Bien	Long An, Tan Hung	Long An, Thanh Hoa
Code	11	12	23	24
District level				
Area (km2)	394.439	400.290	501.88	467.86
Population (thousand persons)	94.468	126.831	49.524	55.5790
Population density (people/km2)	239	317	99	119
% of rural population (%)	82	90	89	90
% of agricultural production land/total land	80.09	84.01	81.66	85.69
Commune level				
No. Villages	9	10	5	4
No. Households	4,227	4,046	996	1,878
Poverty rate (%)	3.69	19.33	3.10	2.30

The interviews were conducted in March 2019 (round 1: Kien Giang) and May 2019 (round 2: Long An). The interviews were mostly conducted with the heads of households or their spouses when household heads were unavailable. It took around one and a half hours to complete each interview. The research team visited 359 farm households, and 9 cases refused to be interviewed or finished the interview. In total, 350 households were interviewed in 13 villages of 4 communes. The response rate was 97.5%.

In the CE initial design, the eight blocks of eight scenarios are equally distributed in the total sample. That is, if there are 350 questionnaires, each block gets around 44 survey forms. In order to avoid possible influences of the enumerators on the respondents' decision-making

[11] Source: (1) Statistical yearbook of Kien Giang; (2) Statistical yearbook of Long An
(3) https://lmhtx.kiengiang.gov.vn/trang/TinTuc/137/1256/Xa-Vinh-Binh-Bac--huyen-Vinh-Thuan-dat-chuan-nong-thon-moi.html
(4) http://baolongan.vn/xa-vinh-chau-b-huyen-tan-hung-dat-19-19-tieu-chi-nong-thon-moi-a75803.html
(5) http://baolongan.vn/thanh-phuoc-don-nhan-xa-nong-thon-moi-a56239.html

process, the enumerators were in charge of different blocks on different days. That is, on each working day, each enumerator was assigned one block of questionnaires that is different from the block she/he took responsibility for in at least three previous days. Due to the higher refuse and replacement rate in Kien Giang, the blocks were not precisely equal as design; however, in general, the block distribution was relatively equal (see Table 2.4).

Table 2.4: Block distribution

Block	B1	B2	B3	B4	B5	B6	B7	B8	Total
Kien Giang	19	19	18	19	19	20	18	18	150
Long An	25	25	25	25	25	25	25	25	200
Total	44	44	43	44	44	45	43	43	350

During the CE, the foremost importance was to make sure the respondents understand the experiment set up and make the choices consistently and based on hypothetical information provided. As trained, the enumerators always asked the reasons of choice for the first scenario to confirm the relevance of the answers. Then, the enumerators also asked for more explanation if there was any clue of random answers or if there was a switch in the choices.

The questionnaires were checked for completion by individual enumerators, the supervisor, and the researchers. After daily interviews, each enumerator was required to check his or her completed questionnaires before submitting them to the supervisor. The enumerators were asked to explain missing answers, and they had to return or make phone calls to the households for any missing or ambiguous answers recorded. Finally, the supervisor and researchers checked all the questionnaires for completion. In addition, after almost working days, all team had meetings to review common mistakes and discuss any problem that happened on that day. During the whole survey, the researchers participated in the interviews as observers to control interviewing quality and take immediate actions if anything went wrong with the research objectives. The researchers were also in charge of interviewing the heads of villages to collect necessary information at the village level.

2.4.5 Data management and analysis

Surveyed data inputting and preliminary data cleaning were done in SPSS by the partner, SISS. Frequency counts and other descriptive statistics were employed to detect any error that may have appeared during data entry. Then, the SPSS data files were sent to the researchers and exported to STATA. Further activities were done on the STATA working data file while the copies of the original SPSS data files were kept untouched. Additionally, all 350 questionnaires were copied and kept by the researchers for checking whenever necessary.

2.5 Results

2.5.1 Descriptive analysis results

2.5.1.1 Demographic background

Table 2.5 provides a snapshot of the respondents' demographic characters. More males than females were interviewed (70.86 percent versus 29.14 percent, respectively), partly because household heads or the people who mainly make important decisions in the household were targeted for interviews. In the areas surveyed, husbands are usually household heads and major decision-makers. Sixty percent of the respondents were of age 40-59, 96.57 percent were married, and 94 percent belong to the Kinh[12] ethnic group. People in the areas surveyed have relatively low educational levels. Particularly, more than 85 percent of the respondents had completed only secondary or less than secondary education. The average household size, 4.7 members, is higher than the national average level of 3.78[13]. The most common household size in the fields is from 4 to 6 members, which accounts for 70.86 percent of the total sample size.

Table 2.5: Demographic and socio-economic characteristics of respondents

Characteristics	Categories	Percentage (%)
Gender	Male	70.86
	Female	29.14
Age	<40	23.43
	40-59	60
	>= 60	16.57
Marital status	Married	96.57
	Widowed	2.29
	Divorced	1.14
Household size	1-3	20
	4-6	70.86
	7 and above	9.14
Education level	Illiterate	4.29
	Elementary school	41.43
	Secondary school	44.57
	High school	8
	College equivalent or higher	1.71
Ethnic	Kinh	94
	Khmer	5.43
	Chinese	0.57

[12] Kinh (Viet or Vietnamese) is the majority in Vietnam. According to the 1999 census, the Kinh made up 85.7% of the population. Khmer and Chinese are two of the ethnic minorities in Vietnam.
[13] Source: 2009 Census - GSO

2.5.1.2 Likelihood of migration

Table 2.6 presents a descriptive analysis of the people who said they would never move (i.e., never-move people) and those who said they would move in at least one scenario (i.e., move people). The descriptions enable a comparison of the main features of the two groups of people. The t-test and Pearson chi-square test were applied to compare the means and proportions, respectively, of the same variables for two groups of people. The test results are presented in *Appendix Table 1*. The results show that the null hypotheses (i.e., the means and proportions of stated variables for move people are not different from those for never-move people) should be rejected ($p<0.05$). In other words, the observed differences are statistically significant.

Table 2.6: Main characteristics of move and non-move people

	Move people			Never-move people		
	Mean	Min	Max	Mean	Min	Max
Frequency	139			211		
Percentage (%)	39.71			60.29		
Age	45.73	26	72	50.12	26	78
Education	6.35	0	13	5.90	0	14
Household size	4.53	2	12	4.82	2	15
Land (cong)	23.24	2	100	28.72	1.3	250
Annual income per capital (million VND)	25.20	3.33	100	29.00	2.67	140
Number of current migrant	0.74	0	4	0.53	0	4
	Percentage (%)			Percentage (%)		
Having migration experience	59.71			47.87		
Being severely impacted by climate change	56.12			42.65		
Drought damage	50.36			46.45		
Saline intrusion damage	26.62			20.85		
Flood damage	15.11			10.9		
Storm damage	25.9			18.48		
Unusual heavy rain damage	38.85			30.81		

On average, the people who said they would move in at least one scenario are younger and have slightly higher educational attainment than those who said they would never move. Moved people, in general, own less land and earn less than those who choose to stay. Additionally, the more members there are in a family, the more likely people are to choose to stay. People with past and current experiences of migration in their families are more likely to choose to move. Finally, the experience of climate changes events appears to have an effect on the migration decision. Particularly, the more badly affected by climate change events, the more likely they are to choose to move. Those differences provide suggestions for the selection of control variables in the next section.

2.5.2 Test for choice consistency

Test for choice consistency was employed aiming at examining respondents' ability to understand or willingness to take the CE questions seriously. The test is based on a basic aspect of logical consistency, which underlies the axioms of choice: namely dominance (Foster, 2002). Dominance is the only test of logical consistency that can be applied in single question survey (Foster, 2002). One scenario is said to weakly dominate a second when it is at least as good as a second in terms of every attribute. In other words, A weakly dominates B means all attributes in B have a score at least as high as in A, and for at least one attribute, the score for A is strictly lower[14]. It is expected that the higher scores are, the more incentive for people to move. Then, a person should never be having a lower intention to move in B, compared to A. That is, an individual who chooses to stay in B but moving in A would fail the test. We examined whether or not each respondent's responses conform to this requirement, and then the number of failures was counted up.

In the current CE, we found 18 pairs of dominate-dominated questions in 6 out of 8 blocks, which cover 75.4 percent of the total sample size. The result of the test shows that 93.93

[14] The scores are the levels of attributes, presented in Table 2.1.

percent of the tested sample pass the test of logical consistency. Consistency failures as low as 6% of the test sample indicate that the CE was well designed and implemented. We, therefore, move to examine the CE results.

2.5.3 CE results

The Ordered Logit models were employed to estimate the influences of six attributes and some other elements on intention to migrate. The dependent variable is the four choices of migration intention (i.e., 4-definitely move, 3-probably move, 2-probably stay, and 1-definitely stay). The Ordered Logit models were used since increasing from choice 1 to choice 4 illustrates the increase in the likelihood of migration decision.

It is possible that not all respondents value competing factors similarly when making migration decisions. Therefore, in order to account for observed preference heterogeneity, individual-specific characteristics and interactions between those elements and CE attributes are included in the model. Those control regressors are socio-economic variables such as age, gender, income, land, and household size and variables accounting for migration and climate change experiences. Additionally, risk attitude, a dummy for Long An, and distance to the most common destination are included to capture the possible influence of those elements on migration decisions. Table 2.7 presents a description of the included individual-specific variables and the employed coding.

Table 2.7: Description and employed coding of explanatory variables

Variables	Description and coding
Age	Age of respondent
Income	The logarithm of annual income per capita
Household size	Household size
Current_migrant	Number of people who have been migrating and not returned home yet
Land	Agricultural land ownership
Land2	Square of agricultural land ownership
Risk attitude	Risk attitude in agricultural activities
Climate change	=1 if climate changes seriously affect household's income; =0 otherwise
Drought 2016	=1 if 2016 drought seriously affected household; =0 otherwise
Gender (female)	= 1 if female; =0 if male
Migration experience	=1 if having migration experience since 2000; =0 otherwise
Province (Long An)	= 1 if the surveyed province is Long An; = 0 if the surveyed province is Kien Giang
Distance	Distance from the origin to Ho Chi Minh city

The inclusion of interactions terms between individuals' characteristics and attributes enable researcher to estimate the influences of each attribute across groups of people. Given the high numbers of main attributes and control variables included in the model, the numbers of possible interactions can reach substantial amounts. The selections of interaction terms were based on theoretical points of view and empirical evidence in the literature. Since the particular focus of this study is on climate change variables, we paid considerable attention to the interaction terms of climate change attributes with other control variables. First, climate change attributes (i.e., drought and flood) interacted with variables indicating respondents' climate change experiences (i.e., climate change and 2016 drought). It is argued that experiences of climate-related phenomena are likely to change people's perception of climate change and then affect how they assess the upcoming events. Therefore, the influences of climate change on migration decisions may be varying on the consequences of the past events. Second, climate change attributes were interacted with socio-demographic variables to capture the fact that environmental impacts are the interaction between climate-related events and the underlying social vulnerability of the population (Abu et al., 2014). The vulnerability of an individual or a household to climate-change-related events can be characterized by socio-demographic variables such as age, gender, household size, migration status, risk attitude, and income (Abu et al., 2014; Black, Kniveton, & Schmidt-Verkerk, 2011).

Besides preference heterogeneity related to climate-change-related variables, preference heterogeneity related to other variables was also examined by introducing another six interaction terms. First, given that contribution of having a network may be highly correlated with the respondent's migration profile, network attributes interacted with variables indicating past and current migration experience (i.e., migration experience and current_migrant, respectively). Second, the interaction of network attribute and gender variable considers the hypothesis of gender differences in migration network. The literature on gender and migration has shown that the effect of social networks on the probability of migration may be different for men and women because the costs, risks, and benefits of migration differ by gender (Curran, 2003; Toma, 2014). Additionally, network resources are not similarly available to men and women (Curran, 2003), and women's social networks appear to be more limited and disintegrated than men's (Abu et al., 2014). Third, interaction terms of province dummy with income and crop restriction variables are expected to capture the main differences of the two surveyed provinces. Finally, the income gap attribute interacted with the respondent's risk attitude index. It is expected that risk attitude and economic behavior are closely linked, and therefore, prospective migration income may matter disproportionately across individuals with a different attitude toward risks.

In the table below, we present and analyze one model that contains ten of the above-justified interactions (i.e., Model 3: with interactions). The main effect model (model 1) and model with demographic variables (model 2) are included for reference. Although this model cannot include all possible interactions, it can cover significant preference heterogeneities that are justified and of interest. As an example of a robustness check, Appendix Table 3 contains a fuller regression, which produces similar results.

Each attribute level rather than the base will produce one interaction with the interacted variable, resulting in 13 interaction terms in total (see Table 2.8 for model estimation result). Marginal effects (MEs) and willingness-to-pay (WTP) will be analyzed to examine how CE attributes and other control variables affect the intention to migrate.

Table 2.8: Regression results

VARIABLES	Model 1: Main effects model		Model 2: With demographic variables		Model 3: With interactions	
Drought_moderate	0.330*	(0.173)	0.363**	(0.181)	-0.155	(0.289)
Drought_severe	1.116***	(0.130)	1.192***	(0.140)	0.864***	(0.191)
Flood_frequency	0.619***	(0.161)	0.647***	(0.170)	0.325	(0.243)
Income gap	0.198***	(0.0288)	0.210***	(0.0299)	0.468***	(0.0898)
Network	0.436***	(0.107)	0.464***	(0.112)	0.369**	(0.185)
Neighbour	0.320***	(0.112)	0.342***	(0.120)	0.347***	(0.121)
Crop_restrictions_partial	-0.126	(0.137)	-0.109	(0.136)	-0.198	(0.201)
Crop_restrictions_total	0.355**	(0.175)	0.368**	(0.180)	0.620**	(0.242)
Climate change			0.222	(0.199)	-0.186	(0.265)
Drought 2016			0.0772	(0.224)	-0.246	(0.280)
Age			-0.0351***	(0.0128)	-0.0367***	(0.0128)
Income			-0.227	(0.168)	0.0286	(0.235)
Household size			-0.282***	(0.0904)	-0.287***	(0.0911)
Current migrant			0.493***	(0.145)	0.586***	(0.160)
Migration experience			0.451	(0.277)	0.375	(0.301)
Long An			-0.421*	(0.227)	9.480*	(5.691)
Risk attitude			0.0651	(0.0529)	0.122**	(0.0585)
Female			-0.120	(0.222)	-0.257	(0.239)
Drought_moderate * Climate change					0.539*	(0.286)
Drought_severe * Climate change					0.644**	(0.258)
Drought_moderate * Drought 2016					0.531*	(0.279)
Drought_severe * Drought 2016					0.0986	(0.260)
Flood_frequency * Climate change					0.164	(0.231)
Flood_frequency * Drought 2016					0.513**	(0.226)
Income gap * Risk attitude					-0.0388***	(0.0135)
Network * Current migrant					-0.237*	(0.123)
Network * Migration experience					0.216	(0.249)
Network * Female					0.485**	(0.193)
Crop_restrictions_partial * Long An					0.0550	(0.279)
Crop_restrictions_total * Long An					-0.562*	(0.300)
Income * Long An					-0.584*	(0.336)

Robust standard errors in parentheses; Clustered at household level
*** p<0.01, ** p<0.05, * p<0.1

Marginal effects of the CE attributes, which are presented in Figure 2.3, explain whether those attributes influence migration intention. Marginal effects show the change in predicted probability when the predictor or independent variable increases by some units. In other words, marginal effects indicate the difference in outcome probability between one level of predictor and its base level. For example, marginal effect of severe drought on outcome 3's probability (i.e., probably move) is 8.19 percentage points, meaning that the incidence of severe drought rather than no drought increases the probability of choosing 'probably move' by 8.19 percent. That is, the existence of severe drought raises the likelihood of choosing to move. As can be seen from Figure 3, marginal effects of all attributes except partial crop restriction are significantly negative for outcome 1 (i.e., definitely stay) and significantly positive for outcome 3 and 4 (i.e., probably move and definitely move, respectively), indicating that all selected attributes have significantly positive impacts on the intention to migrate, as expected.

Figure 2.3 also sheds light on to what extent those attributes influence migration intention. Marginal effects of severe drought are bigger than those of moderate drought, indicating that the more serious the drought is, the more likely people choose to migrate. As can be seen, drought, which shows the largest gap between marginal effects on outcome 1 and outcomes 3 and 4, stands out as a dominant driver of the decision to stay or leave. Other attributes would also prompt respondents to consider leaving; however, the effects are weaker than for drought. Although partial crop restrictions seem to have no effect on migration decisions, total crop restrictions trigger people to move.

The findings indicate that both sudden-onset and slow-onset events significantly increase the likelihood that an individual opts for migration. While this result aligns with some of the existing empirical literature (e.g., Berlemann & Tran, 2020; Warner et al., 2012), it tends to contradict the findings by Koubi et al. (2016), who find that slow-onset disasters significantly reduce the likelihood of migration. One possible explanation is that Koubi et al. (2016) examine the occurrence of the slow-onset events rather than examine the intensity of those environmental stressors (i.e., any mention of salinity, drought, or desertification was coded as slow-onset stressor). However, the occurrence of an event with different intensity levels may lead to different migration decisions. The occurrence of a disaster with trivial loss is unlikely to lead to migration, while the occurrence of a disaster with considerable loss tends to induce migration (Trinh et al., 2021). Therefore, Koubi et al. (2016)'s findings do not capture the fact that droughts have become more severe in Vietnam over the preceding decade, which may significantly raise the positive impacts of drought on the likelihood of migration. Another explanation is the possibility of location selection bias in Koubi et al. (2016). Although they proposed to select two provinces with sudden-onset events and two provinces with slow-onset events, descriptive analysis reveals that the incidence of sudden-onset events is nearly three times higher than the incidence of slow-onset events. More than 81 percent of the sample mentioned their experience of sudden-onset events, while only 29 percent of the sample experienced slow-onset events. Given the equal proportions of migrants and non-migrants in the sample, there is a strong possibility that insignificant and negative impacts of slow-onset events found by Koubi et al. (2016) are linked to low incidence of those events in sampled locations.

Figure 2.3: Marginal effects of CE attributes

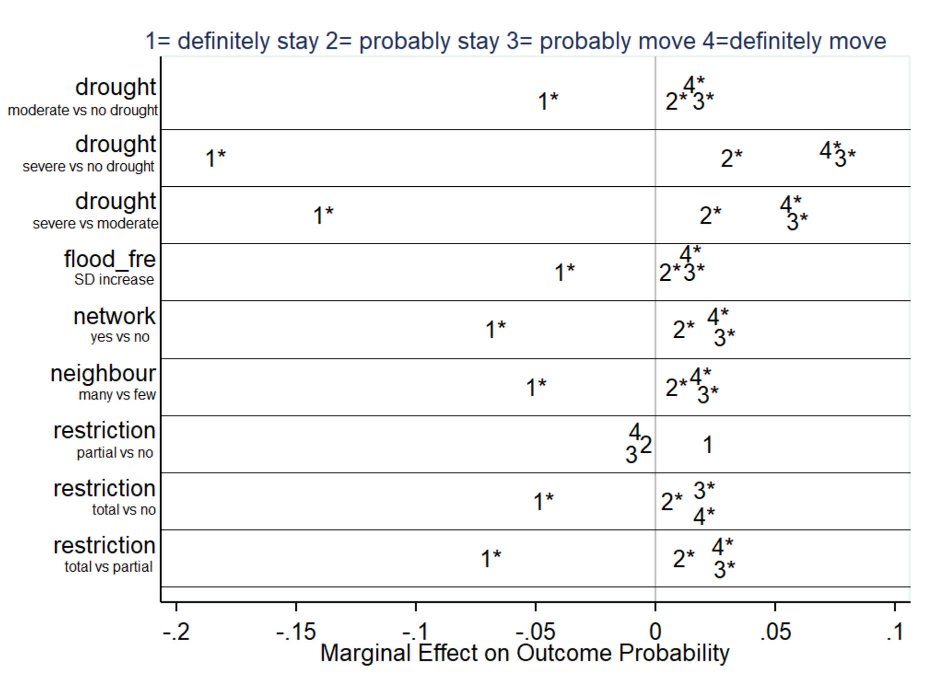


Table 2.9 indicates the marginal effects of the control variables for outcome 3 (i.e., probably move) and outcome 4 (i.e., definitely move). In other words, the table shows the impacts of control variables on the likelihood of choosing probably move and definitely move. The results show that specific individual characteristics such as age, household size, current migration experiences, level of income, and a dummy variable for Long An have significant impacts on people's decision to migrate. Particularly, household size shows a negative coefficient value, suggesting that the more members a household has, the lower probability for it to make a decision to move to another place. One possible explanation is that a bigger family may involve higher migration costs and then hinder migration intention. Bigger family may coincide with more dependents and, therefore, require more complicated arrangements to settle down in the new place, such as education for kids or health care for the elderly. A

negative coefficient for the age variable suggests that the older a respondent is, the less likely she/he wants to move. The finding is in line with the results reported in Koubi et al. (2016) and Warner et al. (2012). Similar to other studies (e.g., Abu et al., 2014; Koubi et al., 2016), we find that current migration experiences have positive and significant impacts on the decision to migrate. This finding conforms to our expectation that a household's members may be more willing to migrate when their family member(s) is/are migrating since those current migrants can provide substantial information, networks, or supports. Results also show that richer families would be less likely to choose to move.

Table 2.9 indicates that people from Long An are less likely to choose to migrate than people from Kien Giang. The result can be attributed to the distinctions between the two surveyed provinces. Appendix Table 2, which presents the MEs of main attributes for sub-samples, Kien Giang and Long An, provides evidence to explain the main differences between those two provinces. First, Kien Giang is more vulnerable to climate change, and then has higher MEs for drought and flood attributes than Long An. Second, Kien Giang is relatively poorer than Long An[15] , and therefore, the income attribute is valued more in Kien Giang than in Long An. Therefore, on the whole, under CE's scenarios, people in Long An have less incentive to move than people in Kien Giang.

We examine whether risk attitude has any effect on migration decisions. This risk attitude variable was collected by asking to what extent the respondent assesses his/her willingness to take risks in agricultural activities. An increase in risk attitude variables indicates an

[15] From data shown in Table 2.3 and Footnote 2, Kien Giang has higher poverty rates and less average income per capital than Long An.

increase in the willingness to take risks or less risk-averse. There are two arguments to support the relevance of using risk attitudes toward agricultural activities as determinants of migration decisions. First, both risk attitude and CE choices are with respect to the respondent's source of income. While the index describes risk attitude toward respondents' main source of income, this study focuses on migrating behavior for an alternative source of income. Second, agriculture is respondents' main livelihood that they have been involved in for a long time; risk attitude toward agricultural activities may, to some extent, reflex their actual risk attitude in general. However, the results show that risk attitude does not have significant impacts on the probability of choosing to move.

Past migration experience, climate change experience, gender, distance, and land ownership are not significant predictors of migration decision, even though the signs of coefficients on climate change, migration experience, and income are consistent with our expectations. We do an LR test for land and distance variables since the coefficients' magnitude appears to be very negligible. The LR ratio statistic is equal to 1.92, for a p-value of 0.3836, falling to reject the null that land variables are not different from zero at the conventional levels (i.e., 10%, 5%, and 1% significance). For the distance variable, the LR ratio statistic of 1.04 and a p-value of 0.3069 suggest that we cannot reject the null that the distance coefficient is not different from zero. The inclusion of the distance variable in the model may not be necessary because the dummy variable for Long An may already cover differences in distances between the two surveyed provinces. The test results support the decision to exclude those variables from the main model.

Table 2.9: MEs for outcome 3 (probably move) and outcome 4 (definitely move)

	Probably move		Definitely move	
VARIABLES	MEs	SEs	MEs	SEs
Climate change	0.0132	(0.0123)	0.0132	(0.0101)
Drought 2016	0.00702	(0.0134)	0.00597	(0.0115)
Age	-0.00219***	(0.000727)	-0.00186***	(0.000653)
Income	-0.0176*	(0.0101)	-0.0140	(0.00892)
Household size	-0.0171***	(0.00531)	-0.0145***	(0.00479)
Current migrant	0.0311***	(0.00922)	0.0263***	(0.00786)
Migration experience	0.0262	(0.0172)	0.0212	(0.0135)
Long An	-0.0264*	(0.0142)	-0.0216*	(0.0118)
Risk attitude	0.00406	(0.00329)	0.00298	(0.00277)
Female	-0.00712	(0.00329)	-0.00580	(0.0110)

Standard errors in parentheses; Clustered at household level
*** p<0.01, ** p<0.05, * p<0.1

For interaction terms, we calculated WTP to examine the influences of CE attributes conditional on specific control variables. By definition, WTP is the reduction in income gap needed to offset the change in the attribute (i.e. - ($\beta_{attribute}$/ $\beta_{income\ gap}$)). A reduction in income gap can be interpreted as either the increase in rural income or the decrease in city income. Because the income gap and all other CE attributes are proved to foster the intention to move, WTPs turn out to be negative. Therefore, WTPs can be interpreted as 'having/facing a specific attribute is equivalent to an increase in city income, or equivalently, a decrease in rural income'. Depending on the natures of the attributes, we may need slightly different interpretations for different attributes for better and easier understanding. For example, a negative WTP for drought attribute means that the incidence of drought is equivalent to a decrease in rural income, or equivalently, the respondent is willing to pay a positive amount of money to avoid such drought. In another instance, a negative WTP for network means that having a network is equivalent to an increase in city income.

Results of interactions suggest that prior experiences of climate change, but not socio-demographic characteristics, significantly influence how people value drought and flood attributes. When drought and flood attributes interact with both climate-change-related and socio-demographic variables, interaction terms with socio-demographic variables turn out to be insignificant while interactions terms with climate-change-experience variables are most significant (see Appendix Table 3 for regression result). This result also indicates that although previous climate change experiences do not have direct effects on intention to migrate (refer back to Table 2.8), they have indirect impacts through altering the importance of climate change-related determinants in migration making decisions.

Table 2.10: WTP for drought and flood conditional on previous climate change experiences

VARIABLES	(1) Base	(2) With CC experience	Differences (2) – (1)	(3) Damaged by 2016 drought	Differences (3) – (2)
Drought_moderate	0.310	-0.794	-1.104*	-1.880***	-1.086*
	(0.613)	(0.567)	(0.651)	(0.555)	(0.607)
Drought_severe	-1.837***	-3.201***	-1.364**	-3.405***	-0.204
	(0.510)	(0.784)	(0.621)	(0.774)	(0.552)
Flood_frequency	-0.703	-1.013*	-0.310	-2.058***	-1.044**
	(0.540)	(0.525)	(0.495)	(0.560)	(0.485)

Standard errors in parentheses; Clustered at household level
*** p<0.01, ** p<0.05, * p<0.1

Notes: (1) Base: WTP of people who have not been seriously affected by climate change events and the 2016 drought; (2) WTP of people who have been seriously affected by climate change events but not by the 2016 drought; (3) WTP of people who have seriously affected by climate change events and the 2016 drought.
Unit: Millions Vietnam Dong

Table 2.10 compares WTPs for drought and flood attributes of three groups of people: (i) people who have not been seriously affected by climate change events and the 2016 drought; (ii) people who have been seriously affected by climate change events but not by the 2016 drought; and (iii) people who have seriously affected by climate change events and the 2016 drought. The results show significant differences in contributions of climate change attributes in migration decisions among the three groups. First, WTPs of the respondents who underwent serious climate change experience in the past are higher than of those who have not been seriously affected by climate change phenomena. That is affected people would be willing to pay more to avoid climate change events. However, we only found significant differences in WTP for drought attribute, but not for flood attribute (refer to column difference (2) – (1)). Specifically, the differences in WTP to avoid incidences of drought reach the amount of more than 1.1 million Dong, equivalent to around one-third of average monthly income per capita. The insignificant WTPs for flood point out that the values of flood attribute are identity between people who experienced severe climate change and those who did not. It is a fact that, over the last ten years, droughts have occurred with increasing frequency and intensity and affected a large population of the Mekong River delta[16]. In addition, drought, a slow-onset environmental change event, may have long-term effects on affected people. Therefore, previous damages of climate change phenomenon arouse people's concern about upcoming droughts rather than floods.

[16] According to survey data, 80% of the respondents said that droughts happen more frequently and 50% of the respondents said that droughts are more severe over the last 10 years. Whereas, those proportion for flood are 18% and 13%, respectively.

Second, the 2016 drought, which is considered the most severe climate change event that happened in the last five years, also induces a change in how people assess upcoming droughts and floods. In particular, people who were seriously affected by the 2016 drought and saline intrusion are willing to pay more than those who were not affected by the event to avoid drought and flood. Interestingly, while we cannot observe a sufficiently significant difference in WTP to avoid severe drought between the two groups, we see relatively big and significant differences in WTP to avoid moderate drought and flood (refer to column difference (3) – (2)). It seems that severe damages of the 2016 drought have changed people's perception. Affected people become more concerned about the occurrence of upcoming climatic hazards even if those events would cause relatively moderate damages.

Table 2.11: WTP for a network of male and female

	(1)	(2)	(3)
VARIABLES	base	having migration experience	with one current migrant
network_female	-1.820***	-2.252***	-1.316**
	(0.537)	(0.680)	(0.537)
network_male	-0.804*	-1.236**	-0.300
	(0.418)	(0.527)	(0.473)

Standard errors in parentheses; Clustered at household level

*** p<0.01, ** p<0.05, * p<0.1

Notes:

(1) Base: WTP of having networks for male and female with no current migrant and no migration experience;

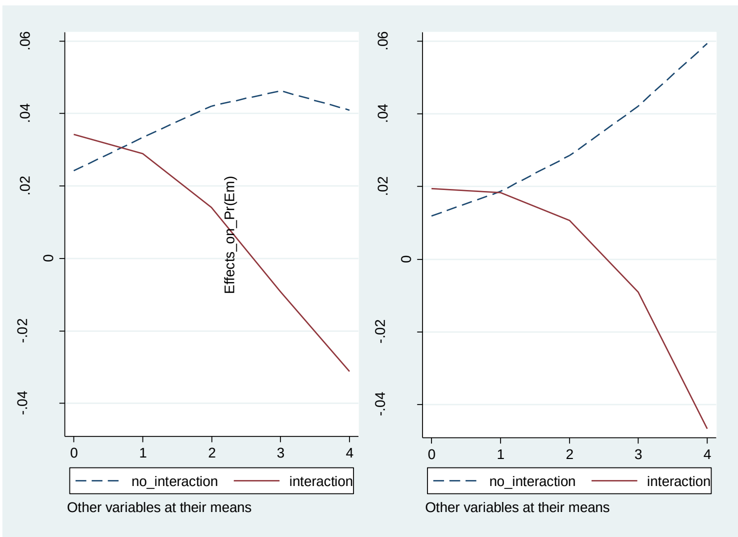
(2): WTP of having networks for male and female when having migration experience and no current migrant;

(3): WTP of having networks for male and female when having one current migrant and no migration experience

Unit: Millions Vietnam Dong

We also found significant effects of interactions between gender (i.e., female) and migration experience with network attributes (see Table 2.11 and Figure 2.4). It is interesting to find that females would value network attributes more than males. That is, for instance, having a network in a potential destination is equivalent to 1.820-million-Dong increase in city income for females, but only 0.804-million-Dong increase for males (refer to the base case in Table 2.11). One explanation may be that females in rural areas tend to have less social experience than males. They might feel more secure when they have some connections in the potential destinations; and therefore, weight network attributes are more important than males do. Moreover, we found that a respondent would value network attribute more when his/her household has prior migration experience. This makes sense because past migrants may truly understand the importance of having a network when migrating and therefore put more value on it. Another finding is that the more family members are currently migrating, the less importance respondents put on network attributes when considering migrating. This can also be seen through Figure 2.4, which shows that network has a negative impact on the likelihood of migrating when being conditional on the number of current migrants. The importance of having a network declines because current migrants can provide supports to prospective migrants.

Figure 2.4: ME of network conditional on numbers of current migrants (outcome 3,4)



We expect that people from the Kien Giang and Long An may assess the crop restriction attribute differently because people in these two provinces are implementing different crop patterns. Specifically, in Kien Giang, farmers have adjusted to the shrimp-rice pattern after the 2016 drought and get used to this new cropping pattern, whereas, in Long An, farmers are implementing a rice-rice pattern. The current model allows us to confirm this expectation by interacting province dummy with crop restriction variables. Indeed, the results point out that people in Kien Giang are willing to pay 1.172 million Dong more than people in Long An to avoid total crop restrictions (see Table 2.12). This result indicates that the influences of crop restriction on migration decisions vary depending on the current cropping models implemented at the fields.

Table 2.12: WTP for Crop restrictions for Long An and Kien Giang

VARIABLES	Long An	Kien Giang	Differences
Crop_restrictions_partial	0.292	0.427	-0.134
	(0.399)	(0.435)	(0.592)
Crop_restrictions_total	-0.128	-1.299**	1.172*
	(0.484)	(0.551)	(0.658)

Standard errors in parentheses; Clustered at household level

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

From this model, we also find that level of income matters when people consider migrating. Table 2.13 presents MEs of income levels between the two surveyed provinces. It can be seen that while income level significantly influences migration decisions for Long An people, those influences are insignificant for Kien Giang people (i.e., for Long An people, the richer the respondents are, the less likely they choose to move). The average income gap between these two provinces may attribute to this difference. It seems that poorer people would put more value on the income gap between their current community and potential destination but do not care much about their current income when considering migration. Indeed, Kien Giang province has a lower income level and a higher poverty rate.

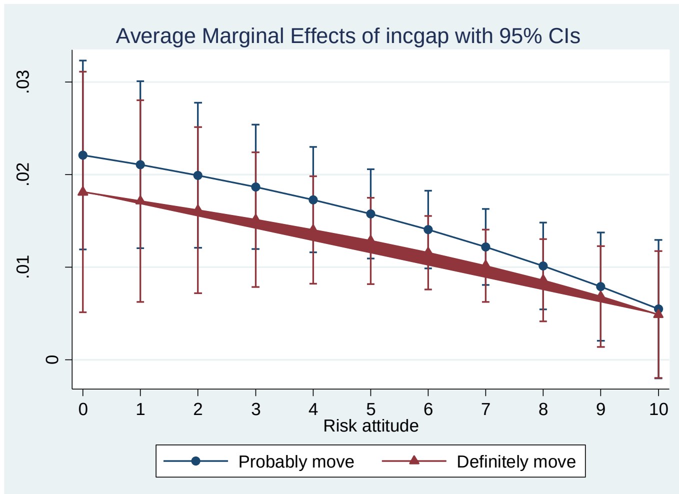
Table 2.13: MEs of Income for Long An and Kien Giang

Predicted probability	Long An	Kien Giang
Definitely stay	0.0686**	-0.00478
	(0.0302)	(0.0361)
Probably stay	-0.0138**	0.000813
	(0.00581)	(0.00614)
Probably move	-0.0305**	0.00205
	(0.0136)	(0.0155)
Definitely move	-0.0243**	0.00191
	(0.0117)	(0.0144)

Standard errors in parentheses; Clustered at household level
*** p<0.01, ** p<0.05, * p<0.1

Finally, we found that risk attitude has some influences on how people value income gap attributes. Figure 2.5 indicates the MEs of income gap conditional on risk attitude for the choices of moving (i.e., outcome 3 and 4). The figure demonstrates that the more risk-averse the respondents are, the more they value the income gap attribute. For risk-averse people, the cost of migration may be more about the uncertainty in potential income after migrating.

Figure 2.5: MEs of Income gap conditional on Risk attitude



2.6 Conclusions and discussions

In this study, we used a choice experiment (CE) approach to examine the causal relationship between climate change and rural-urban migration decisions in the Mekong River delta of Vietnam. In addition to climate change impact, we investigated other significant factors influencing people's migration choice, such as income, network, neighbor's choice, and crop choice restriction. We modeled heterogeneity in these preferences by including socio-demographic variables and their interactions with main migration attributes.

The CE results confirm that increasing intensity and frequency of climate change phenomena raise the likelihood of choosing to migrate, in which severe drought stands out as the most significant factor affecting people's choice. We found considerable heterogeneity in migration behaviors among individuals with different socio-geographic characters. People who are relatively young, poor, have small household sizes, or have current migrant(s) in their families are more likely to choose to migrate. The contributions of migration attributes varied by socio-demographic characteristics. Specifically, the significance of climate change-related attributes varied according to the previous experience of climate change; contribution of network attribute is gendered and dependent on migration experiences; the importance of income gap attribute differs across respondents' risk attitude. Interestingly, we found that prior experience of climate change significantly influence how people value drought and flood attributes, but socio-demographic characteristics did not. The main distinctions between the two provinces surveyed, such as vulnerability to climate change, income level, and cropping patterns, are found to affect migration behavior.

Our results and the derived implications suggest that a CE approach, such as the one proposed and applied here, has merits for gaining an understanding of migration preferences under impacts of climate change and heterogeneity in the above preferences across households. In this study, the CE results have intuitively sensible directions, and a great proportion of the sample passed the consistency test. There is, therefore, solid evidence showing that the CE was well designed and was implemented with good understanding and engagement.

As discussed earlier, since this study focused on province-level assessments, the current model can identify the main distinctions between surveyed provinces that may shape migration behavior. Those factors are useful for generalizing the results to the Mekong River delta region or to other country-case studies. In other words, this model can be used to examine the causal relationship between climatic variabilities and migration decisions in a developing and seriously climate change-impacted country/region.

Another suggestion for further research is to use the results of this model to estimate the projections of environmental-induced migration. Although numerous studies have investigated the climate change–migration nexus and constructed scenarios of climate change phenomena, few studies have combined those findings to project migration caused by climate change impacts. The ex-ante nature and the extensive data provided by the CE approach have considerable advantages for detecting migration trends under different climate change scenarios. One interesting issue is that environmentally induced migration can be a diffusion process. First, there is evidence that climate change will increase the frequency and intensity of extreme climatic events and that future flows will be larger than those currently experienced (Black, Kniveton, et al., 2011). Second, as well established in the migration literature, the impact of migration attributes such as network and neighbors' choices are dynamic. Because the networks are created by the act of migration itself, over time, the impact of networks will be expanded, and as a result, spread out-migration probability (Massey, 1990). The impacts of neighbor attributes may follow the same pattern.

Chapter 3 Using an agent-based model and a choice experiment to simulate climate-change-induced migration: the case of the Mekong River Delta, Vietnam

3.1 Introduction

A large number of studies have confirmed the impact of climate change on migration. It is expected that climate change will induce a large volume of climate-related migration in the next few decades (Entwisle et al., 2016). The Vietnamese Mekong Delta (VMD), one of the areas in the world most strongly affected by climate change, is predicted to face mass migration triggered by climate and environmental change. To investigate that risk requires an estimation of the magnitude of migration flows under climate change scenarios. From the perspective of policymakers, projections of climate-induced migration are particularly important for the formulation of policy strategies aimed at securing resilience and the development prospects of migrants and of those in the sending and receiving communities (Rigaud et al., 2018).

Migration decisions are usually both multi-causal and shaped through individual entities, their interaction with other agents and the environment, and the feedback of that interaction to the decision-making process. As a result, in the literature, agent-based models (ABMs) present a huge potential for the modeling of migration. The ABM has at least three major advantages over other methods. First, at the core, ABM focuses on individual agents and their decision processes (Klabunde & Willekens, 2016). As a result, ABM enables users to model the behavior of individual decision processes and easily deal with heterogeneities of behavior between agents (Piguet, 2010).

Second, ABM is the only method that allows for the explicit modeling of social interactions between agents and the feedback loops that result from those interactions (Bruch & Atwell, 2015; Klabunde & Willekens, 2016). As a result, ABM can capture the self-reinforcing process of migration that originates with interactions on the micro-level. For example, networks shape available opportunities for migration decisions; and in turn, more migrants provide more networks and, therefore, more incentive for the remaining agents to leave.

Third, ABM can provide a practical link between policies and theoretical concepts through its feedback mechanism between micro and macro levels. An understanding of how people's behavior changes in response to an intervention can support the creation of better policy design (Bruch & Atwell, 2015). The key advantage of ABM's ability to integrate data and theories from many different sources and at many levels of analysis allows researchers to explore how people react to different policy-related scenarios.

However, the use of ABM in the study of the environment-migration nexus is still hindered by two main obstacles. First, the selection of a decision-making theory is difficult because knowledge about how people react to the environmental stress of specific subgroups is very limited (Piguet, 2010). One current widely adopted behavioral theory among social scientists is the social psychological theory of planned behavior (e.g., (Kniveton et al., 2011; C. D. Smith, 2014)). The theory of planned behavior (Ajzen, 1991) is a preferred means of investigating environment-migration links because it allows for the inclusion of a large number of features (including environmental stimuli) that shape migration decisions. However, psycho-social decision theories tend to be complex and can be criticized for being arbitrary since they theoretically allow for the inclusion of an infinite number of decisive factors and beliefs (Klabunde & Willekens, 2016).

Second, the selection of empirical evidence to validate the ABM model is limited because of the scarcity of high-quality data in the appropriate unit of analysis (Bruch & Atwell, 2015). The current approach to ABM use for the study of environment-migration relationship requires large-scale individual/household level data on migration history; such data is both rare and difficult to collect (C. D. Smith, 2014). Furthermore, historical empirical data have a limitation on covering individuals' migration responses in a diverse range of environmental exposures. Data cannot even be collected in some part of the population because the members of that sector have never coped with climate change events - an obstacle to the prediction of the way an agent will react to climate variabilities and other stimuli.

Choice experiment (CE) is a potentially useful method because it is able to address the aforementioned shortcomings of the current ABM for the study of climate change–migration linkage, thanks to two strengths of the CE method. First, the CE method is based on random utility theory and therefore has the potential to enhance the ABM approach with a well-established economic theory and an empirical basis for simulation. Second, flexibility in CE design allows the researcher to obtain extensive datasets for migration behavior under a diverse range of climate scenarios and other stimuli at the individual or household levels, even for those who have not experienced any impact of climate change.

This paper presents the development of an agent-based model (ABM) integrated with a choice experiment (CE) to simulate future migration out of the rural VMD in response to a variety of future climate scenarios and other migration stimuli. The random utility theory implemented in the CE model is used as the behavioral theory for decision rules in the ABM of migration. Migration attributes in the CE model include climate change phenomena, income gain from migration, network at the potential destination, neighbors' choices, crop choice restriction, and other control variables. The ABM incorporates empirical measures through (1) agent behavior specification parameterized via information elicited from the CE model; (2) population characteristics using the iterative proportional fitting method. This is the first study to combine the ABM and CE methods in the study of environment-migration nexus.

Although CE offers many benefits, as with all methods, it has its own problem. There is a reasonable concern that, in CEs, people's preferences derived from hypothetical questions may not accurately explain their real-world behavior. Nevertheless, there is evidence showing that stated preference provides an accurate guide to individuals' actual preferences (e.g., (Scarpa et al., 2003; Wardman, 1988; Whitehead, Weddell, & Groothuis, 2016)). Although the evidence is limited, stated preferences have been shown to have a significant correlation with actual migration flow (e.g., (Bah & Batista, 2018; M. Lu, 1999; Van Dalen & Henkens, 2013)). As such, CE can be a powerful tool for the collection of migration intention to inform future migration scenarios, especially when historical migration data are not available. For the integrated modeling framework of ABM and CE, a well-designed and implemented CE together with a proper process of ABM validation will improve the model's robustness.

This chapter is organized as follows. Section 2 reviews the existing research on the simulation of migration under the impacts of environmental changes and the related studies for the case of Vietnam. Section 3 justifies the use of ABM and CE methodology in the study of climate change-migration nexus. Section 4 focuses on the design of the ABM model. It explains how the agents' decision-making process was modeled and describes the software and data used. Section 5 demonstrates the process for validating the model. Section 6 discusses simulation results and draws conclusions with the contributions of this research.

3.2 Literature review

The literature on climate-change-induced migration notices two potential modeling approaches to simulate future climate migration. The first method adopts a scenario-based approach developed by (Rigaud et al., 2018) and uses macro-level data on demographic and socioeconomic trends (Shared Socioeconomic Pathways); climate change scenarios (greenhouse gas emission pathways drive climate impact); and projected rural-urban population change to estimate the change in population distribution (and indirectly climate migration), employing a version of the gravity model. The results are a projection of the number of climate migrants up to 2050 for regions and sub-regions including East Africa, South Asia, and Mexico, and Central America. This methodology is more relevant for regions and sub-regions, as can be seen in (Rigaud et al., 2018), than for the provincial level of a specific country, where in general, the required economic, demographic, or environmental drivers data are largely unavailable. Moreover, within the gravity framework, it can be difficult to tease out the specific factors such as social networks, as well as the relative contributions of those factors on migration movement (Rigaud et al., 2018).

The second approach is based on agent-based modeling (ABM), a computational social simulation technique that enables the users to model the behavior of individual migration decision-making in a complex combination of multilevel stimuli that contain environmental factors. They are often parameterized using extensive household surveys and historical data on migration. ABM for environmental migration has been developed for Tanzania (C. D. Smith, 2014), Burkina Faso (Kniveton et al., 2011), Bangladesh (Hassani-Mahmooei & Parris, 2012), and Thailand (Walsh et al., 2013). The ABM method is discussed in detail in the following sections.

Two studies, Kniveton et al. (2011) and C. D. Smith (2014), employ the Theory of Planned Behavior, one of the most prominent behavioral theories, as decision rules. Kniveton et al. (2011) draw upon migration history and rainfall data to develop a conceptual model of migration as an adaptation to rainfall change. In the above case study of Burkina Fuso, that model is used to examine the characteristics of climate migration behavior and to simulate migration flow forward to 2060. That study uses retrospective national-scale representative data on migration history drawn from the survey Enquête Migration, Insertion Urbaine et Environnement au Burkina Faso (EMIUB).

C. D. Smith (2014) develops an alternative conceptual model using an agent-based system to model the impact of changes in rainfall upon human migration. Addressing the fact that the conceptual model developed by (Kniveton et al., 2011) can face limitations related to poor data availability, the conceptual framework developed by C. D. Smith (2014) is designed to accommodate a less data-driven and more heuristic case-study based approach that uses the survey data collected in 2012 in three villages in Tanzania. However, this survey data fails to provide a basis for quantification of the degree of change in variables over time. Overall, the current version of ABM used in the climate-migration field has strength for local analyses but has a limitation in that it lacks empirical evidence on migration intention under varying stimuli.

ABM and Theory of Planner Behavior have been employed to model inter-provincial migration in the VMD (H. K. Nguyen, Chiong, Chica, & Middleton, 2018, 2021). H. K. Nguyen et al. (2018) propose an ABM integrated the Theory of Planner Behavior to explore the dynamics of migration flow across the VMD region and calibrate the model with actual data of migration rate. H. K. Nguyen et al. (2021) extend the previous model with a comprehensive set of empirical data and the use of a genetic algorithm for automated calibration and sensitivity analysis to determine the most critical components and factors that would affect the migration decision of migrants in the VMD region. The study points out that economic reasons (i.e. employment prospects and income) had the largest contribution in forming migration intention (accounting for about 80% of the reasons) and environmental impacts contributed to 5% of the migrants' attitude toward migration. The impacts of environmental factors may be underestimated since the study ignores the indirect impacts of environmental factors on livelihood and income.

Although the study of H. K. Nguyen et al. (2021) provides an understanding of the dynamics of migration flow and the main components shaping migration behavior in the VMD region, they miss to investigate the correlation of climate change phenomenon and migration dynamics and have not intended to create predictions. One difficulty is that there is no previous empirical study and statistical analyses to examine the impacts of environmental change variability and different socio-economic attributes on individual migration decisions.

The climate-migration link seems to be more robust in Vietnam and especially in the VMD region. The VMD region is facing a major challenge of mass migration triggered by climate change phenomena such as salinization, flood, and sea-level rise ((D. Anh, Dipierri, & Leonardelli, 2017; V. T. T. Anh et al., 2020). Increasing environmental and climate change impacts would continue to accelerate the migration process and the number of climate migrants. However, to our knowledge, there has been no study involving the prediction of migration dynamics under future climate change impact in the VMD region.

One related study is (Warner et al., 2010) that uses the exposure mapping method to estimate the number of people displaced due to sea-level rise scenario. The exposure mapping method usually involves overlaying a climate-related hazard (sea-level rise in this case) on the exposed population. Nevertheless, this method makes fairly simplistic assumptions about movement (Rigaud et al., 2018) and ignores the fact that migration responses are the result of a complex combination of multiple attributes and stimuli that shape the behavioral decisions of individuals.

3.3 Methodology

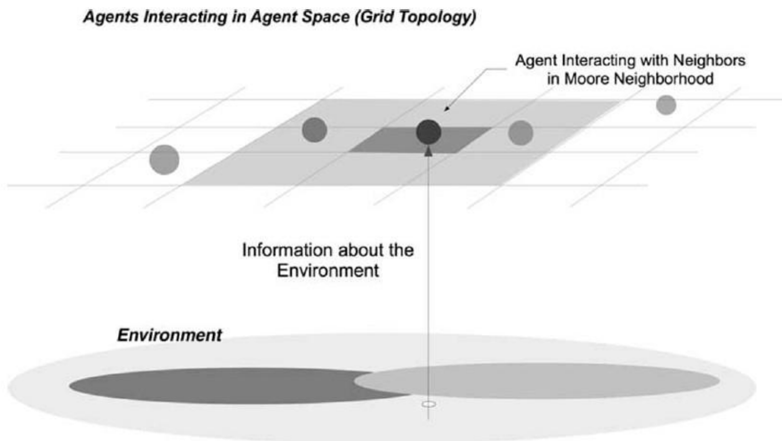
3.3.1 Agent-based model (ABM)

ABM is a computational method for modeling a system of individual components and their behaviors. In an ABM, individuals or agents are described as unique and autonomous entities that usually interact with each other and their environment locally[17] (Railsback & Grimm, 2019). The focus of an ABM is on individual agents, their decision processes, their interactions with other agents, and the effects of those interactions on decision processes (Klabunde & Willekens, 2016). Therefore, ABM is suitable for learning about the collective/emergent behavior of individuals at any level of aggregation.

A typical ABM has three elements: a set of agents with their attributes and behaviors; a set of agent relationships and a method of interaction; and the agents' environment (Figure 3.1). An underlying topology of connectedness defines how and with whom agents interact. To run an agent-based model, a computational engine is required for simulating agent behaviors and agent interactions, i.e., repeatedly executing agent behaviors and interactions. This process often operates over a timeline, in time-stepped, activity-based, or discrete-event simulation structures (Macal & North, 2010).

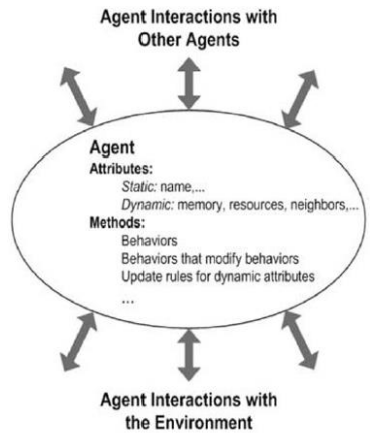
[17] Interacting locally means that agents usually do not interact with all other agents but only with their neighbors—in geographic space or in some other kind of "space" such as a network (Railsback & Grimm, 2019).

Figure 3.1: The structure of a typical agent-based model (Macal & North, 2010)



According to (Macal & North, 2010), there are certain essential characteristics of an agent in the ABM (Figure 3.2). First, an agent is self-contained and uniquely identifiable individuals with certain attributes that can be static, not changeable during the simulation, or dynamic, changeable as the simulation progresses. Second, an agent is autonomous and self-directed. An agent can function independently in its environment and in its interaction with other agents. An agent's behavior can be specified by simple rules or abstract models that may not be grounded in economic theory. Third, an agent has dynamic interactions with other agents that influence its behavior. Agents typically interact with a subset of other agents, referred to as the agent's neighbors. Fourth, an agent may be adaptive, which means it can adjust behavior to the current states of itself, of other agents, and of its environment. Together, an agent's characters form a heterogeneous population of agents.

Figure 3.2. A typical agent (Macal & North, 2010)



The nature of ABM constitutes a powerful tool for the modeling of complex systems with heterogeneous entities and nonlinear relationships and interactions such as feedback, learning, or adaptation. In that light, ABM is a useful method for the examination of climate change-migration linkage. Climate change-related migration is non-linear and is based on a complex adaptive system. In that sense, ABM is a suitable tool for the simulation of the behavioral responses of individuals/households to climate change scenarios and other social variables. The essential step in such simulation is to hypothesize the rules of behavior that lead to migration decision in a context of multiple stimuli; using those rules, a computer simulation can allow integration of the sensitivity of the migratory process to climate variabilities and other contextual parameters (Piguet, 2010).

Model evaluation of reliability in a statistical sense involves model calibration and validation. Model calibration is the process of fitting all variables of the model into real-world data. Model validation means assessing model output in terms of uncertainty, variability, and sensibility. Bruch and Atwell (2015) identify three sources of uncertainty and variability in

ABM: input uncertainty, model uncertainty, and stochastic variability. Input uncertainty arises due to incomplete knowledge of model input parameters. Model uncertainty arises because the model typically requires some set of unverifiable assumptions about key parameters, processes, or social interactions. Stochastic variability is the variation in model estimates that occurs as a result of randomness within the model (Bruch & Atwell, 2015). In this study, the model evaluation takes into account uncertainty inputs and stochastic variability by means of sensitivity analyses and historical data validation through comparison of model output to the real data (see section 3.5).

Grounding the ABM on empirical measures further improves the validity of the model results (Holm, Lemm, Thees, & Hilty, 2016; Rai & Robinson, 2015; Zhang, Gensler, & Garcia, 2011). The need for an empirical basis is essential if the main objective of the ABM is the study of real-world phenomena, predictive modeling, or policy evaluation (Bruch & Atwell, 2015; Rai & Robinson, 2015). Rai and Robinson (2015) argue that ABM's descriptive, explanatory, and predictive power can be enhanced by grounding the agent states, decision rules, and environment variables in empirical patterns. Empirical measures are frequently used to initialize the simulation, parameterize ABM, or evaluate model validity. In this study, the empirical measures used are census data and CE dataset. CE dataset is used to specify agent behavior and agent states, while census data are employed to incorporate population characteristics and calibrate the model output. Details of the datasets will be discussed in session 3.3.3.

3.3.2 Agent-based model incorporating choice experiment methodology

The integration of discrete choice models and agent-based modeling has recently attractive research interest, notably in the fields of transportation (Le Pira et al., 2017), the wood market (Holm et al., 2016), and solar PV (Araghi, Park Lee, & Bollinger, 2014). It could be argued that ABM and CE are complementary. By combining the two approaches, researchers can take advantage of the strength of the two methods, while at the same time addressing their weaknesses. While the CE method is a powerful tool for supplying a micro foundation for behavioral components, it can only provide static estimations: it cannot control dynamic factors in a decision-making process. On the other hand, the ABM approach offers dynamics to complement the static results of CE; however, it lacks micro-foundations for behavioral components. Therefore, the integrated modeling framework discussed above allows the evaluation of agents' behavior, taking into account their heterogeneous preferences and their interactive behavior (Le Pira et al., 2017). CE model is appropriate for the treatment of heterogeneity of individuals' preferences, while ABM is suitable for capturing interactions and dynamics in preferences.

In research in the climate-migration field, the CE method facilitates the widespread use of ABM in the modeling of climate change-induced migration. First, CE provides an empirical basis for ABM of environmental migration. Modeling migration behavior induced by climate change requires input data on the migration preferences of individual agents in response to climate conditions. Adopting the model for use in prediction poses significant challenges because data on behavior change under variabilities of climate change phenomena are required. Data covering such a wide range of environmental evolution and migration behavior are often not available in reality. Therefore, CE is an effective alternative for the collection of the required data and fostering the use of ABM in predictive modeling.

Second, random utility theory, a well-established behavioral economic theory, supports ABM modeling of migration decisions. Klabunde and Willekens (2016) argue that, along with the theory of planned behavior, random utility theory is one of the most commonly used behavioral theories in the ABM of migration. Models that are grounded in theory have the advantage that they can go beyond extrapolation in predicting how agents will react to drastic changes in their conditions (Klabunde & Willekens, 2016). Third, CE has the potential to relax the disciplinary barriers that have been identified as limitations of the use of agent-based modeling of migration (Klabunde & Willekens, 2016); Gray (2010). For example, CE design enables the inclusion of social networks as a decision-making context, which is an important element of the theory of planned behavior.

Fourth, migration intention derived from the CE model is a good source of the projection of migration flows. Past reviews of migration projection reveal the inherent uncertainty about future migration flows resulting from poor quality data, poor availability of historical migration, and the complexity of migration processes (Tjaden, Auer, & Laczko, 2019). Survey data on migration intention has been shown to be a proper candidate for integration into migration forecasting models. Indeed, quite a few studies confirm that migration intention is a relevant predictor of future realized migration (Creighton, 2013; De Groot, Mulder, & Manting, 2011; De Jong, 2000; Docquier, Peri, & Ruyssen, 2014; M. Lu, 1999; Van Dalen & Henkens, 2008; Van Dalen & Henkens, 2013). For example, using the national American Housing Survey, M. Lu (1999) found that 44 percent of individuals who expressed mobility intentions actually moved within two years. Van Dalen and Henkens (2008) examined survey data for the Netherlands and found that 24 percent of those who had stated an intention to emigrate have actually emigrated within two years' time.

A frequently raised question is whether preferences elicited from stated choice experiments are reflected those driving actual behavior. In other words, to what extent are people's responses to hypothetical questions in CEs (or other similar methods) reflected in their realized actions? Although migration intentions derived from stated choice experiments are not perfect predictors of subsequent moving behavior, studies have shown that those stated preferences can explain actual migration decisions. Lagakos, Mobarak, and Waugh (2018) conducted a discrete choice experiment in Bangladesh to estimate the relative weights of migration determinants and validate their model inferred from people's actual migration using the DCE results. Moreover, Bah and Batista (2018) compared experimental data and revealed data from a follow-up survey and reported that intentions to migrate, collected from a lab-in-the-field experiment, correlated strongly with eventual decisions.

The measurement of mobility intention and the size of the discrepancy between migration intention and actual moving behavior are two things that need to be carefully considered when integrating migration intention into the migration-forecasting model. In the first step, intention to migrate should be modeled to best predict behavioral outcomes because problems in the measurement of mobility intentions explain part of the behavioral inconsistency (M. Lu, 1999). In that sense, our CE, which was designed and implemented based on a thorough process of literature and historical data review and piloting, can capture the key determinants of the migration process and thus account well for people's migration intention. Moreover, as pointed out by M. Lu (1999), mobility intention is subject to changes accompanying the factors that shape it. Therefore, our ABM, which offers dynamics for migration attributes, can provide a useful framework for modeling migration intention. It then becomes necessary to measure the size of the discrepancy, or the correlation between intention and realized action, so as to capture the transfer from intention to moving behavior. In this study, that measurement is achieved through calibration using historical migration data.

The procedure for using the CE model to characterize agent behavior will be discussed in detail in session 3.4. In short, the rules and parameterization of ABM are empirically derived from models of the CE. Significant variables from the CE model can be applied to characterize agents, assigning them a corresponding utility function for the evaluation of choice options, i.e., agents make decisions based on the individual characteristics and attributes of the alternatives, where the decision model of the agent is based on random utility theory.

3.3.3 Study area and data collection

3.3.3.1 Study area

In order to investigate rural-urban migration out of the VMD, this study focuses on the rural population in VMD provinces except for Can Tho city. We drop Can Tho city from our simulation given the fact that Can Tho is a city that has a large share of the urban population (i.e., 70 percent of the city population are urban residents). Other provinces have substantial proportions of the rural population, where rural residents range from 68 to 90 percent of the total population.

3.3.3.2 Data collection

In this study, we employ two sources of empirical data, including our survey-CE data and the census data. The details of our survey and CE dataset were explained in the previous chapter 2. Therefore, this session will provide details on the census data.

General Statistics Office of Vietnam (GSO) [18] and its publications, including Vietnam Household Living Standards Survey (VHLSS) 2016, Vietnam Statistical Yearbook 2019, and Vietnam 2019 Population and Housing Census, provide the data on migration flow rates and socioeconomic characteristics of the population. The data content, level of data, unit, and time frame are listed in Table 3.1. Other required data such as climate change impact data and scenarios or Vietnam population aging are obtained from published sources that will be cited in the following sections.

[18] General Statistics Office of Vietnam (gso.gov.vn)

Table 3.1. Data titles and details

Titles	Level of data	Units	Time frame
Household size by income quintile and province	Provincial, regional	Persons	2006 - 2016
Average (rural) population by province	Provincial	Thousand persons	2015 - 2019
Monthly average income per capita in 2019 at current prices by income quintile and by province	Provincial	Thousand dongs	2019
Monthly income per capita by income quintile and province	Provincial	Thousand dongs	2006-2016
Structure of household head by sex	Regional	Percentage	2008 - 2016
Structure of economically active population in working age by age group	Regional	Percentage	2006 - 2016
Structure of household size	Regional	Percentage	2009 & 2019
Annual growth rate of number of households	National	Percentage	1999, 2009, & 2019
Migration rates of cities and provinces in the VMD provinces	Provincial	‰	2005 - 2019

3.4 Model Design

3.4.1 Model description in ODD+D format

This section describes the model according to the Overview, Design, and Details protocol (ODD+D) (Müller et al., 2013), which is an extension of the ODD protocol (Grimm et al., 2006; Grimm et al., 2010). This standard protocol has been widely used to describe ABMs (Railsback & Grimm, 2019). The aim of ODD+D is to provide the reader with a basic understanding of how human decision-making is modeled. A detailed discussion of key design choices is provided after the basic outline in subsequent sub-sections.

3.4.1.1 Overview

Purpose

The purpose of this study is to build a model that can predict the volume of migration out of the rural VMD over time in response to the impacts of climate change. This model focuses on cumulative migration flows under different climate change scenarios and life course dynamics.

Migration factors and individuals' preferences on each factor are obtained by a choice experiment implemented in the VMD. The rules and parameterization of the model are empirically derived from models of the CE.

Entities, state variables, and scales

<u>Entities:</u> the model includes agents representing households in original areas (VMD provinces). Migration decision is assumed to be made as to the household decision. Agents can be connected through links, including migration networks at the potential destination and neighbors at the original area.

<u>State variables</u> (by what attributes are these entities characterized?)

Agents have the following attributes:

- Age: discrete numeric [20,75]
- Income (Logarithm of income per capita - loginc_cap): continuous numeric

- Household size (hhsize): discrete numeric [2, 6]
- Current migration (current_migrant) : discrete numeric [0,1]
- Migration experience (Whether the respondent has prior migration experience - exper_migr): binary (yes, no)
- Hazard experience (Whether the household has been seriously affected by climate change phenomenon - hazard_exper): binary (yes, no)
- Network at destination (network): binary (yes, no)
- Neighbors' migration decision (whether many or few neighbors of the respondent have migrated – neighbor): binary (many, few)
- Gender: binary (female, male)
- Risk attitude index (Willingness to take risks – RA_agri): discrete numeric [0, 10]

<u>Exogenous factors</u>

- Drought (severity of annual drought at the original area): categorical (no, moderate, severe)
- Flood (frequency of annual major flood at the original area): continuous numeric [0, 1]
- Crop restrictions: categorical (no, partial, total)
- Income gap (between rural area (origin) and city (destination)): continuous numeric

In this simulation, exogenous factors can change over time. One time step represents one year; simulations were run for 30 years.

Process overview and scheduling

The model includes the following actions that are executed in this order each time step.

Decision involvement (classification of move and never-move people). There is evidence showing that some people will not move in any scenario (we call them the never-move group). In this model, demographic characters and previous experiences on climate change and migration are used to separate them out, employing a Latent Class Model. Migration intention is made only within the move people, but not within the never-move people. Each time step, the classification of the two groups is recalculated based on updated values of covariates explaining class membership.

Migration intention. The agents express their intention to migrate for each scenario at a specific time interval based on the predicted probabilities. The predicted probability of each outcome for each agent (i.e., definitely stay, probably stay, probably move, definitely move) are calculated employing the CE model's parameters and attributes. The realized choice is made using a multinomial selection that considers the estimated utilities of all alternatives and samples one of them according to the probability p(i).

Migration decision. Parts of the agents that have intentions to move will actually move in the simulation. Calibration using historical migration data is employed to specify the proportions, or in other words, the gap between migration intention and actual movement.

All details of agents' decision-making rules, including decision involvement, migration intention, and migration decision, will be discussed in Section 3.4.2.

Update-network. Each migrant (the agent who chose to migrate) becomes a migration network for a proportion of people of the same origin (in this model, people who come from the same community[19]). People at the origin update their network status based on the migration decision in each time step. The process of define and update network attributes is provided in Section 3.4.5.1.

Update-neighbor. The number of neighbors who have moved is updated every time step. Accordingly, the status of 'neighbor' attribute is updated (i.e., few or many). The neighbors of an agent are those agents who come from the same community as him/her. More details will be discussed in Section 3.4.5.2.

Reproduce (Population growth): A random proportion of the agents generate new agents (households). The new agent inherits attributes from the parent agent except for age, household size, and gender (random gender). The new agent has a relatively small household size ([2,4]) and is at a young age ([20,30]) since they are a new household. The rate of reproducing is based on the annual growth rate of the number of households at a national level, which is fixed at 1.8%.

Aging and dying. The age of all agents is incremented every time interval. In order to capture the situation of population aging in Vietnam over the simulation period, we assign mortality rates for each age group. Mortality rates and prediction of Vietnam population aging are obtained from published sources (see Section 3.4.9). Agents are assumed to die at the age of 75. This does not mean that those agents die physically but means they will not consider migrating.

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[19] Agent's community is defined by blocks in the provincial population. More details will be presented in Section 3.4.3, which explains the process of populating agents.

3.4.1.2 Design concepts

Theoretical and empirical background

The decision model of the agents is based on random utility theory, which is one of the bases of models and theories of decision-making in psychology and economics. According to the random utility theory, the decision-maker (i.e., agent) will select the alternative that provides the largest utility. The utility of migration decision is comprised of the deterministic component (V), and an error component (ε), which is independent of the deterministic part and follows a predetermined distribution.

$$U_{ij} = V(x_{ij}) + \varepsilon_{ij}$$

where X_{ij} is the vector of observed attributes involved in migration intention. In this model, observed attributes include CE attributes and agents' characteristics.

The utilities are obtained from the CE model. The details of the econometric specification and CE design are demonstrated in the previous chapter in section 2.3.4. The reduced form of the CE model is:

Intention to migrate

= *f* (CE attributes, individual characteristics, CE attributes * individual characteristics)

Adaptive behavior. How do agents make decisions and change their state in response to changes in their environment and themselves?

The adaptive behavior can happen for agents who are not currently considering migration. This happens through updating agents' networks, neighbors, and age. Each time step, the utility function (i.e., predicted probability) is recalculated with those updated values, and then, the agents who choose to stay at the previous iteration decide whether they stay or migrate from the current iteration.

Learning. Do individuals change their adaptive traits over time as a consequence of their experience?

Learning is not included in the model.

Prediction. How do agents predict future conditions in their adaptive trait? What assumptions or mechanisms were the basis for how prediction is modeled?

In this model, individuals know about future conditions. Climate change scenarios (frequency and intensity of drought and flood), policy (crop restriction), and individual profile (e.g., income) can vary over time.

Sensing. What variables of their environment and themselves are agents assumed to sense and therefore be able to consider in their behavior?

Agents are assumed to sense their own state variables, climate change scenarios, and policy on crop restriction without error. They also know migration decisions (migrate or not) and migration experience of their current migration network and neighbors.

Interaction.

There is an interaction between migrants (people who choose to move) and other agents who have the same origin. Agents in origin know the migration status of all people in their neighborhood area and will update their migration network to 1 (i.e., having a network) if they are connected to any migrant in the destination.

There is an interaction between agents in the same block. An individual knows migration experience and migration decisions of other people in his block and updates neighbor attributes according to the number of migrants in the block.

There is an interaction between parent and offspring household. Offspring households share parents' attributes except for age, gender, and household size.

Stochasticity. (How are stochastic processes (based on pseudorandom numbers) used in the model, and why?)

The following processes include random components:

- Agents are placed at random locations when the model is initialized. Since each agent has attributes to present their original area (i.e., block, province), agents' locations shown in the interface (map) are not necessary.
- Random numbers draw to assign agents' status such as drought severity, flood damage, or natural hazard experience, etc., and to define migration intention. A random seed can be set to allow reproducible results. The use of random numbers will be presented in the following sections.
- Some attributes of offspring households (age, household size, gender) are randomly chosen from a fixed range.

Collectives. (Do the individuals form or belong to an aggregation that affects and is affected by the individuals?)

People in the same block (i.e., neighbor) are collective: migration experience and migration decision of people in the same village determine the value of an agent's neighbor attribute.

Observation. Results show the cumulative migration flows over time (ticks/years). The output files report the number of migrants and migration rate at each time step.

3.4.1.3 Initialization.

The model is initialized separately for 12 provinces in the VMD region according to the population size of the province. The numbers of agents for each province represent the estimated number of rural households at the end of 2019 (see Table 3.2). Each agent in the model represents 100 households and is put in a random position.

Table 3.2 Number of agents for model initialization by province

		Average household size (1)	Average rural population (2)	Number of households (2) / (1)
		Persons	Hundred persons	Hundred households
1	Long An	3.7	14226	3845
2	Tien Giang	3.7	15190	4105
3	Ben Tre	3.2	11627	3633
4	Tra Vinh	3.5	8352	2386
5	Vinh Long	3.6	8528	2369
6	Dong Thap	3.8	12941	3405
7	An Giang	3.9	13048	3346
8	Kien Giang	4.1	12349	3012
9	Hau Giang	3.7	5344	1444
10	Soc Trang	3.9	8110	2080
11	Bac Lieu	3.9	6560	1682
12	Ca Mau	3.9	9226	2365

Agents' demographic characters, including age, gender, household size, income, are assigned based on synthesized population obtained from the Iterative Proportional Fitting (IPF) method (see Section 3.4.3). Initial values of other agent's statuses are obtained based on estimations of the survey data. Details are explained in Section 3.4.8.

3.4.1.4 Input data. Does the model use input from an external source such as a data file or other models to represent a process that changes over time?

We generate a simulation data file for each province using Stata and R, and save it in comma-separated values (CSV) format. The files are then imported into the simulation software to generate agents.

Exogenous factors including flood frequency (section 3.4.4.1), drought severity (section 3.4.4.2), crop restrictions (section 3.4.6), and income gap (section 3.4.7) are obtained from published sources and imported into the simulation. Those values are allowed to vary among simulations to investigate the impacts of different scenarios of climate changes and other attributes on migration decisions. We integrate simulations of Vietnam's flood and drought risks over time to define climate scenarios. Values of drought severity and flood frequency change over time and vary across agents.

3.4.1.5 Flow map of the ABM

Figure 3.3 provides a snapshot of our ABM in terms of methodological framework and simulation process. The details of each component in this flow map will be explained in the upcoming sections (see *Table 3.3* for a brief description and navigation).

Figure 3.3. Flow map of the ABM

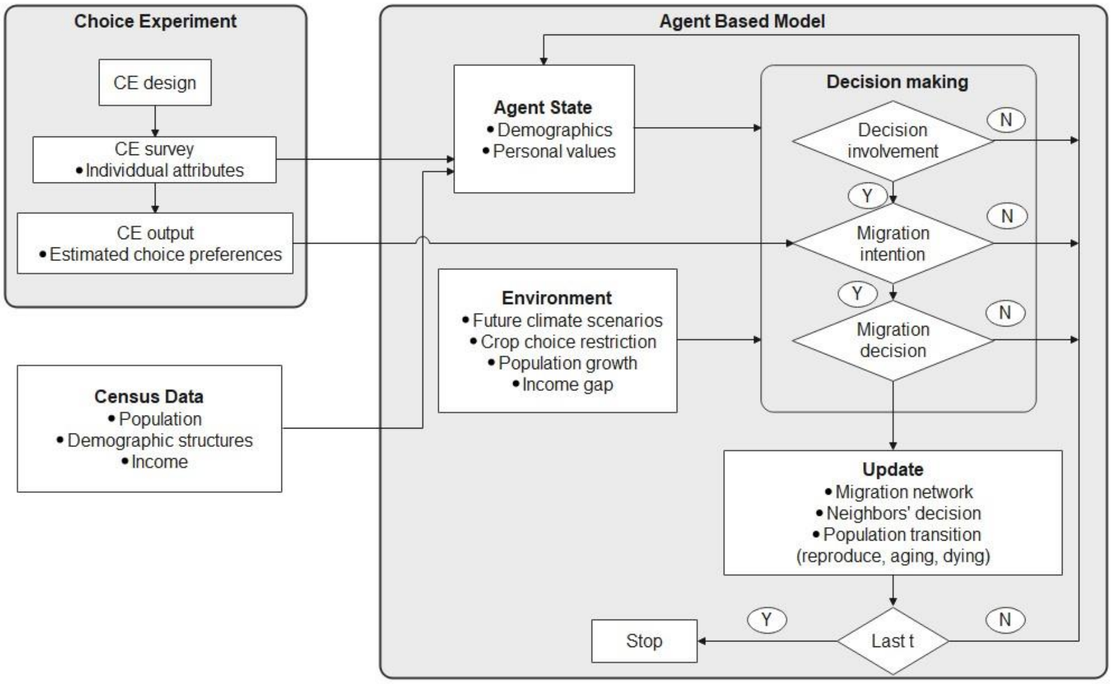


Table 3.3. Steps for model specification

Section	Problem	Solution
3.4.2	Agent decision-making rules	Latent class model, CE model, calibration
3.4.3	Populating agents	Iterative Proportional Fitting
3.4.4	Defining climate scenarios	Integrate published sources on Vietnam's flood and drought risks
3.4.5	Social feedback effects (How past migration affects current choices)	Model through migration network and neighbors' choices
3.4.6	Crop choice restriction effects	Project the impact for affected provinces.
3.4.7 3.4.8	Other agent attributes (e.g., income gap, migration experience, natural hazard experience, risk attitude)	Econometric estimations using survey data; census data
3.4.9	Population transition (e.g., growing, aging, dying)	Historical data and published population aging projection for Vietnam
3.4.11	Simulation software	NetLogo, R

3.4.2 Agent Decision-Making process

3.4.2.1 Decision involvement – Latent Class Model

Based on the survey data, we can observe that only a proportion of the sample involves in the process of migration decision-making under different scenarios; whereas, a large proportion of the sample never move under any scenario. Move and never-move[20] people seem to be significantly different in terms of age, income, migration experience, and natural hazard experience (see Table 2.6 in Chapter 2). Therefore, in this study, we employ the Latent Class model[21] with the aim of statistically separating move and never-move people in the sample. Then, the results of the Latent Class model will be used to predict and separate out the agents who will involve in the next step of the decision-making process in the ABM simulation. The process of migration intention is made only within the group of move people.

Four variables are chosen as covariates explaining class membership (see Table 3.4 for variable descriptions and the employed coding). Table 3.5 presents the conditional probabilities for each observed covariate on each class. The table shows that individuals in class 2 are likely to have less climate change experience, more migration experience, higher income, and higher age than people in class 1. This class 2 might be our hypothesized never-move people.

[20] We define never-move people being people who never choose to migrate in any scenario and move people being those who choose to migrate in at least one scenario.
[21] Latent class analysis (LCA) is used to model situations where there are different subgroups of individuals, and class membership is not directly observed. There might be covariates to explain class membership.

Table 3.4. Variable descriptions and coding

Variables	Descriptions and coding
Natural hazard experience (hazard_exper)	=1 if climate change phenomena seriously affect household's income; =0 otherwise
Migration experience (exper_migr)	=1 if having migration experience since 2000; =0 otherwise
High income (linc)	= 1 if the respondent belongs to income quintile 4 or 5; =0 if the respondent belongs to income quintile 1, 2, or 3
High age (lage)	=1 if >= 54 years old; = 0 if < 54 years old

Table 3.5. Conditional probabilities for each observed character on each class

	Class 1		Class 2	
	Margin	SE	Margin	SE
Climate change experience	0.591	0.528	0.408	0.066
Migration experience	0.409	0.183	0.599	0.188
High income	0.281	0.508	0.456	0.067
High age	2.95e-07	1.35e-06	0.491	0.764

The comparison of predicted class from LCA and survey data are demonstrated in *Table 3.6* and *Table 3.7*. We can see from *Table 3.6* that predicted class sizes are relatively matched with the proportions of never-move and move group in the survey data. The results show that the predicted class 2 can explain about 70% of the never-move people. From this result, we can label class 2 as never-move people and class 1 as move – people.

Table 3.6. Predicted and given proportion for each class

LCA		Survey data	
Class 1	Class 2	Move	Never-move
40.29	59.71	39.71	60.29

Table 3.7. Comparison of predicted latent class to the given class

	Predicted class		
Given class	1	2	Total
Never-move	68	143	211
	32.23	67.77	100
Move	73	66	139
	52.52	47.48	100
Total	141	209	350
	40.29	59.71	100

Based on the result of the latent class model, we classify each agent in the simulation into move or never-move groups by calculating posterior probabilities of class membership (i.e., individual's probability of being in each class). The calculation of posterior probabilities follows two steps as below.

i. Calculation of the probability of an agent has a specific character given she is in class m is defined by:

$$P(y_i|\eta = m) = \prod_{k=1}^{K} p_{km}^{y_{ik}}(1 - p_{km})^{1-y_{ik}}$$

where p_{km} is the probability of having character k given latent class m. Because we are using logistic regression, the marginal means are actually the predicted probabilities.

y_{ik} is observed character k of agent i (0 = no, 1 = yes)

ii. We sum up the probability of observed pattern given membership in each of classes and weight by class prevalence to calculate the posterior probability of class membership:

$$P(m_i) = \frac{\prod_{k=1}^{K} p_{kj}^{y_{ik}} \left(1 - p_{kj}\right)^{(1-y_{ik})} \pi_m}{\sum_{m=1}^{M} \prod_{k=1}^{K} p_{km}^{y_{ik}} (1 - p_{km})^{(1-y_{ik})} \pi_m}$$

where π_m is the probability of being in class m (i.e., class size).

We then generate a predicted class variable (i.e., pre-class) for each agent as the class of higher posterior probability. That is:

- P(Class_1$_i$) > P(Class_2$_i$) → Predclass = 1 (move people)
- P(Class_1$_i$) < P(Class_2$_i$) → Predclass = 2 (never-move people)

Since some observable covariates affecting class membership can change over time (e.g., age, natural hazard experience), the simulation updates the status of move and never more people every time interval.

3.4.2.2 Migration intention – CE model

This section discusses how to calculate predicted probabilities and define migration intention. Parameters of decision attributes are taken from the Ordered Logit model as presented in the previous chapter section 2.5.3. The employed regression in this chapter has two adjustments to the main CE model reported in the previous chapter (see Table *3.8* for the regression used for ABM). First, we drop the explanatory variable Drought 2016 from the CE model when integrating into ABM because we expect that the impact of the historic drought in 2016 on migration decisions will be faded and become insignificant over time. The exclusion of the drought 2016 variable does not substantially change the regression results and significant levels of other variables (see *Appendix Table 4*). Second, instead of using a dummy for province variable, we employ provincial indexes of 12 VMD provinces to account for the impact of provincial characters on migration decisions. The inclusion of the provincial index enables the generalization of the CE model to the whole VMD region[22]. The estimation of the provincial index will be presented in section 3.4.10.

Table 3.8. CE regression used for ABM

VARIABLES	Coefficients	SE
Drought_moderate	0.0405	(0.253)
Drought_severe	0.877***	(0.181)
Flood_frequency	0.506**	(0.222)
Income gap	0.457***	(0.0883)
Network	0.368**	(0.185)
Neighbour	0.348***	(0.122)
Crop_restrictions_partial	-0.145	(0.134)
Crop_restrictions_total	0.356**	(0.180)
Natural hazard experience	-0.265	(0.261)
Age	-0.0359***	(0.0128)
Income	-0.222	(0.169)
Household size	-0.281***	(0.0896)
Current migrant	0.564***	(0.158)
Migration experience	0.390	(0.302)
Province index	0.135**	(0.116)
Risk attitude	0.126**	(0.0581)
Female	-0.252	(0.238)
Drought_moderate * Hazard experience	0.673**	(0.279)
Drought_severe * Hazard experience	0.657***	(0.244)
Flood_frequency * Hazard experience	0.288	(0.227)
Income gap * Risk attitude	-0.0380***	(0.0133)
Network * Current migrant	-0.240**	(0.120)
Network * Migration experience	0.217	(0.243)
Network * Female	0.474**	(0.189)
Constant cut1	-3.065	(3.046)
Constant cut2	-2.660	(3.047)
Constant cut3	-1.520	(3.054)

Robust standard errors in parentheses; Clustered at household level
*** p<0.01, ** p<0.05, * p<0.1

[22] Because our sample contains two provinces, the use of province index, in general, does not change the magnitude and significant level of other model variables.

There might be arguments concerning the validity of the CE model when being generalized to the whole VMD region. However, there are reasons supporting the generalization of the CE model to the whole region. All 12 VMD provinces belong to one economic region and share the same livelihoods, cultural factors, and natural conditions, etc. Over the last decade, aquaculture has become more popular in some VMD provinces since drought and saline intrusion exert considerable impact on rice production. We, therefore, pay attention to investigate whether different livelihoods (rice and aquaculture in this case) provoke different migration preferences. Our analysis of the survey data shows that there is no significant difference in behavioral responses between rice and shrimp farmers (see Appendix 3.1 for details of the analysis). In addition, different characteristics among provinces that may significantly influence migration decisions can be captured by provincial index variable and income variable in our CE.

An agent’s migration intention is transformed into a value between 1 and 4 presenting to each outcome (i.e., 1- definitely stay; 2 – probably stay; 3 – probably move; 4 – definitely move) using the Ordered Logit framework. In particular, an agent's predicted probability of each outcome (i.e., p1, p2, p3, p4) is determined as follow:

$$P(Y_i = 1) = 1 - \frac{\exp(X_i\beta - \kappa_1)}{1 + [\exp(X_i\beta - \kappa_1)]}$$

$$P(Y_i = j) = 1 - \frac{\exp\left(X_i\beta - \kappa_{j-1}\right)}{1 + \left[\exp\left(X_i\beta - \kappa_{j-1}\right)\right]} - \frac{\exp\left(X_i\beta - \kappa_j\right)}{1 + [\exp\left(X_i\beta - \kappa_j\right)]}$$

$$j = 2, \dots, M - 1$$

$$P(Y_i = M) = \frac{\exp(X_i\beta - \kappa_{M-1})}{1 + [\exp(X_i\beta - \kappa_{M-1})]}$$

where κi is the cut point; M is the number of choices

In order for agents to make a realized choice, these probabilities must be transformed into actual decisions. Currently, two methods are implemented that are (i) multinomial selection, which considers the estimated utilities of all alternatives and samples according to the probability p(i), and (ii) best-response selection which selects the alternative with the highest estimated utility. In this study, we employ the first approach since sampling from predicted probabilities incorporates a random component into the choice process, which is consistent with the specification of discrete choice models (Bruch & Atwell, 2015; Hörl, Balać, & Axhausen, 2019). This approach assures the choice selection describing the likelihood of all choices jointly. Accordingly, we suggest a process to define the migration intention of each agent at one time step as below.

In each period, a random number between 0 and 1 is generated for each agent (i.e., p).

- If p is between [0, p1], agent migration intention is defined as 'definitely stay'.
- If p is between [p1, p1+p2], agent migration intention is defined as 'probably stay'.
- If p is between [p1+p2, p1+p2+p3], agent migration intention is defined as 'probably move'.
- If p is between [p1+p2+p3, 1], agent migration intention is defined as 'definitely move'.

3.4.2.3 Migration decision

As discussed previously, there are discrepancies between migration intention and migration realized movement even when the measurements of migration intention were implemented to best predict migration decisions. In this section, we propose a transition process from migration intention to migration decision by setting the probabilities of a successful migration from intention and calibrating the model to fit the historical migration data.

One essential step before calibration is that we need to convert household migration rate to individual migration rate. Because one agent in our ABM represents one household, decision-making in the simulation results in household migration rate. Without the consideration of individual movements among households' migration decisions, resulted migration rates will be overestimated and not comparable with the historical migration rates. Within the scope of our current ABM, we base on proportions of individual, accompanied, and whole-household migration obtained from historical data to propose a calculation to convert the simulated household rate to individual rate. Although this process may not capture migration decisions at individual levels, in the aggregate, the simulated results reflect migration rates at individual levels and are comparable with the official historical data.

The process goes through two steps. First, we need to make the assumption of the proportions of individual and whole-household movements out of total movements. According to the 2015 National Internal Migration Survey (GSO, 2016), 61.7% of the migrants traveled alone, and about 31.4% of the migrants went with family members[23]. For simplification, we consider only individual and whole-household movements in this simulation. Therefore, the percentage of whole-household migration is expected to be smaller than the percentage of the migrants moving with family members reported in the National Internal Migration Survey. We assume that 15% of the migration decisions are whole-household migration, and the rest

[23] The rest, 6.9% are accompanied by other persons.

is individual migration. Suppose that we have N households, and n households decide to migrate, resulting in the household migration rate being $n/_{N}$. Then, we calculate the individual migration rate being equal to $0.376\, n/_{N}$. The details of the calculations are presented in Table 3.9.

Second, we choose proportions of successful movements that best fit the historical data. The Root Mean Square Error (RMSE), which measures the squared differences between simulated values and reference values, is chosen to measure the deviation of model outputs with respect to real data. The comparison of simulation results and the actual migration is presented in section 3.5.2. We select proportions of successful movements that returns the smallest RMSE value, which are:

- 100% of agents who intend definitely stay or probably stay will stay
- 30% of agents who intend probably move will move
- 60% of agents who intend definitely move will move

Using the result from step 1, we calculate the probabilities of migration intentions that will lead to realized movements at an individual level. The calculation process and results are shown in Table 3.9. It should be noted that changing the probabilities would change the fit to the historical data.

Table 3.9. Converting household migration to individual migration

I. Calculating individual migration rate		
Number of individuals (1)	Number of migrants (2)	Migration rate = (2)/(1)
N * 3.75[24]	= 0.15 * n * 3.75 + 0.85 * n = 1.4125 n	$= {1.4125\text{n}}/{3.75\text{N}}$ $= {0.376\ \text{n}}/{\text{N}}$
II. From migration intention to individual migration decision		
Migration intention	Migration decision (households)	Migration decision (individuals)
Probably move (C3)	30% of who decided to probably move will move = 0.3 * C3	= 0,3 * C3 * 0.376 = 0.1128 C3
Definitely move (C4)	60% of who decided to definitely move will move = 0.6 * C4	= 0.6 * C4 * 0.376 = 0.2256 C4

3.4.3 Populating ABM

This section describes the process of populating agents for our ABM. In this section, we will explain the rationale of using the IPF method, IPF process, and results of populating agents in terms of age, household size, income, and gender. Initialization and update rules of other agent attributes are presented in the following sections.

3.4.3.1 How to define agents' demographic characteristics

In a case study context, researchers have multiple but incomplete sources (i.e., census data, survey, field observations, and remotely sensed data) available to define population attribute values. The first approach is using survey data. Survey data is relatively straightforward to

[24] Average household size of VMD provinces is 3.75

define agents because it contains the joint distribution of agent attributes. Few studies base on rich survey data to present the population of a province/city/country, which is called population-wide household level empirical initialization (e.g., (Entwisle et al., 2016), (Rai & Robinson, 2015)). However, such rich and representative survey data is rare or difficult to collect. In many ABM studies, survey data is a relatively small sample; therefore, the scope of those ABMs is limited and cannot be generalized.

The second approach is using population (census) data to initialize agents (e.g., (Hassani-Mahmooei & Parris, 2012; H. K. Nguyen et al., 2018)). A key challenge in initializing agent-based models using census data is adapting the aggregated or discrete nature of these data to a more finely grained context since census data typically do not contain the full joint distribution of household or population traits (Bruch & Atwell, 2015). In addition, Bruch and Atwell (2015) argue that continuous attributes are often collapsed into discrete categories, challenging the identification of population in small geographical units where available information is very few and commonly collapsed into categories. Therefore, in the studies that employ census data, the analyst may assume an arbitrary distribution of agent attributes. Nevertheless, in many studies, large amounts of disaggregated data with detailed information for the observations are required.

The third approach is combing survey data and census data to generalized microdata to the target population. There are well-developed methods for converting a set of incomplete marginal tables into a full table when the joint distribution of variables is known from a separate source. The most common method for generating individual-level data from incomplete aggregated census data is Iterative Proportional Fitting (IPF) (Bruch & Atwell, 2015). IPF is a mathematical scaling procedure that can be used to ensure that a two-dimensional table of data is adjusted so that its row and column totals agree with constraining row and column totals obtained from alternative sources. IPF acts as a weighting system whereby the original table values are gradually adjusted through repeated calculations to fit the row and column constraints (Norman, 1999). In other words, IPF can be used to adjust disaggregated data (i.e., survey data) to aggregated data (i.e., census) using a weighting process. Then the seed matrix values are set based on survey data joint distribution. Given the advantages of the IPF method, we adopt this approach to initialize agents in our ABM.

3.4.3.2 IPF for Kien Giang province

In this section, we provide the details of the IPF process and results for one VMD province, Kien Giang. The same processes are applied for the rest 11 VMD provinces. Here, we use IPF to fit the cross table of survey data to four constraints (i.e., age, gender, household size, and income) derived from the census data. This four-dimension application is implemented using 'mipfp' in R, a fast and versatile package designed for the multidimensional implementation of IPF.

A cross-tabulation of the survey data of four age groups, five income quintile groups, two household size groups, and gender (Table 3.10) can provide the initial seed values for IPF in these four dimensions. One can realize that there are four 'zero' cells in the seed table. Having "too many" zero-cells in the seed table may prevent convergence and lead to accordingly zero-cells in the estimated table (Lomax & Norman, 2016; Suesse, Namazi-Rad, Mokhtarian, & Barthélemy, 2017). After further analysis, we accept this level of zero-cells in the seed table, given that those zero-cells are small in quantity and not undesirable (see Appendix 3.2 for more information).

Table 3.10. Survey data - Four-way table

		HH size 2-4						HH size >=5					
Gender	Age_cat	Inc1	Inc2	Inc3	Inc4	Inc5	Total	Inc1	Inc2	Inc3	Inc4	Inc5	Total
Male	<35	2	3	4	4	0	13	2	2	3	4	2	13
	35 to 44	5	5	10	5	9	34	5	3	7	4	6	25
	45 to 54	6	9	6	6	12	39	14	13	8	8	2	45
	>= 55	5	5	7	5	16	38	10	11	5	10	5	41
	Sum	18	22	27	20	37	124	31	29	23	26	15	124
Female	<35	1	1	2	0	2	6	1	2	2	1	1	7
	35 to 44	2	4	6	4	6	22	3	2	5	2	2	14
	45 to 54	2	5	1	5	3	16	7	3	6	4	0	20
	>= 55	2	1	1	3	4	11	3	1	1	1	0	6
	Sum	7	11	10	12	15	55	14	8	14	8	3	47

The constraints are then obtained from census data (see *Appendix Table 5* for details of statistics and data sources). In particular, the number of households by age group (row totals), income group (column totals), gender group (slice totals), and household size group (stack totals) are known but not the cross-tabulation between these four variables (*Table 3.11*). The seed is adjusted and constrained to the available totals (i.e., first by age, then income, then gender, and finally household size) until convergence. The IPF result presumes that the same interaction between the dimensions exists at the disaggregated level as at the aggregated level (Table 3.12).

Table 3.11. Census data for Kien Giang- Total sum of row, column, slice, and stack (Unit: hundred households)

Age	Total	<35	35 to 44	45 to 54	>=55	
	3012	1108	870	822	211	
Income	Total	Inc1	Inc2	Inc3	Inc4	Inc5
	3012	603	603	602	602	602
Gender	Total	Male	Female			
	3012	2196	816			
Household size	Total	2-4	>=5			
	3012	2172	840			

The simulation for Kien Giang province is then initialized with 3012 households based on the synthesized population obtained from the IPF method. An agent's age is a uniformly distributed random value within the range of his/her age group. Household size of each category is the average value obtained from the survey data. Income of an agent is the logarithm of income per capita of the corresponding quantile at the provincial level by the end of 2019. The population is divided into a number of blocks representing for agents' community where they can interact and share information with other agents. The number of blocks varies across provinces according to their population. One block consists of about 100 agents.

Table 3.12. IPF results for Kien Giang province

		HH size 2-4						HH size >=5					
Gender	Age_cat	Inc1	Inc2	Inc3	Inc4	Inc5	Total	Inc1	Inc2	Inc3	Inc4	Inc5	Total
Male	<35	109	136	146	184	0	575	43	36	43	73	38	233
	35 to 44	82	68	109	69	128	456	32	16	30	22	34	134
	45 to 54	77	96	52	65	135	425	71	55	27	34	9	197
	>= 55	19	16	18	16	54	123	15	14	5	13	7	54
	Sum	287	316	326	333	317	1579	162	121	106	141	87	617
Female	<35	42	35	56	0	73	206	17	27	22	14	14	95
	35 to 44	25	42	50	42	66	225	15	8	17	8	9	57
	45 to 54	20	41	7	41	26	135	27	10	16	13	0	66
	>= 55	6	2	2	7	10	28	3	1	1	1	0	6
	Sum	92	120	115	91	175	593	62	46	55	36	23	223

3.4.4 Climate scenarios

To define climate scenarios over the simulation period, we integrate published sources on the VMD's flood and drought risks in the present and in the future (i.e., 2050). Two variables constituting climate change scenarios are matched with our CE model, which is annual flood frequency and drought severity (i.e., none, moderate, and severe). Future scenarios are determined based on the Representative Concentration Pathway (RCP), which is a greenhouse gas concentration trajectory adopted by the Intergovernmental Panel on Climate Change (IPCC). The intermediate scenario (RCP 4.5) and the worst scenario (RCP 8.5) are chosen for analyses.

3.4.4.1 Flood frequency

This sub-section explains the process of estimating flood frequency index and constructing flood scenarios for simulation. In particular, flood frequency of province i at time t (i.e., present or future) is calculated as follow:

$$\text{Flood frequency}_{it} = (\text{flood vulnerability}_{it} * \text{flood hazard frequency}_{t})$$

1. <u>Flood vulnerability</u>

In this study, we employ the assessment of flood risk across VMD provinces conducted by Wassmann et al. (2019) to define the present flood vulnerability index for each province. Wassmann et al. (2019) is selected because their definition of risk level is relevant to our study, which is the percentage of the rice area being exposed to the flood risk. Moreover, the findings by Wassmann et al. (2019) are relatively consistent with the findings of other available studies[25].

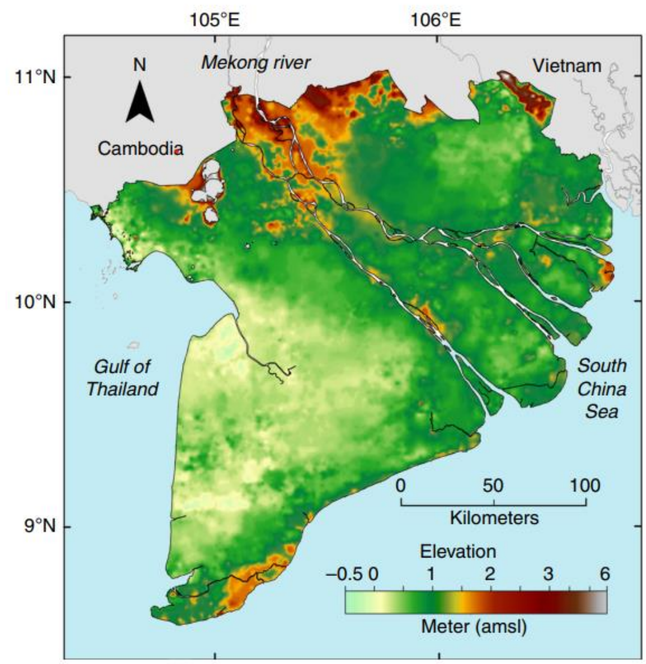
Wassmann et al. (2019) use various data sources ranging from land use, cropping map, canal network to hydrological data for the development of a hydrological model and mapping method to provide a comprehensive flood risk assessment for the VMD region. They group VMD provinces into four categories with distinct flood risk intensities and characteristics (Table 3.13). In general, upstream and further inland provinces have higher flood risk than coastal provinces, in which two provinces that face the highest flood risk are An Giang and Dong Thap. Coastal provinces such as Bac Lieu, Ben Tre, Ca Mau, Soc Trang, Tra Vinh, and Vinh Long expose to low or no flood risk. Figure 3.4 displays the sketch of flood risk across VMD provinces and their elevation for reference. We then assign a flood vulnerability index for each province based on flood risk mapping. In particular, high, intermediate, low, and no flood risk provinces are assigned the vulnerability index of 1, 0.6, 0.3, and 0, respectively.

[25] Other available studies include (Luu, von Meding, & Mojtahedi, 2019; V. K. T. Nguyen, Nguyen, Merz, & Apel, 2018; Yen, Son, Amjath-Babu, & Sebastian, 2019). We review available studies on flood and drought risk in the VMD and choose the most suitable source for integrating in our model. Appendix 3.3 provides comparison of available studies on flood and drought risk in the VMD.

Table 3.13. Groups of flood risk intensity and characteristics in the VMD

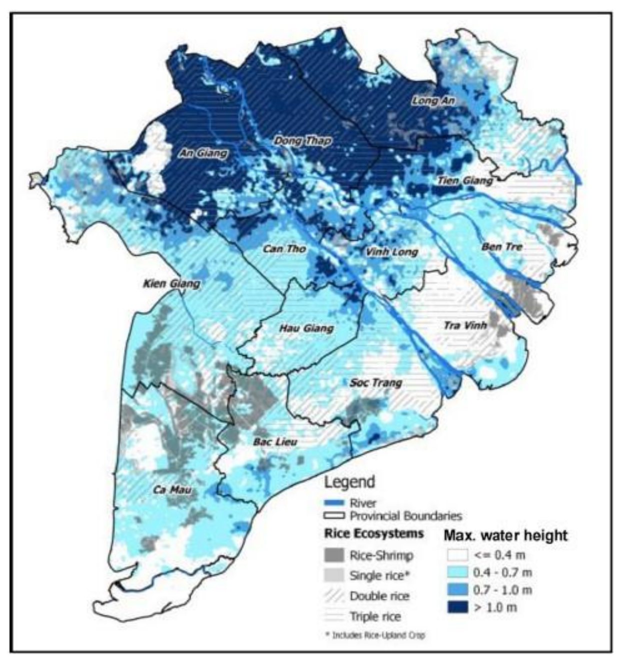
Group	Risk intensity and characteristics	VMD provinces
High flood risk	almost the entire flood risk area is also affected for prolonged periods of > three months (about 90% of the area exposed to flood)	Dong Thap, An Giang
Moderate flood risk	comprising 45–70% of the risk area	Tien Giang, Hau Giang, Kien Giang, Long An
Low flood risk	with<15% of the area exposed to flood risk	Bac Lieu, Soc Trang
None	No flood risk	Vinh Long, Tra Vinh, Ca Mau, Ben Tre

Figure 3.4. Maps of (a) the VMD elevation and (b) peak flood risk showing maximum levels of water height in high-water years



(a)

Source: (Minderhoud, Coumou, Erkens, Middelkoop, & Stouthamer, 2019)



(b)

Source: (V. K. T. Nguyen et al., 2018; Wassmann et al., 2019)

To construct future scenarios, we need to examine the possible change in flood vulnerability over time. Indeed, there is evidence showing that the flood risks are expected to be more severe in the coastal provinces because of the tidal regime (Dinh, 2016; Van et al., 2012). (Dinh, 2016) found that under a 2050 scenario with big climate change and low hydropower and land use, Ca Mau and Kien Giang will experience an 84% and 76% increase in the provincial area flooded and Ben Tre, Tra Vinh, and Tien Giang will experience 64-67% increases in the flooded area. We base on the above findings to reclassify the flood vulnerability index for those VMD provinces. Following Wassmann et al. (2019), flood risk classification is defined as below:

- Percentage of exposed area being more than 70% is classified as high risk;
- Percentage of exposed area ranging from 40 to 70% is classified as moderate risk;
- Percentage of exposed area being less than 40% is classified as low risk.

As a result, with the exception of Tien Giang, the other four provinces will change their risk levels in the future. Particularly, Ben Tre and Tra Vinh flood risk changes from none to low level; Kien Giang changes from moderate to high, and Ca Mau changes from none to moderate (see Table 3.14 for calculation details).

Table 3.14. Reclassifying flood vulnerability level

	Present percentage of flood risk area (Wassmann et al., 2019) (1)	% increase in provincial area flooded (Dinh, 2016) (2)	Future percentage of exposed area (3)	Future flood vulnerability (4)
Tien Giang	40	65.5	66.2	Moderate
Ben Tre	0	65.5	32.75	Low
Tra Vinh	0	65.5	32.75	Low
Kien Giang	52	76	91.52	High
Ca Mau	0	84	42	Moderate

Notes: For Tien Giang and Kien Giang, (3) = (1) * (1 + (2)/100));
For Ben Tre, Tra Vinh, Ca Mau, (3) = (1) + (2)/2

2. Present flood frequency from (Park et al., 2020)

Park et al. (2020) calculate flood frequency maps for the Mekong Delta during 1995-2005 and 2005-2015 using hydrological data and dyke construction and irrigation canal information from the various government reports. They found that the flood frequency of the An Giang province over the 20-year period reveals a distinct decrease. More specifically, the annual flood frequency dropped by 7.8%, from 36.7% between 1995 and 2005 to 28.9% between 2005 and 2015. It should be noted that An Giang is a province that is most vulnerable to flood hazards in the VMD region. We, therefore, set the present flood hazard index to be 0.3 for the whole VMD region, then multiply by the flood vulnerability index of each province to obtain the flood frequency index at a provincial level, as presented in Table 3.15.

Table 3.15. Present flood frequency

	Province	Present flood vulnerability (Wassmann et al., 2019) (1)		Present flood hazard (Park et al., 2020) (2)	Flood frequency (present) (3) = (1) * (2)
1	Long An	Moderate	0.6	0.3	0.18
2	Tien Giang	Moderate	0.6	0.3	0.18
3	Ben Tre	None	0	0.3	0
4	Tra Vinh	None	0	0.3	0
5	Vinh Long	None	0	0.3	0
6	Dong Thap	High	1	0.3	0.3
7	An Giang	High	1	0.3	0.3
8	Kien Giang	Moderate	0.6	0.3	0.18
9	Hau Giang	Moderate	0.6	0.3	0.18
10	Soc Trang	Low	0.3	0.3	0.09
11	Bac Lieu	Low	0.3	0.3	0.09
12	Ca Mau	None	0	0.3	0

3. Flood frequency projections from (Try et al., 2020)

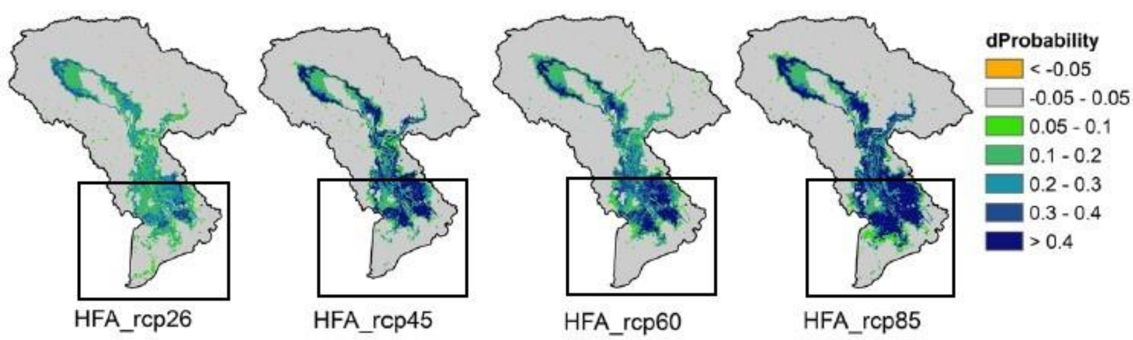
There are very few studies investigating flood frequency projections. To the best of our knowledge, (Try et al., 2020) is the only study that projects the changes in flood inundation probability from the present to the future. Try et al. (2020) employ present climate and future projected climate (2075-2099) datasets from high-resolution atmospheric general circulation models (AGCMs) to assess the effects of climate change on flood inundation in the Lower Mekong River Basin (MRB)[26]. They project the flood inundation probability, and the difference of probability of flood inundation from present to future based on based on degree

[26] The MRB is the largest river in Southeast Asia traveling across China, Myanmar, Laos PDR, Thailand, Cambodia, and Vietnam.

of GHG emission ranking from low emission (RCP2.6) to high emission (RCP8.5), namely as HFA_rcp26, HFA_rcp45, HFA_rcp60, and HFA_rcp85, respectively (Figure 3.5) .

As can be seen from Figure 3.5, the difference of probability of flood inundation from the present to future (dP) indicates a positive value for all projected future scenarios, meaning that the probability of flood inundation will increase in the future under the effects of climate change. This finding is consistent with other studies, which found that the flood extents will be increased in the Lower Mekong Basin and the VMD under future climate change scenarios (e.g. (Perera, Sayama, Magome, Hasegawa, & Iwami, 2017; Triet et al., 2020). We can also see that the change mostly occurs at the lower part of Lower Mekong Basin, where the VMD is located.

Figure 3.5. Spatial distribution of the difference of probability of flood inundation from present to future (dP) in the Lower Mekong Basin



Source: (Try et al., 2020)
VMD region inbounded in the square frame

In the VMD, the largest dP is mainly seen in its floodplain area (i.e., upstream inland provinces). A large proportion of the VMD floodplain area has dP ranging from 0.1 to 0.4 for RCP4.5 and being equal or more than 0.3 for RCP 8.5. Based on this map, we set dP by

2050 for RCP4.5 being 0.2 and for RCP8.5 being 0.3 in our simulation. Future flood frequency for each province are then estimated as below (see Table 3.16):

Future flood frequency RCP 4.5 $_i$ = (flood hazard RCP 4.5 * future flood vulnerability $_i$)

where: flood hazard RCP 4.5 = Present flood hazard + dP(RCP4.5) = 0.3 + 0.2 = 0.5

Future flood frequency RCP 8.5 $_i$ = (flood hazard RCP 8.5 * future flood vulnerability $_i$)

where: flood hazard RCP 8.5 = Present flood hazard + dP(RCP8.5) = 0.3 + 0.3 = 0.6

Table 3.16. Future flood frequency

	Future Flood vulnerability (Dinh, 2016; Wassmann et al., 2019) (1)		Future flood hazard RCP 4.5 (dP =0.2) (Park et al., 2020; Try et al., 2020) (2) = 0.3 + 0.2	Future flood frequency (RCP 4.5) (3) = (1) * (2)	Future flood hazard RCP 8.5 (dP =0.3) (Park et al., 2020; Try et al., 2020) (4) = 0.3 + 0.3	Future flood frequency (RCP 8.5) (5) = (1) * (4)
Long An	Moderate	0.6	0.5	0.3	0.6	0.36
Tien Giang	Moderate	0.6	0.5	0.3	0.6	0.36
Ben Tre	Low	0.3	0.5	0.15	0.6	0.18
Tra Vinh	Low	0.3	0.5	0.15	0.6	0.18
Vinh Long	None	0	0.5	0	0.6	0
Dong Thap	High	1	0.5	0.5	0.6	0.6
An Giang	High	1	0.5	0.5	0.6	0.6
Kien Giang	high	1	0.5	0.5	0.6	0.6
Can Tho	Moderate	0.6	0.5	0.3	0.6	0.36
Hau Giang	Moderate	0.6	0.5	0.3	0.6	0.36
Soc Trang	Low	0.3	0.5	0.15	0.6	0.18
Bac Lieu	Low	0.3	0.5	0.15	0.6	0.18
Ca Mau	Moderate	0.6	0.5	0.3	0.6	0.36

4. Integrating flood scenarios into ABM simulation

Flood scenarios are then incorporated into the ABM simulation. Flood frequency for each province (Table 3.17) is linearly interpolated from the present (2020) to the future (2050). As a result, flood frequency is identical for all agents in one province and changes over the simulation period based on two climate scenarios, RCP 4.5 and RCP 8.5. The functions to assign flood frequency to agents is presented in *Appendix Table 6*.

Table 3.17. Present and future flood frequency

	Province	Present flood frequency	Future flood frequency (RCP 4.5)	Future flood frequency (RCP 8.5)
1	Long An	0.18	0.3	0.36
2	Tien Giang	0.18	0.3	0.36
3	Ben Tre	0	0.15	0.18
4	Tra Vinh	0	0.15	0.18
5	Vinh Long	0	0	0
6	Dong Thap	0.3	0.5	0.6
7	An Giang	0.3	0.5	0.6
8	Kien Giang	0.18	0.5	0.6
9	Hau Giang	0.18	0.3	0.36
10	Soc Trang	0.09	0.15	0.18
11	Bac Lieu	0.09	0.15	0.18
12	Ca Mau	0	0.3	0.36

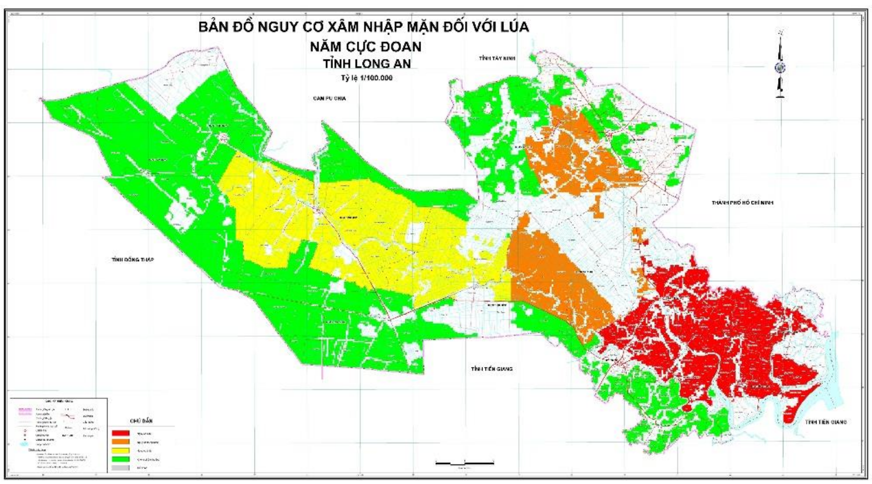
3.4.4.2 Drought severity

1. Present drought severity

Proportions of drought severity profiles are taken from (Yen, Son, Tung, Amjath-Babu, & Sebastian, 2019). Yen, Son, Tung, et al. (2019) provide maps of salinity intrusion risk for rice production in a normal year and severe year[27]. Each map illustrates affected areas and their risk levels of one VMD province (see Figure 3.6 for an example). The risk levels are defined as follow:

- High risk (red): possible loss of more than 70% of rice production
- Medium risk (orange): possible loss of 30% – 70% of rice production
- Low (yellow): possible loss of less than 30% of rice production
- Not affected (green): no impact on rice production.

Figure 3.6. Salinity risk for Long An province – Severe year



(Yen, Son, Tung, et al., 2019) is selected among available candidates because the study focuses on risks in rice areas, which is relevant to our study's scope. Furthermore, when matching with future projections, using Yen, Son, Tung, et al. (2019)'s findings results in

[27] The maps are available on Climate-Smart Maps and Adaptation Plans (CS MAP) of the 13 provinces in Vietnam's Mekong River Delta (cgiar.org).

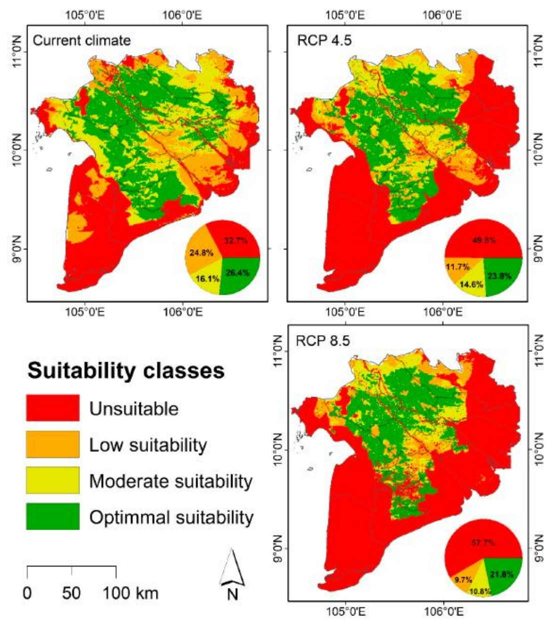
reasonable and smooth trends. In general, the risk profiles taken from Yen, Son, Tung, et al. (2019) are relatively matched with those in other relevant studies (see Appendix 3.3).

Almost all maps we took from (Yen, Son, Tung, et al., 2019) are for the severe year. The reason is that during recent years, the VMD has been continuously hitting by severe drought and saline intrusion (i.e., 2015-2016, 2019, and 2020). Many studies argue that drought and saline intrusion are becoming more severe in the VMD (e.g. (A. T. Dang, Kumar, & Reid, 2020; J.-B. Kim, So, & Bae, 2020; Thilakarathne & Sridhar, 2017)). There is one exception of Hau Giang province, which we use normal year's proportions. Using normal year for Hau Giang province is more consistent with findings in other available studies and data (see details in Appendix 3.3).

2. Future drought severity

Future drought severity is taken from (A. T. Dang et al., 2020). A. T. Dang et al. (2020) investigate the impacts of future climate change on rice cultivation in the VMD region using an ensemble-modeling approach. They provide maps of salinity and sea-level rise (SLR) risks for RCP 4.5 and RCP 8.5 scenarios of the year 2050 (Figure 3.7).

Figure 3.7. Habitat suitability of rice under climate scenarios of salinity intrusion and SLR



Based on present and future drought risks, we create drought scenarios as presented in Table 3.18. The table illustrates the proportions of drought severity levels within each VMD province at present and in the future. We can see from the table that VMD coastal provinces are seriously affected by drought and saline intrusion. In the future, more provinces will be affected by the higher severity level. Table 3.19, which presents the changes in the proportion of severe drought between present and future, provides a clearer picture of future drought impacts. We see from the table that Tien Giang, Tra Vinh, Soc Trang, Bac Lieu have the highest differences. It means that provinces facing low and moderate risk in the present will face severe risk in the future. It is consistent with findings in the literature. For example, Vu, Yamada, and Ishidaira (2018) model future saline intrusion under SLR scenario corresponding to the RCP 6.0 emission scenario and point out that Tien Giang, Ben Tre, Tra Vinh, and Soc Trang will be severely impacted by salinity intrusion in the context of sea-level rise.

Table 3.18. Present and future drought scenarios

	Province	Present (Yen, Son, Tung, et al., 2019)			Future RCP 4.5 (A. T. Dang et al., 2020)			Future RCP 8.5 (A. T. Dang et al., 2020)		
		None	Moderate	Severe	None	Moderate	Severe	None	Moderate	Severe
1	Long An	40	40	20	20	40	40	20	30	50
2	Tien Giang	50	47	3	35	5	60	15	25	60
3	Ben Tre	13	2	85	5	5	90	0	0	100
4	Tra Vinh	0	50	50	0	45	55	0	5	95
5	Vinh Long	40	55	5	20	70	10	15	65	20
6	Dong Thap	100	0	0	80	20	0	75	25	0
7	An Giang	90	10	0	65	25	10	60	30	10
8	Kien Giang	70	0	30	25	25	50	25	15	60
9	Hau Giang	70	30	0	40	60	0	30	70	0
10	Soc Trang	30	40	30	35	10	55	10	20	70
11	Bac Lieu	30	55	15	30	10	60	25	5	70
12	Ca Mau	15	5	80	0	0	100	0	0	100

Table 3.19. Changes in the proportion of severe drought between present and future

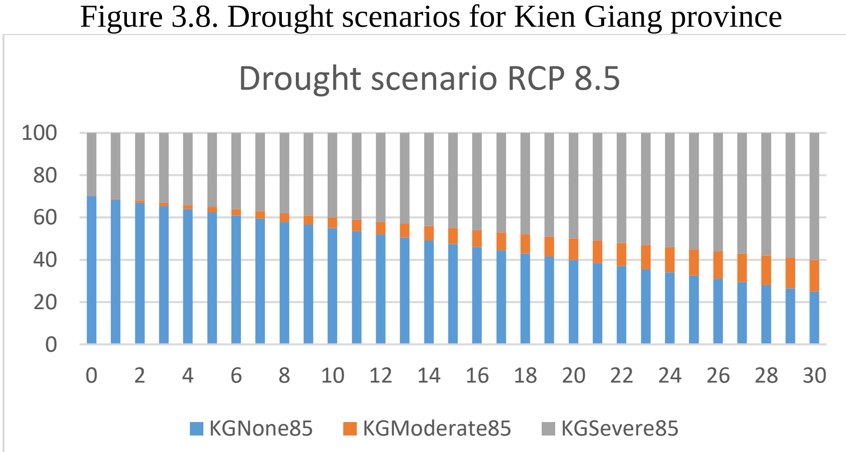
	Province	Present	RCP 4.5	(RCP 4.5 - present)	RCP 8.5	(RCP 8.5 - present)
1	Long An	20	40	20	50	30
2	Tien Giang	3	60	57	60	57
3	Ben Tre	85	90	5	100	15
4	Tra Vinh	50	55	5	95	45
5	Vinh Long	5	10	5	20	15
6	Dong Thap	0	0	0	0	0
7	An Giang	0	10	10	10	10
8	Kien Giang	30	50	20	60	30
9	Hau Giang	0	0	0	10	10
10	Soc Trang	30	55	25	70	40
11	Bac Lieu	15	60	45	70	55
12	Ca Mau	80	100	20	100	20

3. <u>Integrating drought scenarios into ABM simulation</u>

Drought severity levels (i.e., severe, moderate, none) are assigned to specific groups of agents based on drought scenarios. Over the simulation period, there are agents whose drought severity levels are changed. In order to minimize random changes in the risk level of each agent over time, we assign drought severity based on a random number between zero and one (called drought_random) that is stuck to each agent and fixed over time. More specifically, suppose we have 'a' percent of the population facing no drought impacts, 'b' percent of the population facing severe drought, and '1-a-b' percent of the population facing moderate drought. Then, the smallest 'a' percent of the drought_random are agents having no drought risk. The largest 'b' percent of the drought_random are agents having severe drought risk. The rest agents have moderate drought risk.

The proportions of severity levels are linearly interpolated from the present (2020) to the future (2050). The functions to assign drought severity to agents are presented in Appendix Table 7. Figure 3.8 below provides an example of a drought scenario over time for Kien Giang province.

Figure 3.8. Drought scenarios for Kien Giang province

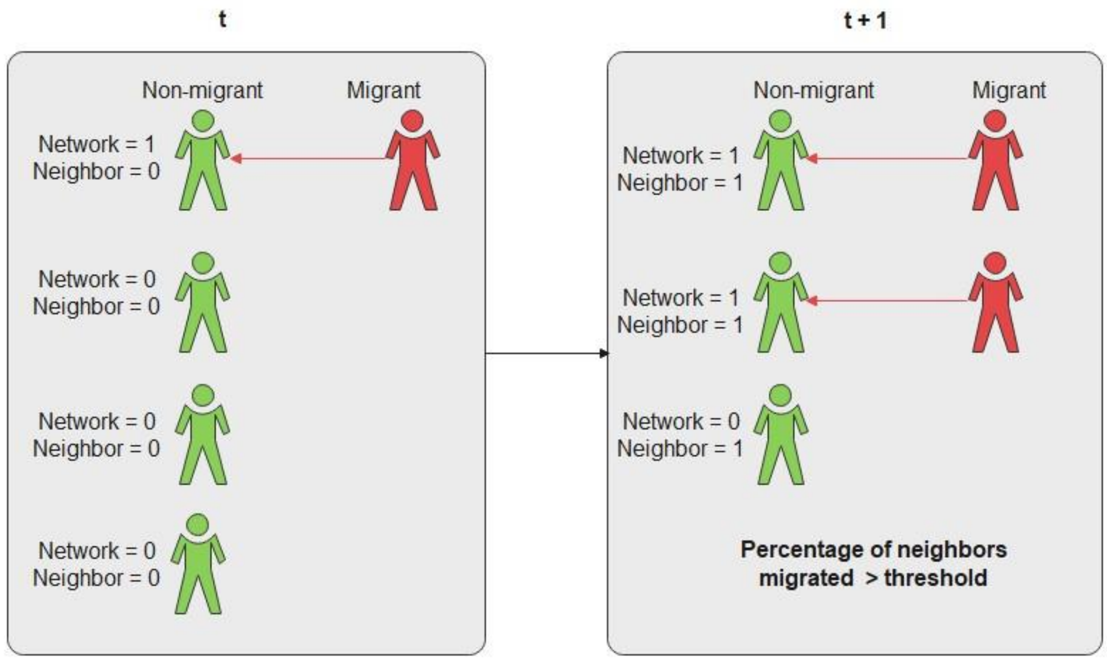


3.4.5 Network and neighbor attributes

This part investigates the endogenous feedback mechanism of the migration process through migration network and peers' decisions (i.e., network and neighbor attribute). In the literature, migration network is the most mentioned migration-facilitating feedback dynamic. In the current ABM, we additionally account for the feedback effect of the neighbor attribute given the fact that in Vietnam and especially in the VMD, friends and neighbors are important institutions of social exchange besides family ties and kinship. Incorporating feedback dynamics in the migration process is the merit of ABM. The ABM permits internal dynamics to the system over time as a result of social feedback mechanisms (C. D. Smith, 2014). As a result, we can estimate the impacts of network and neighbor attribute on future migration flows for the case of the VMD.

In this section, we discuss the process of setting up migration network and neighbor attribute in terms of initialization and updating rules. Network and neighbor attributes are updated every time step according to migration decisions. Basic descriptions are illustrated in Figure 3.9.

Figure 3.9. Network and neighbor attribute



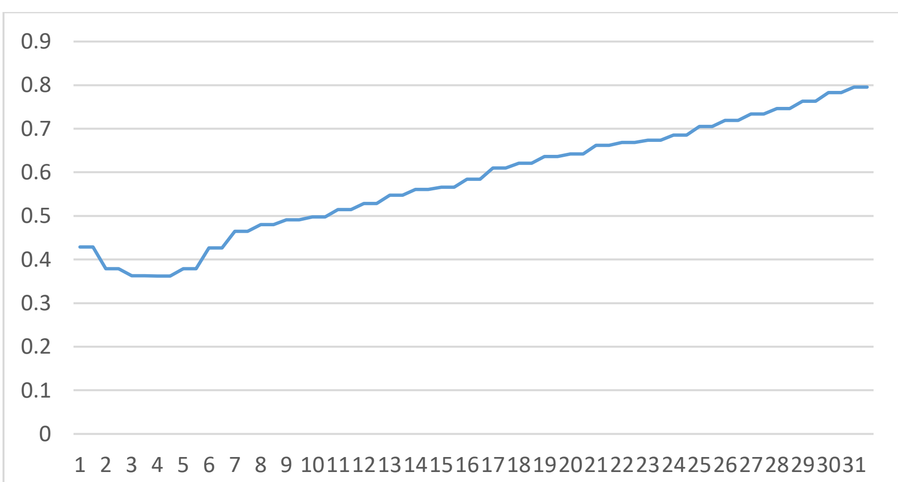
3.4.5.1 Network attribute

For initialization, a random of 40% of the population having a migration network at a potential destination. The number is chosen based on survey data in the research area. According to the survey data, around 60% of the respondents who have migration experience have some networks while migrating. For respondents who have not had migration experience, this number is expected to be lower. Therefore, for the whole population, it is assumed that 40% of the population has some migration network.

In the simulation, each migrant will create a migration network for a certain number of people who come from the same block. More specifically, at each time step, the migrants will create a link with another agent in the origin area. The agent who has the link with any migrant will update his/her network attribute value being one. In our CE, migration networks in the destination can provide supports in finding jobs, accommodation, or financial issues to people in origin. Therefore, it is reasonable to limit the number of networks that one migrant can provide. In our simulation, it is assumed that the maximum number of links at a time (tick) of one migrant is five.

Additionally, migration networks may not last forever. We assume in our model that a migration network will be faded after five years of establishment, i.e., the link between one specific migrant and one of his/her neighbors lasts for five years. We create a variable named network-counter to countdown the duration of having a migration network. In order to avoid a sudden decrease of network proportion after the first five years, 40% of the population having network at initial setup have a random network-counter value between the range of [1 5]. An example of the proportion of agents having networks over time for Kien Giang province is shown in Figure 3.10.

Figure 3.10. Proportion of having a network – Kien Giang province



3.4.5.2 Neighbor attribute

The argument to set up neighbor attribute is that people who live in the same block are collective, which means migration experience and migration decision of people who live nearby determine individuals' value of the neighbor attribute. During the simulation, the proportion of the neighbors who have migrated is calculated for each agent. This number depends not only on the migration decision of his/her neighbors but also on population movement (e.g., population size, birth, and death). One agent's neighbor attribute is set to be one (i.e., many neighbors migrated) when the proportion of neighbors migrated is over a certain threshold; otherwise, his/her value of the neighbor attribute is zero (i.e., few neighbors migrated). At each time step, an agent recalculates the proportion of neighbors migrated and updates his/her status of neighbor attributes.

An important step of determining neighbor attribute is the selection of a proper threshold. This process follows two steps. First, we select an appropriate range of threshold from the range between zero and one for further investigation by looking at the boxplots of the proportion of the agents having neighbor attribute being one (hereafter called 'neighbor percentage'). The rule of the selection is that we avoid the threshold that leads to extreme values of neighbor percentage (zero or one) over all the simulation period. If the neighbor attribute is all zero or one over the simulation, we cannot estimate the dynamics of the neighbor attribute's contribution over time. Indeed, we expect that, in reality, the impact of the neighbor attribute should be varying according to the changes in migration volume. We find that the appropriate range to choose threshold is between 0.16 and 0.2, where the average neighbor percentage ranges from around 0.1 to 0.9 for all provinces (see Appendix 3.7 for the boxplots of the screening of threshold parameter)[28].

Second, between the appropriate ranges, we choose the value that leads to the least Root Mean Square Error (RMSE) with historical data. We use two historical data that is average of out-migration rates period 2005-2019 and the out-migration rate of the year 2019. Correlation coefficients are also used as a supplementary comparing index. As can be seen from Table 3.20, threshold 0.16 and 0.2 lead to the least RMSE when compared to out-migration rate 2019 and average out-migration rate, respectively. We select threshold being 0.2 since the average out-migration rate (2005-2019) is used as the main historical data for comparison. We also conduct sensitivity analysis for threshold values to explore how the model output is sensitive to a different level of threshold. Results of sensitivity analyses will be discussed in section 3.5.1.

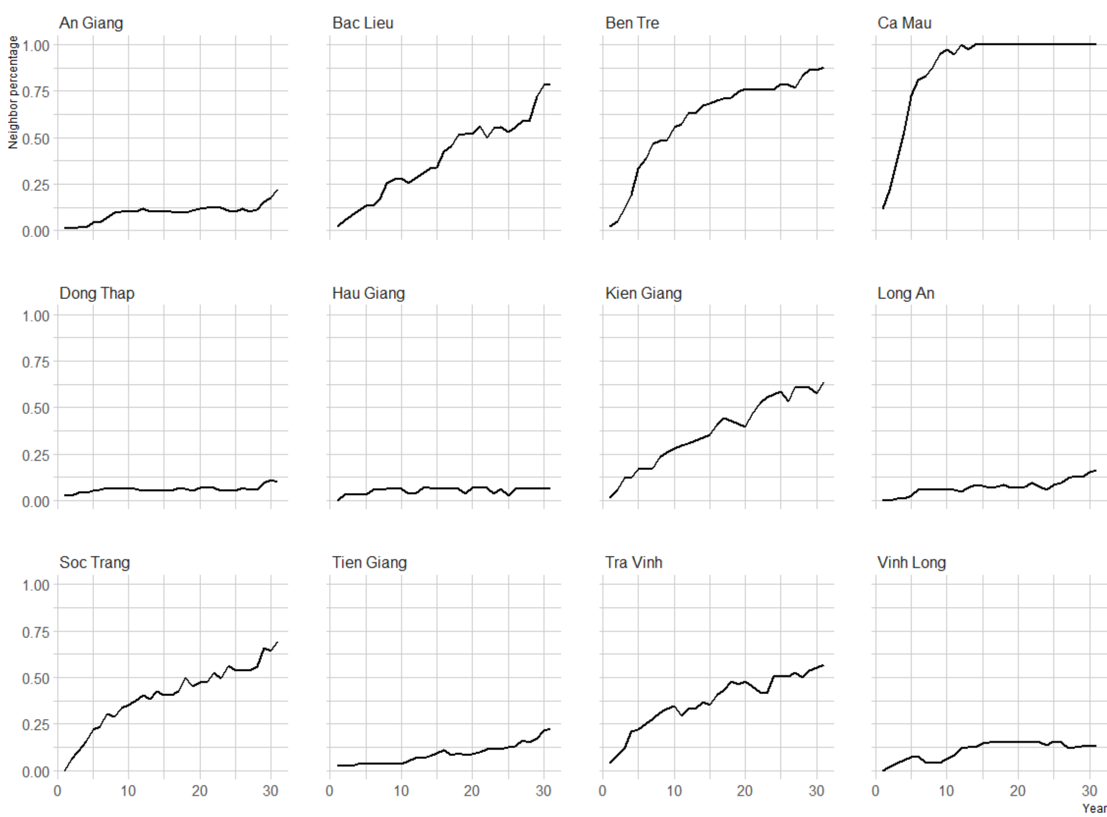
Table 3.20. RMSEs and correlation coefficients with historical data

Threshold	Average of out-migration rates period 2005-2019		Out-migration rate of 2019	
	RMSE	Corr. coefficient	RMSE	Corr. coefficient
0.16	1.915	0.766	2.472	0.741
0.17	1.888	0.749	2.496	0.746
0.18	1.853	0.753	2.523	0.746
0.19	1.853	0.753	2.523	0.746
0.2	1.845	0.756	2.525	0.747

[28] We fix the climate scenario being RCP4.5 when determining the threshold because scenario RCP 4.5 is expected to be the most likely happen in the future.

Figure 3.11 shows neighbor percentage over simulation time with the threshold at 0.2. We can see that most of the provinces have an upward trend except that four provinces, An Giang, Dong Thap, Hau Giang, and Vinh Long, have flatter patterns. The slope of neighbor percentage is positively correlated with the trend of migration flows because, in the simulation, the neighbor attribute is endogenously affected by migration decisions. Thus, the neighbor percentage curves tend to be flat for the provinces that have low and flat migration flows.

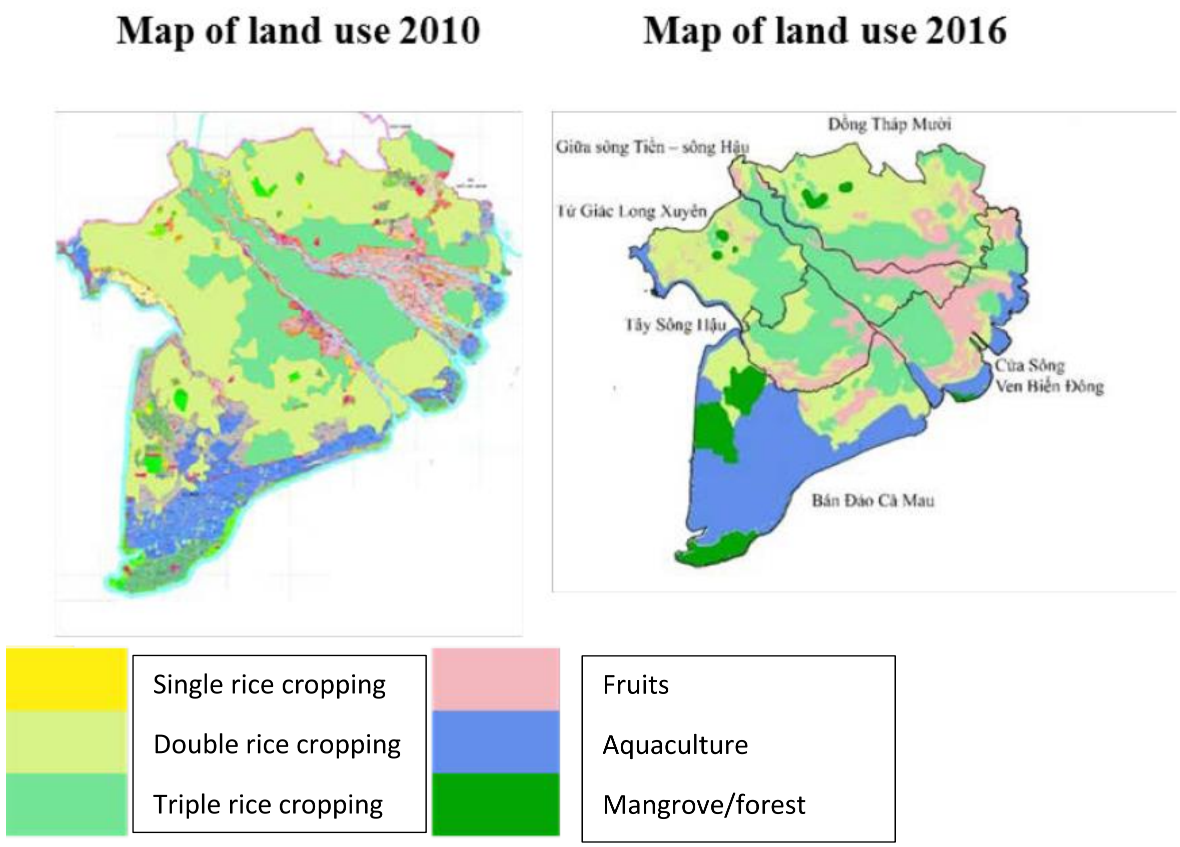
Figure 3.11. Proportion of having many neighbors migrated over simulation time



3.4.6 Crop choice restrictions

In this section, we will explain how crop choice restriction is designed in our simulation. Before that, it would be necessary to investigate how current crop choice restrictions affecting the use of land in the VMD. Under the increasing impacts of climate changes on the VMD region (e.g., sea-level rise and salinization), some parts of the VMD have become marginal for rice production, especially in the coastal area. Recognizing this, Vietnam's Ministry of Agriculture and Rural Development (MARD) issued some amendments to the current Lands Law to relax the crop choice restrictions. However, the revised policies still restrict the farmers from converting paddy land for more permanent purposes (World Bank Group, 2016). As a result, there are considerable changes in land use from 2010 to 2016 (see Figure 3.12). Crop rotations between rice and one other crop/aquaculture have become popular in coastal provinces. Meanwhile, upstream provinces are mostly rice cropping.

Figure 3.12. Map of land use in 2010 and 2016



Source: (Bong et al., 2018)

Given the changes in land use and the trend of climate change impacts, crop choice restrictions are expected to have significant impacts on migration decisions in coastal provinces. When sea-level rise and salinity intrusion become more severe in the future, more provinces may opt to change the use of land dramatically. They are coastal provinces that are currently implementing double rice cropping or triple rice cropping. For those provinces, the current crop restrictions might be a barrier to sustain income and secure livelihood. One exception is Ca Mau, the VMD southernmost province, where crop restriction is currently relaxed to adapt to saline intrusion conditions (see the map of land use 2016). Based on that justification, we divide 12 VMD provinces into three groups:

Group 1: coastal provinces that are likely to be affected by crop choice restriction, including Kien Giang, Bac Lieu, Soc Trang, Tra Vinh, and Ben Tre.

Group 2: Ca Mau where crop choice restriction is much relaxed

Group 3: inland provinces where the uses of land will not be changed.

In the simulation, we assign crop restriction impacts to provinces in the group 1 but mute those impacts for provinces in the group 2 and 3. Furthermore, we also interact crop restriction with climate change impact to create four scenarios as below.

Table 3.21. Scenarios of interacting climate change and crop choice restriction

No. of scenario	Crop restriction	Climate change scenario
RCP4.5 – none	No	RCP 4.5
RCP4.5 – total	Total	RCP 4.5
RCP8.5 – none	No	RCP 8.5
RCP 8.5 – total	Total	RCP 8.5

3.4.7 Income gap

In the first part of this section, we explain the calculation of the income gap between potential destination and origin for agents in the simulation. In the second part, we discuss the feedback effects of migration on the rural-urban income gap and propose a hypothesis for the change of income gap over the simulation period.

3.4.7.1 Calculation of income gap

In the simulation, the income gap between potential destination and origin for an agent living in province *i* is estimated as follow:

Income gap $_i$ = Average income after cost in Southeast region - Income after living cost by quintile $_i$[29]

where:

Average income after cost in Southeast region

= average monthly income per capita – average monthly living expenditure per capita

Income after living cost by quintile

= average monthly income per capita by quintile $_i$ - average monthly living expenditure per capita by quintile $_i$

Income and expenditure levels in the Southeast region are used as data for destination because it is the most common receiving destination from VMD provinces. After calculation, we obtain the value of income gaps by province for each income quintile, as shown in Table 3.22[30]. Agents in each province are randomly divided into five equal groups of income

[29] We do not compare the income by quintile in the origin to the income by quintile in the destination because doing that, the result turns out income gaps in quintile 5 being very high. This makes people in quintile 5 have more incentive to move. This does not make sense because richest people in the origin (if move) may not be the richest people in the destination. Therefore, the comparison of the income by quintile in the origin with the average income in the destination provides a sensible level of income gap.

[30] Note that income gap variable in the CE is ranged from minus one to four million dongs. Maximum value of our estimated income gap is 3.7 million dongs, indicating that the value in the CE and in the calculation from census data are relatively comparable.

quintiles. Each agent in each province is then assigned the income gap value based on his/her income quintile level.

Table 3.22. Income gap between potential destination and origin (thousand dongs)

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Long An	2992.2	2369.2	2090.2	1440.2	-3438.8
Tien Giang	3230.2	2315.2	2006.2	1431.2	-2366.8
Ben Tre	3364.2	2974.2	2676.2	1821.2	-1342.8
Tra Vinh	3635.2	3207.2	3002.2	2529.2	-184.8
Vinh Long	3378.2	2949.2	2795.2	2214.2	-233.8
Dong Thap	3435.2	2822.2	2504.2	2009.2	-1739.8
An Giang	3405.2	2699.2	2447.2	1889.2	-1699.8
Kien Giang	3508.2	2578.2	2242.2	1573.2	-2244.8
Can Tho	2937.2	2357.2	1949.2	1294.2	-3851.8
Hau Giang	3408.2	2627.2	2420.2	1960.2	-1628.8
Soc Trang	3285.2	2911.2	2744.2	2301.2	-2965.8
Bac Lieu	3710.2	2904.2	2769.2	2343.2	1303.2
Ca Mau	3658.2	2987.2	2768.2	2294.2	-85.8

3.4.7.2 Effects of migration on income gap

Migration may have positive or negative impacts on rural-urban income gap. On the one hand, rural-urban migration can reduce rural-urban income gap by contributing to the social and economic development of the origin through improved human capital, technological diffusion to rural areas, and remittance. Evidence from Vietnam shows that migration and remittance have positive and significant effects on rural households' income and consumption expenditure (Bui & Imai, 2019; L. D. Nguyen, Raabe, & Grote, 2015). Migration allows poor households to structurally escape poverty and reduce the depth and severity of poverty (Amare & Hohfeld, 2016; L. D. Nguyen et al., 2015). D. L. Nguyen, Grote, and Nguyen (2017) find that remittance helps to stimulate Vietnam rural economic development by improving infrastructure and healthcare services.

On the other hand, it is well known from the agglomeration literature that urbanization and urban concentration are associated with increasing inequality (Behrens & Robert-Nicoud, 2008; Castells-Quintana & Royuela, 2014; Hamaguchi, 2008)[31]. Agglomeration, as measured by urbanization and urban concentration, is partly due to the increase in population, natural and by migration, as well as a pull factor that motivates people to migrate to urban areas. In the rural-urban context, agglomeration can exacerbate regional income disparities. First, this process enhances growth in cities, leading to higher income paid in urban areas compared to those paid in rural areas (Castells-Quintana & Royuela, 2014). If this process encourages a large share of working-age people in rural areas to migrate to cities, the problem of lacking labor force and aging of society may further hamper economic development in rural areas. Furthermore, agglomerations can also lead to an increase in congestion in the cities. Excessive housing price inflation, pollution, or less accessibility to social welfare and public services decline the quality of life in the cities and leave a huge population under informal living conditions (Hamaguchi, 2008). Rural migrants in big cities tend to be the more vulnerable group compared to city residents.

There is evidence showing that migrants receive substantially lower wages than non-migrants in Vietnam (Marx & Fleischer, 2010; C. V. Nguyen & Minh, 2016). In addition, migrants'

[31] Urban agglomeration is defined to be a contiguous area in which every part is functionally interrelated to other parts within the area, usually through commuting and trade (Mera, 1973). One measure of agglomeration at the country level is urbanization and urban concentration rate (Castells-Quintana & Royuela, 2014).

access to social, health, and employment insurance are limited in the destination areas (Marx & Fleischer, 2010). Vietnam is implementing a system of household registration that limits the access to public services such as education and healthcare of migrants without a household registration book or permanent residence permission. Migrants who migrate because of agricultural and economic shocks in the rural areas are even more vulnerable. L. D. Nguyen et al. (2015) find that in Vietnam, households' income losses due to shocks may negatively affect a migrant's situation in the city.

Historical evidence does not confirm the impact of migration on rural-urban income gap in Vietnam. Bui and Imai (2019) find that remittance generally improves rural welfare but do not reduce rural-urban inequality. L. D. Nguyen et al. (2015) also do not find any significant effects of migration on improving inequality. In addition, rural-urban income gap is also determined by development strategies in rural areas such as high-value agricultural development (Bui & Imai, 2019) and rural labor market development (L. D. Nguyen et al., 2015). A declined income gap, in return, could slow down rural-urban migration flow.

In this study, along with the estimation of the effects of the income gap on migration predictions, we are also curious about how a declined income gap affects rural-urban migration flows. Therefore, in the simulation, we design income gaps to be declined over time. In particular, we examine migration flows with income gaps being fixed and decreased by 50 percent over simulation time. Results will be presented in section 3.6.5.

3.4.8 Other agent attributes

This section explains the specification of the rest agent attributes, including natural hazard experience, current migration, migration experience, and risk attitude. The main processes are demonstrated in Table 3.23, while more details will be discussed in the following subsections.

Table 3.23. Specifications of other agent attributes

Variable name	How to	Value
Natural hazard experience	We define the natural hazard experience of agent i based on its regression on the experience of drought and flood. Because the experience of drought and flood vary over time, the natural hazard experience attribute is updated every time step.	= -1.672983 + 0.7237707 * $moderate\_drought_{it}$ + 2.435163 * $severe\_drought_{it}$ + 1.19826 * $flood\_damage_{it}$ <u>See part (1) below for more details</u>
Current migrant	We assign the current migrant variable based on its regression on age and household size	= -2.888338 + 0.0338122 * age_i + 0.2009855 * $hhsize_i$ <u>See part (2) below for more details</u>
Migration experience	We assign migration experience variable based on its regression on age and hhsize	= -2.64211 + 0.0425308 * age_i + 0.1486435 * $hhsize_i$ <u>See part (2) below for more details</u>
Risk attitude	Because risk attitude seems not to be affected by demographic characters, we can randomly assign risk attitude value based on survey data (*Appendix Table 8*)	Three values of risk attitude (i.e., 2, 5, and 8) represent 3 risk attitude groups (i.e., 0-3, 4-6, and 7-10, respectively). Proportions of three values of risk attitudes – 2, 5, and 8- are 9, 45, and 46 percent, respectively.

1. <u>Natural hazard experience</u>

From survey data, we find that natural hazard experiences are significantly correlated with drought and flood damage. Analyses show that one respondent's experience on natural hazards depends on his/her experience of drought and flood impacts (Table 3.24) but not on his/her demographic characters (*Appendix Table 8*). The predicted value can explain about 76% of the respondents who have experienced severe impacts by natural hazards (*Table 3.25*).

Table 3.24. Regression of natural hazard experience on drought and flood damage

VARIABLES	Natural hazard experience
Moderate drought damage	0.724*
	(0.396)
Severe drought damage	2.435***
	(0.384)
Flood damage	1.198***
	(0.435)
Constant	-1.673***
	(0.343)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.25. Comparison of predicted and observed natural hazard experience variable

	Predicted		
Observed	No	Yes	Total
No	129	53	182
	70.88	29.12	100
Yes	40	128	168
	23.81	76.19	100
Total	169	181	350
	48.29	51.71	100

We then model the natural hazard experience of agent i based on regression results in Table 3.24. Drought and flood damage are obtained from corresponding drought and flood scenarios. That is, we assign initial natural hazard experience to the agents based on drought and flood scenarios of the first simulation year. Agents' natural hazard experience will be updated every year based on changes in drought and flood scenarios. Predicted probabilities of experiencing natural hazards are calculated following the Probit framework and then compared to 0.5 to define the variable value.

While acquiring drought damage variables from drought scenarios is effortless, it is not straightforward to obtain flood damage variable from flood scenarios. The reason is that the flood damage variable in the regression is a dummy indicating whether or not a specific household is being severely affected by flood; however, flood scenarios in the simulation are flood frequency index. Moreover, flood damage variable varies across households, while flood frequency in simulation is identical for all households in one province. To address this issue, we use the value of flood frequency index to generate flood damage that varies across agents. That is, in year t, the flood frequency index is 'x', 'x' percent of the population will face severe flood impact (i.e., flood damage = 1).

2. Current migrant and migration experience

Using survey data, we find that demographic characters, including age and household size significantly influenced agents' current migration and migration experience (see regression results in *Table 3.26*). Initial regressions add other demographic variables, including income and gender. However, LR tests show that income and gender are jointly insignificant. Therefore, income and gender are dropped from the regression.

The results show that age and household size have positive impacts on agents' current migration and migration experience. It means that the longer the agent lives and the bigger household he/she has, the more likely his/her family member is currently migrating and has migration experience in the past 20 years.

We then assign current migration and migration experience attributes to agents in our simulation based on regression results shown in Table 3.26. Predicted probabilities are calculated following the Logit framework and compared to 0.5 to define variable values.

Table 3.26. Regression of migration experience on demographic characters

VARIABLES	Current migration	Migration experience
Age	0.0338***	0.0425***
	(0.0101)	(0.0111)
Household size	0.201**	0.149*
	(0.0850)	(0.0884)
Constant	-2.888***	-2.642***
	(0.669)	(0.702)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.4.9 Population aging

In our simulation, we incorporate the predicted population and the trend of Vietnam's future population aging by employing findings from a recently published journal (Handong, Hongngoc, & Tianmin, 2020). Handong et al. (2020) use a population prediction model to predict the population structural changes in Vietnam from 2010 to 2049 and analyze the trend of Vietnam's future aging population. They provide the population pyramids of Vietnam in 2019, 2029, 2039, and 2049 (see *Appendix Figure 5*). The results show that although Vietnam's population will continue to increase in the future, its demographic structure will change significantly. The median age will increase from 27.91 to 40.47, with an average annual increase of 0.31. The working-age population in Vietnam continues to grow from 2010 to 2040, but it will begin to decline after 2040.

In the literature, in order to generate a dynamic synthetic population to model population aging, statistics of age-specific death, birth, and leaving the parental home are usually required, in which death rate is commonly used (e.g. (Namazi-Rad, Mokhtarian, & Perez, 2014)). Based on the findings of (Handong et al., 2020), we estimate the mortality rate for each age group of the rural population and apply into to the simulation. In the current simulation, we use mortality rates of the year 2019, and the rates are fixed over simulation time. We consider the birth rate at the same time to control the trend of population aging is as targeted. Our growth rate of agents is matched with the estimated rural fertility rate under the medium scenario calculated by Handong et al. (2020). More details are explained in Appendix 3.4 Population aging.

3.4.10 Provincial index

In our model, the province index demonstrates provincial characters that influence migration flows. We calculate province indexes for 12 VMD provinces using aggression of out-migration on the distance between the original province and the most common destination (i.e., HCM city), multi-dimensional poverty index (MPI), and unemployment rate. The selection of explanatory variables is explained in Appendix 3.5 Provincial characters that influence migration flow. Because those three variables are time-invariant variables, time dummies (yearly) are added to control for changes over time. This allows the intercepts to have different values across years. The estimation procedure is OLS.

Table 3.27 illustrates three regressions of all three explanatory variables (M1), without MPI (M2), and without unemployment (M3). The results of three regressions show that distance has significant impacts on migration rates, but the sign of the coefficient is not as our expectation. The positive sign of distance coefficient indicates that the provinces that are farther away from HCM are more likely to have a higher out-migration rate. This correlation might be explained by two reasons. First, it might be the case that the pull effects of the most common destinations such as HCM/Binh Duong offset the cost effects of distance. The further distance to HCM city may represent the fewer industrial zones that provide non-farm employment opportunities for the local people. As a result, people in those provinces have to move to the city to find a job. Second, because the distance from VMD provinces to HCM/Binh Duong is not long-distance (between 10 to 400km), there might be a group of people who live in HCM neighboring provinces but work in the city; therefore, they are not categorized as migrants[32]. The sign of the unemployment coefficient is unexpected, but the magnitude is relatively negligible. MPI coefficient has an expected sign but is insignificant. A positive sign means that higher MPI leads to higher migration flows from VMD provinces.

[32] More discussion on the link between distance and migration in Vietnam is presented in Appendix 3.6 Correlation between distance and migration in Vietnam.

Table 3.27. Regressions of out-migration rates on provincial characters

VARIABLES	M1 Full	M2 (without MPI)	M3 (without unemployment)
distance	0.0102***	0.0107***	0.00956***
	(0.00277)	(0.00272)	(0.00298)
MPI	0.929		0.978
	(0.967)		(0.861)
unemployment	-0.00233	-0.00253	
	(0.00314)	(0.00313)	
Time dummies	Yes	Yes	Yes
Correlation coefficient	0.7790*	0.7568*	0.7658*
Observations	168	168	168
R-squared	0.545	0.542	0.543
F-Stat	11.30	12	12.29
Prob > F	0	0	0

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The province index is then calculated based on predicted values when ignoring time effects (equation 3.1). I choose regression M1 to calculate the province index since its predicted values are most correlated with average out-migration rates (i.e., the correlation coefficient is 0.779). Province indexes for 12 VMD provinces are presented in Table 3.28.

$$\text{Province index}_j = 0.0101747 * \text{distance}_j + 0.9287163 * \text{poverty}_j - 0.0023255 * \text{unemployment}_j \quad (3.1)$$

Table 3.28. Province indexes of 12 VMD provinces

No.	Province	Index	No.	Province	Index
1	An Giang	0.84	7	Kien Giang	0.53
2	Bac Lieu	1.44	8	Long An	-1.28
3	Ben Tre	-0.58	9	Soc Trang	0.89
4	Ca Mau	1.56	10	Tien Giang	-1.09
5	Dong Thap	0.24	11	Tra Vinh	-0.16
6	Hau Giang	0.80	12	Vinh Long	0.37

3.4.11 Software

The model was implemented in NetLogo 6.0.4 (Wilensky, 1999), and the results were analyzed using R (RStudio Team, 2019). NetLogo is one of the powerful software platforms with free access and considerable references and tutorial (Railsback & Grimm, 2019). For simulation and sensitivity analyses implementation, we use an R-package named *nlrx* (Salecker, Sciaini, Meyer, & Wiegand, 2019). The *nlrx* package provides efficient tools to set up, run, and analyze NetLogo model simulations in R (Salecker et al., 2019). Using R facilitates post-estimation analyses and visualization. Moreover, the package nlrx consists of tools for different types of sensitivity analysis.

3.5 Model evaluation

In this section, we will discuss model verification and validation. We implement two validation techniques that are commonly used in the literature, which are parameter variability – sensitivity analysis and historical data validation (Sargent, 2013). Sensitivity analysis consists of changing the value of the model input and internal parameters that may generate uncertainty to determine the effect upon the model's output. Those parameters that are sensitive, i.e., cause significant changes in the model's behavior or output, should be made sufficiently accurate prior to using the model (Sargent, 2013). Historical data validation involves using historical data to determine whether the model behaves as the system does. In other words, our goal is to compare output from the model with historical data to evaluate the overall goodness of fit (Bruch & Atwell, 2015).

3.5.1 Sensitivity analysis (SA)

3.5.1.1 *Purpose of sensitivity analysis, parameters of interest, and choice of output*

The sensitivity analysis is conducted to serve three main purposes, which are (i) defining areas in parameter space that result in realistic behavior; (ii) determining the parameter to which output is very sensitive; and (iii) estimating stochastic effects caused by variation of random seed. Table 3.29 provides the description of model parameters and range for sensitivity analysis. We first implement local sensitivity analysis for all parameters of interest to figure out a realistic range of parameters for further investigation. In the local SA, we consider a small change in one of the parameter values, given that other parameters are fixed, to measure the change in the model outcome. The details of local SAs are discussed in Appendix 3.7. The results of local SAs provide a basis to define the range of model parameters for global SA.

Table 3.29. Model parameters and range for sensitivity analysis

Parameter	Description	Nominal value	Range for local SA	Range for global SA
threshold (percentage point)	Threshold to define whether the agent have many neighbors migrating. If the proportion of the neighbors who have migrated of an agent is larger than the threshold, his/her neighbor attribute is set as 1.	0.2	0.1-0.3	0.16-0.22
pct_nw (percentage point)	Proportion of agents having migration network at initial setup.	0.4	0-1	0.3-0.6
nw_counter (years)	Maximum duration that a migration network exists.	5	5-10	5-10
age_of_death	The maximum age of agent	75	75; 80; 85	NA
seed		7000	NA	0-111000

We choose the number of migrants as the main output of interest. Moreover, other outputs, including migration rate, network percentage, and neighbor percentage, are also considered to investigate the effects of model parameters for other specific purposes. For example, we use neighbor percentage as the output to investigate the realistic range of the threshold parameter.

3.5.1.2 Global sensitivity analysis

While local SA ignores the interactions between parameters, global SA aims to ascertain interaction effects by sampling the model output over a wide range of parameter values. Many specific parameter settings, usually determined randomly, are drawn from the parameter space, and the corresponding model outcomes are combined in a statistical measure, namely the variance of the output of the model. In this part, we conduct two methods of global SA, including Morris's elementary effects screening and Latin Hypercube sampling.

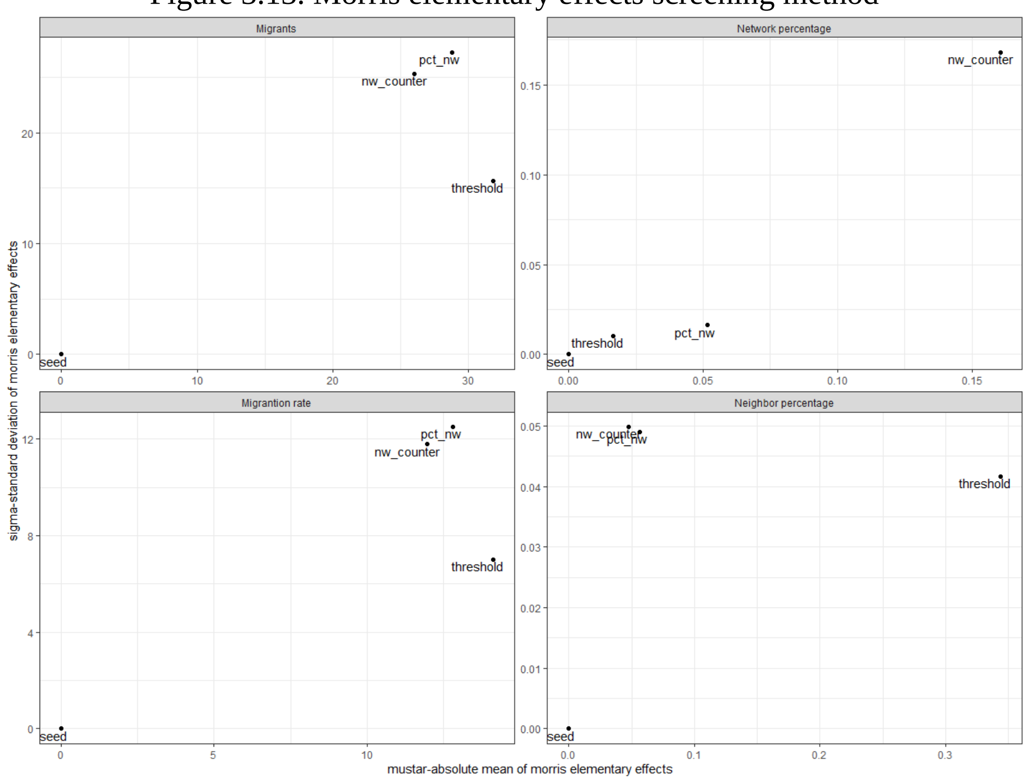
Morris's elementary effects screening method (Morris, 1991)

Morris's method bases on individually randomized one-factor-at-a-time designs (i.e., one parameter out of all model parameters is changed at each step) to estimate the effects of changes in the parameter values, which are called elementary effects (EEs). The EEs are statistically analyzed to measure their relative importance. The EEs include μ^*, the absolute mean of the elementary effects, as an estimate of the overall influence of a parameter, and σ, the standard deviation of the elementary effects, as an estimate of higher-order effects, i.e., non-linear and/or interaction effects (Iooss & Lemaître, 2015).

High μ* indicates that a parameter has an overall important influence on the output and that this effect always has the same sign. Large σ means either that the corresponding parameter has a non-linear effect on the output or that this parameter is involved in interactions with other parameters.

Figure 3.13 shows the results of the Morris method. Out of the four chosen parameters, the threshold has important overall influences on migration flow, compared to other parameters (left-hand-side panels). Threshold has high μ*and low σ, indicating that the elementary effect is almost independent of the values of other parameters. Pct_nw and nw_counter, in contrast, have high σ, indicating that the elementary effects strongly depend on the choice of other parameters. Nw_counter does not have a large influence on migration flow. Stochastic variability caused by different values of seed is negligible.

Figure 3.13. Morris elementary effects screening method



The two right-hand-side panels show elementary effects of parameters on network percentage and neighbor percentage. For neighbor percentage output, the threshold has an important influence as expected. For network percentage output, the result shows that nw_counter is a highly influential parameter while pct_nw is not. It is in line with what we find from local sensitivity analysis. In addition, nw_counter is shown to have a high non-linear impact on model output and/or interaction effects between parameters.

From Morris's elementary effects screening method, we can observe the relative significance of the parameters. Although the Morris method is easy to understand, does not depend on assumptions about the model (e.g., monotonicity), and is computationally inexpensive, the EEs are dependent on the unit of the output (Wu, Dhingra, Gambhir, & Remais, 2013). Consequently, we cannot quantify the contribution of a parameter to the variability of the output. In the next sub-section, we will present global SAs using the Latin Hypercube sampling method that provides quantification of the influence of model parameters as well as the direction of the relationship.

Latin Hypercube sampling method (LHS)

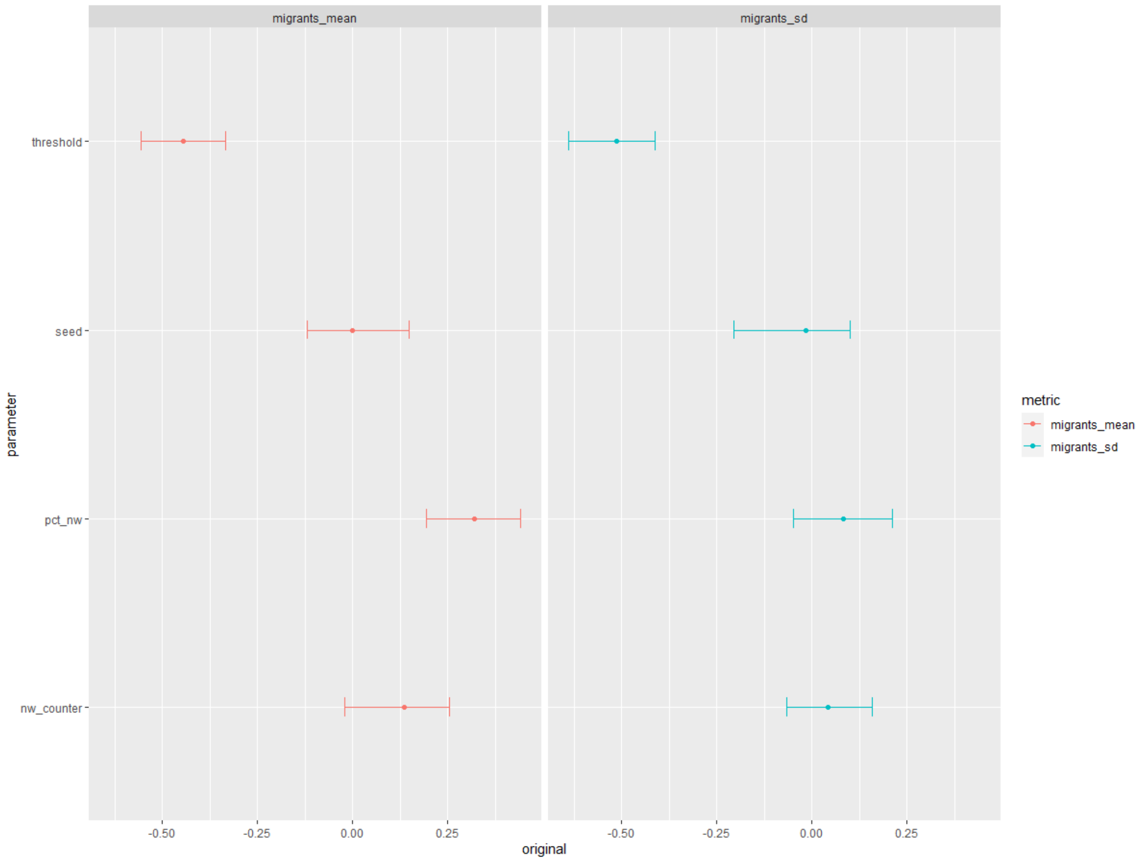
This method involves successive runs of the model with different sets of the parameters of interest, using Latin Hypercube sampling. Model outputs and the parameters are then transformed into different statistical measures to determine the sensitivity effects of the model parameters (Manache & Melching, 2008; Wu et al., 2013). Two common statistical measures are based on the regression method (e.g., SRC – standard regression coefficient) and correlation analysis (e.g., PCC – partial correlation coefficient). The coefficients fall between -1 and +1, with an absolute value close to 1, indicating the parameter has a strong impact on the model output. The coefficients are used to provide a measure of parameter importance and the sign of the correlation between model parameters and model output.

Figure 3.14 presents SA results using standard regression coefficient (SRC) between model parameters and the number of migrants as model output[33]. The result indicates a strong negative linear relationship between threshold parameter and model output. Pct_nw and nw_counter have positive and less significant correlations with the number of migrants as model output. The relative influence of those parameters is consistent with results obtained from the Morris method.

In conclusion, SAs reveal that threshold is the most sensitive parameter among parameters of interest. Therefore, we conduct further steps to justify the threshold parameter. As shown in section 3.4.5.2, we compare model output with historical data to select the most appropriate value of the threshold parameter. Details of the comparison of model output to historical data will be provided in the following section.

[33] Partial correlation coefficients (PCC) are presented in the Appendix Figure 6.

Figure 3.14. Latin hypercube sampling - Standard regression coefficient (SRC)



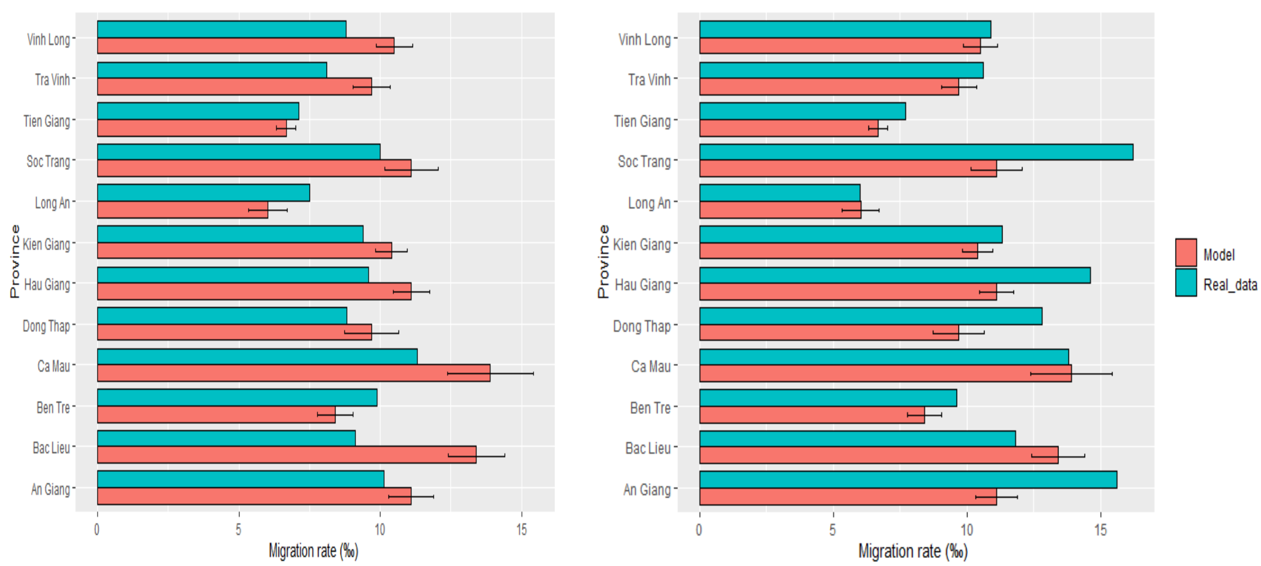
3.5.2 Modelled vs. historical migration

In this section, simulation results of baseline scenario (i.e., climate change variables are fixed as the current situation) for the first step (year) is used to compare to historical data. In the simulation setup, all data input is collected using the latest available data. Therefore, simulation results for the first step (year) are expected to reflect migration flow in reality.

The reference values are the average out-migration rate of each province from 2005 to 2019 and the out-migration rate of each province in 2019. The migration rate is expressed as a rate per 1000 population. Reported simulation results are the average of 50 runs using different seeds. The migration rate is calculated to match with real data format, which is a rate per 1000 population.

Figure 3.15 depicts bar charts comparing the simulation results and the actual migration rates across 12 VMD provinces. As discussed in previous sections, parameter values that result in the smallest sum of RMSE are selected to run the simulation. Correlation coefficients are provided for reference. The results show that the modeled results closely reflect actual migration rates in the VMD, with RMSE values ranges between 1.9 and 2.5‰. In some provinces, such as Ca Mau and Bac Lieu, we observe relatively big gaps when compared with the average out-migration rate, but small gaps when compared with the out-migration rate 2019. The fact is that out-migration rates of those two provinces substantially increase in 2019, and the simulation capture this trend.

Figure 3.15. Comparison of simulated results and the average out-migration rate, and out-migration rate in 2019



Average out-migration rate (2005 -2019)
Correlation coefficient: 0.754 (0.995 significant level)
Root mean squared error (RMSE): 1.845‰

Out migration rate 2019
Correlation coefficient: 0.736 (0.995 significant level)
Root mean squared error (RMSE): 2.525‰

3.6 Results and discussion

In order to investigate the contribution of climate change phenomena and other external stimuli to future migration flows, we design a series of experiments by varying migration attributes, including climate scenario, social feedback effect (i.e., network and neighbor), crop restriction, and income gap. The list of experiments and brief descriptions is provided in Table 3.30. In the first part of the section, we present the results of the experiments. The remaining part presents a discussion and analysis of model results, followed by concluding remarks.

Table 3.30. Agent-based model results – List of experiments

	Name	Description	Climate change	Network Neighbor	Income gap	Crop restriction
1	Baseline	Current climate change impact	✕	✓/✕	✓/✕	✕
2	Climate change	Future RCP4.5 and RCP8.5 scenarios	✓	✓	✓	✕
3	Social feedback	Network and neighbor effects	✓ (RCP 4.5)	✓/✕	✓	✕
4	Crop restriction	Crop restriction interacts with climate scenarios	✓	✓	✓	✓/✕
5	Income gap	Income gap decreases overtime	✓ (RCP 4.5)	✓	✓/✕/decreased	✕

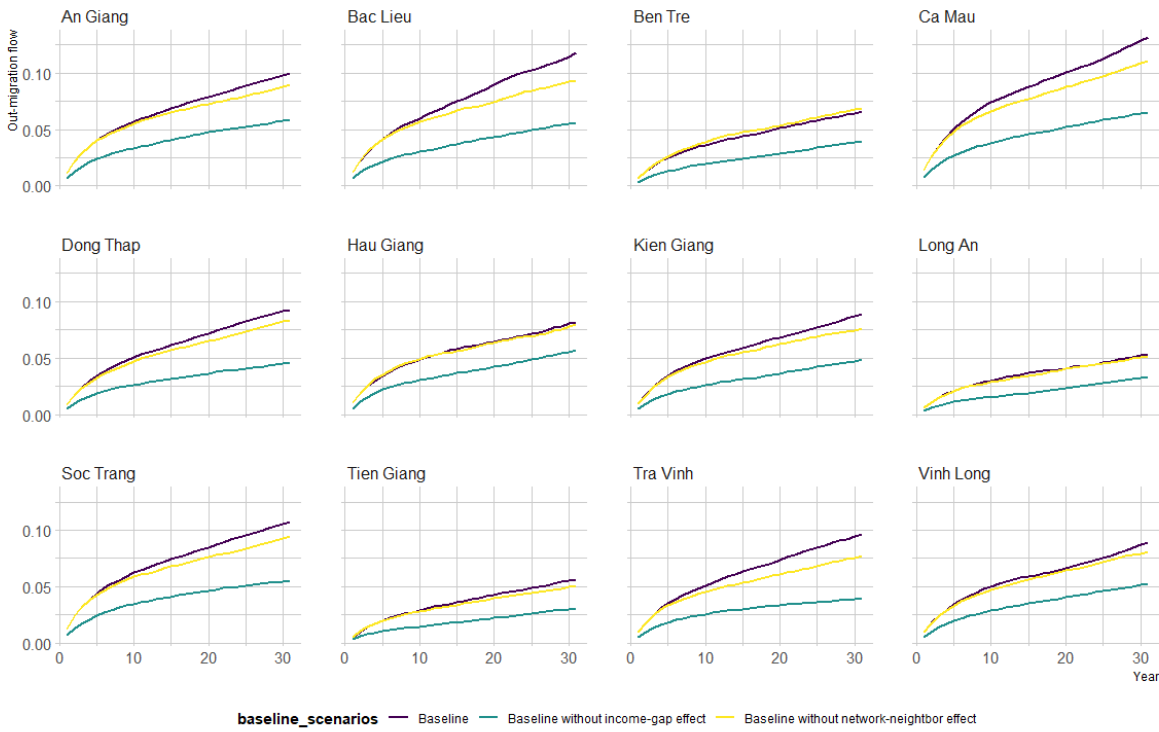
✓- with, ✕ - without, ✓/✕ - with or without

3.6.1 Migration flows for baseline scenario

In the baseline scenario, we fix climate change phenomena (i.e., drought and flood) at the current situation and ignores the crop choice restriction attribute. In order to examine the contribution of migration drivers in the baseline scenario, we shut down some of the key drivers (including income gap and network-neighbor) in turn. Figure 3.16 displays cumulative outmigration flows, normalized at the current population, for the baseline scenario, baseline without income gap effect, and baseline without network-neighbor effects for 12 VMD provinces. The model projects that by 2050 about 1.1 million people — around 6.4 percent of the VMD current population — could move out of the VMD rural area[34], assuming the impacts of climate change phenomena to be the same as in the current situation. For comparison, according to V. T. T. Anh et al. (2020), over the past decade (2009–2019), nearly 1.1 million people, roughly equivalent to the population of one province in the region, or about 6.4 percent of the current population of the region, left the region. The projected migration for the next three decades for the baseline scenario is smaller than the migration flow of the past decade because the baseline scenario ignores increasing climate change impact over time. In the next experiment (sub-section 3.6.2), we consider climate change impact, which results in higher migration projections.

[34] This study covers rural population of 12 VMD provinces (excluding Can Tho city), which is equivalent to 72.6 percent of the whole region's population.

Figure 3.16. Baseline scenario



Cumulative flows – normalized at the current populations

The green line and yellow line in Figure 3.16 depict cumulative migration flows without income gap effect and without network-neighbor effect, respectively. Note that in addition to income gap and network-neighbor effects, migration flows in this figure are determined by the current situation of climate change events, current demographic characteristics, and demographic trends over time. By comparing those two lines with the baseline, we can estimate the effects of the income gap and network-neighbor on migration. In particular, the gap between baseline and without-income-gap line represents the income gap effect, and the gap between baseline and without-network-neighbor expresses network and neighbor effects.

The left side of Table 3.31 summarizes the contribution of social feedback and income gap effects to total migration flow in the baseline scenario for 12 VMD provinces. The result indicates that income gap contributes considerably to out-migration, confirming the identification in migration literature of income differences as the most important migration determinant. Network and neighbor have negligible impacts on the migration trend of the baseline scenario. This finding is as expected since the modest flux of migration limits the expansion of social feedback mechanisms.

Table 3.31. Drivers of migration flow by 2050 – Baseline and RCP 4.5 scenario

	Baseline		RCP 4.5	
	Persons	Percentage	Persons	Percentage
Climate change	-	-	1,800,000	55.9
Social feedback	115,810	11	566,100	17.6
Income gap	490,250	46	899,000	27.9
Crop restriction	-	-	336,000	10.4

Note: The contribution of each migration attribute is calculated by taking the difference between migration flow with and without this specific attribute, given other attributes are identical.

3.6.2 Migration flows by climate change scenarios

Figure 3.17 displays cumulative outmigration flows, normalized at the current population, across climate change scenarios for 12 VMD provinces. Environmentally induced migrants are calculated by subtracting migration flows of baseline scenario from flows of climate change scenarios[35]. The model projects that by 2050 about 1.8 million people—or around 10.4 percent of the VMD current population—could migrate under the impact of climate change RCP 4.5 scenario. Under the RCP 8.5 scenario, the number of climate change-induced migrants is estimated at around 2 million people or around 11.6 percent of the current VMD population. The right side of Table 3.31 summarizes the contribution of migration drivers to total migration flow in the RCP4.5 scenario for 12 VMD provinces[36]. Simulation results here support the conclusion that climate change is a crucial determinant of out-migration from VMD provinces.

The simulation results reveal that migration patterns are not uniform across provinces. Different levels of and trends in climate change impact on VMD provinces gave rise to three types of variation in migration flows. First, the volume of climate change-induced migration varied across provinces because climate change phenomena affect VMD provinces differently. For the coastal provinces, including Ca Mau, Ben Tre, Bac Lieu, Kien Giang, Soc Trang, and Tra Vinh, which are predicted to be highly vulnerable to both saline intrusion and flooding, the simulation showed higher out-migration flows than for other provinces. In those coastal provinces, the scale of change in migrant numbers ranged from 15 to 30 percent of the current population higher than the baseline scenario. Ca Mau province has the maximum positive change compared to the baseline scenario, which reaches about 30 percent of the current population. Ca Mau, the southernmost VMD province, is currently, and is

[35] Total estimated out-migration flows are 2.9 million people for RCP 4.5 and 3.1 million people for RCP 8.5 scenario.

[36] The sum of the contribution of migration attributes is over 100% because there are interaction effects within attributes. As a result, the contribution of one attribute comprises part of the effects of other attribute.

expected to continue to be, the province most strongly affected by saline intrusion and inundation in the context of climate change and sea-level rise.

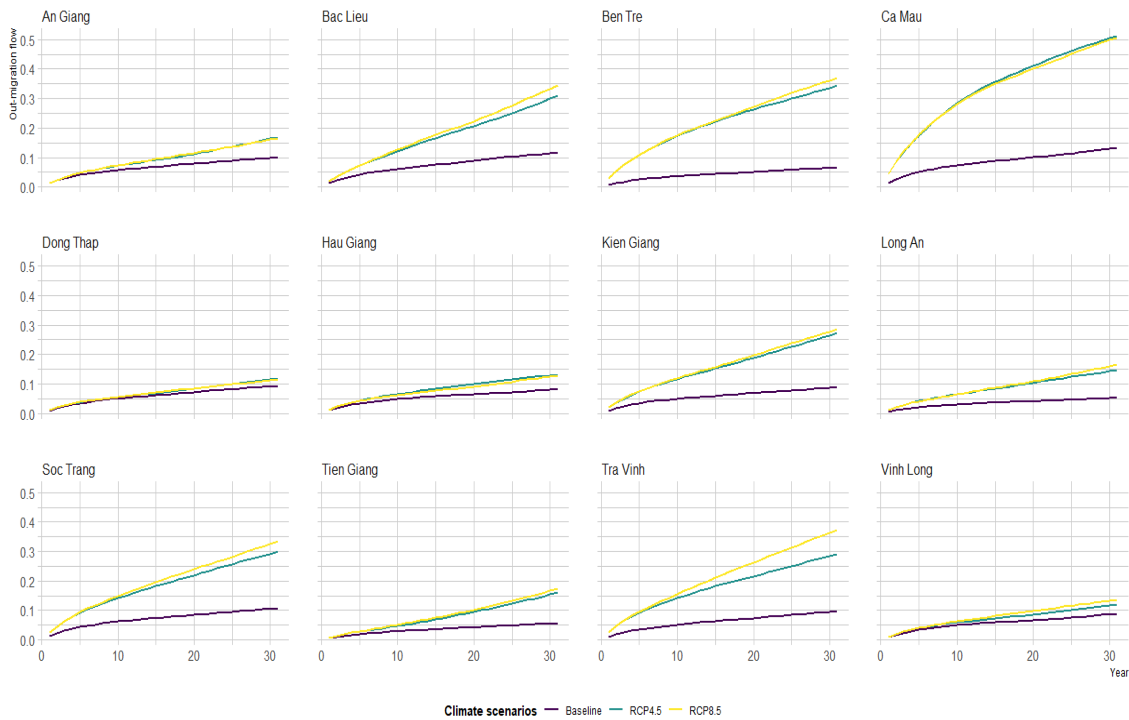
The other provinces, An Giang, Dong Thap, Hau Giang, Long An, Tien Giang, and Vinh Long, are expected to have slight to moderate positive changes in migrant numbers compared to the baseline under climate change scenarios, with the scale of change ranging between two and 10 percent of the current population. The provinces that have moderate change—between five and 10 percent—have either high flood risk or high risk of drought and saline intrusion. For example, Long An and Tien Giang have high drought risk; An Giang has high flood risk. The provinces have slight changes in migrant numbers—less than five percent change—have either no/mild drought risk or no flood risk. For example, Dong Thap and Hau Giang have no and mild drought risk, respectively; Vinh Long has no flood risk.

Second, we observe the variation in sensitivity across climate change scenarios. The range of difference between the two climate change scenarios is from zero to 10 percent of the current population. The differences between the two scenarios mainly come from the change in drought and saline intrusion severity by 2050. Ca Mau, Dong Thap, and Tien Giang have a very negligible gap because there is no change in the level of drought severity across two scenarios (i.e., severity level is highest in Ca Mau, zero in Dong Thap, and moderate in Tien Giang). In contrast, Tra Vinh, which has the largest increase in the proportion of experiencing severe drought–40 percent from RCP4.5 to RCP 8.5–shows a maximum gap between the two scenarios. The change in flood risk level does not lead to considerable differences between the two climate scenarios. The reason is not only the smaller impact of flood on migration than of drought but also the subtle change in flood frequency between the two scenarios.

Indeed, the largest change in annual flood frequency between RCP4.5 and RCP8.5 is only 0.1 unit point.

Third, Figure 3.17 reveals slightly different slopes of migration flows, in which almost all provinces show similar patterns, which are concave curves except four provinces – Bac Lieu, Kien Giang, Long An, and Tien Giang. Those four provinces show more upward lines rather than concave curves. It means that in those four provinces, the number of migrants increases faster than in the other provinces. The reason is that those provinces have the largest changes in drought severity and flood frequency from baseline scenarios to climate change scenarios. For example, the proportion of experiencing severe drought in Tien Giang and Bac Lieu increases by 57% and 45%, respectively, from baseline to RCP4.5, while the average change is only around 17%. Another explanation is that the population in those provinces is large enough to offset the negative effect of shrinking populations on migration outflow. Indeed, among the provinces in the VMD, Tien Giang and Long An have the largest number of households (Table 3.2).

Figure 3.17. Migration flows by climate change scenarios



Cumulative flows – normalized at the current populations

3.6.3 Network and neighbor effects

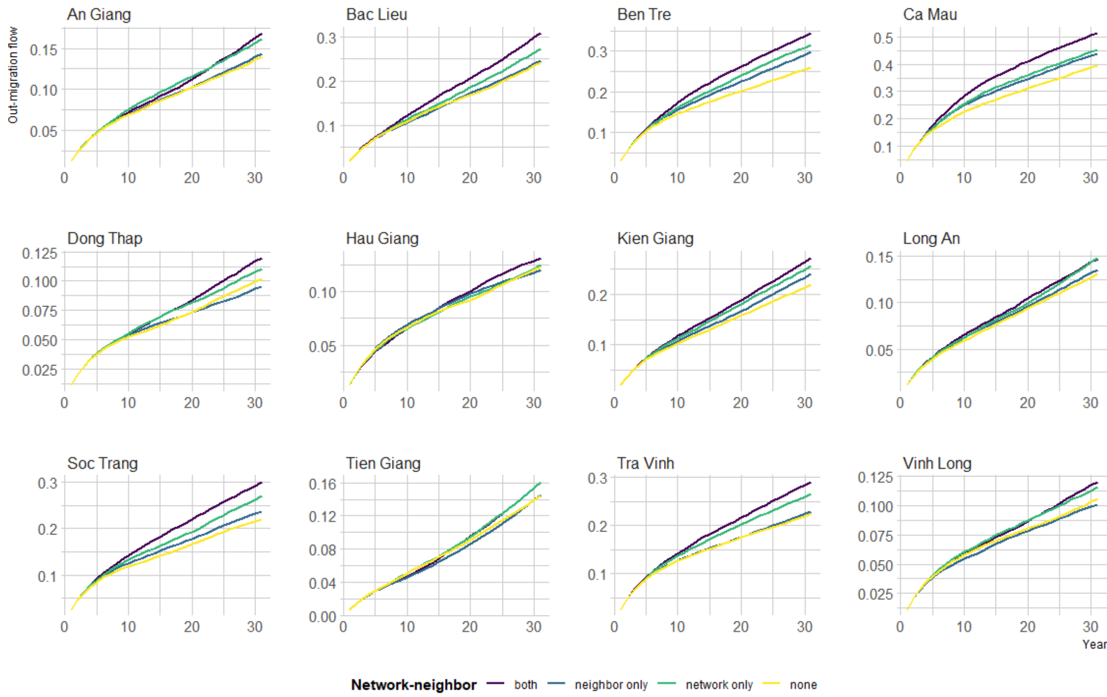
This section presents an investigation of the impacts of social feedback effects on migration flows. Figure 3.18 presents cumulative outmigration flows for 12 VMD provinces with and without network and neighbor effects, given RCP 4.5 climate scenario and no crop choice restriction. The simulation result shows that if future climate conditions match the RCP 4.5 scenario, network and neighbor effects can increase migration flows by from one to 10 percent of the current provincial population. The social feedback effects scale up by the rate of migration. Ca Mau province is expected to have the highest migration flow under the RCP

4.5 scenario and, therefore, the biggest network and neighbor effects—accounting for about 10 percent of the province's current population. In contrast, Hau Giang province, one of the provinces with low migration flows due to climate change, has the smallest network and neighbor effect—accounting for about one percent of its current population.

One argument for investigation is that feedback-internal dynamics tend to operate in a fundamentally non-linear way, depending on the changes of other macro-contextual conditions underlying the migration process (De Haas, 2010). For example, when considering the climate change impacts of the RCP 4.5 scenario, it is estimated that about 18 percent of migration is driven by a combination of network and neighbor effects (*Table 3.31*). Compared to the baseline scenario, social feedback effects have expanded and contributed significantly to migration. This indicates the migration-facilitating feedback dynamic of migration network and peer choice in our ABM model. The model results also reveal that the network and neighbor have a significant influence on migration in Vietnam; that finding is consistent with those of other studies (e.g., N. A. Dang, Tacoli, & Hoang, 2003).

Other examples of feedback effects that may counteract migration networks and migration systems over time are income inequality and policy interventions. In the following sub-sections, we will discuss the influences of crop choice restriction and income gap on the migration diffusion process in more detail.

Figure 3.18. Network and neighbor effect – RCP4.5 scenario

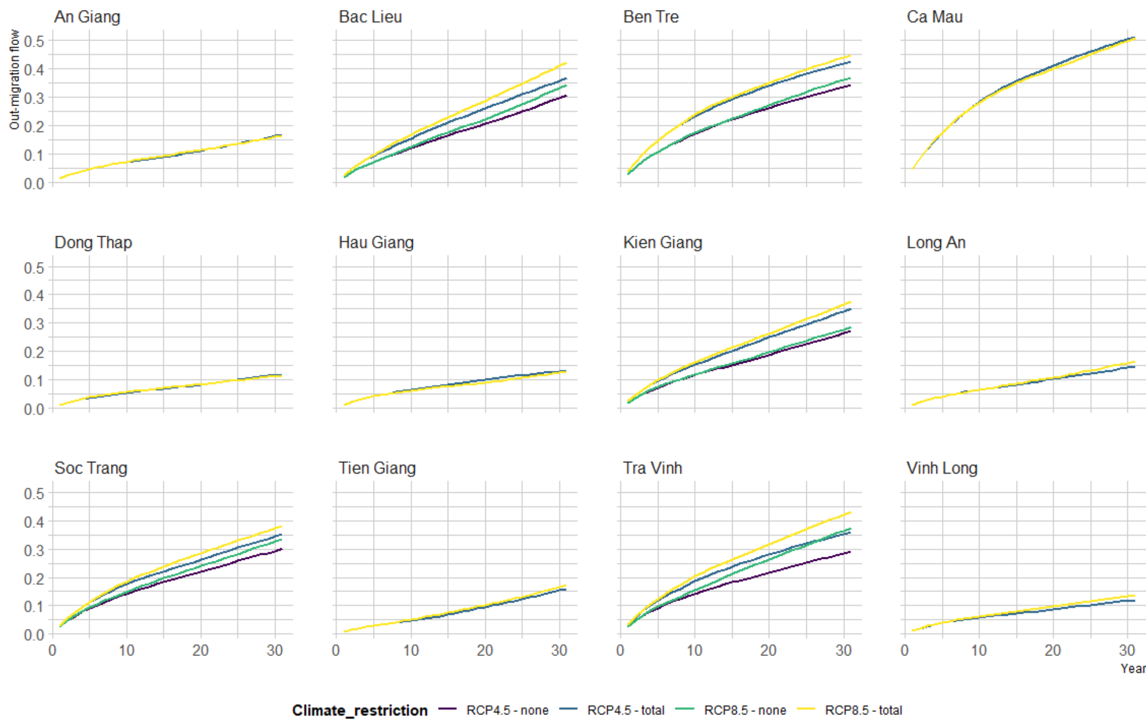


3.6.4 Migration and crop choice restriction

As discussed in section 3.4.6, under the context of climate change and sea-level rise, some VMD provinces are expected to change the use of land dramatically. Those are VMD coastal provinces that are currently implementing double rice cropping or triple rice cropping. For those provinces, crop restrictions are expected to have a significant impact on migration decisions. This section examines the impacts of crop choice restriction on migration flows under different climate change scenarios. Figure 3.19 projects migration flows of four scenarios interacting crop restriction and climate change projections.

Figure 3.19 reveals that a future severe climate change scenario (RCP 8.5) for the VMD is predicted to produce the largest out-migration flow when combined with crop restriction policy in VMD coastal provinces. The implementation of total crop choice restriction may contribute to nearly 350,000 migrants out of VMD coastal provinces under the severe climate change scenario by 2050. Under intermediate climate change scenario (RCP 4.5), crop choice restriction can result in 336,000 migrants, or roughly equivalent to 10.4 percent of the total out-migration (Table 3.31).

Figure 3.19. Migration flows under scenarios interacting with crop restriction and climate change



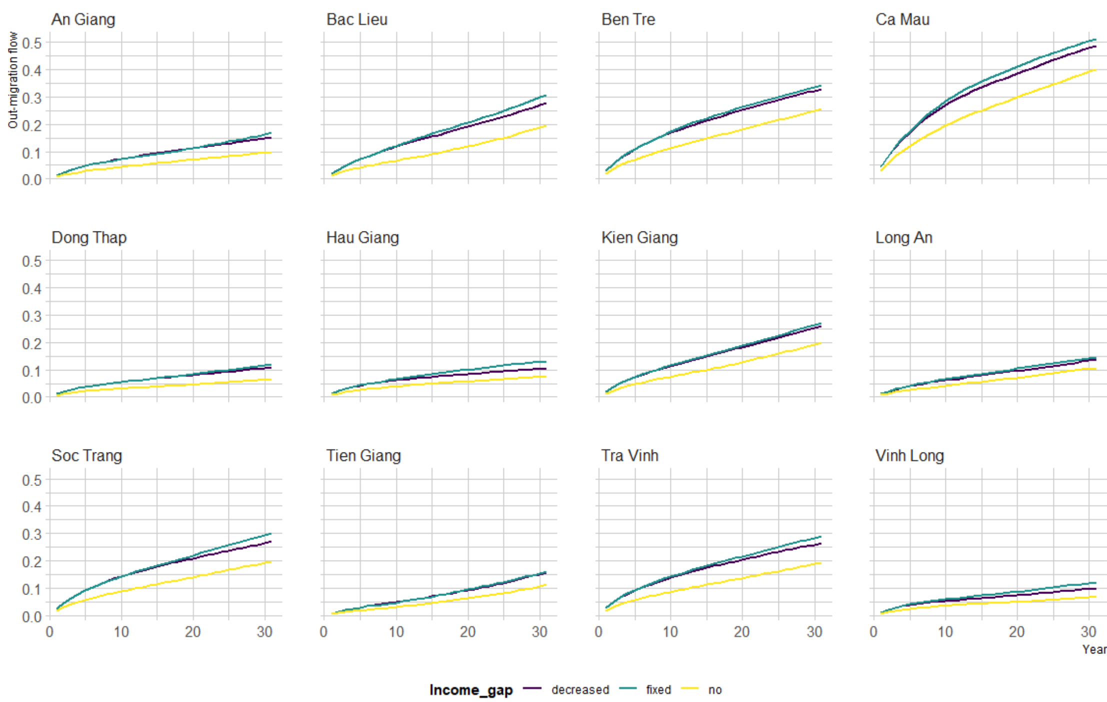
Sea level rise and salinity intrusion will almost certainly impact the geography of the VMD rice production in the future (World Bank Group, 2016). Therefore, enabling greater choice and flexibility in land-uses might be critical for better adapting to climate change impacts, managing migration flows out of VMD provinces, and improving farm household welfare.

3.6.5 Migration and income gap

As discussed in section 3.4.7.2, migration may have positive or negative impacts on rural-urban income gap; and in return, the income gap provides feedback effects on migration flow. In this section, we examine how much income gap contributes to migration as well as how much a declined income gap influences migration projection. Figure 3.20 demonstrates migration flows with fixed, no, and 50-percent-decreased income gaps. The gap between migration flows with fixed and no income gap indicates the contribution of income gap attribute to migration. Similarly, the gap between migration flows with fixed and decreased income gaps illustrates the feedback effect of a decreased income gap on migration.

The results show that by 2050, about 28 percent of migration is driven by the income gap between rural and urban, given climate scenario RCP 4.5 (see summary in Table 3.31). If by 2050, rural-urban income gaps were to decrease by 50 percent, total migration outflows would decrease by around 250,000 people, equivalent to 7.8 percent of total out-migration.

Figure 3.20. Migration flow with fixed, 50-percent-decreased, and no income gap – RCP 4.5



3.6.6 Discussion

To the best of our knowledge, no previous study has predicted future migration flow for the case of the VMD. Therefore, sources for comparison with the results of our simulation are scarce. Here, we compare our results with historical trends and with the results of few related case studies of Vietnam and other parts of the world. Our simulation predicts that rural migration from the VMD will be 2.9 and 3.1 million people for RCP 4.5 and RCP 8.5, respectively, which are in accordance with the historical data (Table 3.32).

Based on this study's model outputs, it is predicted that climate change can cause a massive migration flow out of the rural VMD in the two or three decades, with higher flows expected in coastal provinces. Around 10 to 12 percent of the current VMD population would migrate under the impact of climate change. We found only one related study, Warner et al. (2010), that estimated the displacement of people caused by sea-level rise in Vietnam. Warner et al. (2010) predict that a sea-level rise of one meter would displace more than ten percent of the population of Vietnam as the result of flooding in the Mekong Delta.

The scale of climate migration forecasted in the VMD is larger than the scale projected in other parts of the world[37]. This indicates that the VMD is the region at great risk of mass migration triggered by climate and environmental change. Indeed, studies argue that climate change impact is one of the most important reasons for the increasing number of people migrating out of the rural VMD to major cities (D. Anh et al., 2017; V. T. T. Anh et al., 2020)). The VMD is the largest migrant sending region in Vietnam (D. Anh et al., 2017; Entzinger & Scholten, 2016). Increasing environmental and climate change impacts over the last few decades continue to accelerate the migration process. As a result, the last decade (2009-2019) experienced a remarkably high number of people migrating out of the VMD, posing a big challenge to the region in terms of labor force quantity and quality (V. T. T. Anh et al., 2020).

[37] For example, Rigaud et al. (2018) estimate that by 2050, up to 143.3 million people or around 2.8 percent of the population of Sub-Saharan Africa, South Asia, and Latin America could be internal climate migrants under the pessimistic reference scenario.

Table 3.32. Migration predictions by 2050 by climate change scenarios

	Baseline	RCP4.5	RCP8.5
Migration predictions (2020-2050):			
Migration flow (mil. pers.)	1.1	2.9	3.1
Percentage of current population (%)	6.3	16.8	18
Historical out-migration flow (2009-2019): 1.1 million persons			

Massive migration flows from the rural VMD to the urban area also affect the population size and density of the destinations. HCMC is the largest gainer of migration inter-provincial migration, mainly from the VMD and the north of Vietnam. The population of HCMC has proportionally nearly doubled between 1995 and 2015 (HCMC Statistics Office, 2016) and reaches nearly 9 million people in 2019. Migrants now make up 21 percent of the population of Ho Chi Minh City (D. Anh et al., 2017). HCMC absorbs on average about 100,000 in-migrants per year throughout the 1990s and doubles that number over the following decade (Peters, 2012). Based on our simulation results, it seems that for the next decades, HCMC will receive more than 1.2 million migrants from the VMD[38]. This amount may be within the absorbable level of the HCMC; however, it would certainly increase the current congestion of the city.

Simulation results reveal significant effects of network and neighbor on migration that is in common with other studies (e.g., (N. A. Dang et al., 2003)). De Haas (2010) also argues that

[38] Using RCP 4.5 scenario and assuming that about 40 percent of the VMD migrants move to HCMC.

social feedback effects are more likely to occur among relatively poor communities where social organization and trust are mainly based on kinship ties and 'bonding' social capital. In other words, relatively poor, low-skilled migrants who face relatively high material, social and psychological migration costs are generally more dependent on social capital in the forms of networks in order to migrate than relatively wealthy, high-skill migrants (De Haas, 2010). This argument is closely connected with the situation in the VMD.

From simulation results, we obtain different profiles in terms of sensitivity to migration drivers across provinces. Variation of sensitivity comes from different characteristics as well as future projections of VMD provinces. Table 3.33 presents some examples where provinces have distinct differences in sensitivity profiles[39]. For example, Ca Mau and Tra Vinh are both coastal provinces and highly sensitive to climate change impacts. However, Tra Vinh is highly sensitive to the change of climate scenario and crop choice restriction, while Ca Mau province shows low/no sensitivity to those two migration drivers. The current severity level of climate change impact and use of land in those two provinces results in different sensitivity profiles. Similarly, although Dong Thap and Tien Giang are two adjacent provinces, they are differently sensitive to climate change and climate scenarios. The reason is that while Tien Giang is expected to face moderate drought risk in the future, Dong Thap faces no risk. Here, geographical features drive the differences between the two provinces.

[39] Sensitivity profiles of all 12 VMD are presented in Appendix Table 9.

Table 3.33. Sensitivity to migration drivers across provinces – 4 VMD provinces

Province	Climate change	Across climate scenarios	Social feedback	Income gap	Crop choice restriction
Tra Vinh	High	High	High	High	High
Ca Mau	High	Low	High	High	No
Dong Thap	Low	Low	Low	Moderate	No
Tien Giang	Moderate	Moderate	Low	Moderate	No

3.7 Conclusion

In this study, we integrate a choice experiment into an agent-based model to predict future migration flows out of the rural VMD region due to climate change scenarios and the changes of other migration drivers. This is the first time ABM and CE are integrated with the topic of climate change and migration linkage. Given the complex adaptive nature of migration decision-making and the scarcity of comprehensive data on migration behavior under the variabilities of climate change phenomena, this framework can be a viable alternative to foster the predictive modeling of climate-induced migration.

The model predicts that the rural VMD region would experience substantial outmigration flows, and the negative impact of climate change is one of the main reasons. It is in accordance with the analysis by V. T. T. Anh et al. (2020), which confirms that the high migration from the region is continued and inevitable. Beyond the scale of climate migration, the simulation results indicate that migration patterns are not uniform across provinces. The coastal area, which is forecasted to face both drought and flood high risk, will be hardest hit.

Besides, provinces are differently sensitive to climate change scenarios and other migration stimuli depending on their own current and future situations. Our findings of different sensitivity to migration drivers can serve as a reference for the policymakers to take targeted action on each specific province.

Given the fact that a huge scale of migration will be a reality in the VMD, the region is expected to face a serious challenge of labor shortage. According to V. T. T. Anh et al. (2020), the current situation in the VMD is the aging of the workforce and a high rate of young labor migration. The continuingly high rate of migration is leaving behind the aging, low-skilled and inflexible workforce. As a result, this increases the scarcity of human resources and worsens the population aging in the VMD. Apart from the labor shortage, the quality of labor in the VMD has long been an unresolved issue (V. T. T. Anh et al., 2020). Those problems of human resources will be a burden on the region in the medium or long term.

Our model analysis suggests some policy actions that could reduce the volume of migration flow. First, relaxation of the current crop choice restriction in the VMD can reduce out-migration from coastal provinces. Second, reducing rural-urban inequality via the improvement of migration outcomes can help to slow down the out-migrating speed. For example, higher educational attainment of migrants and policies that support migrants at the destination may be the key contributors.

Chapter 4 Discussion, conclusions, and implications

This final chapter concludes the thesis by linking the main results of this research to the current literature and integrating individual results to build the overall research picture. The thesis ends with policy implications, limitations of the study, and directions for future research.

4.1 Main findings and conclusions

The potential impacts of climate change on migration have been a subject of intense interest in academic arenas for the last few decades. However, there are still significant gaps in our understanding of the complex relationship between climate change and migration. This thesis sheds light on the mechanism by which climate change influences migration decisions and the prediction of future environmentally induced migration, with a focus on farmers in the Mekong Delta, the major agricultural region of Vietnam.

Chapter 2 employs a CE to examine the causal relationship between climate change and rural-urban migration and investigate other significant factors influencing people's migration choices. Based on prior literature and initial piloting, six attributes are selected to capture the main migration drivers: sudden-onset and slow-onset climate change phenomena (i.e., flood frequency and drought intensity); income gap between origin and destination; migration network; neighbors' choice; crop choice restriction. The CE approach has shown its worth in examining the heterogeneity of migration intentions under the impacts of climate change and other migration determinants. Moreover, the CE approach provides an alternative to overcome the shortcomings of using the revealed preferences within the climate-migration field by providing extensive data (on different types of climate change events, variations in intensity and frequency of the event, and abundant data for each subject) and guaranteeing temporal order between environmental factors and migration intention to establish causation. Migration intention has been shown to be a good predictor of realized migration (Creighton, 2013; De Groot et al., 2011; De Jong, 2000; Docquier et al., 2014; M. Lu, 1999; Van Dalen & Henkens, 2008; Van Dalen & Henkens, 2013). The validity of our CE has been acknowledged through the process of design and implementation that results in good understanding and engagement and intuitively sensible preferences from the respondents.

The main findings from the CE models suggest that increasing intensity and frequency of climate change phenomena raise the likelihood of choosing to migrate, with severe drought standing out as the factor most strongly affecting people's choice. While the positive correlation between flood and migration has been found in other studies (e.g. (Entzinger & Scholten, 2016; Koubi et al., 2016)), our study is the first empirical study confirming the strong and positive influence of change in drought severity on migration for the case of Vietnam. The impact of drought becomes significant since, over the last decade when the VMD has experienced great losses on agricultural production resulting from drought and saline intrusion. In other countries, drought has been found to induce migration (e.g., Ethiopia (C. Gray & V. Mueller, 2012), Burkina Faso (Kniveton et al., 2011)) and produce higher fluxes than the wet scenario (Burkina Faso (Kniveton et al., 2011)).

The findings from Chapter 2 also suggest that migration behavior and contribution of migration attributes to movement decision vary according to socio-demographic characteristics. Socio-demographic characters significantly affect migration behavior coverage, income, household size, and migration experience. Other variables such as gender, climate change experience, province dummy, and risk attitude do not directly influence migration decision, but the extent to which individuals weigh the migration attributes in their decision. For instance, the significance of drought and flood attributes vary according to prior experience of climate change phenomena.

Chapter 2 also investigates the effect of crop choice restriction on the intention to migrate. Studies have shown that crop choice restrictions are becoming a barrier to agricultural productivities (Le, 2020; World Bank Group, 2016). In particular, Le (2020) found that the elimination of all land-use restrictions leads to a 37.89% increase in agricultural productivity and an 8.03% increase in real GDP per capita in Vietnam. In this study, we link the impact of crop choice restriction with farmers' migration intention and find that the implementation of crop choice restrictions raises the likelihood of choosing to migrate.

In Chapter 3, we develop a framework to model the migration decision-making process and to forecast future migration flows using ABM and CE approach. The CE model from the previous chapter is integrated into the ABM as a behavioral theory for decision rules and parameterization for behavior specification. Integration of CE approach into an ABM is novel in the study of climate change and migration linkage and offers a feasible alternative to the use of ABM in predictive modeling. This framework allows the integration of future climate scenarios into the ABM to forecast future migration flows out of the rural VMD by 2050 in response to different impacts of climate change.

The results of the simulation in Chapter 3 suggest that the scale of the climate migration out of the rural VMD could be substantial. By 2050, up to 2 million or 11.6 percent of the current regional population could be climate migrants under the pessimistic scenario (i.e., RCP 8.5). The total migration flow is predicted to reach 3.1 million people under RCP 8.5 by 2050. As discussed in Chapter 3, those figures are high compared to other parts of the world; however, they are in line with the historical trend observed in the VMD region over the last decade. Severe impacts of climate change accelerate the scale of out-migration in the VMD. Indeed, Rigaud et al. (2018) highlight the climate out-migration hotspots, including low-lying areas, coastlines vulnerable to sea-level rise, and areas of high agricultural stress, which are the case of the VMD. Furthermore, we can observe the similarly large volume of rural-urban migration in other developing countries going through urbanization. For example, in Brazil, at the peak of its urbanization process, it is estimated that over 20 million people moved from rural to urban areas between the 1950s and 1970s. In comparison, 20.5 million people in India (30% of national urban growth) moved from rural to urban areas in the 1990s (Lall & Selod, 2006). Developed countries also experienced massive rural-urban migration flows during their process of urbanization and industrialization. For instance, Tokyo's population was about 7 million–about the current size of HCMC–, by 1955 and reached 10 million only seven years later (Okazawa & Murakami, 2019).

The model highlights different types of feedback between human migration and social and economic processes. The simulation results suggest positive feedback loops generated from migrant networks and neighbor choices in transmitting information about migration experience and opportunities. Moreover, the model investigates a possible negative feedback loop generated from decreasing the income gap over time. The mechanism behind this process may be the contextual feedback mechanism, through which migration indirectly affects the income gap between the origin and the destination (i.e., rural-urban income gap in this study).

4.2 Discussion and policy implications

The results of this thesis indicate that climate change phenomena can be the major factor that pushes people in the affected area to migrate and that massive climate migration may be a reality in the future. It is now germane to examine where it fits into policy context in terms of better plan and preparation for future climate migration. Climate migration is a broad and complex issue because it can be viewed as an adaptation strategy to as well as a consequence of climate change. As a result, actions should consider both views and target both migrants and people in the sending and receiving communities.

Migration can be an effective adaptation strategy if supported by a good development strategy and targeted investment (Rigaud et al., 2018). Without a long-term pathway to viable livelihoods, perverse incentives to stay in places where conditions are deteriorating could undermine community well-being (Rigaud et al., 2018). In that case, migration could provide a way for people to escape the severe impacts of climate change and reduce the vulnerability of such population (Pachauri et al., 2014). For the case of the VMD, strategies aimed at improving migration outcome becomes vital. Improving human resources via education and skill training are the keys to enhance migration outcomes. C. V. Nguyen and Minh (2016) found that migrants receive substantially lower wages than non-migrants in Vietnam mainly due to the difference in educational attainment. Therefore, skill training for potential migrants as a short-term strategy and policies to motivate schooling as a long-term strategy is primary actions to increase the income of migrants. In addition, as discussed in the previous chapter, policies supporting migrants' access to social welfare, healthcare, education, and employment insurance in the destinations would play an important role in improving migration outcome in Vietnam.

As discussed in Chapter 3, a high volume of rural-urban migration would certainly pose problems that burden both sending and receiving areas. Under the impact of climate change, agricultural structure in the VMD region has been suggested to change from rice-aquatic products-fruit to aquatic products-fruit-rice (V. T. T. Anh et al., 2020). As such, land policies should be redesigned to support the mobility of agricultural land within each sector and between agricultural production activities. Our research suggests that the removal of crop choice restrictions could help counter the upward trend and reduce the overall scale of climate migration. In addition, a transition towards sectors that are less sensitive to climate change needs to be part of the longer-term solution (Rigaud et al., 2018). These shifts can help strengthen the resilience of the region's economy and, therefore, offer local working-age population incentives to stay in place. For example, the processing industries and logistic services of agri-aqua products may improve agricultural products quality and provide alternative job opportunities for local people in the VMD region.

We learn from our study that climate migration patterns will play out differently across provinces depending on each province's climate vulnerability and development context. It suggests that successful adaptation should not ignore the different characteristics and vulnerability of each province. Recently, the central government and many VMD provinces have been developing action plans to respond to climate change. At the same time, they are taking steps to integrate climate change responses and disaster prevention into the socio-economic development plan of the localities. Given the possible acceleration of climate migration trends, climate migration should be adequately embedded into policies and long-term planning. It is a fact that in most regions, policies and strategies for dealing with human movements from increasing climate risks and enabling positive development outcomes are weak or absent (Rigaud et al., 2018).

We also learn from the study that old people are in general reluctant to move. As discussed in the previous chapters, a high rate of young labor migration would shrink the size and reduce the quality of the workforce in origin. Moreover, the larger share of elderly in origin may lead to an increasing burden of health expenditure and pension system. This has important implications for public policy and cost management in the origin area. Securing access to health care provision and pension reform in origin might be adequate considerations for policymakers.

A large scale of migration toward urban areas could exert great pressure on the receiving societies and environments. Indeed, the high rate of in-migration has created continuous and increasing pressure on the demand for infrastructure and public services in HCMC (V. T. T. Anh et al., 2020). Our study suggests that this trend will continue to go further upward due to climate change impact. Therefore, in-migration hotspots will need to prepare for an influx of people, including through improved housing and transportation, infrastructure, social services, and employment opportunities (Rigaud et al., 2018). Policies should also be careful not to constrain individuals who would benefit from moving by creating financial, informational, or other constraints (McKenzie & Yang, 2015).

In addition to the climate-related factors, human interventions both locally and upstream would likely disrupt agricultural production in the VMD and may affect migration patterns. Hydropower developments in the upstream part of the Mekong Basin, such as the instruction of dams, have been shown to drastically affect the hydrological regime and sediment dynamics of the Mekong (Räsänen et al., 2017; Van Manh et al., 2015), making inhabitants in the delta more vulnerable to flood and saltwater intrusion. Moreover, the current over-extraction of riverbed sand that has disrupted the flood regime and reduced sediments in the VMD would endanger the livelihoods of millions of inhabitants (Park et al., 2020). Consequently, those non-climate-related factors, in addition to climate-related ones, would likely lead to considerable migration flows out of the VMD region. Since these human interventions work by affecting the frequency and intensity of flooding and salinity, they could be taken into account by incorporating them into our current model.

4.3 Limitations and future research

Although much effort was put into the research, some shortcomings were unavoidable within the limited timeframe and financial arrangements. Furthermore, given the complex, multi-causal, and contextual nature of migration, investigation of migration and climate change confronts considerable challenges. This section discusses the limitations of the current research and suggests some directions for future research.

The survey was conducted with a representative from farm households (mostly the heads of the households) rather than all household members. As a result, in our model, households are the units of analysis for migration decision-making. Although this perspective is supported by the new household economics theory and is particularly salient for developing countries (Gubhaju & De Jong, 2009), our model is unable to account for individual movements but only household movements[40]. In our prediction, we convert household movements to individual movements to reflect the migration rates reported in official sources. However, future research that requires more information about all household members rather than just household heads will provide a more comprehensive analysis of individual movements mediated by household decisions.

Although the sampling was carefully administered to obtain an adequately represented sample, and survey implementation was undertaken with much care, a limited sample size has been employed in this research. This limitation was due to financial and time constraints. It is a fact that in some VMD provinces, local people are implementing other alternatives to raise income and adapt to climate change, such as planting fruit or raising aquaculture. Because our sample focuses on rice farmers, only a small proportion of the respondents are raising aquaculture or implementing rice-aquaculture rotation. Although our analysis indicates an insignificant difference in behavior preferences between rice farmers and shrimp farmers, a small sample of farmers who are raising other crops/aquaculture rather than rice

[40] In contrast to the new household economics theory, the neoclassical microeconomic theory argues that individual choice is at the center of decision-making (Gubhaju & De Jong, 2009). Some ABMs base on this theory to model migration decision made by individual actors. Nevertheless, they ignore the household context in which an individual is making such decision.

might overestimate the impact of climate change on migration decisions. Further research should execute a broader survey (e.g., all provinces of the Mekong Delta). That would help to generate further insights into migration intentions of farmers who are implementing different crops and aquaculture in response to the impact of climate change.

Uncertainty of migration prediction surrounds not only climate scenarios but also the socio-economic, political, and demographic drivers that might be dynamic and interacted. Even if methodologically sound, statistical methods cannot always make accurate future migration projections (Cattaneo et al., 2019). The trend of migration drivers over time and the interactions among them will influence individuals' migration decisions, and therefore migration predictions. Our ABM model does take into account demographic trends and climate scenarios; however, it does not consider socioeconomic and political scenarios. Moreover, current and future mitigation and adaptation strategies can raise people's resilience to climate change and then may counter their intention to migrate. For example, ongoing projects of mega irrigation systems could be one important means for adapting to severe droughts in the VMD. Information on the possibility of modern irrigation systems in respondents' provinces may affect their migration behavior. As a result, future climate scenarios that incorporate such adaptive strategies would be useful to predict climate migration. Therefore, further research may incorporate one or more of those factors into the investigation to obtain more future migration scenarios. This will certainly complicate the model; however, it is worth anticipating key changes in migration flows. From a policymaker's point of view, it is important to set up systems that can deal with different alternative outcomes and adjust flexibly.

Although the CE approach offers great advantages in the investigation of climate change – migration linkage (as discussed in previous chapters), it suffers a limitation that only a limited number of attributes can be included. CE method will bear considerable costs when adding too many attributes into the choice set. One more attribute will lead to an exponential increase in the number of choice set combinations. In our CE design, we control the number of attributes at an appropriate level aiming that the number of choice set combinations is manageable. Moreover, given the respondents are those with relatively low educational attainment, a choice set with limited attributes will facilitate the respondents' understanding and engagement. Consequently, we may not include all the attributes of migration into the CE. This limitation is actually inherent and difficult to address. In order to minimize possible errors, we went through a thorough process of review and piloting to select the main migration drivers.

Our current model does not account for different types of migration (e.g., long-term, short-term, or seasonal). Given limited resources, predictions by type of migration would be meaningful for policymakers because different types of migration may infer to different policy targets. For example, if long-term migration outflows are considerable, policies targeted to relieve burdens in potential destinations and to develop less labor-intensive industries in origin may be necessary for the long term. In contrast, if seasonal and short-term migration is dominant, policies targeted to create on-farm or off-farm alternative livelihoods for a large volume of the working-age population in origin may be suitable. Therefore, further research should develop the current model to provide more insights into different migration responses.

Another suggestion for future research might be a focus on the indirect feedback mechanisms, which have not been well studied in the literature. Decisions to migrate can fluctuate with time according to how people change their perceptions of the migration environment (Jolivet, 2015). Information on and ideas about migration, origins, and destinations can cause 'feedback processes' that either stimulate or discourage future migration (Mabogunje, 1970). For example, information on changing policies or adaptation strategies in origin regions may change people's perception of their own living situation in their place of residence, and therefore, indirectly influence migration decisions. Moreover, information on the opportunities and social rights of current migrants in the desired destination may shape people's migration aspiration and decisions.

Appendix 3.1 Rice-farm versus shrimp-farm

1. 100% rice farm vs. x% aqua farm ($0 < x \leq 100$).

In this section, we examine the migration intentions of rice farmers and aqua-farmers who either raise aquaculture for all crops or implement rice-shrimp rotation. We create a dummy to specify a specific household raising aquaculture regardless of the percentage of aqua-farming out of total agricultural activities (i.e., aqua_farm). Aqua_farm then interacts with drought and flood variables to investigate whether rice-farmers and aqua-farmers weigh drought and flood attributes differently. The results show that there is no significant difference in how rice-farmers and aqua-farmers consider drought and flood attributes when making migration decisions.

Table A - 1. Crosstab of aqua-farm by provinces

	Aqua-farm		
Province	0	1	Total
Kien Giang	38	112	150
	25.33	74.67	100.00
	10.86	32.00	42.86
Long An	186	14	200
	93.00	7.00	100.00
	53.14	4.00	57.14
Total	224	126	350
	64.00	36.00	100.00

Table A - 2. WTP of drought and flood for aqua-farm and rice-farm

VARIABLES	(1) aqua-farm	(2) rice-farm	(3) Differences
drought_moderate	0.154	-0.188	0.341
	(0.673)	(0.626)	(0.642)
drought_severe	-1.378***	-2.284***	0.906
	(0.505)	(0.624)	(0.578)
flood_frequency	-1.152*	-0.981*	-0.171
	(0.656)	(0.535)	(0.535)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

2. Rice farm vs. 100% aqua farm

In this section, we examine the respondents who are only raising aquaculture and have no land for rice farming (i.e., dummy aqua100_farm = 1). Results indicate that there is no significant difference in how rice-farmers and aqua-farmers consider drought and flood attributes when making a migration decision

Table A - 3. Crosstab of aqua-farm

Province	Aqua100-farm 0	 1	 Total
Kien Giang	129	21	150
	86.00	14.00	100.00
	36.86	6.00	42.86
Long An	199	1	200
	99.50	0.50	100.00
	56.86	0.29	57.14
Total	328	22	350
	93.71	6.29	100.00

Table A - 4. WTP of drought and flood for aqua100-farm and rice farm

VARIABLES	(1) aqua100-farm	(2) rice-farm	(3) Differences
drought_moderate	0.268	-0.0937	0.362
	(1.248)	(0.548)	(1.150)
drought_severe	-1.403*	-1.922***	0.519
	(0.852)	(0.507)	(0.785)
flood_frequency	-1.445	-1.069**	-0.376
	(0.974)	(0.521)	(0.837)

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 3.2 Population synthesis - Zero cells in the survey data cross table

There are two problems of having zero cells in the seed table when using the iterative proportional fitting (IPF) method.

First, “too many” zero cells in the initial matrix might prevent convergence (Lomax & Norman, 2016) (Suesse et al., 2017). (Norman, 1999) notes that in practice, “too many” is found to be around 30 percent of the values within the seed table if they are distributed evenly. There are cases that even with zero cell counts, IPF still converges when the number of zero cells is not “too many”. Indeed, our IPF using the survey sample still converge, although we have several zero cells in the seed table. It might be better if we minimize the number of zero cells by reducing the age category numbers from five to four. As can be seen from Table 1, now we have four zero-cells in the seed table.

Second, the estimated cells are zero if those cells of the initial table (seed) are zero. This means some combinations of attributes of the synthetic populations will be impossible to sample due to the zero estimates. This will cause a problem if the synthetic simulation process does not aim at excluding particular combinations of attributes (Suesse et al., 2017).

A common practice is to add a small constant to all the zero cells (Lomax & Norman, 2016; Suesse et al., 2017; Wickramasinghe, 2019). However, even after adding a small constant to the zero cells, the obtained cells in the synthesized population are still zeros. This is a realistic scenario for multidimensional tables, as in practice, some population counts will indeed be small and often be zero (Suesse et al., 2017). I tried to add a small constant to the zero cells in our seed table; the smallest constant required to have nonzero cells in obtained populations is 0.15 for Kien Giang province. This is a relatively big constant compared to the constant common used in literature (e.g., 10^-3). One possible reason may be that our population size (N)/sample size (n) is not big enough.

Therefore, if the zero cells in the seed table (and then in the synthesized population table) are not undesirable, we may accept our current IPF results with some zero cells (see Table 2). Let look at the seed table (Table 1) for further analysis. We have four zero-cells. All of them are at very high-income group, in which two in young age and small household size, and two in the female group, older age, and big household size. Those zeros can be sensible in the sense that there may be a very small number of young households (i.e., small household size and young household head) that have a high or very high income. Big households with old female heads may earn less than those with male heads do. Because the total number of households with female heads is relatively small compared to those with male heads, the proportion of the old female head-big household size-very rich cells should be very negligible in reality.

Appendix 3.3 Reviews of available studies on flood and drought risk in the VMD

I. Flood risk

Table A - 5 demonstrates the assessments of flood risk from four available studies. There are common assessments (i.e., in at least 3 out of 4 cited references) as follow:

- Upstream and further inland provinces have higher flood risk than coastal provinces.
- The highest flood risk provinces in the region are An Giang and Dong Thap
- No or very low flood risk provinces are Ben Tre, Tra Vinh, Soc Trang, Bac Lieu
- Moderate flood risk provinces are Tien Giang, Kien Giang, Can Tho, Hau Giang

Table A - 5. Assessments of flood risk from available studies

Province	(Wassmann et al., 2019)	(Yen, Son, Tung, et al., 2019)		(V. K. T. Nguyen et al., 2018)	(Luu et al., 2019)
		Severe	Normal		
Long An	Moderate	High	Moderate	High	Moderate
Tien Giang	Moderate	Moderate	NA	Moderate	Moderate
Ben Tre	None	NA	NA	None	Low
Tra Vinh	None	NA	NA	None	Low
Vinh Long	None	Low	None	Moderate	Moderate
Dong Thap	High	High	High	High	High
An Giang	High	High	Moderate	High	High
Kien Giang	Moderate	Moderate	Low	Low	Moderate
Can Tho	Moderate	High	Moderate	Moderate	Moderate
Hau Giang	Moderate	High	Moderate	Moderate	Low
Soc Trang	Low	NA	NA	None	Low
Bac Lieu	Low	NA	NA	None	Low
Ca Mau	None	Low	None	None	High

In general, assessments from Wassmann et al. (2019) seem to be reliable and can be used because their findings are mostly consistent with other available studies. Moreover, the definition of risk levels employed in Wassmann et al. (2019) is relevant to the scope of our study, which is the rice area being exposed to the flood risk (see Table A - 6 for the description of risk level definition, data used, and methodology in available studies).

Table A - 6. Description of risk level definition, data used, and methodology of available studies

Study	Definition of risk level	Data	Methodology
(Wassmann et al., 2019)	Percentage of the rice area being exposed to the drought/flood risk	land use, cropping map, the configuration of the canal network comprising dimensions, soil type, and hydrological data	Hydrological model Mapping
(Yen, Son, Tung, et al., 2019)	Percentage of rice production damaged by the hazards		Qualitative Mapping
(V. K. T. Nguyen et al., 2018)	Flood damages and risks to rice cultivation. Specific loss is calculated in USD/ha/a	Topography data, tidal levels, scheme of flood control structures, and rice cropping system and planting calendar	Large-scale hydraulic Model Mapping
(Luu et al., 2019)	Total flood loss	total economic loss, human loss, housing damaged, education impact, health-care impact, agriculture impact, irrigation impact, transportation impact, etc.	Multiple linear regression

II. Drought and saline intrusion risk

Table A - 7 provides the comparison of the assessment of drought and saline intrusion risk from available studies and sources. There are common assessments as follow:

- Can Tho, Dong Thap, An Giang have no drought and saline intrusion risk
- Ca Mau has high drought and saline intrusion risk
- Tra Vinh and Soc Trang have a moderate risk
- Hau Giang has low risk

Other provinces have different risk levels across cited studies; however, the differences are not so large (low to moderate or moderate to high).

Table A - 7. Assessments of drought and saline intrusion risk from available studies

Province	(Wassmann et al., 2019)	(Yen, Son, Tung, et al., 2019)		Drought 2016[41]
		Severe	Normal	
Long An	None	Moderate	Low	Low
Tien Giang	Moderate	Low	Low	Low
Ben Tre	High	High	Moderate	Moderate
Tra Vinh	Moderate	Moderate	Moderate	Moderate
Vinh Long	Low	Moderate	Low	Moderate
Dong Thap	None	NA	NA	None
An Giang	None	Low	None	None
Kien Giang	Moderate	Moderate	Low	High
Hau Giang	Low	Moderate	Low	Low
Soc Trang	Moderate	Moderate	Low	Moderate
Bac Lieu	High	Moderate	Low	Moderate
Ca Mau	High	High	Low	High

[41] Rice area damaged (ha) - see *Table A - 8* for more detail.
Source: Central Steering Committee for Natural Disaster Prevention and Control, MARD - https://www.mard.gov.vn

Table A - 8. Rice area damaged (ha) by the drought in 2016

Province	Rice area damaged (ha)
Kien Giang	54093
Ca Mau	48600
Tra Vinh	32051
Soc Trang	24530
Ben Tre	20368
Vinh Long	17654
Bac Lieu	12814
Long An	9653
Tien Giang	3559
Hau Giang	1230

Another comparison is taken from (A. T. Dang et al., 2020), which is the paper we get the future drought and saline intrusion projections (Table A - 9). We decide to base on (Yen, Son, Tung, et al., 2019) instead of (A. T. Dang et al., 2020) because (Yen, Son, Tung, et al., 2019) only consider rice area while (A. T. Dang et al., 2020) consider the whole province area; therefore, the risk profiles from the former relatively illustrate the real situation. Furthermore, when matching with future projections, using the former results to reasonable trends. In general, the risk profiles taken from these two papers are relatively matched in terms of severe drought proportion, except the two provinces Bac Lieu and Ben Tre.

Table A - 9. Present drought severity from (Yen, Son, Tung, et al., 2019) and (A. T. Dang et al., 2020)

	Province	(Yen, Son, Tung, et al., 2019)			(A. T. Dang et al., 2020)		
		Severe	Moderate	None	Severe	Moderate	None
1	Long An	20	40	40	10	70	20
2	Tien Giang	3	47	50	3	67	30
3	Ben Tre	85[42]	2	13	30	40	30
4	Tra Vinh	50	50	0	40	60	0
5	Vinh Long	5	55	40	5	75	20
6	Dong Thap	0	0	100	5	15	80
7	An Giang	0	10	90	10	10	80
8	Kien Giang	30	0	70	30	40	30
10	Hau Giang[43]	0	30	70	0	30	70
11	Soc Trang	30	40	30	25	20	55
12	Bac Lieu	15[44]	55	30	60	15	25
13	Ca Mau	80	5	15	80	20	0

[42] Large difference compared to (A. T. Dang et al., 2020) because (Yen, Son, Tung, et al., 2019) only consider rice area while (A. T. Dang et al., 2020) consider the whole province area.
[43] Drought and saline intrusion risk for normal year.
[44] large difference compared to (A. T. Dang et al., 2020) because (Yen, Son, Tung, et al., 2019) only consider rice area while (A. T. Dang et al., 2020) consider the whole province area.

Appendix 3.4 Population aging

The main indicator for measuring population aging is the old-age coefficient, which is the ratio of the elderly population to the total population (Handong et al., 2020). The elderly population is those who are over 60 or 65 years old. Handong et al. (2020) find that the proportion of the population over the age of 60 in Vietnam will increase to 25.05% by 2049 from 8.69% in 2010; the proportion of the population over 65 in Vietnam will increase to 18.42% by 2049 from 6.4% in 2010.

Table A - 10. Mortality rates by age cohorts for Vietnam rural population (calculated from (Handong et al., 2020))

Age cohorts	Mortality rate 2019	Average mortality rate (2019 – 2050)
< 35	0.000548	0.000354
35-44	0.001211	0.00081
45-54	0.003623	0.002706
55-64	0.010411	0.008462
65-74	0.030363	0.02613
>= 75	1	1

As a result, the population aging structure at the end of the simulation period is relatively in line with the prediction derived by Handong et al. (2020). Table A - 11 presents proportions of the old-age population to the total adult population taken from Handong et al. (2020) and some provinces in our simulation[45]. In general, our simulation can capture the trend of population aging in Vietnam in the future.

[45] Handong et al. (2020) find that the ratio of the labor population in Vietnam to the total population was 66.93% in 2010 and then fell to 57.96% by 2049. Basing on that, we calculate the proportion of elderly to the total adult population as shown in Table A - 11.

Table A - 11. Proportion of elderly to the total adult population in 2050 – Simulation results of Kien Giang and Long An province

	Elderly (>60)	Elderly (>65)
(Handong et al., 2020)	32.80	24.12
Kien Giang	35.5	24.0
Long An	30.73	21.3

Appendix 3.5 Provincial characters that influence migration flow in the VMD

There are some candidates for provincial characteristics as migration determinants for the case of Vietnam. Phuong, Tam, Nguyet, and Oostendorp (2008) find that migrants tend to move from provinces with low GDP per capita, low Human Development Index (HDI), and high underemployment rates to provinces with high GDP per capita levels, high HDI, and low underemployment rates. In (Nguyen-Hoang & McPeak, 2010), the authors use indexes for provincial efforts in labor training (i.e., one indicator of Provincial Competitive Index) as an instrument for the unemployment rate. In addition, Nguyen-Hoang and McPeak (2010) find that the quality of public services (e.g., healthcare, education) and infrastructure influence migration flows.

We check available data sources to sort out some candidates for provincial characteristics as migration determinants, as being shown in Table A - 12. Table A - 13 demonstrates the correlation coefficients of provincial indexes with the VMD out-migration rates.

Table A - 12. Provincial characteristics that might affect migration

	Name	Description	Source
1	Poverty rate by province	Period 2016-2019 Higher index lower rank	GSO Statistical Yearbook of Vietnam 2019
2	Multi-dimensional poverty (MPI) 2008	MPI is calculated based on the level of deprivation in education, healthcare, living standard, and level of monetary poverty. A higher index means a lower rank.	The United Nations Development Programme (UNDP) Vietnam (Elfick, 2011)
3	Human development index 2008	Sub-indexes include the life expectancy index, education index, and income index. A higher index means a higher rank.	UNDP Vietnam (Elfick, 2011)
4	Unemployment rate by province Underemployment rate by province	Period 2011-2018 A higher index means a lower rank.	CEIC – Vietnam General Statistic Office[46]
5	Provincial competitiveness index (PCI)	There are PCI rank and rank groups (very good, good, moderate, and low). PCI is a system of indicators used to evaluate and rank provinces and cities in Vietnam for the ease of doing business at the provincial level. PCI is constructed with 10 sub-indices reflecting different areas of economic governance that affect private sector development. Lower index means higher rank.	Vietnam Chamber of Commerce and Industry (VCCI)[47]

[46] Vietnam Unemployment: Mekong River Delta | Economic Indicators | CEIC (ceicdata.com)
[47] The Provincial Competitiveness Index (PCI) (pcivietnam.vn)

Table A - 13. Correlation of provincial indexes with out-migration rates for VMD provinces

	Average of out migration (2005-2019) Coeff. (p-value)	
Human development index (HDI)	0.0177 (0.8200)	Unexpected
Multi-dimensional poverty index (MPI)	0.2344 (0.0022)	As expected
Provincial competitiveness index (PCI)	-0.2406 (0.0017)	Unexpected
Poverty rate	-0.0862 (0.2667)	Unexpected
Unemployment rate	0.0663 (0.3929)	As expected
Underemployment rate	-0.0170 (0.8274)	Unexpected

Two out of 6 candidates show an expected correlation with migration rates, which are MPI and unemployment rate. However, the correlation coefficient of unemployment is insignificant. MPI seems to be the potential candidate because the index not only accounts for provincial monetary poverty level but also the level of public services and living standards.

Besides those above candidates, we also expect that distance from the original province to the most common migration destination (HCM city) may have effects on migration flows. Appendix 3.6 Correlation between distance and migration in Vietnam will provide more information on the relationship between distance and migration for the case of the VMD. As a result, distance, MPI, and unemployment rate are chosen as provincial characteristics that influence migration flows.

Appendix 3.6 Correlation between distance and migration in Vietnam

I. Literature review

In the literature on migration, distance is commonly used as a proxy for the costs of moving, job search, information acquisition, and psychological costs. Greater distance should increase these costs and hence deter migration (Phan & Coxhead, 2010). The literature on migration and distance mostly focuses on migration flows between pairs of provinces – sending and receiving – and choices of destination, but not on the decision of move or stay. The most popular methodology is based on the gravity model that hypothesizes that the flow of migrants between locations is a function of population, distance, income differentials, and other control variables. Distance is proved to have a negative correlation, indicating that the farther two locations are from each other, the lower will be the migration flow between them.

For the case of Vietnam, most studies on this topic also examine the effects of distance on migration flow between two provinces/regions. Some examples are (Fukase, 2013; Huy & Nonneman, 2016; Nguyen-Hoang & McPeak, 2010; Phan & Coxhead, 2010). Except (Huy & Nonneman, 2016) focuses on out-migration from VMD provinces, other studies focus on nationwide samples to analyze inter-provincial migration in Vietnam. Therefore, the distance variable ranges from 20 to about 4000 km, with the mean is at about 400-500km. These studies find a negative and significant effect of distance on migration flows, showing that distance is an important determinant of migration costs.

Studies show inconclusive evidence of considering distance as a determinant of moving decision (i.e., move or stay). Almost all studies for the case of Vietnam do not include distance as a determinant of the decision move or stay (e.g. (Fukase, 2013; Koubi et al., 2016)¸ except when the sending areas are at remoted region (e.g., via a variable named distance to the nearest town (Coxhead et al., 2015)). We found only one study - (De Brauw, 2010) - that includes distance to Hanoi and HCM city variables into the regression of migration decisions. From this study, distance to a big city seems not to have significant effects on the out-migration rate. In particular, the author finds an insignificantly positive correlation between distance to Hanoi and distance to HCM and the share of out-migration in 1993; and an insignificantly negative correlation between the change in the number of seasonal migrants between 1993 and 1998 and distance to Hanoi and HCM.

To sum, findings from the literature confirm the significant negative effects of distance on migration flows between two locations, indicating that migration flows between any two sending-receiving locations will reduce when distances between them increase. The distance elasticity would depend on push-pull factors from origin and destination such as income differential, the unemployment rate in destination, etc. However, there is evidence showing that distance has an insignificant effect on out-migrating decisions. These findings suggest distance as one determinant of destination choices but not a determinant of staying or moving decisions.

II. Correlation between distance and migration experience in the survey sample and VMD provinces

We need to distinguish the two possible effects of distance on migration, which are:

(i) The effects of distance on the decision to move or stay.

(ii) The effects of distance on destination choice. The hypothesis here is that migration flows between two places decrease when the distance between them increases.

We find that while distance does not have a negative influence on the decision to move or stay, it does have significant negative impacts on the selection of destination. Our findings align with evidence from the literature.

1. Distance does not negatively influence out-migration rates

From survey data, we do not find a significant correlation between distance to HCM city and migration experience. According to *Table A - 14*, we do not observe that provinces that are closer to HCM have a higher out-migration rate.

Table A - 14. Out-migration rate at VMD provinces sorted by distance (2015-2019)

Provinces	Distance to HCM	2015	2016	2017	2018	Prel. 2019
Long An	60	6.5	6.3	4	7.1	6
Tien Giang	70	5.3	3.2	3.5	5.1	7.7
Ben Tre	90	7.4	6.3	4	6.8	9.6
Tra Vinh	125	5.5	3.9	3.1	12.4	10.6
Dong Thap	140	9.1	7.6	7	6.2	12.8
Vinh Long	150	7.7	3.5	7.8	4	10.9
Can Tho	200	7.7	6.3	2.6	6.3	7.2
Hau Giang	210	6.1	3.8	8.9	6.4	14.6
Soc Trang	220	6.2	6.6	8.3	15	16.2
An Giang	235	11.8	10.4	5	11.9	15.6
Kien Giang	260	9.9	11	10.8	6.8	11.3
Bac Lieu	300	7.6	7.5	4.4	6.9	11.8
Ca Mau	310	7.7	9.1	9.4	7.7	13.8

Three possible explanations are discussed. First, the range of distance from VMD provinces to the most common destination, HCM city, is not varied enough to display the negative effects of distance. Arguably, the maximum distance from a VMD's province to HCM – about 400km – is considered a short distance. For example, Phan and Coxhead (2010) consider migration from the VMD region to HCM as being a short-distance rural-urban move. Additionally, the distance of 400km is smaller than the mean migration distance of nationwide data (see (Fukase, 2013; Phan & Coxhead, 2010)). According to our survey data, a large proportion of out-migrants from the survey site - about 74 to 80 percent - have traveled a distance no more than 400km.

Second, given the current development of transportation infrastructure connecting VMD provinces to the Southeast region and the availability of various means of telecommunications, recent migrants would bear fewer migration costs than before. This seems reasonable to infer that traveling a distance from VMD provinces to the most common destinations may not incur a high cost for the migrants. In addition, other costs embedded under the distance between the origin and the destination, such as disconnection from migrants' social-family network (psychological cost), can be decreased thanks to the development of telecommunications and the abundant networks at the destinations.

Third, there might be the case that income–distance tradeoff (i.e., the elasticity of increasing expected income at destination given an increase in origin-destination distance) for the case of the VMD is lower than other comparisons. Equivalently, it means that people are more willing to move further to get an increase in expected income. (Phan & Coxhead, 2010) calculated Vietnam's tradeoff being 0.73 - meaning that a 0.73% increase in destination income is needed to offset a 1% increase in distance. Given significantly high out-migration rates in VMD provinces, the distance elasticity for that region might be higher than the national index because of the large pull effects of big cities.

2. Migration flows between two places decrease when the distance between them increases

In order to examine the impacts of distance on the choice of destination, we create the destination zone variable to indicate the range of migration distance (*Table A - 15*). A higher zone indicates further migrating distance.

Table A - 15. Destination zones and descriptions

Zone	Destination
1	Within province
2	Adjacent province (<100km)
3	Non-adjacent close province (100-250km)
4	Non-adjacent far province (250-400km)
5	International/ inter-regional migration (>400 km)

We then run a conditional logit model of destination choices. In the model, each migrant in the sample faces five choices of destination zone. Two choice characteristics include the distance from the origin to the destination zone and a dummy to indicate whether the destination choice is the most common destination or not (i.e., HCM/Binh Duong). The results show that distance has a negative and significant impact on the destination choice of the migrants (*Table A - 16*). In other words, the respondents are more likely to choose the destinations in smaller zones.

Table A - 16. Conditional logit model of destination choices

VARIABLES	Destination zone
Distance	-0.678***
	(0.0999)
Common destination	19.88
	(765.9)

Standard errors in parentheses

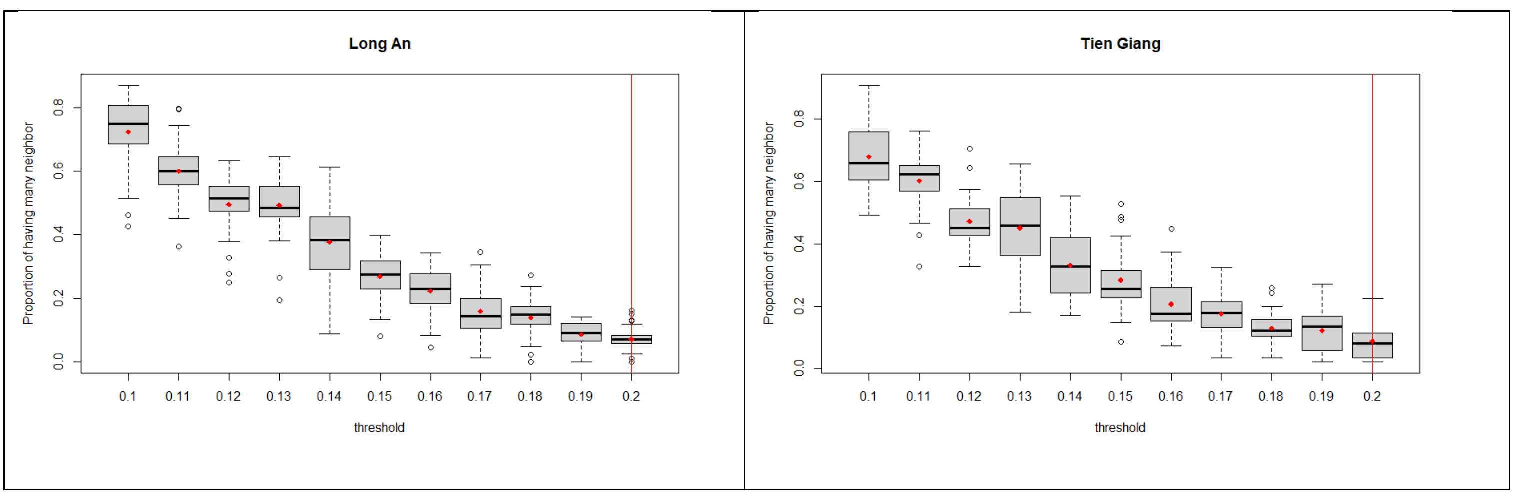
*** p<0.01, ** p<0.05, * p<0.1

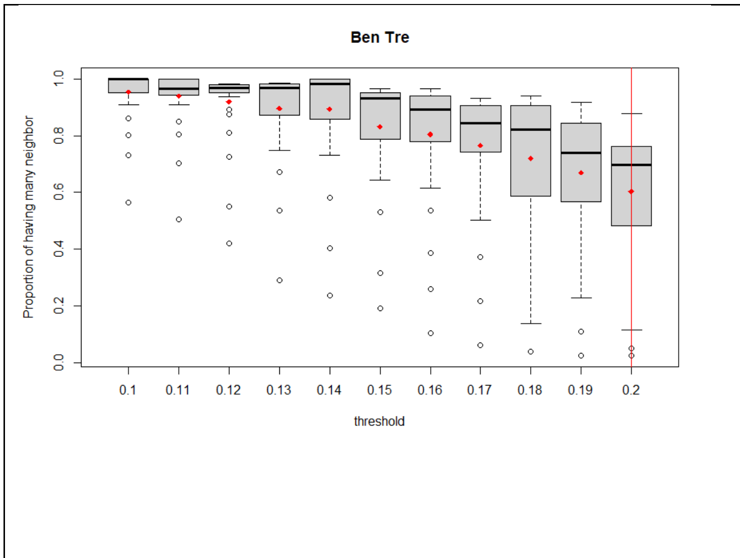
Appendix 3.7 Parameter screenings and local sensitivity analysis (SA)

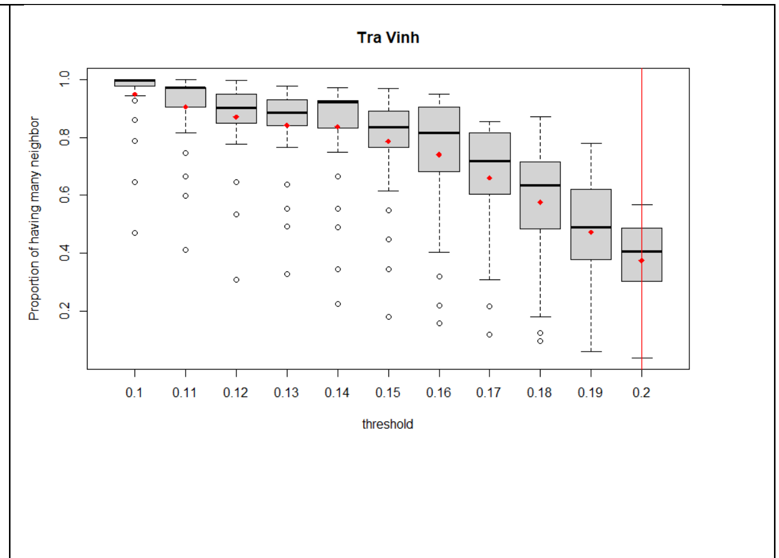
1. SA for threshold for neighbor on the percentage of having many neighbors migrating

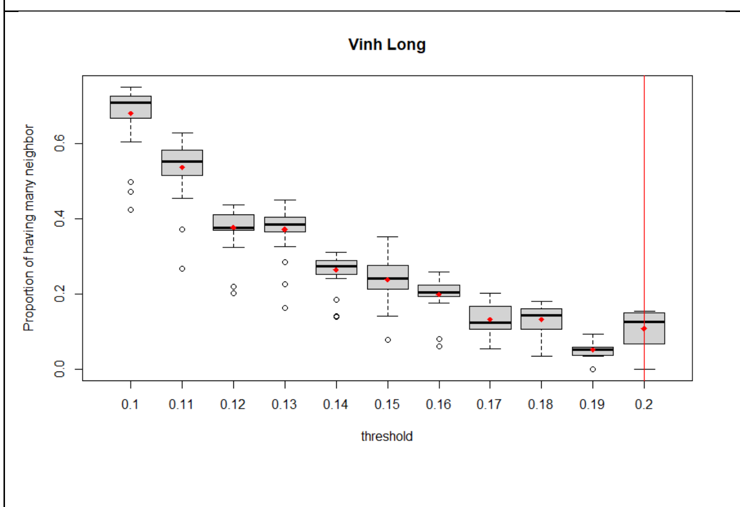
The purpose of this SA is to screen the threshold parameter and figure out a realistic range of parameters for further investigation. The range for screening neighbor threshold is from 0.1 to 0.3. For the values that are smaller than 0.1 and larger than 0.3, neighbor percentages are all one or zero. *Figure A - 1* shows box plots of neighbor percentage over simulation duration for 12 VMD provinces. Red dots show the mean values. We expect that the range of neighbor percentage should not be too close to 1 or zero. The result shows that the threshold value from 0.16 to 0.2 is the suitable range for the threshold, where the average neighbor percentage ranges from around 0.1 to 0.9 for all provinces and thus is chosen for further global SA.

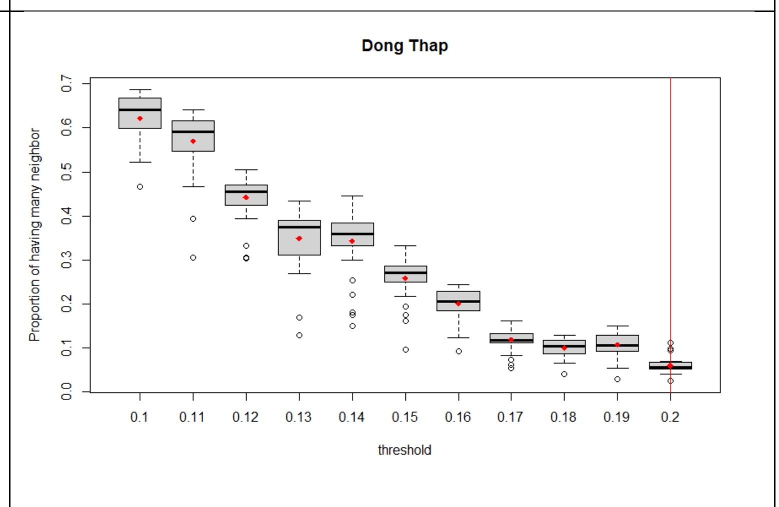
Figure A - 1. Boxplots of neighbor percentage over simulation time

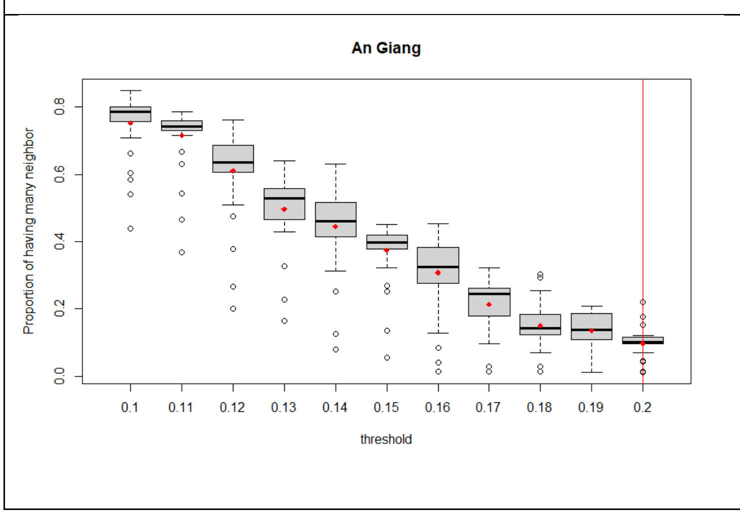


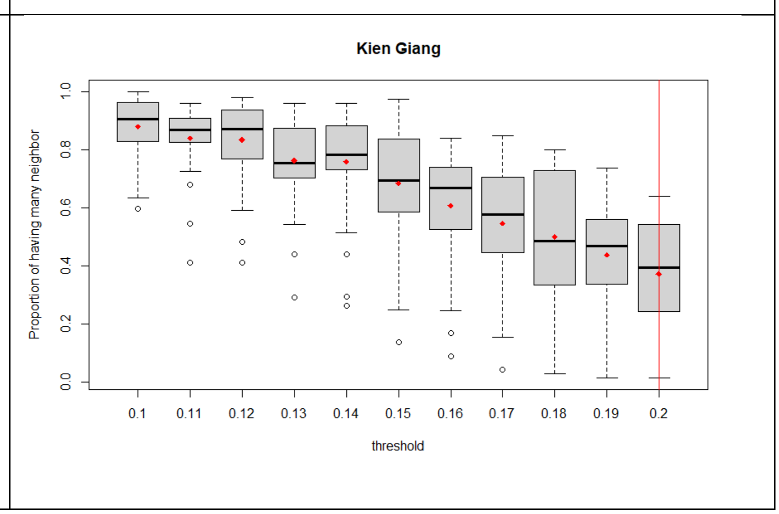

Ben Tre
Proportion of having many neighbor
0.0 0.2 0.4 0.6 0.8 1.0
0.1 0.11 0.12 0.13 0.14 0.15 0.16 0.17 0.18 0.19 0.2
threshold

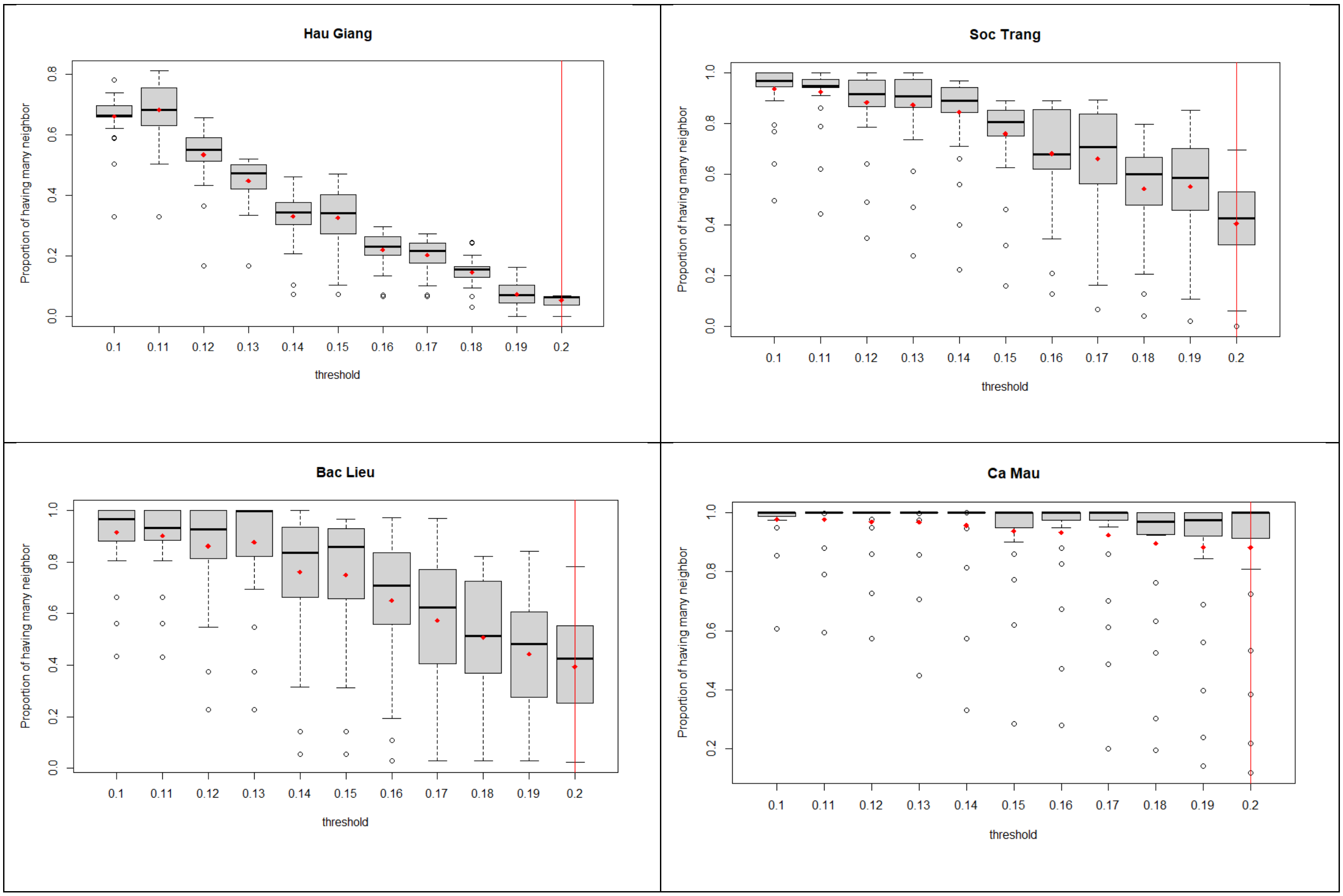

Tra Vinh
Proportion of having many neighbor
0.2 0.4 0.6 0.8 1.0
0.1 0.11 0.12 0.13 0.14 0.15 0.16 0.17 0.18 0.19 0.2
threshold


Vinh Long
Proportion of having many neighbor
0.0 0.2 0.4 0.6
0.1 0.11 0.12 0.13 0.14 0.15 0.16 0.17 0.18 0.19 0.2
threshold


Dong Thap
Proportion of having many neighbor
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7
0.1 0.11 0.12 0.13 0.14 0.15 0.16 0.17 0.18 0.19 0.2
threshold


An Giang
Proportion of having many neighbor
0.0 0.2 0.4 0.6 0.8
0.1 0.11 0.12 0.13 0.14 0.15 0.16 0.17 0.18 0.19 0.2
threshold


Kien Giang
Proportion of having many neighbor
0.0 0.2 0.4 0.6 0.8 1.0
0.1 0.11 0.12 0.13 0.14 0.15 0.16 0.17 0.18 0.19 0.2
threshold



2. SA for initial proportion of having migration network

The purpose of this SA is to examine how variation in the initial proportion of having a network affects the proportion over time. *Figure A - 2* shows boxplots of the proportion of having a network over time for different initial values for Kien Giang province. *Figure A - 3* illustrates the proportion of having a migration network over time for selected values of pct_nw. We see that different values of pct_nw do not lead to big fluctuations in the proportion of having network over time. One possible reason is that the network attribute is set up to die out after several years (5 to 10 years).

Figure A - 2. Boxplots of proportion of having network over time for different initial values

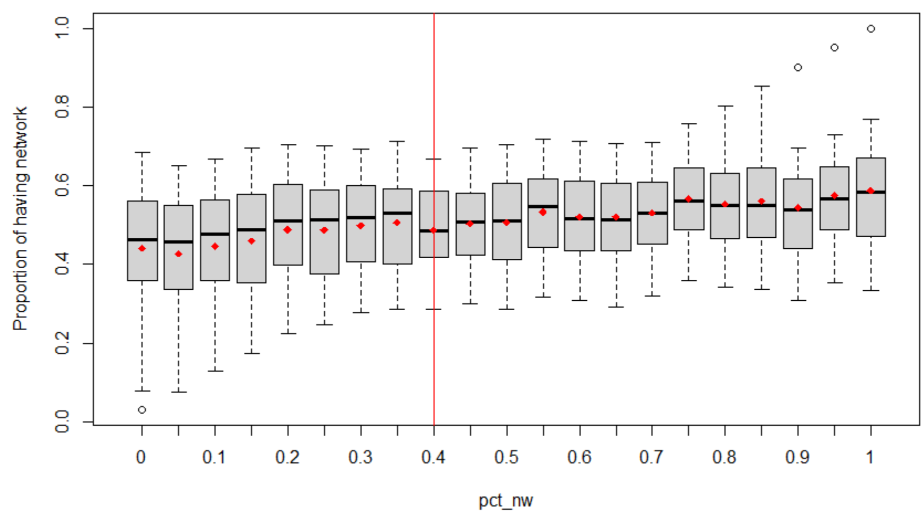
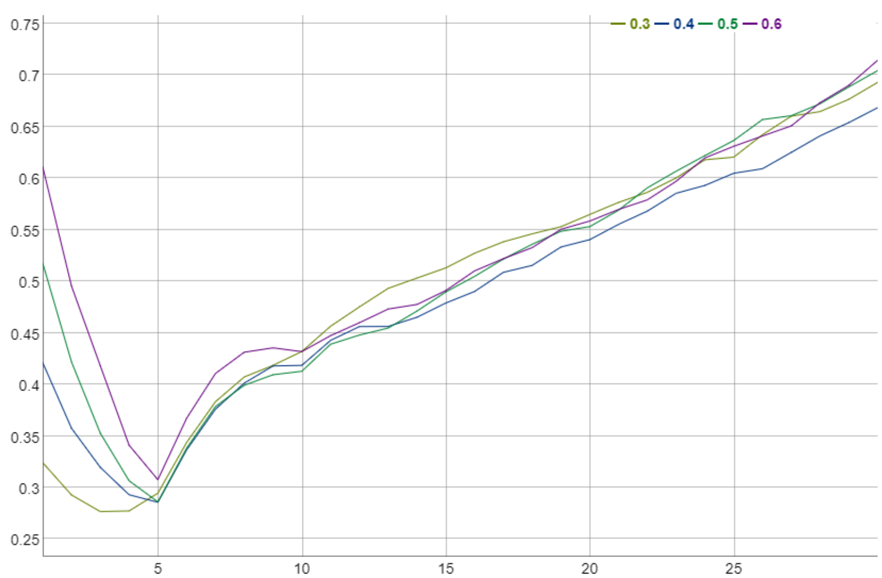


Figure A - 3. Trend of network percentage using selected pct_nw



3. SA for the duration of having migration network

In the model setup, the network is assumed to die out over time. In this SA, we test the variation network percentage if the duration of having a network ranges from 1 to 10 years (Figure A - 4 for Kien Giang province). In the current model setup, at year 0, 40% of the agents having a migration network. The result shows that the longer the network duration is, the higher proportion of having a network on average. For the duration from 5 to 10 years, the proportions of having a network are at a reasonable range, where the highest values range between about 60 to 85 percentage points (Figure A - 5). We choose the range from 5 to 10 years to further investigate parameter nw_counter in a global sensitivity analysis.

Figure A - 4. Proportion of having network over time for network duration ranging from one to 10 years

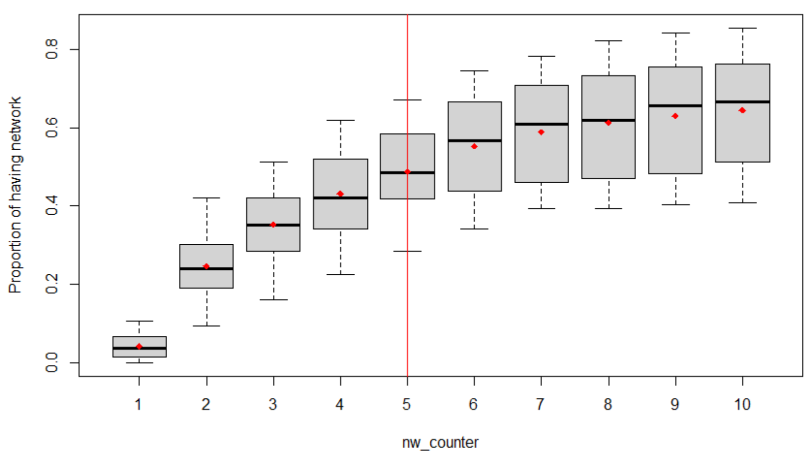
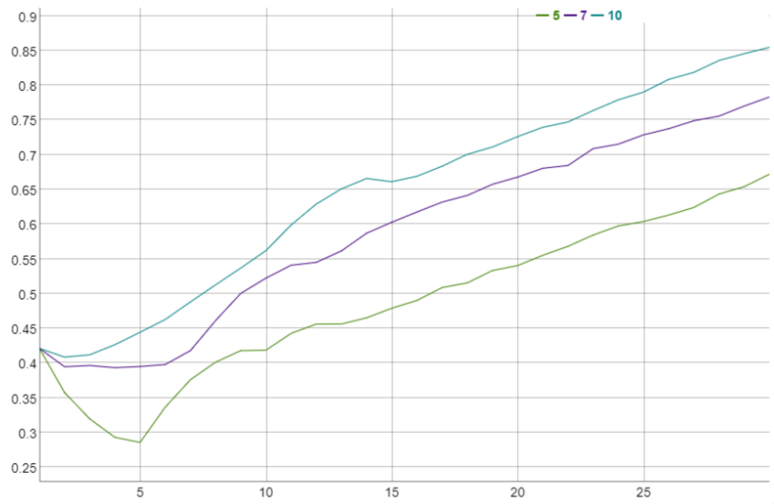


Figure A - 5. Trend of network percentage using selected nw_counter

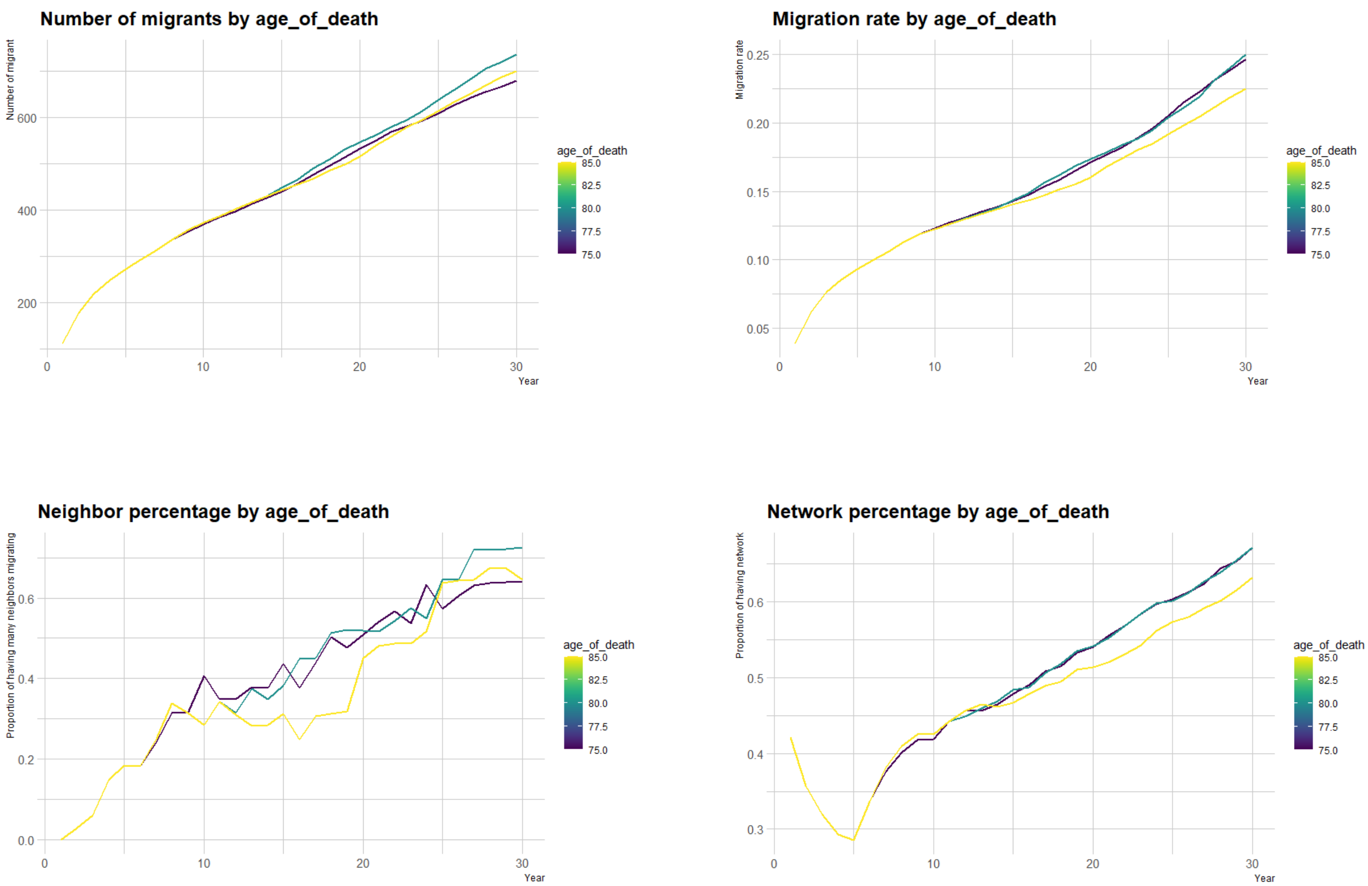


4. SA for age of death

Figure A - 6 below shows the impact of age_of_death on selected simulation outputs. The results show that the age_of_death parameter does not large impact on absolute value output (i.e., number of migrants) but does have a large impact on percentage value outputs (i.e., the rest of three outputs). The reason is that the age of death affects population size and thus influences ratios that using population as denominators. Therefore, in this current study, the number of migrants is chosen as the main output for results analysis.

We see from Figure A - 6 that the impact of age_of_death on the number of migrants is not monotonic. Further investigation of this parameter is needed to conclude the sign and magnitude of the parameter impacts. The impacts of age_of_death on the other three outputs indicate little variation when age_of_death is set among 75 to 80. When the age of death reaches 85, we observe a relatively large decrease in percentage outputs.

Figure A - 6. Selected outputs for different values of age_of_death



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Appendix Table 1. T-test and Pearson chi-square test results for differences between move and never-move people

T-tests

Variables	t-statistic	DF	p-value
Age	10.9271	2798	0.0000
Education	-3.797	2798	0.0001
Household size	4.6434	2798	0.0000
Land	5.6961	2798	0.0000
Income per capital	4.9447	2798	0.0000
No. current migrant	-6.4733	2798	0.0000

Chi square test

Variables	chi2	DF	p-value
Having migration experience	37.722	1	0.0000
Being severely impacted by climate change	48.667	1	0.0000
Drought damage	4.1149	1	0.043
Saline intrusion damage	12.5288	1	0.0000
Flood damage	10.7973	1	0.0000
Storm damage	21.897	1	0.0000
Unusual heavy rain damage	19.3267	1	0.0000

Appendix Table 2. MEs of outcome 3 (i.e. probably move vs definitely stay) – main effects – subsamples

VARIABLES	Kien Giang	Long An
Drought_moderate	0.0261**	0.0156
	(0.0104)	(0.00962)
Drought_severe	0.0820***	0.0774***
	(0.0112)	(0.0104)
Flood_frequency	0.0442***	0.0334***
	(0.0109)	(0.0101)
Income gap	0.0144***	0.0118***
	(0.00235)	(0.00201)
Network	0.0309***	0.0280***
	(0.00767)	(0.00717)
Neighbour	0.0223***	0.0210***
	(0.00773)	(0.00734)
Crop_restrictions_partial	-0.0117	-0.00809
	(0.0119)	(0.0104)
Crop_restrictions_total	0.0410**	0.00342
	(0.0168)	(0.0136)
Observations	1,200	1,600

Standard errors in parentheses; Clustered at household level
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3. Regression results – extended models with more interactions

VARIABLES	Coefficients	SEs
Drought_moderate	5.171	(4.207)
Drought_severe	1.503	(3.782)
Flood_frequency	1.144	(3.300)
Income gap	0.461***	(0.0976)
Network	0.365*	(0.197)
Neighbour	0.366***	(0.122)
Crop_restrictions_partial	-0.245	(0.206)
Crop_restrictions_total	0.561**	(0.240)
Climate change	-0.150	(0.256)
Drought 2016	-0.265	(0.281)
Age	-0.0257	(0.0165)
Income	0.0534	(0.264)
Household size	-0.139	(0.117)
Current migrant	0.528***	(0.205)
Migration experience	0.379	(0.300)
Long An	8.927	(5.667)
Risk attitude	0.119	(0.0828)
Female	-0.338	(0.298)
Drought_moderate * Climate change	0.492*	(0.293)
Drought_severe * Climate change	0.600**	(0.261)
Drought_moderate * Drought 2016	0.591**	(0.290)
Drought_severe * Drought 2016	0.0958	(0.260)
Drought_moderate * Age	-0.00875	(0.0178)
Drought_severe * Age	-0.00696	(0.0143)
Drought_moderate * Female	0.267	(0.312)
Drought_severe * Female	-0.215	(0.265)
Drought_moderate * Household size	-0.413***	(0.137)
Drought_severe * Household size	0.0167	(0.0936)
Drought_moderate * Current migrant	0.287	(0.176)
Drought_severe * Current migrant	0.0304	(0.138)
Drought_moderate * Risk attitude	0.00663	(0.0791)
Drought_severe * Risk attitude	0.0600	(0.0602)
Drought_moderate * Income	-0.206	(0.224)
Drought_severe * Income	-0.0431	(0.206)
Flood_frequency * Climate change	0.142	(0.228)
Flood_frequency * Drought 2016	0.535**	(0.227)
Flood_frequency * Age	-0.0204	(0.0133)
Flood_frequency * Female	0.248	(0.248)
Flood_frequency * Household size	-0.160	(0.106)
Flood_frequency * Current migrant	-0.0134	(0.156)
Flood_frequency * Risk attitude	-0.0443	(0.0584)
Flood_frequency * Income	0.0644	(0.181)
Income gap * Risk attitude	-0.0387***	(0.0147)
Network * Current migrant	-0.233	(0.144)
Network * Migration experience	0.217	(0.253)
Network * Female	0.511**	(0.208)
Crop_restrictions_partial * Long An	0.110	(0.284)
Crop_restrictions_total * Long An	-0.485	(0.296)
Income * Long An	-0.552*	(0.335)

Robust standard errors in parentheses; Clustered at household level
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 4. CE regression with and without Drought 2016 variable

VARIABLES	Model 3-1: With drought 2016 variable		Model 3-2: Without drought 2016 variable	
Drought_moderate	-0.155	(0.289)	0.0224	(0.255)
Drought_severe	0.864***	(0.191)	0.885***	(0.182)
Flood_frequency	0.325	(0.243)	0.490**	(0.223)
Income gap	0.468***	(0.0898)	0.465***	(0.0884)
Network	0.369**	(0.185)	0.381**	(0.185)
Neighbour	0.347***	(0.121)	0.351***	(0.123)
Crop_restrictions_partial	-0.198	(0.201)	-0.207	(0.201)
Crop_restrictions_total	0.620**	(0.242)	0.578**	(0.241)
Climate change	-0.186	(0.265)	-0.244	(0.263)
Drought 2016	-0.246	(0.280)		
Age	-0.0367***	(0.0128)	-0.0363***	(0.0129)
Income	0.0286	(0.235)	0.0274	(0.233)
Household size	-0.287***	(0.0911)	-0.280***	(0.0908)
Current migrant	0.586***	(0.160)	0.585***	(0.159)
Migration experience	0.375	(0.301)	0.373	(0.299)
Long An	9.480*	(5.691)	8.991	(5.661)
Risk attitude	0.122**	(0.0585)	0.125**	(0.0584)
Female	-0.257	(0.239)	-0.245	(0.238)
Drought_moderate * Climate change	0.539*	(0.286)	0.676**	(0.281)
Drought_severe * Climate change	0.644**	(0.258)	0.664***	(0.245)
Drought_moderate * Drought 2016	0.531*	(0.279)		
Drought_severe * Drought 2016	0.0986	(0.260)		
Flood_frequency * Climate change	0.164	(0.231)	0.285	(0.229)
Flood_frequency * Drought 2016	0.513**	(0.226)		
Income gap * Risk attitude	-0.0388***	(0.0135)	-0.0389***	(0.0134)
Network * Current migrant	-0.237*	(0.123)	-0.245**	(0.121)
Network * Migration experience	0.216	(0.249)	0.217	(0.248)
Network * Female	0.485**	(0.193)	0.466**	(0.191)
Crop_restrictions_partial * Long An	0.0550	(0.279)	0.0824	(0.278)
Crop_restrictions_total * Long An	-0.562*	(0.300)	-0.493*	(0.299)
Income * Long An	-0.584*	(0.336)	-0.557*	(0.335)

Appendix Table 5. Census data – Kien Giang province

Source	Content	Value	Unit
VHLSS 2016 - 1.2	Household size by income quintile and province	4.1	persons
Statistical book 2019 - 25	Average rural population	1234.9	thousand persons
	Total number of rural households	301.195	thousand households
VHLSS 2016 - regional data	Gender		
	Male	72.9	percentage
	Female	27.1	percentage
VHLSS 2016	Age structure of economically active population in working age		
	1 (<35)	36.8	percentage
	2 (35-44)	28.9	percentage
	3 (45-54)	27.3	percentage
	5 (>= 55)	7	percentage
Population and Housing Census on 1st April 2019 – regional data	hhsize_cat		
	1 (2-4)	72.1	percentage
	2 (>=5)	27.9	percentage
Income quintiles	Income		
	1	20	percentage
	2	20	percentage
	3	20	percentage
	4	20	percentage
	5	20	percentage

Appendix Table 6. Functions to assign flood frequency

	Province	Flood 45	Flood 85
1	Long An	0.18 + 0.004i	0.18 + 0.006i
2	Tien Giang	0.18 + 0.004i	0.18 + 0.006i
3	Ben Tre	0.005i	0.006i
4	Tra Vinh	0.005i	0.006i
5	Vinh Long	0	0
6	Dong Thap	0.3 + .0066667i	0.3 + 0.01i
7	An Giang	0.3 + .0066667i	0.3 + 0.01i
8	Kien Giang	0.18 + .0106667i	0.18 + .014i
9	Hau Giang	0.18 + 0.004i	0.18 + 0.006i
10	Soc Trang	0.09 + 0.002i	0.09 + 0.003i
11	Bac Lieu	0.09 + 0.002i	0.09 + 0.003i
12	Ca Mau	0.01i	0.012i

i: time interval

Appendix Table 7. Functions to assign drought severity

Province	Severe drought 45	Severe drought 85	None 45	None 85
Long An	80 - 0.6666667i	80 - i	40 - 0.6666667i	40 - 0.6666667i
Tien Giang	97 - 1.9i	97 - 1.9i	50 - 0.5i	50 - 1.1666667i
Ben Tre	15 - 0.1666667i	15 - 0.5i	13 - 0.2666667i	13 - 0.4333333i
Tra Vinh	50 - 0.1666667i	50 - 1.5i	0	0
Vinh Long	95 - 0.1666667i	95 - 0.5i	40 - 0.6666667i	40 - 0.8333333i
Dong Thap	100	100	100 - 0.6666667i	100 - 0.8333333i
An Giang	100 - 0.3333333i	100 - 0.3333333i	90 - 0.8333333i	90 - i
Kien Giang	70 - 0.6666667i	70 - i	70 - 1.5i	70 - 1.5i
Hau Giang	100	100	70 - i	70 - 1.3333333i
Soc Trang	70 - 0.8333333i	70 - 1.333333i	30 + 0.1666667i	30 - 0.6666667i
Bac Lieu	85 - 1.5i	85 - 1.833333i	30	30 - 0.1666667i
Ca Mau	20 - 0.6666667i	20 - 0.6666667i	15 - 0.5i	15 - 0.5i

i: time interval

Appendix Table 8. Regressions of risk attitude and natural hazard experience on demographic characters

	(1)	(2)
VARIABLES	Risk attitude	Natural hazard experience
Age	-0.0119	-0.00754
	(0.00977)	(0.00639)
Income	-0.244	-0.159
	(0.166)	(0.104)
Household size	-0.0759	-0.0309
	(0.0541)	(0.0436)
Female	0.103	0.0369
	(0.208)	(0.149)
Constant		3.142*
		(1.882)

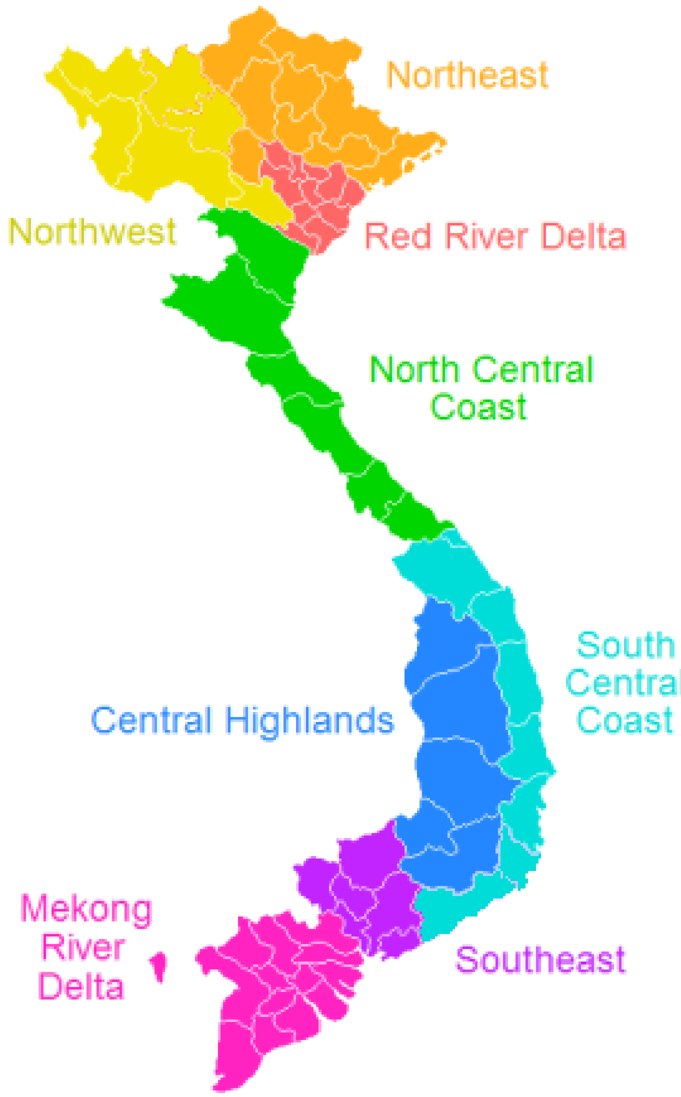
Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 9. Sensitivity to migration drivers – 12 VMD provinces

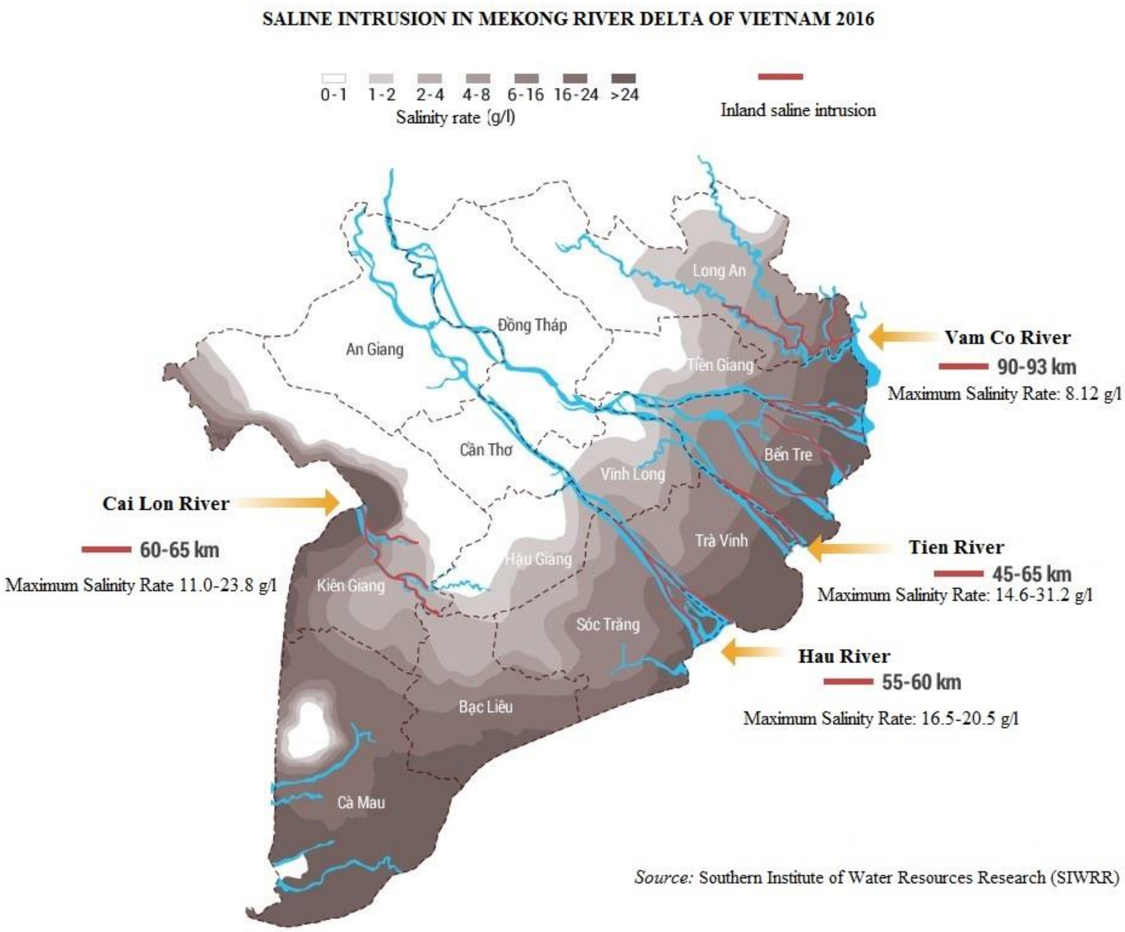
Province	Climate change	Across climate scenarios	Social feedback	Income gap	Crop choice restriction
Tra Vinh	High	High	High	High	High
Ca Mau	High	Low	High	High	No
Bac Lieu Ben Tre Soc Trang	High	Moderate	High	High	High
Kien Giang	High	Moderate	High	Moderate	High
Dong Thap Hau Giang Vinh Long	Low	Low	Low	Moderate	No
An Giang	Moderate	Low	Low	Moderate	No
Long An	Moderate	Moderate	Low	Low	No
Tien Giang	Moderate	Moderate	Low	Moderate	No

Appendix Figure 1. List of regions in Vietnam

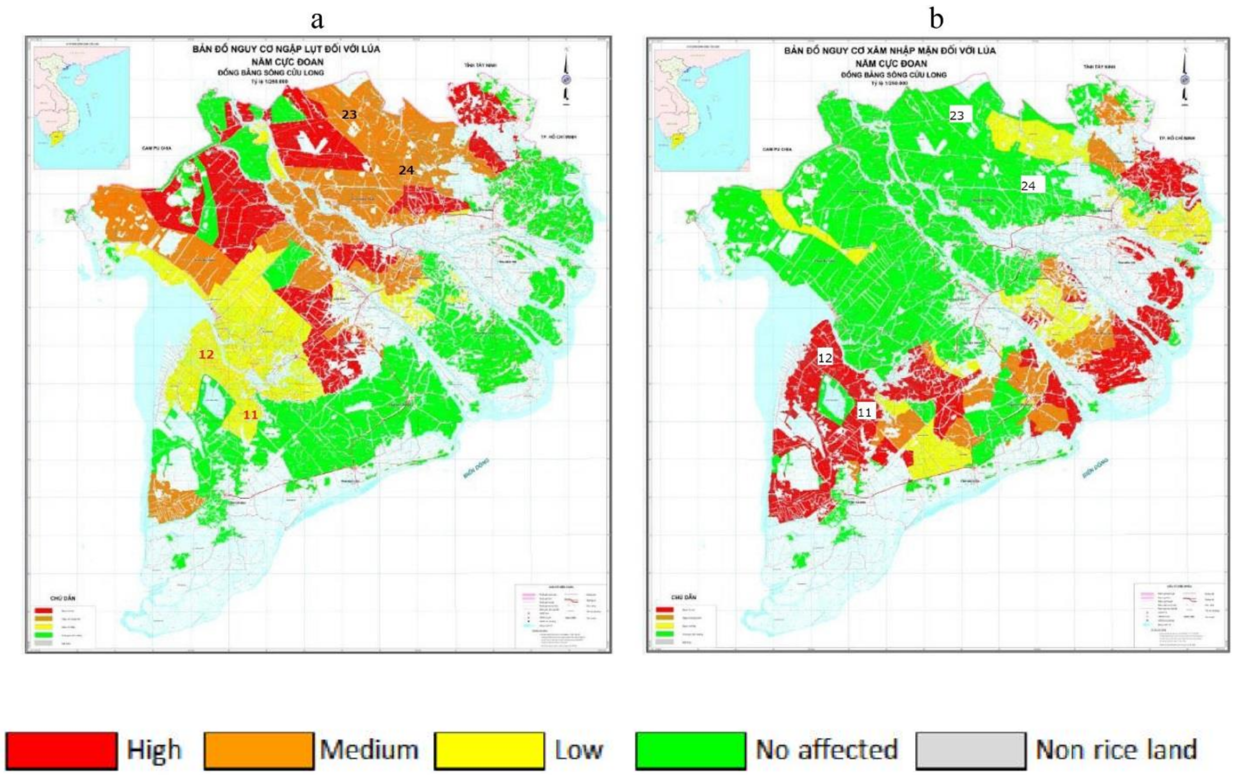


Source: https://en.wikipedia.org/wiki/List_of_regions_of_Vietnam

Appendix Figure 2. Drought and saline intrusion 2016

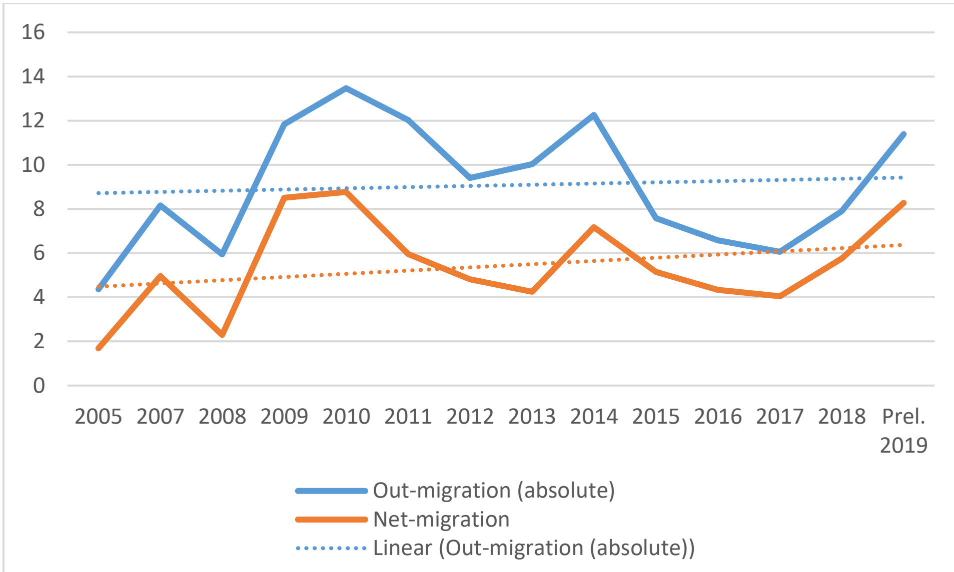


Appendix Figure 3. Map of flooding (a) and salinity intrusion (b) risks for rice production in severe years of the VMD



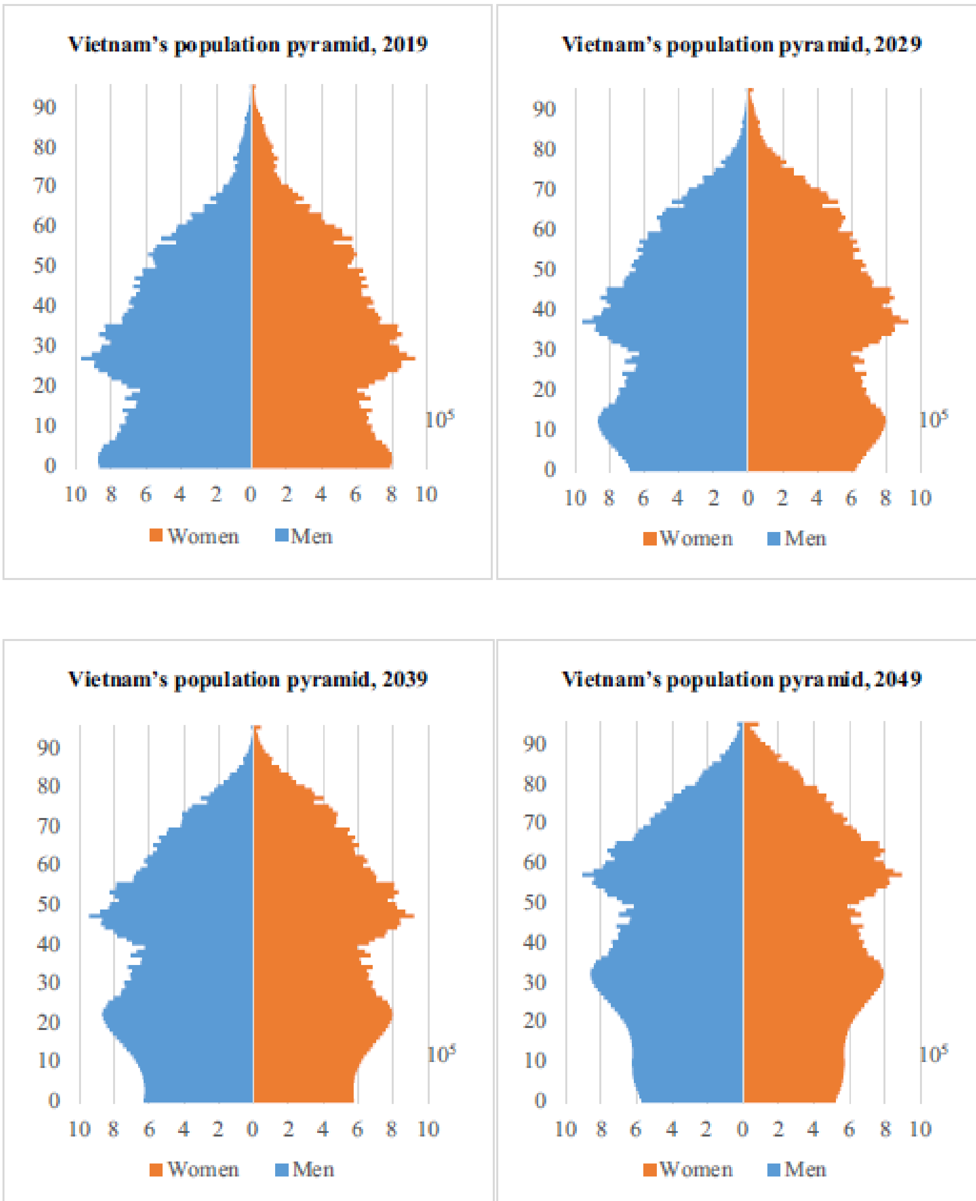
Source: (Yen, Son, Tung, et al., 2019)
Note: Site codes: Kien Giang – 11, 12; Long An – 23, 24

Appendix Figure 4.Out-migration and net migration rate of the VMD



Appendix Figure 5. Vietnam’s population pyramid in 2009, 2019, 2029, 2039, and 2049

(Handong et al., 2020)



Appendix Figure 6. Latin hypercube sampling – Partial correlation coefficient (PCC)