Flood Risk Management in coastal areas: The application of Agent Based Modeling to include farmer-flood interaction

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To my husband and my family

Abstract

One of the major challenges in current flood management studies is to include human-flood interaction in their modeling approach in order to investigate how individuals respond to flooding and how their involvement results in a more effective flood risk management (FRM). Furthermore, humans are heterogeneous in their socio-economic attributes as well as their risk awareness which result in feedbacks between humans and the environment. Therefore, individual adaptation responses, knowledge exchange, flood memory, and flood risk perception shape a new mode of interaction and temporal changes in exposure and vulnerability. All these factors cause nonlinear behaviors in the subsystems exposing the whole system to major changes beyond the scope of traditional FRMs. Moreover, there are limitations to the availability of information as well as to the processing capacities of decision makers in reality resulting in non-optimizing behaviors and bounded-rationality. Therefore, formalizing the individual adaptive behavior on the basis of rational behavior and economic optimizing as well as perfect information has its limitations. In addition, FRM studies assume static conditions in which humans and their surrounding environment are inactive and their vulnerability is constant.

Under such assumptions, time dependent features such as interactions, adaptations, and technology innovation cannot be incorporated in current models and there is lack of modeling approaches to include social aspects of human behavior in FRM. To fill these knowledge gaps, interdisciplinary approaches, which allow formulating adaptive individual decision-making under uncertainty, are in demand. More specifically, there is a need to a technique that allows us to model social processes and complexities of human behaviors from the bottom-up approach and in combination with engineering practices. Agent Based Modeling is such an approach that relies on a more realistic set of assumptions.

This study employs Agent Based Modeling within the framework of FRM, particularly for the agricultural sector, and presents an experimental platform to simulate farmers' adaptive strategies in coastal regions. An Agent Based Model (ABM) of farmers' behaviors is developed including three parts: farmers' decision-making module, flood risk analysis module as well as risk perception module. It is then linked to the hydrological module and hydrodynamic module designed in the study for this purpose. The coupled model, which is called the "**A**gent **B**ased **M**odel for **fa**rmer-**flo**od interaction (ABMFaFo)", introduces the interactions among farmers and includes individual risk judgment in their decision-making. Additionally, farmers' decisions are formulated in the model through bounded-rationality theory to consider limited information availability as well as limited information processing capacities of people.

Pellworm Island in north of Germany is chosen as the virtual study area and the established ABMFaFo is applied to 37 semi-hypothetical farmers living on the Island. The model is run using a series of in silico experiments to investigate farmers' decision-making in flood-prone areas in response to coastal flooding. More specifically, the effect of flood frequency, risk perception, social interaction, past experience, and flood memory are examined and discussed. In addition, the interdependencies between vulnerability of the agricultural sector at farm-level and regional-level are explored using several macro-metrics. Every experiment is run for the time horizon 2005-2016, including one year of warm up period for the model.

Table of contents

List of figures

List of tables

Chapter 1 Introduction

1. Problem statement

One of the main challenges in current flood risk management (FRM) studies is to include individual adaptive strategies in their modeling approach to investigate how individuals respond to flooding and how their engagement contributes in FRM. People living in the flood prone-areas are exposed to flooding and suffer from that in different ways. Floods not only destroy properties and belongings of people but also cause loss of life and psychological problems. Even in some less severe floods, inhabitants such as farmers lose their expected incomes due to damage to soils and cultivated crops (FAO, 2015) which may continue for a number of years. These effects lead to selling farms, migrating from the area, and increasing the unemployment (FAO, 2015).

To reduce the adverse impacts of flooding, it is important to involve the public in FRM (EU, 2007). Public engagements in FRM include strategies such as households' self-protection measures, self-insurance, and private agricultural adaptation employed by farmers. Studies show that people are more motivated to respond to flooding if they are aware of the dangers and perceive them (Becker *et al.*, 2015). As a result, individuals employ strategies to cope with flooding and reduce their vulnerability, which results in communication, human interaction, and adaptation (Becker *et al.*, 2015). In this regard, flood memory can increase the resilience of the society for an effective flood risk management (Bhattacharya-Mis and Lamond, 2014).

Individual adaptive strategies are constrained by their economic situation, demographic characteristics, and socio-psychological factors that may decrease or reinforce their adaptive capacities (Dang *et al.*, 2012; Unsworth *et al.*, 2013). Furthermore, social interaction plays an important role in the degree of individual involvement in FRM (Giordano *et al.*, 2017). These all lead to change in vulnerability of people over time as well as to heterogeneity in individual decision-making under risk. Moreover, there are limitations to the availability of information as well as to the processing capacities of decision makers in reality, which result in non-optimizing behaviors and bounded-rationality (Simon, 1990).

These aspects related to human-flood interaction are, however, poorly understood in flood risk management studies (Nabinejad and Schüttrumpf, 2016). Although, these studies have provided decision makers with valuable insights, they fail to address the mentioned aspects, which result in possible misapprehension of individual adaptation policies in FRM. Therefore, interdisciplinary approaches are in demand that allow the implementation of public engagement in FRM, contribute to formulation of adaptive individual decision-making under uncertainty, and conceptualize the link between agents' heterogeneity, their social interaction, and adaptation responses.

Agent Based Modeling is one of such approaches that relies on a more realistic set of assumptions. Agent Based Modeling is a style of modeling which allows representing high levels of complexity as well as communication among individuals and provides new insights into policy analysis and practical applications. It simulates the actions of the individuals based on some defined decision-making rules as well as current spatial and temporal situation.

2. Objectives and research questions

The primary objective of this study is to develop an experimental platform to couple farmers' decision-making and FRM for a population of semi-hypothetical farmers in order to (i) include farmers-flood interaction in FRM through private adaptive responses, (ii) understand the influence of farmers' interactions through social networks in their adaptive responses, (iii) investigate the relationship between flood risk perception and farmers' adaptive behaviors, (iv) explore the role of flood memory, and (v) model farmers' adaptive decision-making under bounded-rationality. To achieve its objective, the thesis answers the following questions:

1- What are the strengths and weaknesses of previous approaches in FRM studies regarding human-flood interaction and individual adaptive behavior? What is the suitable approach for this study?
2- How do individual risk perceptions play role in the adaptive behavior?

3- How do farmers adjust their behaviors under the influence of social interactions over time?
4- How do the adaptive behaviors result in changing in flood risk?
5- How do individuals' flood memories contribute to their resilience and effective flood risk management?
6- How do individuals make decisions under limited information availability and limited information-processing capacities?

3. Methodology of the research

To achieve the research goals, this study employs Agent Based Modeling within the framework of FRM, particularly for the agricultural sector, and presents an experimental platform to simulate farmers' adaptive behavior patterns in coastal regions. An Agent Based Model (ABM) of farmers' decision-making is developed and linked to the hydrological module as well as hydrodynamic module designed for this purpose, to examine the change in flood risk and the dynamic of farmers' behavior under the influence of individual risk perception, social interaction, flood memory, and limited access to information. The model, which is called the "**A**gent **B**ased **M**odel for **fa**rmer-**flo**od interaction (ABMFaFo)", introduces the interactions among farmers about new coping strategies and market opportunities and includes individual perception and assessment of flood risk in their decision-making. Additionally, farmers' decisions are formulated in the ABMFaFo through bounded-rationality theory to consider limited information availability as well as limited information processing capacities of people in their decision-making under uncertainty.

The ABMFaFo includes the perspectives from engineering and socio-economics with the aim of examining the decision-making processes of individuals (farmers) in coasts. In this model, the main agents are farmers whose yearly decisions depend on climatic conditions, crop yields, costs and prices, flood damage, personal risk perception, and flood memory as well as their social interactions. The ABMFaFo consists of five main modules including two external and three internal parts.

Figure 1-1 depicts integration of the five modules and their elements for yearly simulation. The hydrological module is used to simulate the annual crop yields at the field-level as the result of farmers' yearly decision-making, which is fed into other modules. This module is based on the Soil and Water Assessment Tool (SWAT) (Arnold *et al.*, 1998). In order to compute water levels and velocities as well as inundation areas under different flooding scenarios, the hydrodynamic module is designed based on Protection Measures against Inundation Decision Support (ProMaIDes) (Bachmann, 2012). The ABM platform is then established to model annual farmers' decision-making. For this purpose, farmers' decision-making module, risk perception module, and flood risk analysis module are developed and embedded in the ABM platform which are then linked to the two developed external modules. The module of farmers' decision-making is based on socio-economic approaches and mathematical programming principles, which is equipped with individual risk judgment and adaptive responses in risk perception module. In connection with other modules, the flood risk analysis module computes agricultural flood damage and associated risks under the given seawater salinity and temperature by means of the modeling framework that is developed in the study with the aim of building flood damage function of agricultural crops in coasts.

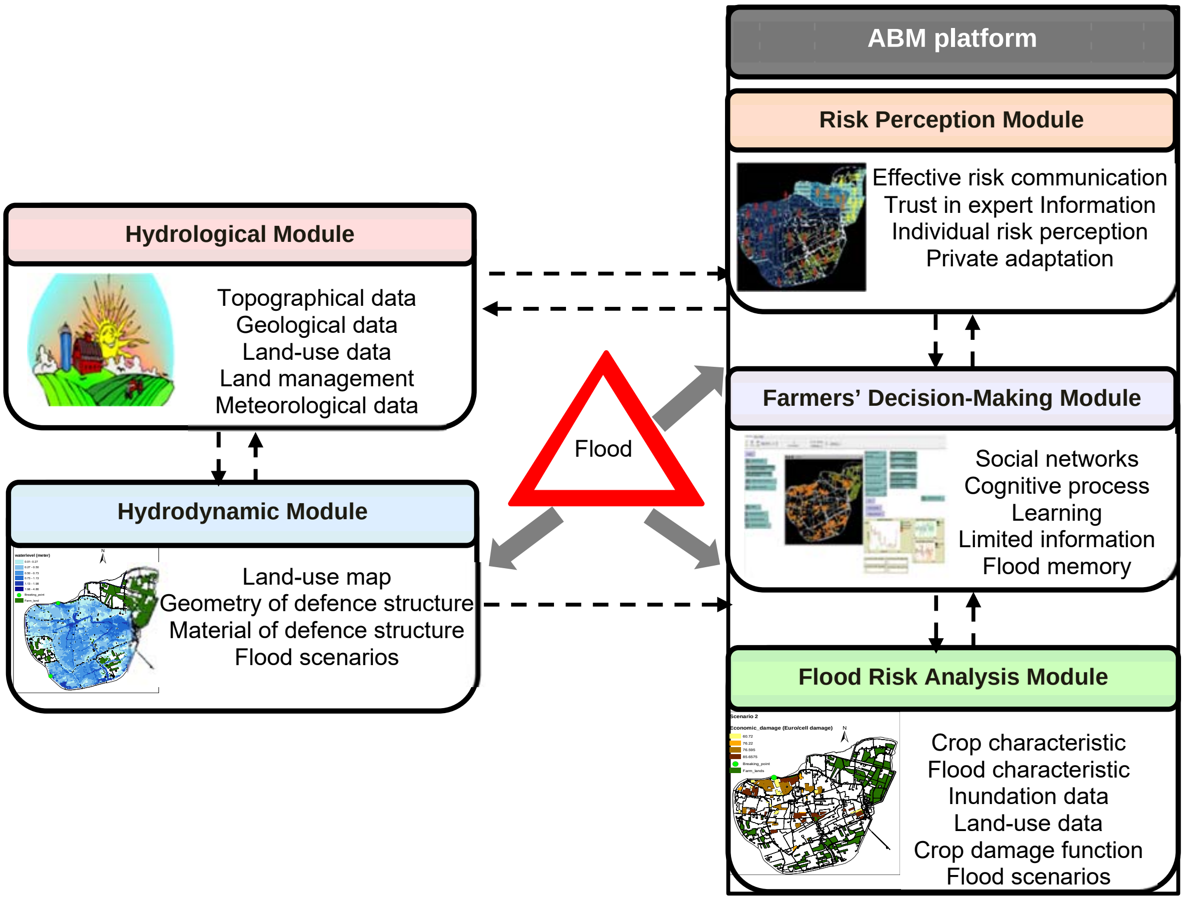


Figure 1-1. Submodels of the ABMFaFo for land use planning in flood management

Figure 1-2 provides the flow diagram of the developed ABMFaFo in which farmers choose yearly crop pattern over the time horizon of 11 years under the influence of crop prices, individual experiences and expectations, and observing others' decision as well as risks associated with flood. As seen, climatic condition of the area such as precipitation and temperature, soil conditions, topology, and the spatial distribution of farmers' fields are fed into the hydrological module to calculate the annual crop yield of each individual farmer.

In the next step, the water levels and spatial distribution of inundated lands on the farmers' fields are investigated. For this aim, the hydrodynamic analysis is performed for various probable flood scenarios. To explore how flood damage influences farmers' decision-making at the micro-level, the generated inundation maps as well as computed crop yields are fed into the flood risk analysis module. As a result, the flood damage and associated risk experienced by each individual farmer are computed, which are then used in risk perception module to define different flood zones for varying levels of danger. Consequently, a danger degree is assigned to each defined zone.

In the last step, farmers observe their crop production and will be aware of their crop yield. In addition, they are informed about the actual and potential flood damage in the current year. Accordingly, at the end of the year, they choose crops for the next year based on their profit. Hence, farmers assess their farm income for the resulted crop yield which are used to evaluate the level of farmers' satisfaction by comparing the actual and potential profit as well as their uncertainty in terms of the ratio of the actual to the expected profit for the current year. Depending on farmers' satisfaction and uncertainty level, each farmer follows a certain cognitive and behavioral strategy to adapt her/his decision for the next year. Farmers, who have high level of satisfaction, will engage in the imitation strategy or repeat their previous behavior. In contrast, those, who are dissatisfied with the outcomes of their decision in the last year, try to obtain more satisfied outcomes by deliberating or engaging in social comparison. Flood memories of dissatisfied farmers play role in their objective functions.

Afterwards, the land use policies adopted by farmers will be fed back into the hydrological module to compute crop yields for the next year under the related climatic and topological condition of the area. This process will be continued year by year over the time horizon.

The ABMFaFo is applied to a semi-hypothetical example case of farmers in the Pellworm Island in north of Germany. Farm agents are heterogeneous in terms of their field areas, crop yields, risk perception, adaptation options, uncertainty, satisfaction, and behavioral rules. It should be noted that the model takes advantage of real data in establishing the hydrological module, hydrodynamic module, and flood risk analysis module. However, due to lack of empirical (behavioral) data, we make assumptions about the require parameters of decision-making module as well as risk perception module. Therefore, Pellworm Island is used as a virtual Island during the study. Detailed information about the activity diagram of the ABMFaFo and its components is provided in chapter 6.

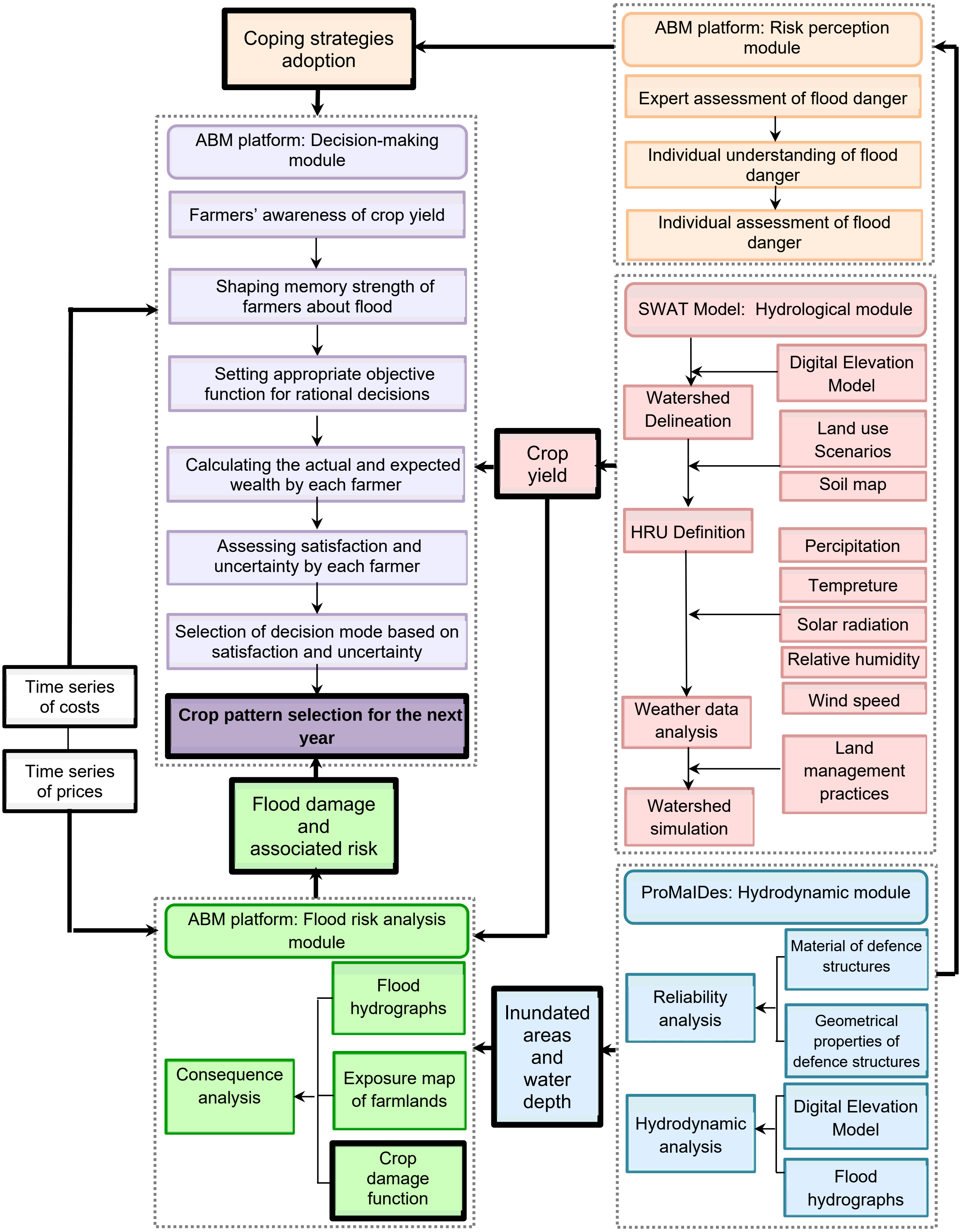


Figure 1-2. Flow diagram of the ABMFaFo in each year, the modules, their input data, and their interlinkage

4. Study area

The Pellworm Island is a municipality in the state of the Schleswig-Holstein state and bordering on the municipalities of Nordstrand, Hallig islands, and Eiderstedt, as shown in Figure 1-3. The total population of the area is 1158 people living on the area of about 37 km^2. The distance between the northern and southern part is approximately 7 km. Its mean height is about 0.23m above sea level, and 28 km of sea dikes up to a height of 8.80m NHN protect the island. During two devastating floods in 1362 and 1634, in which thousands of people died, Pellworm Island was separated from Alt-Nordstrand. In the beginning of the 19th century, outer dike was constructed to secure the Island against further floods and storm surges. Pellworm is located in mudflats covered with rich soil appropriate for growing agricultural crops. The main economic sectors are agriculture and tourism and most of the Island's area is covered by agricultural lands.

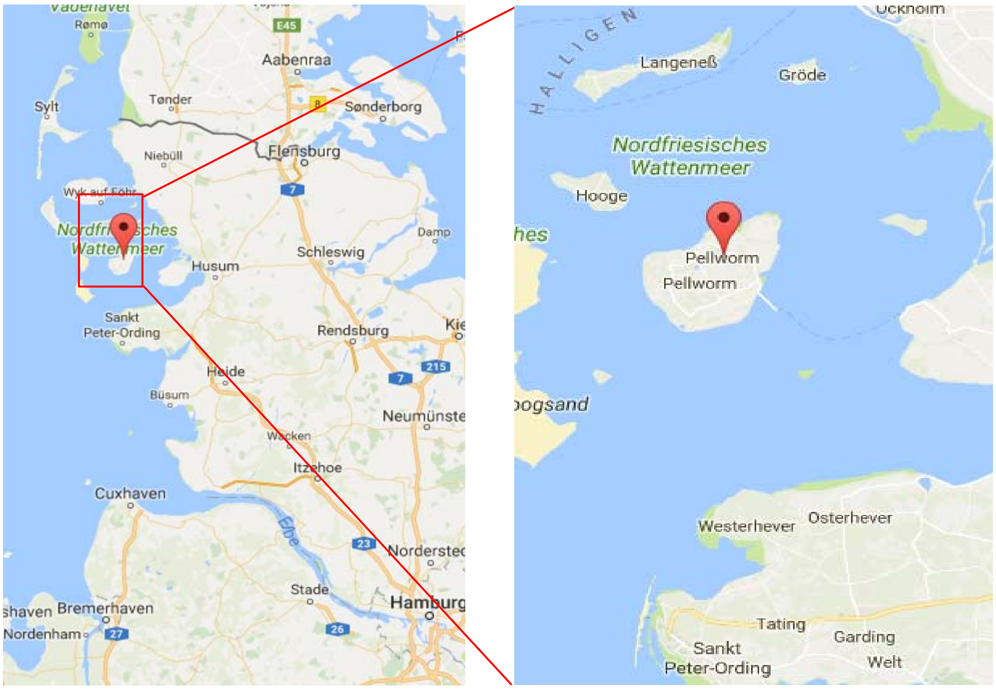


Figure 1-3. Pellworm Island in Northern Germany (Google map)

5. Contributions of the thesis

This dissertation contributes to the area of human-flood interaction and introduces a novel thinking to the flood management, living with water, and the public engagement in FRM. The major contribution of the study is to take Agent Based Modeling as a new approach to overcome the shortcomings of traditional methods in FRM in addressing individual adaptive responses in flood-prone areas. It also contributes to equip the individual decision-making under uncertainty of flood events with a variety of cognitive behaviors rather than pure maximization. Another contribution includes the integration of human interaction through social networks. The study also contributes to the modeling of individual risk perception and its role in adaptive behaviors. In addition, the study takes into account individual flood memory and its impact on community resilience. The thesis also establishes a modeling framework to formulate agricultural crop failure due to the saltwater intrusion from the sea in the hinterland under any level of seawater salinity and temperature. Another topic to which the study makes a major contribution is to predict annual crop yields on the field-scale to assist individual decision-making and micro economic analysis. Finally, it provides a complete representation of the whole system through coupling five main modules including hydrological analysis, hydrodynamic analysis, flood risk analysis, individual decision-making, and risk perception module in the ABM platform. Such an integrated approach provides a feedback mechanism between farmers and surrounded environments in flood-prone areas which is useful for normative research on FRM on the human-flood interaction.

6. Thesis outline

Figure 1-4 shows an overview of the thesis outline including eight chapters. Chapter 1 presents the problem statement and research objectives, a brief overview of the suggested methodology, and thesis outline. Chapter 2 provides background information of human-flood interaction and investigates the challenges which form the foundation for the proposed method in the next chapters. It also introduces Agent Based Modeling and explains its advantages and disadvantages in more details. It is then followed by chapter 3, which is the first of four chapters outlining the method used in this study. It describes how to predict the yearly crop yields on the field-scale as a function of climatic condition and geographic characteristics of the area and thus a calibrated-validated hydrological module is developed for this aim. Chapter 4 is the second method chapter which describes the hydrodynamic module to identify the inundated areas and spatial distribution of hazard parameters for the probable flood scenarios. Then in chapter 5, a function-based framework for developing flood damage curve of agricultural crops in coasts is presented and further applied to perform damage assessment in the flood risk analysis module. In chapter 6, the last of the method chapters, a spatial Agent Based Model of farmers' decision-making is established into which the risk perception as well as flood risk analysis module are fully integrated. The resulted ABM platform is linked to the hydrological module and hydrodynamic module developed in chapter 3 and 4. Chapter 7 presents and discusses the simulation results obtained for various scenarios at both micro-and macro-level. The overall conclusion is provided in chapter 8, which also discusses the ideas and the research gaps that should be addressed in the future researches.

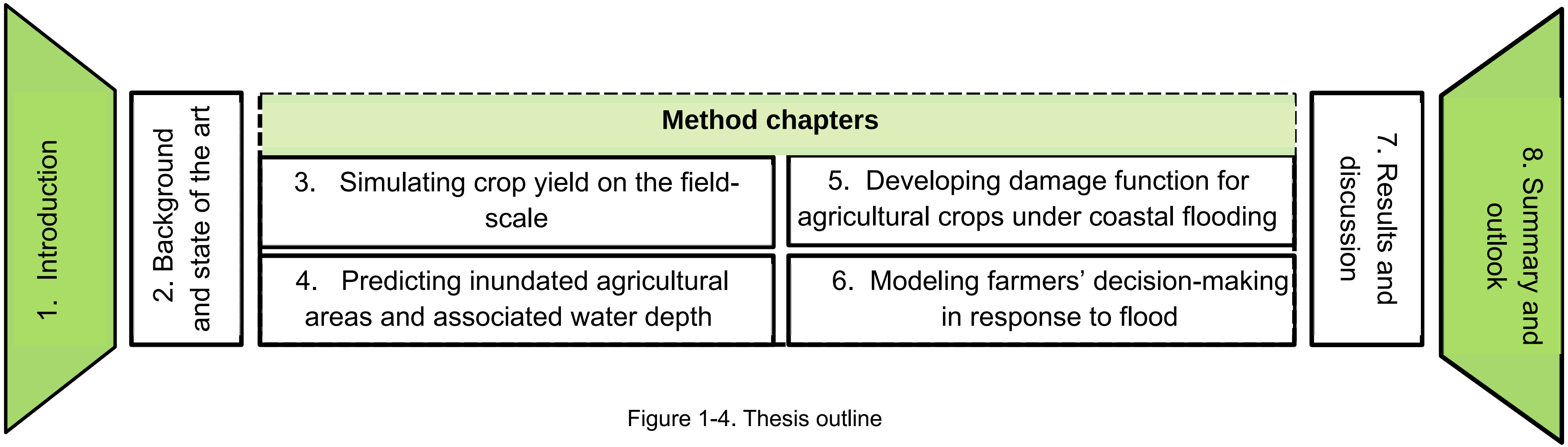


Figure 1-4. Thesis outline

Chapter 2 Background and state of the art

1. Introduction

Lessons learned from the major flood disasters in the past decades showed the limited protection of infrastructural measures and thus the need to reduce flood risk using adaptation strategies. Public adaptation policies have a long history in flood risk management (FRM) practices through structural measures. However, private adaptive strategies originating from the paradigm shift in FRM in the recent decades, impose new conditions to the system related to the human behavior, risk perception, and social interaction. Since the current FRM studies are based on pure economic models, they are not able to address those aspects of social behavior patterns. Therefore, current FRM models face challenges in including human-flood interaction and the resulted feedbacks in the system. A more realistic method, which formulates a system from the perspectives of individuals and allows representing human behaviors, is Agent Based Modeling.

This chapter gives background information on adaptive strategies in FRM in section 2. This section firstly sheds light on adaptation to flooding, types of adaptation strategies, and the influential factors on adaptation. It is then continued with a brief history of human-flood interactions and how flood studies deal with such interactions and their shortcomings. Section 3 presents information on Agent Based Modeling as a proper method to address the challenges regarding the inclusion of human behavior and micro-level decision-making. It also describes basic terminology used in the Agent Based modeling and the advantages and disadvantages of the method. Then the application areas of Agent Based Modeling in various disciplines and more specifically in FRM are presented. Section 4 reviews the most common decision-making models under uncertainty and their limitations. Then, an alternative decision-making model is introduced, which is able to capture the main behavioral aspects and used in this study.

2. Adaptive strategies in FRM

In recent years, natural hazards have caused tremendous damage all over the world. Among them, floods constitute a large share of the most devastating natural events, which are becoming more severe due to climate change and human interferences (IPCC, 2007). Recently, significant floods have affected several parts of the world such as East Africa, China, Iran, Greece, Germany, South Asia, and America (WMO, 2017). In 2018, Europe experienced heavy rainfalls, storm surges, and flash floods with adverse effects on human life and socio-economic activities (FloodList, 2018).

In comparison to a slow-onset event such as drought, which lasts from weeks to even years and whose effects are accumulated slowly over time, in a flood water rises quickly, moves forward, destroys the elements in its way, and causes instant loss of life, economic damage to properties, and socio-psychological problems during or shortly after the disaster. Therefore, it is essential to identify the effects of flooding, to assess the damage and, to manage the flood risk before, during, and after flooding.

2.1 Flooding effects

Flooding affects the environment in different ways. On the one hand, it has negative impacts on the economy, industry, agricultural sector, and human population. On the other hand, flooding leads to positive long-term impacts such as spreading the nutrients and enriching floodplains soil especially in coastal areas. Coasts with easy access to trade and transports have been attractive settling grounds for humans as they provide fertile soil for agriculture. However, agricultural lands are also threatened by storm surges that transport saline seawater into the hinterland. Consequently, the salt-inundated farms may not produce crops for a period of more than one year. Therefore, agriculture is particularly vulnerable to coastal floods as it is highly exposed to salinity intrusion associated with global warming.

Storm surges can affect the agricultural sector negatively at different levels. They cause damage to agricultural crops and the amount depends on hazard parameters, crop characteristics, and fertility of the soil. At farm-level, farmers suffer from the negative impacts of coastal flooding on crops in various growing stages and lose their income that may change their decision-making in the following years. The desire to sell the farms and to migrate grows as well, which causes an increase in unemployment in the area. This will be followed by economic shocks to prices, supply, and demand, thus negatively affecting peoples' welfare (Allahyari *et al.*, 2016). As a result, the regional agricultural sector and related organizations tackle economic problems, which have originated from the individual level, spread around, and then affected the agents at the macro-level. These facts address the interconnection between the vulnerability of agricultural agents at different levels, as illustrated in Figure 2-1.

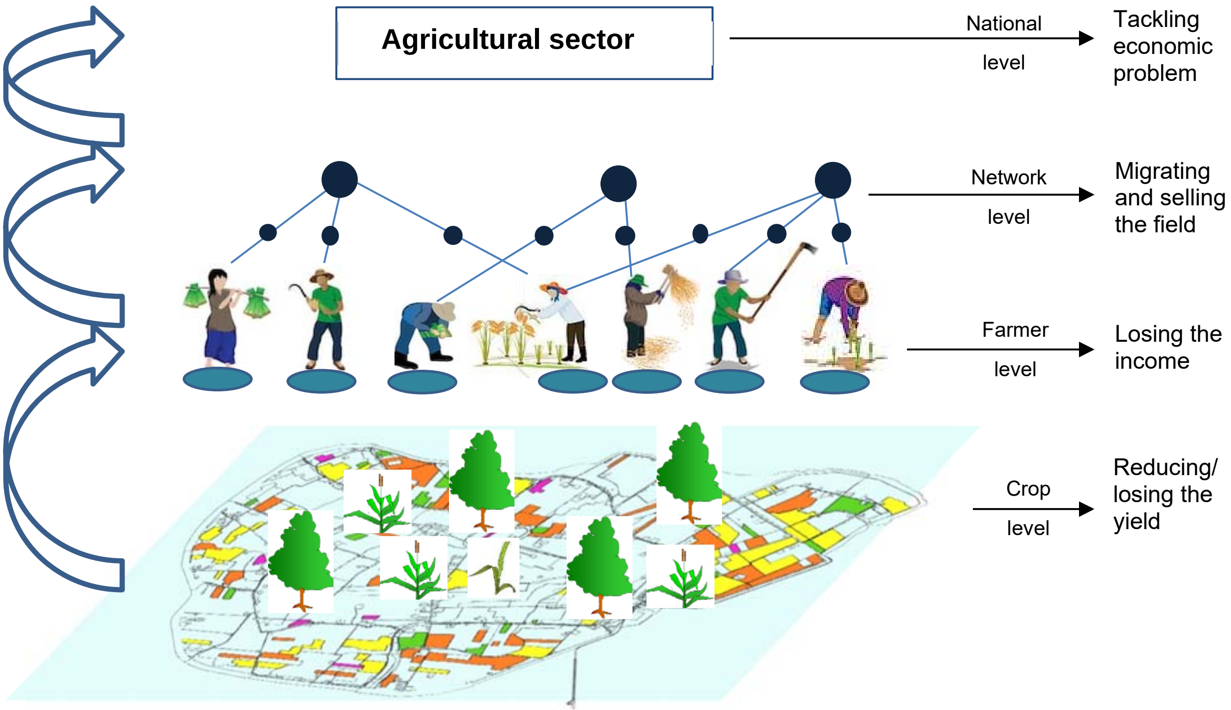


Figure 2-1. Various levels in agricultural sector, their interconnection, and the effects of coastal flooding on them

2.2 Adaptation to flooding

Flood adaptation is crucial to decrease the negative impacts of flooding. In general, adaptation refers to the process of change to make the environment more suitable for surviving. Flood adaptation is a set of activities to adjust the existing system to the actual or expected floods. It includes strategies to reduce the hazard, mitigate vulnerabilities and exposures, improve adaptive capacities, and increase the resilience of population. Adaptation is a multidimensional concept in which the time when the action is taken (before or after flood), the actors by whom the strategy is implemented (public or private), and the level of individual risk awareness (low or high) play role (IPCC, 2002).

Figure 2-2 shows different types of adaptation strategies based on the above factors. As can be seen, adaptation strategies can be taken by public or private. While governments implement public adaptation measures aiming to reduce the flood risk of the whole system, individuals such as households, farmers, and private sectors make private adaptation to decrease their individual vulnerability, which is a part of individual decision-making under risk. However, to mitigate the adverse consequences of flooding on agricultural sector and its components, flood adaptation in both regional- and farm-level is needed. Farmers as the most vulnerable group in farming community need to be informed about the flood risk and perceive that which may motivate them to pursue private adaptive responses. Therefore, they interact with floods and their decisions before, after, and during floods can change the flood risks. Such human-flood interactions contribute to FRM at the individual level. It is of high importance since private adaptive behaviors, which are taken at the farm-level, play key role in the vulnerability and exposure reduction of the individual farmer over time as well as successful promotion of governmental adaptation policies.

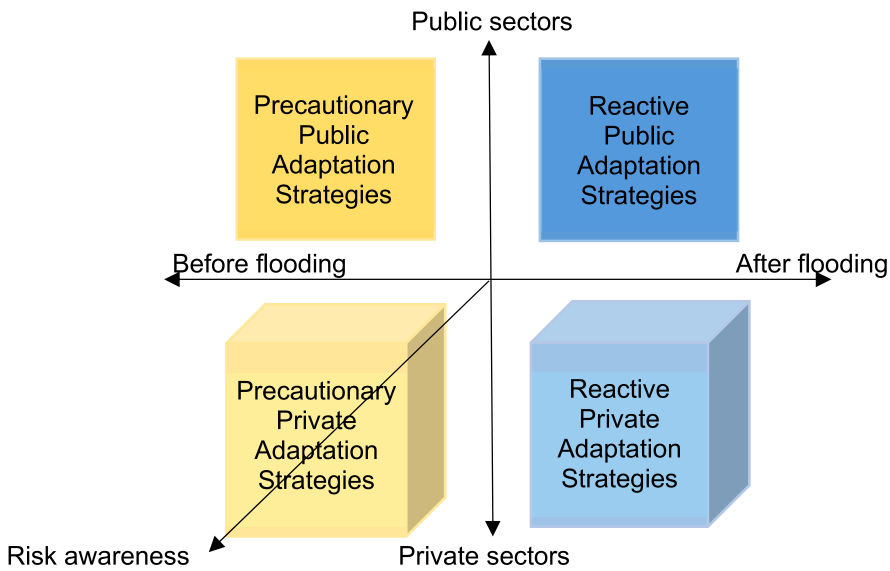


Figure 2-2. Types of adaptation strategies

Agricultural adaptation polices include strategies such as change in crop patterns (cultivating flood-tolerant crops), land management practices (planting dates), and livelihood strategies (selling farms or migration) as well as financial supports from government and insurance (Allahyari *et al.*, 2016). These policies are influenced by social interaction, economic situation, demographics characteristics, and socio-psychological factors that may decrease or reinforce farmers' adaptive capacities (Dang *et al.*, 2012). In addition, how farmers perceive the flood risk, update their expectation, and translate the perceived risk into decisions are of high importance in developing and implementing individual adaptation policies in FRM. In that case, governments can stimulate people to take individual adaptations through public adaptation policies such as financial support options, increase in the risk awareness of the public, and provision of information about coping strategies (Grothmann and Reusswig, 2006).

In addition to the influence of private adaptations on the individual level, they play vital role in the successful promotion of governmental adaptation measures in FRM due to the linkage between vulnerability of the agricultural sector at macro- and micro-level. Therefore, individual adaptive responses need to be well understood and included in FRM practices.

2.3 Influential factors on flood adaptive behavior

Economists often focus on economic features as the most influential factors in adaptation (Grothmann and Reusswig, 2006). However, socio-psychological studies provide insights into other determinants such as risk perception, coping appraisal, past experience, demographic characteristics, and social interaction in addition to the economic variables (Dang *et al.*, 2012). These influential factors are unevenly distributed across the population causing dissimilarities in their decision-making and policies.

According to the Protection Motivation Theory (PMT) (Rogers, 1975; Maddux and Rogers, 1983), one of the major theories in socio-psychological research, protective response against a threat is the output of three sequential processes: information observation, threat appraisal, and coping appraisal. Figure 2-3 shows the influential factors for the three mentioned processes.

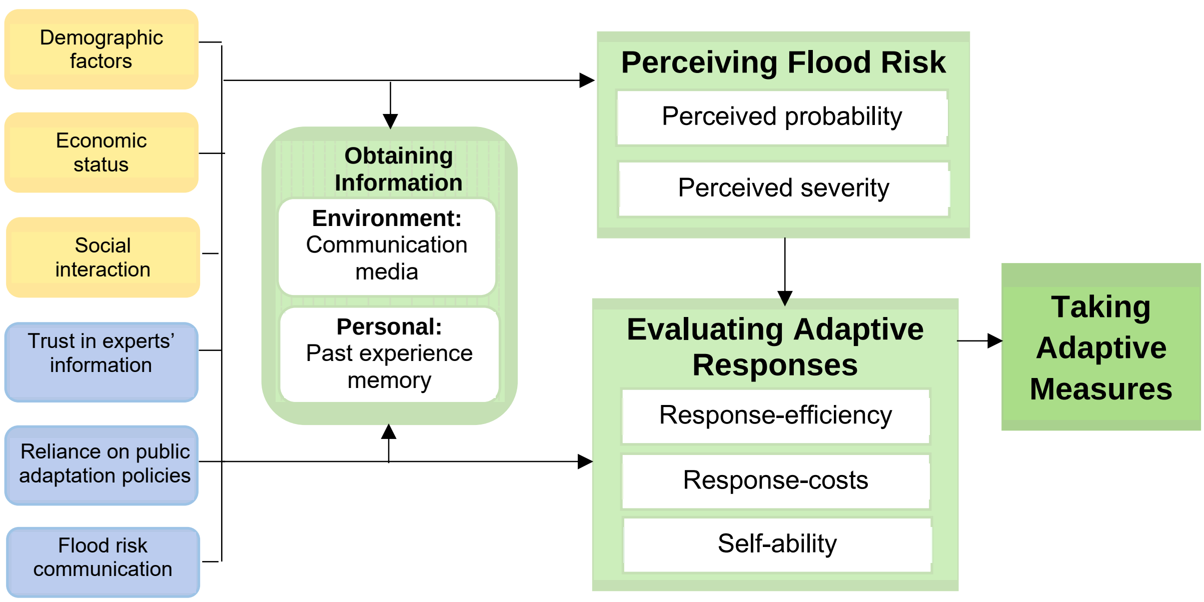


Figure 2-3. Influential factors for private adaptation policies

Various factors influence risk perception since there is a difference between objective flood risk, as the product of probability of flood occurrence and associated damage, and subjective flood risk, as the individual risk judgment (Tversky and Kahneman, 1973). While the former relies exclusively on the expert risk assessment, the latter is influenced by individual feelings, previous flood experience, memory, and personality as well as expert risk assessment and public adaptation polices. In addition, how well experts and governments communicate with people and inform them about flood risk can affect the probability judgment of individuals.

In literature, both socio-economic and psychological factors have been emphasized for adaptive responses (Hassan and Nhemachena, 2008; Bryan *et al.*, 2009). Personality, belief, level of concern, and fear affect both flood risk perception and coping appraisal (Bryan *et al.*, 2009). Demographic and economic criteria such as age, gender, education, and income are other underlying factors (Dang *et al.*, 2012). In addition, flood memory plays role in fostering resilience and taking affective responses to floods (Garde-Hansen *et al.*, 2017) and a number of studies have suggested a link between memories and decision-making under risk (Hertwig and Pleskac, 2010; McEwen *et al.*, 2012).

Social interaction plays an important role in reshaping risk perceptions and adaptation strategies over time. Kasperson et al. have found that social interaction amplifies individual risk perception, which likely results in behavioral changes (Kasperson *et al.*, 1988). Farmers exchange the information not only with their friends and relatives but also with other farmers located nearby or those with similar farms, crops, or income. In addition, farmers are informed about new strategies to cope with climate change and flood through social networks, media, and advertisement. In individual decision-making process under uncertainty such as flood events, people seek reliable information about the probable flood risks and ways to protect themselves and their properties. Therefore, they communicate with others, gain new information, and learn about risks and private adaptation policies. These factors may lead to dissemination of adaptive policies and new strategies. As a result, individual adaptive capacity and behavioral strategies are subject to change.

2.4 Flood risk assessment studies

Traditionally, FRM practices in Europe have focused on hazard control through flood protection measures such as dams and dikes (Sayers *et al.*, 2013). The primary aim at designing such physical constructions has been to fully protect the hinterland against flooding. On the other hand, structural measures have been costly and they need to be financed and implemented by the government. Such public adaptation strategies and the related regulations can be considered as the first traces of human interaction with flood where humans influence the system from the outside through measures and policies adoption. Such interplay can only be included in flood risk analysis if human agents are considered as the boundary conditions of the system and thus their decisions are imposed as the external forces.

For a long time, it was assumed that structural measures provide complete protection against flooding. Lessons learned from the major flood disasters in the past decades showed the limitations of infrastructure protection. Therefore, the strategy was changed over time from employing the traditional, technical engineering approach to managing the flood risk and “living with water” (Begum and Gelder, 2005). This new way of thinking, which accepts the limited protection of structural measures, focuses on warning the society about probable dangers and the associated socio-economic consequences.

Meanwhile, integrated flood risk management (IFRM) has been developed as a strategy (WMO, 2009) seeking to reduce the damage as well as the probability of flooding through adaptation policies. Accordingly, IFRM comprises both structural responses such as dikes, reservoirs, and levees (WMO, 2017) and non-structural ones such as legalization, land use policies, public engagement, and early warning.

Recently, IFRM became the basis for the EU Floods Directive through which the shift in the EU strategy regarding “living with water” was officially introduced. In 2007, the EU Floods Directive defined obligations for all European Member States to approach IFRM by coordinated actions at river basin level as well as at coasts in order to reduce the risks of floods for people, properties, and the environment (EU, 2007). The Directive particularly requires all Member States to carry out preliminary flood risk assessment and identify at-risk areas, to develop flood risk maps for those areas, and to draw up FRM plans including flood prevention, protection, and preparedness. Furthermore, the Directive places great emphasis on public participation (Charalambous *et al.*, 2018) involving farming communities and residents who contribute to FRM through accepting the most cost-effective measures as well as displaying individual adaptive behavior. More importantly, it is pointed out that the Member States should inform the public about the risk and coping strategies to actively involve them in FRM.

To be in line with EU Flood Directive and follow the new shift toward “living with water”, FRM studies started paying attention to humans as components that are exposed and vulnerable to flooding. As a result, much progress was made to include exposure analysis in FRM to identify the at-risk elements and to estimate the negative impacts of flooding (Oumeraci *et al.*, 2012). One of the popular approaches in this domain is the Source-Pathway-Receptor-Consequences (SPRC) model, which has originated from environmental engineering (Sayers *et al.*, 2002). The SPRC model relies on the identification of hydro-meteorological events (sources), the connection between the source of hazard and properties (pathways), and the elements at-risk (receptors), which are then followed by assessing the negative consequences on receptors such as economic, social, or environmental damage.

In this regard, FRM studies employ economic models to quantify the flood risk, which is the most commonly used measure to inform policy makers about their decisions and the cost effectiveness of flood reduction strategies. Based on the economic models, flood risk is expressed as the expected annual damage (EAD), which is best understood as the average of flood damage over years. Due to the uncertain nature of floods, EAD is calculated as the product of the probability of flood occurrence and the resulting damage after the failure of flood defenses (Ran and Nedovic-Budic, 2016). Consequently, flood risk is the function of flood hazard and the exposure of assets as well as their susceptibility.

Flood risk can be evaluated from two different perspectives: individual perspective and societal perspective. While the former quantifies flood risk at the micro-level, the latter is based on the macro-economic approaches in which the overall loss in the system is computed. Flood studies have been looking mostly at the aggregated flood risk as the sum of the associated risk of all subsystems. In such studies, individuals are assumed to be rational behaving as economic optimizers. These theoretical assumptions are valid as long as the changes in physical attributes or status of the components are small. Under these circumstances, the general behavior of the system remains linear and the superposition principle (Brillouin, 1946) contributes to the linear combination of individual risks. Such micro-economic assumptions on individual decision-making allows aggregating the risk from individual to societal level and using the overall risk as the metric of the society vulnerability.

However, humans are heterogeneous in their socio-economic attributes as well as their risk awareness (see section 2.2 and 2.3), which results in interactions and feedbacks between humans and the environment. Therefore, individual adaptation responses, knowledge exchange, flood memory, and flood risk perception shape a new mode of interaction and temporal changes in exposure and vulnerability. All these factors cause nonlinear behaviors in the subsystems and expose the system to major changes beyond the scope of the superposition principle. Moreover, there are limitations to the availability of information as well as to the processing capacities of decision makers in reality resulting in non-optimizing behaviors and bounded-rationality.

Therefore, formalizing the individual adaptive behavior on the basis of rational behavior and economic optimizing as well as perfect information has its limitations. In addition, FRM studies assume static conditions in which humans and their surrounding environment are inactive and their vulnerability is constant. Under such assumptions, time dependent features such as interactions, adaptations, and technology innovation cannot be incorporated in the current models and there is lack of modeling approaches to include social aspects of human behavior in FRM.

Overall, there is a need to change the perspective in flood risk assessment and management from macro- to micro-level and apply an alternative approach that can address such aspects.

To fill this knowledge gap, interdisciplinary approaches, which allow formulating adaptive individual decision-making under uncertainty, are in demand. More specifically, there is a need to a technique that allows us to model social processes and complexities of human behaviors from the bottom-up approach and in combination with engineering practices.

3. Human behavior and social processes

Although the first examples of simulating the social processes date back to the 1960s (Gilbert and Troitzsch, 2005), social simulation became widespread in the 1990s after the availability of powerful computers. Social simulation introduces a new way of thinking about social activities. Moreover, it provides the opportunity to understand complex patterns of behavior which may emerge from relatively simple activities (Simon, 1990).

In general, simulation is classified as one type of modeling which simplifies the real world through fewer details and less complexity in order to understand the system in question. Attributes and parameters of the system components constitute the inputs for social simulation. The output consists of their responses over time under predefined conditions. One of the main differences of social simulation from other types of modeling is its ability to include human behaviors in the model and formulize them through decision rules.

According to Gilbert and Troitzsch, social simulation can be used for different purposes (Gilbert and Troitzsch, 2005). One classic use is to forecast the changes over time or to explore the future states of the system. A second use of the simulation is to gain insights into such features of the social system for which responses are observable but the underlying behavior of people are not easily recognizable. Another use is for experimental purposes, where a model is developed for a hypothetical society to investigate the desired social aspects. The main reason that has made the use of computer simulation grow increasingly for modeling the social process is, however, its ability to formulize and hence help to better understand human behaviors.

Although mathematics and equation-based modeling are the most traditional ways of formulizing the governing rules, they are not sufficient to represent the social processes and their complexities, particularly when people are heterogeneous in their attributes and decisions (Matthews *et al.*, 2007).

3.1 Social simulation techniques

In order to embed human behaviors in the simulating environment, several social techniques are available, each with its own application areas. System Dynamics, Cellular Automata, Learning models, Micro-simulation, and Agent Based Modeling are the examples of potential social techniques. System Dynamics represents the whole target system at the macro-level using differential equations. Cellular Automata models a world in which space is represented as a uniform grid, the laws are represented by a uniform set of rules, and the interactions are local and only with close neighbors. Learning models such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are able to incorporate learning and are particularly useful for finding optimal solutions. Another approach is Micro-simulation based on a large random samples of population using a set of transition probabilities. However, the interaction between entities is not modeled.

Social science simulation techniques differ in the level of interaction (individual, society, or both), communication among individuals, degree of complexity, and the number of modeled agents (Gilbert and Troitzsch, 2005). Table 2-1 illustrates the comparison of social simulation techniques with respect to the above-mentioned characteristics (Gilbert and Troitzsch, 2005). In this table, the number of level shows whether the technique can model individual (number of level = 1), society (number of level = 1), both individual and society (number of level = 2), or even their interactions (number of level = 2+). As can be seen, most techniques are able to handle much larger number of agents than one would expect to find in social simulation. An exception is the System Dynamics method, which models the whole system as the one and only agent. However, Agent Based Modeling and Cellular Automata are the only techniques capable of modeling the communication among agents.

Table 2-1. Social simulation techniques and their characteristic (Gilbert and Troitzsch, 2005)

Technique	Number of level	Communication	Complexity	Number of agents
System Dynamics	1	No	Low	1
Micro-simulation	2	No	High	Many
Learning models	2+	Maybe	High	Many
Agent Based Modeling	2+	Yes	High	Few
Cellular Automata	2	Yes	Low	Many
Multi-level simulation	2+	Maybe	Low	Many

As discussed in the previous sections, the focus of our study is to investigate human-flood interaction and to incorporate social behaviors in FRM. In such a system, a large number of agents (humans as well as institutions) interact with each other resulting in a high level of complexity. Therefore, among the techniques presented in Table 2-1, Agent Based Modeling is one of the most appropriate methods due to its ability to model the characteristics of the desired system. Furthermore, it provides FRM with new insights into policy analysis as well as defined engineering problems.

3.2 Agent Based Modeling

Agent Based Modeling[1] is a new technique of microscopic modeling for understanding how the dynamics of complex systems arise from the characteristics and behaviors of autonomous and interacting agents within an environment. In comparison to top-down mathematical modeling assuming homogenous agents and aggregating them into a single system, Agent Based Modeling preserves the heterogeneity among agents. Accordingly, it provides an innovative bottom-up approach, where behaviors and interactions are captured at the level of agents, which may generate complex macro-behaviors (Mollona, 2008). Overall, Agent Based Modeling is a computational method that allows us to build models of the real world, analyze them, do experiments, and explore the emergent phenomena (Gilbert, 2007).

3.2.1 Basic terminology in Agent Based Modeling

Modeling in general and Agent Based Modeling in particular use specialized terminology, some of which is presented below. The purpose is to familiarize the readers with basic definitions and provide an overview on the subject.

Top-down and bottom-up approaches

Top-down and bottom-up approaches are two styles of modeling differing in the direction of information flow and ordering of knowledge. In comparison with the top-down approach, the bottom-up approach looks into the individuals constituting the whole system and models their relationships as well as their decisions.

Computational methods

Computational methods are models used to represent the existing processes in the world, formulate them as computer programs, and study the system's behavior under different conditions.

[1] Agent Based Modeling is the term that is used throughout this thesis. However, there are some other words that may be used in literature such as Agent Based Simulation, Multi Agent Simulation, and Agent Based Social Simulation.

Experiments

Experiments are scientific procedures established to examine a hypothesis, a phenomenon, or the effect of new conditions. Depending on the aim of the research, experiments are carried out on the real system or on models to simulate and predict the behavior of the components.

Environment

The environment is literally speaking any surrounding physical, chemical, social, or natural forces. In Agent Based Modeling, it refers to the world within which the agents live and act. The environment can represent the real world as a geographical space and the model developed within such an environment is called “spatially explicit”. In these models, agents are located in the environment and their interactions or decisions are influenced by the characteristics of their location. For instance, agents’ relationships with their neighbors are highly parameterized through their locations (Gilbert, 2007). Computing farmers’ crop yields or assessing their flood damage, which are related to their proximity to the seawater, are other examples of such environments. However, an environment can also be virtual and represents the physical features of a city or a group of agents (Gilbert, 2007). Social spaces, which result from social interaction, are examples of conceptual space. From a modeling perspective, an environment can be represented by GIS data, a grid of cells, or be composed of attributes in the model.

Agents

In the real world, an agent is any actor or policy maker whose states consist of mental elements such as beliefs, capabilities, and memories. Individuals, collective entities, a group of people, firms, or organizations are examples of agents. In the model, we capture agents in the computer code as computational objects that interact within their environment. Depending on the modeling purpose and the computer processing power, the model can include any number of agents.

One characteristic of the agents is that they are autonomous decision makers that assess their individual situation on one hand and observe the situation of their peers in the network on the other hand. Subsequently, they make decisions based on predefined behaviors. Their behavior patterns can be based on rationality and profit maximization or be more complex and include socio-psychological factors, learning, adaptation, and evolving.

The second characteristic is the agents’ interaction. Agents interact with each other and with their environment. This can include interactions such as consuming the supplies in the environment or indirect ones such as interaction via social networks. Knowledge sharing and information transmission are two typical examples of interaction.

In addition, agents are heterogeneous in their attributes, behavioral rules, and social interactions. These micro-level attributes and rules are mostly parameterized on the basis of real data, theories, or assumptions.

Emergent phenomena

Emergent phenomena refer to how collective properties arise from the properties of entities. Such phenomena are often unpredictable due to the interaction among entities, nonlinear behaviors of individuals as well as their learning processes and adaptation.

3.2.2 History of Agent Based Modeling

Agent Based Modeling was developed as a concept in the late 1940s by John von Neumann (Von Neumann, 1966) who designed a self-replicating machine without the use of computers. The concept was then used by Stanislaw Ulam as the basis for preliminary work in Cellular Automata (CA) (Ulam, 1952). In 1970, the mathematician John Conway contributed to the evolution of Agent Based Modeling by developing the Game of Life, which consists of a two-dimensional grid of cells and follows simple rules as being dead or alive (Gardner, 1970).

One year later in 1971, Thomas C. Schelling developed a housing segregation model, in which the basic characteristics of an agent based model such as autonomous agents, the shared environment, interacting behaviors, and emergent outcomes were embedded (Schelling, 1971). The model deals with racial dynamics and the preference of the individuals to live in a place with neighbors of the same color. Results suggested that high segregation patterns could exist among individuals even with a low degree of racial intolerance.

Following the emergence of powerful computers and, more particularly, programming languages such as StarLogo in 1990 and other toolkits in the mid of 1990s, Agent Based Modeling was applied more extensively and specifically among social scientists. One of the most popular models in this domain is Sugerscape developed by Epstein and Axtell, which explored given social phenomena such as pollution, combat, and culture (Epstein and Axtell, 1996).

3.2.3 Data gathering for Agent Based Modeling

Since Agent Based Modeling investigates the world from the individual perspective, a large amount of data is required for the model (agents' attributes and decision rules). Depending on the purpose of modeling, various sources of data may be used such as real data, synthetic data, or collected data. Table 2-2 represents the ways in which the required data for various stages of model development are collected or generated.

Table 2-2. Data gathering for Agent Based Modeling

Data	**Methods**
Real data	sample surveys, participant observation, field and laboratory experiments, GIS and remotely sensed spatial data
Synthetic data	random generation of data, using random distribution for parameters
Data for special purposes	surveys, questionnaires, censuses

3.2.4 Challenges and benefits of Agent Based Modeling

Challenges

Some drawbacks are discussed in literature regarding the application of Agent Based Modeling (Bonabeau, 2002; Rixon *et al.*, 2005). One main challenge lies in defining the behavioral rules due to their complexity. It is not a straightforward task to define the heterogeneity in attributes as the required data are mostly not available (Zenobia *et al.*, 2009). Therefore, the collaboration of researchers from different disciplines as well as expert judgments are in demand. Another issue concerns the large amount of data that the model needs in development stages. This data-hungry nature of Agent Based Modeling also makes the validation and calibration challenging tasks. Lack of standard methodology to develop Agent Based Models (ABMs) is another difficulty. Furthermore, the developed model is mostly valid for a specific purpose and can be used in similar cases only.

Benefits

Although Agent Based Modeling faces some challenges, it provides modelers with a number of benefits over other modeling approaches which has attracted interest in the recent years. Firstly, Agent Based Modeling provides insights into the emergent phenomenon- a feature not included in other modeling techniques (Bonabeau, 2002). It preserves the agents' heterogeneity and models the nonlinear behaviors and interactions among them. Secondly, Agent Based Modeling describes the world in a more authentic way closer to reality due to its bottom-up approach and individual-based perspective (Gilbert and Troitzsch, 2005). Thirdly, it is flexible in defining the behaviors and goals of agents, the levels of aggregation and complexity as well as the level of rationality in agents. Another advantage is that Agent Based Modeling allows modelers to combine psychological concepts with socio-economic approaches and engineering methods. Agent Based Modeling is also capable of accommodating dynamic conditions of both agents and the environment and tracks their changes over time. Another advantage of

Agent Based Modeling is its ability to embed learning and adaptation which can be combined with decision-making and heterogeneity of agents.

3.2.5 Application areas of Agent Based Modeling

Agent Based Modeling has been applied across a wide range of disciplines such as traffic management (Helbing *et al.*, 2005), ecological modeling (Grimm and Railsback, 2005), marketing (Palmer *et al.*, 1994), organizational simulation (Prietula *et al.*, 1998), energy policy (Wittmann, 2008), and urban development (Batty, 2005). Although the models differ in terms of the data applied (real vs. non-real data), involvement of stakeholders, governing rules, and calibration process, their domain of application can be generally classified into three main groups (Matthews *et al.*, 2007) as follows.

Agent Based Modeling as an experimental platform

One of the common uses of Agent Based Modeling is to explore given theories or hypotheses. In this way, Agent Based Modeling is an experimental platform by means of which modelers implement theories and ideas about behavioral rules and investigate them at micro-level. Another example is when there is limited access to the real data or the governing behavior patterns and modelers cannot parameterize the model. As a result, Agent Based Modeling can be used as a virtual laboratory to develop an explanatory model.

Agent Based Modeling as an empirical platform

ABMs can be developed based on real data. For this aim, stakeholders or the desired agents may be involved in the development process. This can be achieved through workshops and questionnaires, which provide stakeholders with a platform to express their concerns and exchange their knowledge. Modelers also benefit from such modeling approaches since they can simultaneously record their observations, implement them in the model, and compare their simulated results with the observations.

Agent Based Modeling as a policy analysis and planning platform

Policy analysis and planning platform is another application of Agent Based Modeling to explore the effects of existing policies and to anticipate the likely outcomes of potential plans as well as innovative strategies. To achieve the goals, Agent Based Modeling is an appropriate approach to investigate and analyze the dynamic behavior of the system under various scenarios. In the case of real-world polices, the data is usually available for calibration and validation.

Although Agent Based Modeling is an interesting tool, it is important to investigate initially if it is really an appropriate method for the desired research questions. In general, when agents are heterogeneous in their attributes or decision-making with the behaviors changing over time, or modelers are interested in the interaction among agents and/or the environment, Agent Based Modeling is the potential modeling option since it can capture the complexity of the problem (Parker *et al.*, 2003).

3.2.6 Agent Based Modeling in flood management

Although the history of Agent Based Modeling is traced back to the 1940s, it is relatively a new technique in flood management studies. Maja Bosch et al. focused on the institutional dimension of FRM such as the rules, norms, and shared strategies that guide decision-making behavior in flood risk response, recovery, mitigation, and preparation (Bosch, 2017). They studied the interdependencies and connectivity between institutions in the Caribbean island St Maarten. Abebe et al. carried out the institutional analysis for flood risk reduction (Abebe *et al.*, 2016). Their results show that an institutional model coupled with flood model offers a useful exploratory tool to understand the system as a whole and test policy alternatives that match local conditions. Agent Based Modeling has been also applied to investigate the role of flood insurance in flood risk reduction (Dubbelboer *et al.*, 2017). Filatova et al. designed an ABM to simulate land markets for Dutch coastal towns under risk (Filatova *et al.*, 2011). They employed an agent based computational economics modeling approach to tackle this problem. Nabinejad and Schüttrumpf explained an example of Agent Based Modeling application in coasts to represent human-flood interaction (Nabinejad and Schüttrumpf, 2016).

3.2.7 Toolkit selection for developing ABMs

There are a number of programmable modelling environments for the agent based application. Table 2-3 compares Swarm, Repast, Mason, and NetLogo, as four popular toolkits (Salgado and Gilbert, 2013). In our study, NetLogo has been selected as the programming language since it is freely available and easy to install. Furthermore, it includes a set of libraries as well as a graphical interface (Railsback *et al.*, 2006). NetLogo was designed by Uri Wilensky in 1999 and is well-suited for modeling social behaviors in terms of turtles, patches, links, the observer, and instructions governing agents' behaviors (Wilensky, 1999). It has been used in different research areas including biology, physics, chemistry, mathematics, computer science, and economics. An example of NetLogo implementation is wolf-sheep predation model (Wilensky, 1999). Moreover, there are applications for household water use (Linkola *et al.*, 2013) and a predator-prey model in biology (Wilensky, 1999). Netlogo has been also applied in immunology for formulation the disease mechanisms (Chiacchio *et al.*, 2014).

Table 2-3. Comparison of toolkits used for developing ABMs (Salgado and Gilbert, 2013)

	Swarm	Repast	Mason	NetLogo
Licence	General Public Licence	General Public Licence	General Public Licence	Free
Documentation	Patchy	Limited	limited	Good
Modelling languages	Java	Java, Python	Java	NetLogo
Speed of execution	Moderate	Fast	Fastest	Moderate
Support for graphical user interface development	Limited	Good	Good	Very easy
Ease of learning and programming	Poor	Moderate	Moderate	Good
Ease of installation	Poor	Moderate	Moderate	Good
Link to geographical information system (GIS)	No	Yes	Yes	Yes

4. Individual adaptive decision-making

Representation of human behaviors is an important aspect in developing models with Agent Based Modeling approach. Literature has generally parameterized decision-making rules on the basis of micro-economy assumptions, empirical data, or developed theories (Johnson, 2015).

Decision-making rules based on micro-economy

Traditionally, economic models are applied to formulize individual decision-making (Von Neumann and Morgenstern, 1944). These models assume that people have an objective function to be maximized within a set of constraints, and an analytical solution represents the final decisions of people for such a mathematical problem. Humans are aggregated as a meta-actor and the heterogeneity among population is ignored. One of the primary economic theory is expected utility theory (EUT) developed by Neuman and Morgenstern (Von Neumann and Morgenstern, 1944). In EUT, actors are rational, fully informed, and behave as economic optimizers who choose the strategy with the highest expected utility. However, in an empirical study conducted by Kahneman and Tverksy, it was shown that individuals are biased in their risk judgment and the level of perceived risk may differ from the risk calculated as the product of hazard probability and damage (Tversky and Kahneman, 1973).

Kahneman and Tverksy, therefore, developed Prospect theory as an extension of EUT, in which individuals evaluate the utility outcomes of all possible options using objective risk instead of subjective risk (Tversky and Kahneman, 1973). Prospect theory describes how individuals generally weight the risk based on heuristic and bias, which originates from limited information processing capacities of decision makers and limited information availability. Although Prospect theory addresses the limitations of EUT, it still relies on maximization of utility functions and does not pay attention to the updating of risk perception and the influence of social interaction (Haer *et al.*, 2017). Furthermore, Prospect theory lacks a variety of cognitive behaviors for making decisions as mentioned by behavioral decision studies.

Decision-making rules based on empirical data

Collecting the data of the target population is another way to conceptualize the behavioral rules. For this aim, quantitative methods such as field experiments and questionnaires are widely applied (see Table 2-2), which can be a good representation of the system under study. However, the validity of the provided data is limited since they have been collected in the short time under given specific experimental conditions (Jager *et al.*, 2000).

Decision-making rules based on theories

The third approach in developing the behavioral rules is using existing or recently developed theories that originate from socio-psychological studies. These theories provide the modelers with valuable information particularly when there is lack of data or the purpose of the study is to explore the individuals' behavior more generally. Overall, theory-based decision-making rules contribute to a better understanding of how different attributes of agents or the environment influence the system and its components.

One of the most well-known theoretical models used for parameterizing the decision rules is Consumat approach developed by Jager et al. (Jager *et al.*, 2000). This conceptual model integrates relevant behavioral theories into decision-making under uncertainty. Combining the social psychology with economic principles, Consumat approach is based on satisfaction outcomes rather than optimized ones. In addition, the model conceptualizes learning processes and knowledge exchange through social interaction.

Table 2-4 compares EUT, Prospect theory, and Consumat approach for individual decision-making under uncertainty. Although EUT and Prospect theory provide valuable insights, they are not able to represent the individual behavioral aspects such as heterogeneity, social interactions, and non-optimizing responses. Therefore, in this study, we have chosen Consumat approach as the basic conceptual and theoretical framework to deviate from optimization for representing the decision-making of the individual farmers in coasts under the influence of peers as well as limited information available to them. In comparison with two other approaches, Consumat approach allows agents to switch among various behavioral rules over time horizon due to its capability in modeling the dynamic in the uncertainty and satisfaction function which shows the spatial as well as temporal heterogeneity.

Table 2-4. Comparison of EUT, Prospect Theory, and Consumat approach

Decision-making models under uncertainty	Description
Expected utility model (EUT)	1- Individuals follow optimization as behavioral strategy. 2- Individuals assess the expected utility of various actions based on absolute wealth and take the action with highest expected utility. 3- Expected utility is defined as (objective probability × outcomes). 4- Utility function is risk averse and loss-aversion cannot be defined. 5- EUT accounts for rationality in individual processing of probabilities. 6- Individuals are assumed to be rational, fully informed, and self-interested. 7- The model assumes homogenous population. 8- EUT ignores social interactions.
Prospect theory model	1- Individuals follow optimization as behavioral strategy. 2- Individuals assess gains and losses of various actions based on a referenced point and take the action with highest expected utility. 3- Expected utility is defined as (subjective probability × outcomes). 4- Utility function is risk averse for gains and loss averse for losses. 5- Prospect theory accounts for bounded-rationality in individual processing of probabilities. 6- Prospect theory can only model heterogeneity of individual probability judgment. 7- Prospect theory does not include social interaction and its effects.
Consumat approach	1- Individuals follow a verity of cognitive processes including imitation, repetition, social comparison, or optimizing as behavioral strategies. 2- Individuals assess the level of their satisfaction and uncertainty and engage in one of four cognitive processes. 3- Consumat approach accounts for bounded-rationality in all stages of decision-making. 4- Individuals are bounded-rational and have limited information as well as cognitive ability to analysis information. 5- Consumat approach can model the heterogeneity of individual risk perceptions and adaptive behaviors in terms of influential factors discussed in section 2.3. 6- Social interaction and social networks are taken into account. 7- Diffusion of adaptive policies and interactive behaviors among people and the environment are possible through social networks.

4.1 Consumat approach

Consumat approach has been developed by Jager et al. to explore human behavior and decision-making process (Jager *et al.*, 2000). In the approach, agents engage in various cognitive individual or social processes depending on the level of their uncertainty and satisfaction. Therefore, each agent in the ABM is the consumat who is equipped with various needs and she/he consumes opportunities to satisfy her/his needs. Since every individual may have her/his own satisfaction and uncertainty level and follows a certain heuristic behavior, Agent Based Modeling is suitable technique for the approach. This conceptual model of Consumat approach is shown in Figure 2-4 (Jager *et al.*, 2000).

Consumat approach has been successfully implemented in various systems such as drought management (van Duinen *et al.*, 2015), diffusion of green products (Jager and Janssen, 2012), and vulnerability assessment of farming communities in the Philippine (Acosta-Michlik and Espaldon, 2008).

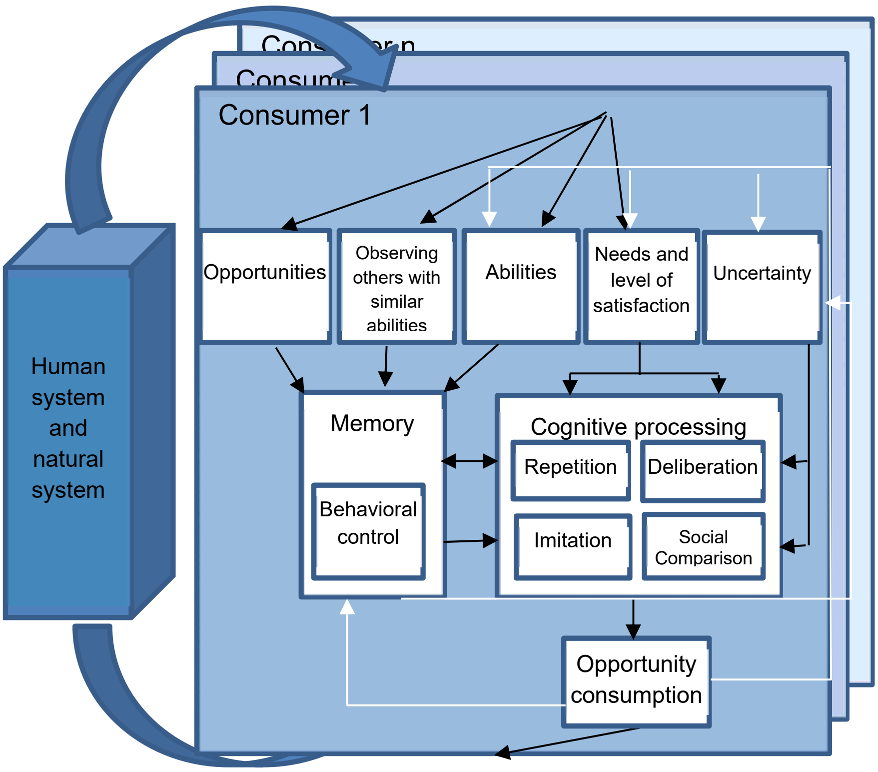


Figure 2-4. The conceptual model in Consumat approach (Jager *et al.*, 2000)

4.1.1 Behavioral rules in Consumat approach

Four cognitive strategies are considered in Consumat approach for the agents' decision-making including deliberation, repetition, imitation, and inquiring (social comparison), as shown in the Figure 2-5.

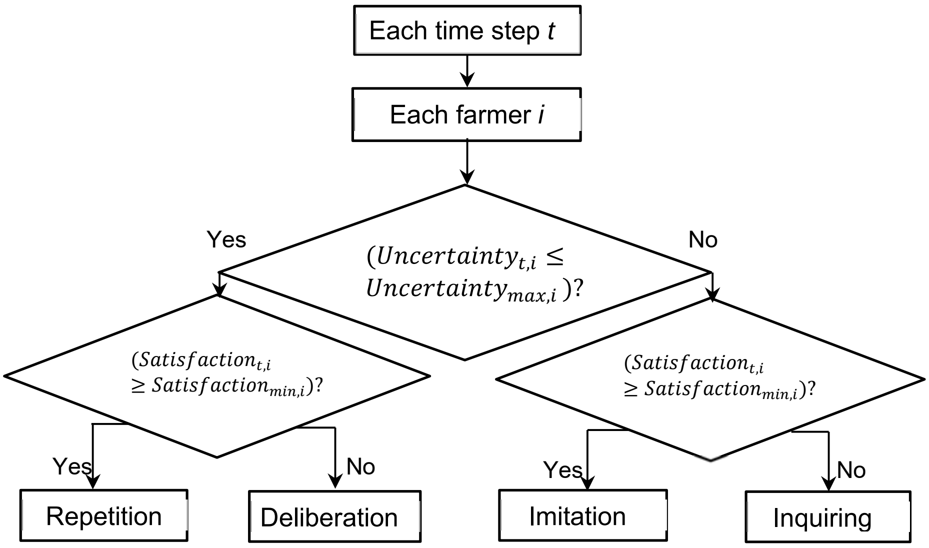


Figure 2-5. Behavioral process in Consumat approach based on satisfaction and uncertainty level

A satisfied and certain agent (engaging in repetition)

This agent will repeat her/his previous decision to remain satisfied. Therefore, she/he will neither update her/his mental map nor rely on her/his social network.

A dissatisfied and certain agent (engaging in deliberation)

This agent will think and assess the possible options to maximize her/his profit. Therefore, she/he needs to update her/his mental map in order to gather some information about the possibilities. This kind of agent may try the options, which have not been used by other agents.

A satisfied and uncertain agent (engaging in imitation)

This agent firstly considers all options, which have been performed by those in her/his social network with strong links. Then, she/he copies the successful behavior performed by the majority in order to reduce uncertainty and remain satisfied.

A dissatisfied and uncertain agent (engaging in inquiring)

This agent chooses a decision among those of her/his previous one and agents in her/his social network (either with strong links or weak links) which results in the higher profit.

Indeed, social networks play a vital role in decision-making of uncertain agents (Jager *et al.*, 2000; Jager and Janssen, 2012). In contrast, dissatisfied agents engage in the processes which need more efforts to make them be satisfied in the future (Jager *et al.*, 2000; Jager and Janssen, 2012).

4.1.2 Validation of Consumat approach

As discussed in the section 3.2.4, validation is one of the challenges of Agent Based Modeling. Jager et al. validated Consumat approach for micro-level rules as well as the dynamics of resulting behaviors. They developed the cognitive processing rules using various psychological theories which increase the agent behavioral richness in comparison to pure-maximizing decision-making. Regarding validating the dynamics of behaviors, they used the approach to check its capacity in replicating empirical findings. Their results indicated that there is a good agreement between their findings and those of empirical studies (Jager *et al.*, 2000).

5. Summary

The traditional methods applied in flood management studies are to impose limitations in modeling human-flood interactions. They assume that humans are inactive-exposed agents whose vulnerabilities are constant over time. However, dynamic responses of people in flood-prone areas prove the need to an alternative method that can address such challenges. Agent Based Modeling is a new approach that allows changing the way of thinking and including humans in modeling process from the individual perspectives. This makes it arguably more realistic as it gives the modeler greater flexibility not to make the assumptions of previous methods in this domain. In order to integrate human-flood interaction in flood management, individuals' behavior can be represented through various decision-making models. Among them, Consumat approach is a reliable method, which allows agents to switch between various behavioral rules over the time horizon due to its capability in modeling the dynamic in the uncertainty and satisfaction function.

Chapter 3 Simulating crop yield on the field-scale

1. Introduction

Coastal areas are attractive settling grounds for farmers since they provide farmers with fertile lands and soil, which are suitable for crop cultivations and farming. Farmers make decisions and select crop patterns for their own field each year and profit from them. The more crop yields are produced, the more profits are achieved, and the more pleased farmers are with their decision. As crop productivity is an essential input for agricultural economic analysis and farmers' decision-making, it is a key need to estimate the annual crop yields for individual farmers in order to compute their yearly profits/losses and to model their yearly decision-making.

Researches in this domain are largely based on crop growth models, which use mathematical equations. On the other hand, crop productivity is the outcome of several complex phenomena controlled by the climatic condition, soil, timing of management practices, and water and nutrient supply. Therefore, some studies have incorporated crop growth models into hydrologic simulation tools to provide a more accurate representation of crop biomass characteristic. The disadvantage of such models, however, is that they simulate crop yields at defined hydrologic units which do not necessarily correspond to the farmers' fields in reality and as a result, they report the crop yields on a more aggregated level rather than on the field level.

2. Research question and objective

A suitable way to develop a model to predict crop yields at the field-scale is a hydrological module that integrates crop growth sub-models on one hand and connects its defined hydrologic units with spatial features of watersheds such as farmers' fields on the other hand. In this way, it is possible to carry out the desired simulations on the field-scale based on the hydrological, soil erosion, and nutrient transport processes. In order to be used as a practice-oriented tool, such a hydrological module must be able to model farmers' crop yields within the hydrologic process as accurately as possible with the least possible calculation effort which will be used further to model farmers' decision-making. To achieve its goal, this chapter answers the following research question: "*How can the yearly crop yields of individual farmers as a function of climatic condition and geographic characteristic of the area be estimated?*"

The main aim of this chapter is to develop a calibrated-validated hydrological module in order to predict crop yields at field-scale. To achieve the main goal, several specific objectives were identified in designing the proper hydrological model: i) to develop uncalibrated baseline scenario, ii) to establish the hydrological calibrated and validated baseline scenario, iii) to improve the performance of the model in crop yield prediction, and iv) to compute annual crop yields on the field-scale to assist individual decision-making and micro economic analysis. The hydrological module developed in this chapter is applied later in connection with flood risk analysis module and farmers' decision-making module for micro-scale analysis.

The structure of this chapter is as follows: Section 3 presents the steps for developing the hydrological module including software selection, modeling steps, input data, model setup, and model calibration. Results and discussion are presented in section 4 followed by conclusions and outlook section.

3. Hydrological modeling

3.1 Software selection

In order to simulate crop yields within hydrological models, physically based models are paid attention as powerful tools. A wide variety of freely and commercially programs are available for this aim. In order to develop such a model, which can be adapted to the existing requirements, a freely accessible open source program is used in this study. Along with other open source models, Soil and Water Assessment Tool (SWAT) has been extensively applied as a suitable one due to its abilities in predicting runoff and crop responses under various land management practices. In addition, it can simulate a wide range of cropping systems and has a good performance in crop yield estimation without the need for crop yield calibration (Neitsch *et al.*, 2011). Besides, SWAT is a public domain software which is supported by United States Department of Agriculture (USDA) and constantly modified by users as well.

3.2 Software explanation and components

The SWAT is a hydrological watershed model developed by Dr. Jeff Arnold (Arnold *et al.*, 1998). Its recent graphical user input interface is ArcSWAT 12, which is an ArcGIS-extension. The software is a continues-time distributed-parameter model that is able to predict long-term effects of land management practices, land cover, and land use changes on hydrological responses, crop yields, and water quality in large complex watersheds on a daily time step (Neitsch *et al.*, 2011).

In ArcSWAT, a watershed is separated into subbasins that are further subdivided into Hydrologic Response Units (HRUs) each presenting a unique combination of soil, slope, and land cover in the whole area. The HRUs are the basic computational units for water balance in the watershed, which includes hydrological components of precipitation, canopy storage, infiltration, redistribution, evapotranspiration, lateral subsurface flow, surface runoff, pond storage, tributary channels, and return flow (Neitsch *et al.*, 2011).

Crop growth in SWAT is based on the Environmental Policy Integrated Climate (EPIC) model and simulates crop growth considering heat units accumulation for reaching the maturity. In each time step, SWAT calculates the potential crop yields under no water, nutrients, and temperature stress that will be then reduced to the actual crop yields due to stress factors. Figure 3-1 shows the interconnection among various hydrological and crop growth components (NASA, 2019).

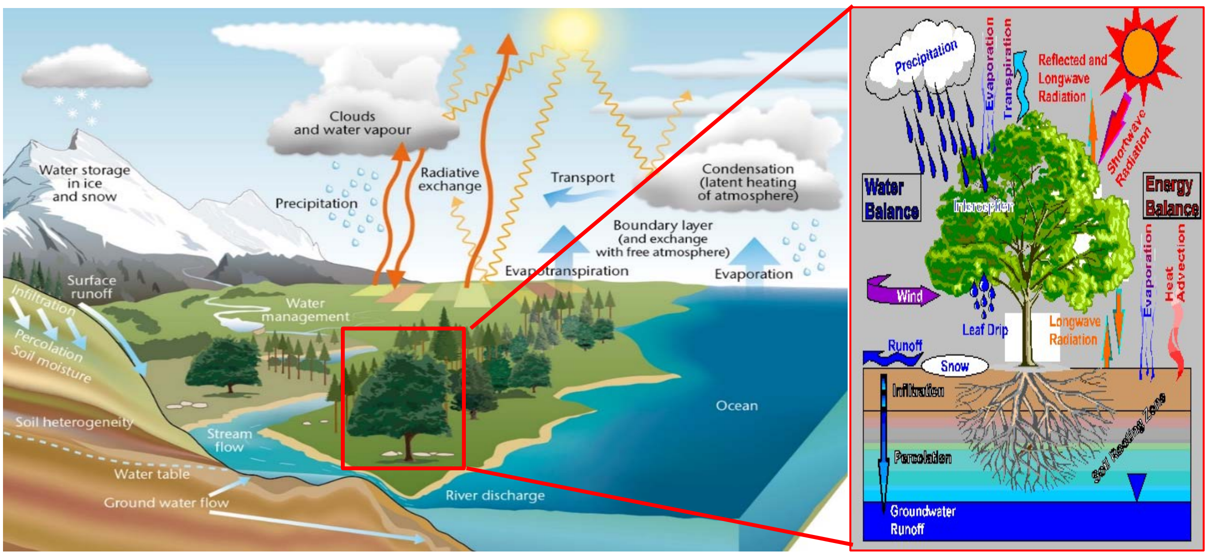


Figure 3-1. Hydrological and crop growth components and their interconnections (NASA, 2019)

3.3 Overview and modeling steps

The methodological approach of the chapter, modeling steps, and required data for developing the desired hydrological module are illustrated in Figure 3-2. The simulation period is 2005-2016 including one year of warm up period for the model.

As seen in Figure 3-2, watershed delineation is the first step for model set up. Preparing the required data and feeding them into the model, the unique HRUs are created and finally the baseline scenario is developed. This uncalibrated baseline scenario describes current topographic, climate, and land use situation of a watershed before any calibration. The next phase is to improve the prediction efficiencies of the developed hydrological module for the baseline scenario. To achieve its goals, a two-stage calibration procedure including hydrological calibration and crop yield calibration is established in this chapter. The detailed explanation of modeling steps can be found in section 3.4 and 3.5.

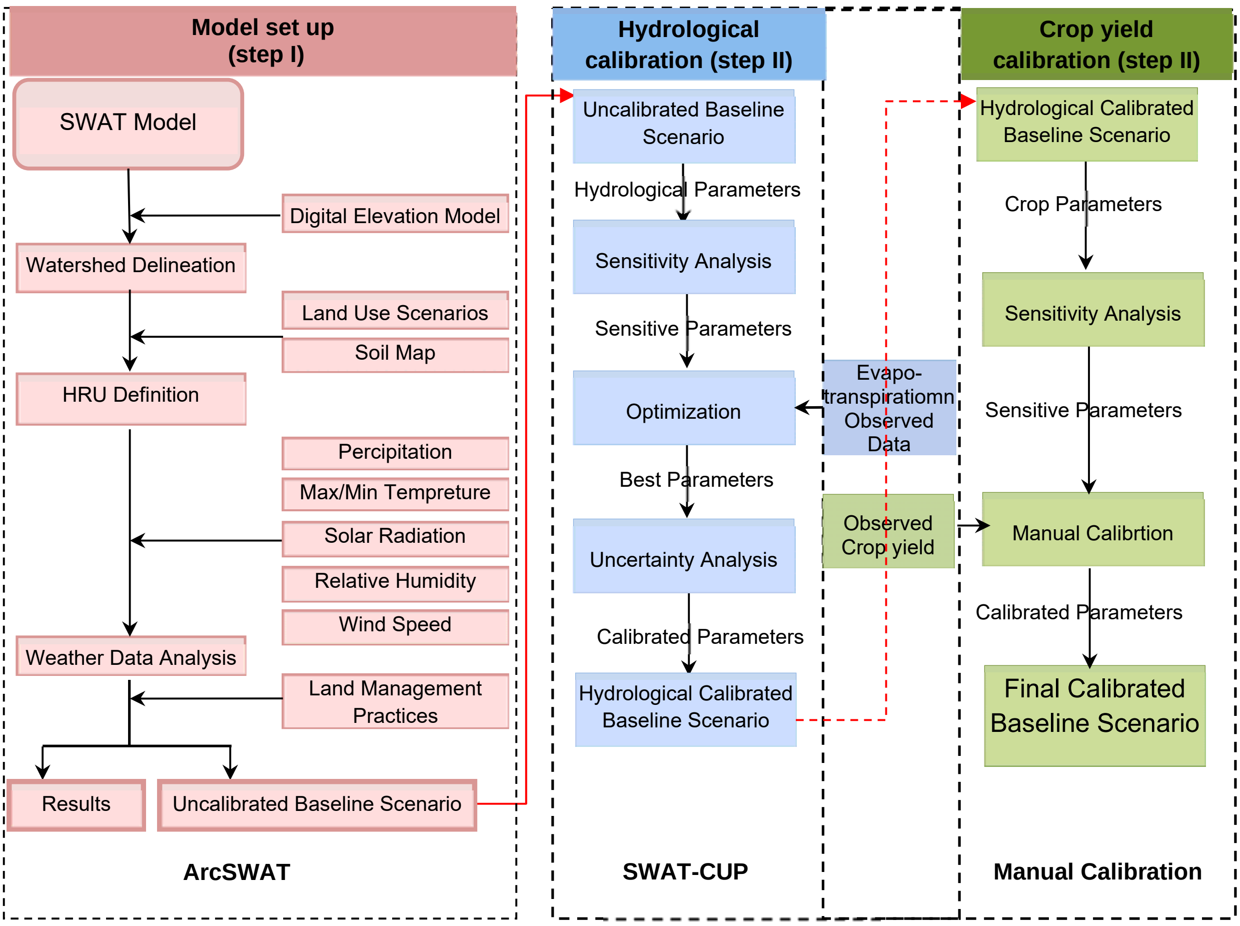


Figure 3-2. The methodological approach of the study and the components of the hydrological module

3.4 Input data and model setup (step I)

As a physically based model, SWAT requires various spatial data to develop a reliable baseline scenario that can represent the correct hydrological system for the whole simulation period. It includes the input data for setup preparation as well as additional data for calibration and validation. Thus, data analysis, preparation, and formatting are the essential steps to successfully model the watershed and achieve high quality outputs. Relevant input data are topographical, meteorological, hydrological, geological, and phonological data as well as land use data. The output of the model setup is an uncaliberated baseline scenario.

3.4.1 Topographical data

The Digital Elevation Model (DEM) of the Pellworm Island was obtained from the State Department of Agriculture, Environment and Rural Areas of Schleswig-Holstein (Schleswig-Holstein, 2016). The cell size of the provided DEM was 1m in the projected coordinated system 'ETRS_1989_UTM_Zone_32N'. Although such a high-resolution DEM results in detailed topographical descriptions, the simulation time is increased. Hence, a 2m resolution DEM was created in ArcGIS for this study. In the next step, the DEM was used as ArcSWAT input to define the stream network and to compute the slope of the watershed. Figure 3-3 illustrates the final DEM and the defined stream network as inputs for ArcSWAT.

3.4.2 Geological data

The State Department of Agriculture, Environment and Rural Areas of Schleswig-Holstein provided a detailed soil map for Pellworm Island differentiating four soil types Dwogmarsch, Kalkmarsch, Kleimarsch, Rohmarsch, and an artificial backfill (Schleswig-Holstein, 2016). However, due to the lack of soil parameters, we extracted a 2 km soil map for the area from the public world soil raster map of the Food and Agriculture Organization (FAO, 2003) as input data.

3.4.3 Land use data

The land use map of the study area was obtained from the State Department of Agriculture, Environment and Rural Areas of Schleswig-Holstein with the projected coordinated system is 'ETRS_1989_UTM_Zone_32N'. The land use map identified 21 major land use categories, which were then aggregated into eight main classes including agricultural land, urban areas, industry, transportation, pasture land, water bodies, and orchard land to be correspondent to ArcSWAT database.

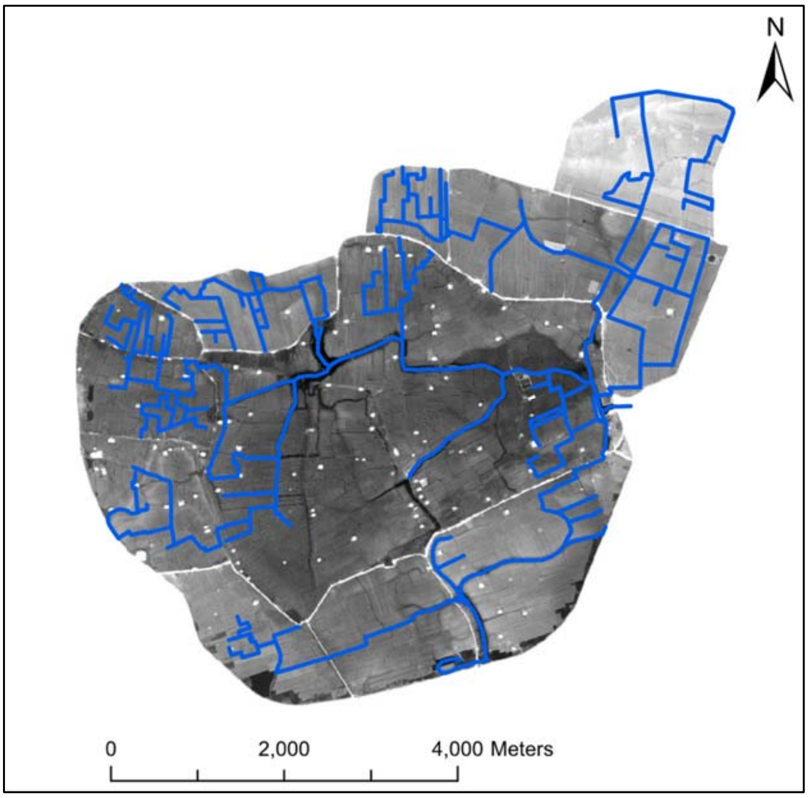


Figure 3-3. DEM including stream network created in ArcGIS

Table 3-1. Land use classifications

Category		**Area [ha]**	**Area (%)**
Residential		37.61	1.10
Industrial		4.19	0.12
Transportation		7.11	0.21
Water		33.58	0.98
Commercial		47.14	1.38
Agricultural land	Spring barley	111.42	3.26
	Barren land	7.58	0.22
	Spring canola	110.65	3.24
	Maise	215.26	6.30
	Winter wheat	250.15	7.32
	Pasture	2593.63	75.87
	Orchard	0.00	0.00

According to Schüttrumpf et al., the four most prevalent crops cultivated by farmers in the Pellowrm Island have been spring canola, maise, spring barley, and winter wheat (Schüttrumpf *et al.*, 2013). Accordingly, we subdivided the agricultural land into those crops cultivated. Table 3-1 depicts the land use classifications and their covered areas. The final land use map fed into SWAT is presented in Figure 3-4 in which each color shows one class of land uses.

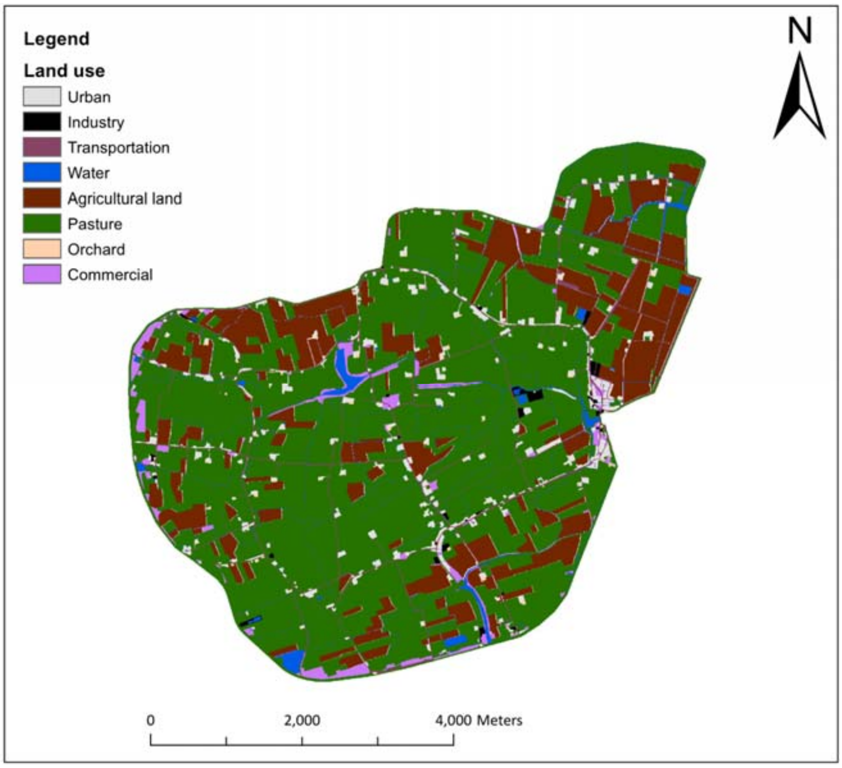


Figure 3-4. Land use map in ArcSWAT

3.4.4 Hydrologic response units (HRUs)

Preparing DEM, land use map, and soil data, the model setup in ArcSWAT is divided into three main steps including watershed delineation, HRU analysis as well as weather and land management input generation. After watershed delineation, 527 subbasins were created which were further subdivided into HRUs with homogeneous soil, land use, and slope characteristics within each subbasin by overlaying land use, soil, and slope maps. The slope classes used for this process were 1% to 2%, 2% to 5%, and 5% and above, resulting in 6177 HRUs.

It should be noted that stream flow, crop yields, and other computed elements by SWAT are reported on HRU scale. The more the number of HRUs, the more the computation time. It is possible to decrease the simulation time through defining thresholds for land use, soil, or slope classes. However, the main disadvantage of this assumption is not to be able to investigate how much yield each farmer can produce within one year since there is no access to the spatial distribution of HRUs. To overcome this issue, we successfully generated the HRU spatial distribution map by adjusting thresholds for those three classes in the overlaying process of ArcSWAT. Then, the group of HRUs comprising each field were determined and as a result, crop yields were computed on the field-scale which have been not achieved in previous studies. Figure 3-5 illustrates the spatial distribution of HRUs in Pellworm Island generated in ArcSWAT.

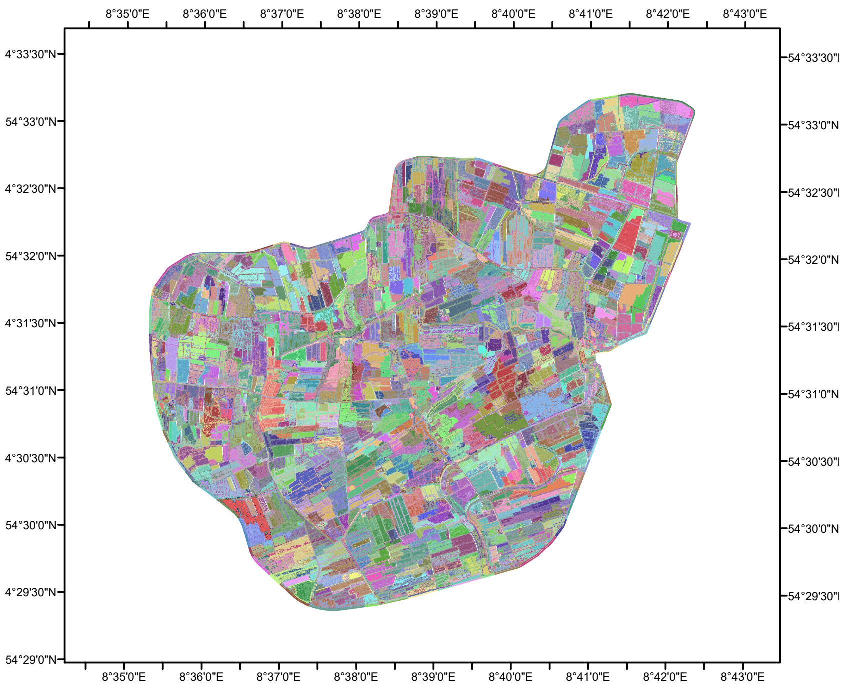


Figure 3-5. HRU spatial distribution map in ArcSWAT

3.4.5 Meteorological data

The Public FTP server (available under: ftp://ftp-cdc.dwd.de/pub/CDC/) of Germany's National Meteorological Service (DWD) provided weather information (CDC, 2016) consisting of daily precipitation [mm], max/min temperature [°C], relative humidity [-], solar radiation [MJ/m^2/d], and wind speed [m/s] data. Since there were no weather stations located on the Pellworm Island, the data of four nearest weather stations were used for preparing the meteorological data. Figure 3-6 shows the location of those weather stations.

Daily solar radiation data were available only for the weather gages of List on Sylt and St. Peter Ording and the weather generators in ArcSWAT replaced missing data during the model setup. Table 3-2 provides information about the weather gages for the simulation period. A summary of the prepared hydrological input data is presented in Table 3-3.

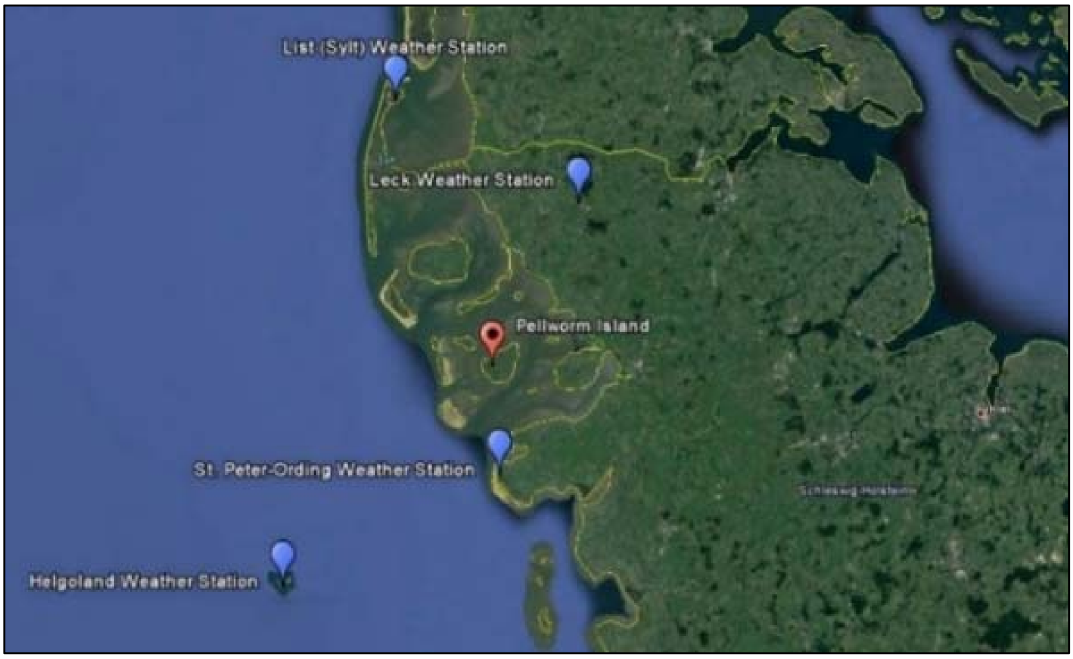


Figure 3-6. Location of selected weather stations created in Google Earth

Table 3-2. Weather data of selected weather stations

Weather station	Distance [km]	Elevation [m]	Available data
St. Peter-Ording	21.14	5	Rainfall, Temperature, Wind speed, Relative humidity, Solar radiation
Leck	36.80	7	Rainfall, Temperature, Wind speed, Relative humidity
List (Sylt)	56.26	26	Rainfall, Temperature, Wind speed, Relative humidity, Solar radiation
Helgoland	60.93	4	Rainfall, Temperature, Wind speed, Relative humidity

Table 3-3. Summary of the prepared hydrological input data

Topography	Land use data	Soil data	Weather data
- Cell size: 2 m - Area: 37 km^2	- Agriculture - Gardenland - Urban - Industrial - Transportation - Waterbody - Others	- Kleimarsch	- Precipitation (mm) - Relative humidity - Real Evapotranspiration - Wind speed (m/s) - Min/Max Temp. (C°) - Solar radiation

3.4.6 Land management data

In order to simulate crop yields in the study area, detailed information of land management practices including crop type, fertilization dates and rates, planting and seeding dates, irrigation data, and harvesting dates are required. Seeding and harvesting dates were obtained from the agrometeorological section of Germany's National Meteorological Service (DWD).

3.5 Model assessment and improvement (step II and III)

The developed baseline scenario is ready to be used for the further analyses. The SWAT model has been developed and successfully applied in watersheds with no monitoring data. However, watershed models are nowadays highly complex due to the inclusion of countless parameters to represent the physical reality of hydrological processes. Therefore, it is necessary to assess the structure, predictive accuracy, and precision of the created baseline scenario (Van Griensven *et al.*, 2006). To achieve its goal, a two-stage calibration procedure is established in this study. Hydrological calibration is carried out firstly to improve the performance of the model in predicting water budget, after which crop yield calibration will be done.

3.5.1 Hydrological calibration (first stage of calibration)

Hydrological calibration is the primary step in SWAT watershed applications for which annual or monthly streamflow is the most common output used. Sufficiently long, sequential, and precise observation data are required to improve the model performance significantly (Gassman *et al.*, 2007). Due to the lack of streamflow data for the Pellworm Island, evapotranspiration values on a monthly time-step obtained from the DWD were applied for calibration and validation processes (Weyer, 2016). The calibration and validation period are 2006-2010 and 2011-2016, respectively. The ten biggest subbasins from all parts of the Island were chosen for calibration and validation of the model, as shown in Figure 3-7. These subbasins include all different land uses and slopes which can reflect various characteristics of subbasins.

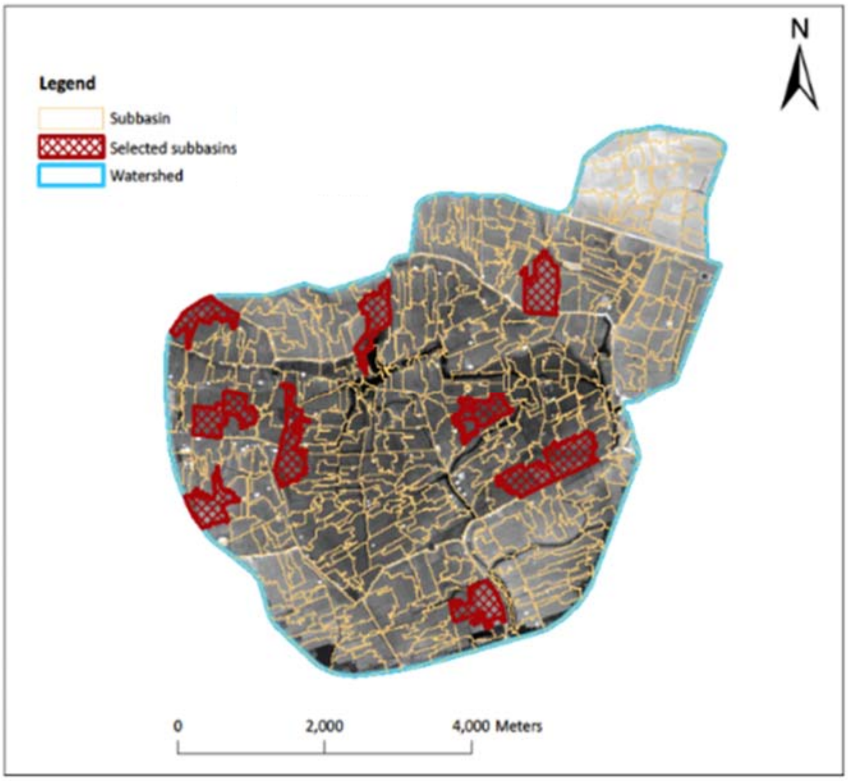


Figure 3-7. Selected subbasins for hydrological calibration and validation procedures

Sensitivity analysis

The first step of model calibration is the sensitivity analysis. Sensitivity measures the rate of change of an output variable to a change in model input parameters. A great rate of change corresponds to a higher sensitivity (Arnold *et al.*, 2012). In simple words, sensitive input parameters are able to influence strongly the outputs, so they are often used as input for model calibration. Moreover, performing sensitivity analysis reduces the number of parameters to be calibrated and non-sensitive parameters can be exempted from calibration, which also reduces uncertainties of a model (van Griensven *et al.*, 2006). In this research 20 parameters, which may potentially influence evapotranspiration, were selected for sensitivity analysis and further for calibration and uncertainty analysis according to literature (Arnold *et al.*, 2012; Samadi, 2016), user manuals (Neitsch *et al.*, 2011; Ashraf Vaghefi *et al.*, 2015), and cognition of the case study Pellworm Island.

Calibration and validation

Once sensitive parameters are identified, the baseline scenario can be improved by calibration and validation. Generally, optimization of hydrological models is a complex step due to missing reliable input data, uncertainties, and the application of hydrological processes in a simplified model. Input data for the optimization process is commonly split into two time periods of similar climatic conditions. Both, calibration and validation periods should include dry and wet periods (Arnold *et al.*, 2012). During calibration, simulated model outputs and observed local data are compared by optimizing the objective function (Immerzeel and Droogers, 2008) which consists of a statistical test for this comparison (Abbaspour, 2015). The final objective function of calibration process is further used for validation to prove if the calibrated parameters achieved from calibration are good enough to generate accurate outputs for other simulation periods which are different from that of calibration.

Evaluating the performance of the ArcSWAT predictions

Finally, the model performance is assessed regarding the calibration process. SUFI-2 offers a wide range of statistics to evaluate the simulated data by ArcSWAT models. According to Gassman et al., R^2 and Nash-Sutcliffe (NS) coefficients are widely used for the performance assessment of calibration and validation procedures (Gassman *et al.*, 2007).

The coefficient R^2 is a measure of dispersion around the mean of the observed and predicted values. It is defined as the squared value of the coefficient of correlation and calculated as:

$$R^2 = \frac{\left[\sum_{t=1}^{T}(y_t - \bar{y})(f_t - \bar{f})\right]^2}{\sum_{t=1}^{T}(y_t - \bar{y})^2 \ \sum_{t=1}^{T}(f_t - \bar{f})^2} \tag{3-1}$$

where $\bar{y}$ and $\bar{f}$ are the mean value of observed and simulated data for the entire evaluation period, respectively. The value of R^2 ranges between zero and one, describing the proportion of total variance in the observed data that can be explained by the model. Thus, a value of zero means no correlation at all, whereas one is a perfect correlation between observed and simulated data (Krause *et al.*, 2005). For reasonable performance assessment, it is essential to use a second statistical method, since R^2 only quantifies dispersion. Models can achieve high R^2 even if all predictions are wrong by systematically over- or underpredicting observed values due to a balance. NS is the Nash-Sutcliffe coefficient defined:

$$NS = 1 - \sum_{t=1}^{T} \frac{(y_t - f_t)^2}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \tag{3-2}$$

NS ranges between minus infinity and one and is applied to evaluate to which degree simulation results match the observation data along the regression line with a slope of one (Arnold *et al.*, 2012). According to Moriasi et al. R^2 values below 0.5 indicate the need for calibration procedures (Moriasi *et al.*, 2007). Additionally, they collected data from various

SWAT studies and designed a general performance rating according to NS values for SWAT studies as presented in Table 3-4.

Table 3-4. Performance rating for NS and R^2coefficient

Performance rating	**NS coefficient**	**R^2coefficient**
Very good	0.75 < NS ≤ 1.00	0.5 < R^2
Good	0.65 < NS ≤ 0.75	0.5 < R^2
Satisfactory	0.50 < NS ≤ 0.65	0.5 < R^2
Unsatisfactory	NS ≤ 0.50	R^2 ≤ 0.50

The software SWAT-CUP (Calibration and Uncertainty Procedure) (Abbaspour *et al.*, 2007) was applied for hydrological calibration and validation. It is a standalone program, which includes five different calibration procedures. The Sequential Uncertainty Fitting program SUFI-2 (Abbaspour *et al.*, 2004) was selected due to its worldwide application and high efficiency. SUFI-2 is semi-automated and incorporates sensitivity, calibration, validation, and uncertainty analysis. The special feature of SUFI-2 is the intimate connection between parameter calibration and uncertainty analysis (Abbaspour, 2015). The user can manually adjust parameters after each auto-calibration run (Arnold *et al.*, 2012).

3.5.2 Crop yield calibration (second stage of calibration)

Although most of the studies apply ArcSWAT in crop yield simulation without any further calibration, in this research we have carried out the second stage of calibration to improve the model performance for crop yields prediction. Key crop parameters were firstly identified from literature (Srinivasan, Zhang and Arnold, 2010; Nair *et al.*, 2011; Arnold *et al.*, 2012; Duffy and Parajuli, 2014) to be used for crop yield calibration in this study. Accordingly, these parameters were adjusted manually to minimize the differences between model estimation and crop yield observations. Field measurements of the cultivated crops for the calibration period were not available. Thus, simulated yield was evaluated against the average reported crop yields between 2006-2008 for the Schleswig-Holstein state.

4. Results and discussion

4.1 Hydrological calibration (first stage of calibration)

Preparing input data, they were fed into the ArcSWAT to develop baseline scenario over the 11-year simulation period in addition to a one-year warm-up to establish reasonable initial conditions. The baseline scenario presents current topographic, climatic, and land use condition of the Pellworm Island which is further applied in this study to develop yearly land use scenarios under constant topographic and soil condition.

The performance of the uncalibrated baseline scenario was assessed by comparing the simulated evapotranspiration data with those provided by the DWD on a monthly time-step. Thereafter, the baseline scenario was optimized based on 10 out of 527 subbasins of the watershed. Subbasin 128 was selected to portray results due to its representative nature.

4.1.1 Uncalibrated baseline scenario

Figure 3-8 illustrates the monthly observed and simulated evapotranspiration data resulted from uncalibrated SWAT model over the 11-year simulation period in the subbasin 128. In this figure, the significant differences between observed and simulated evapotranspiration show the necessity of hydrological calibration and validation.

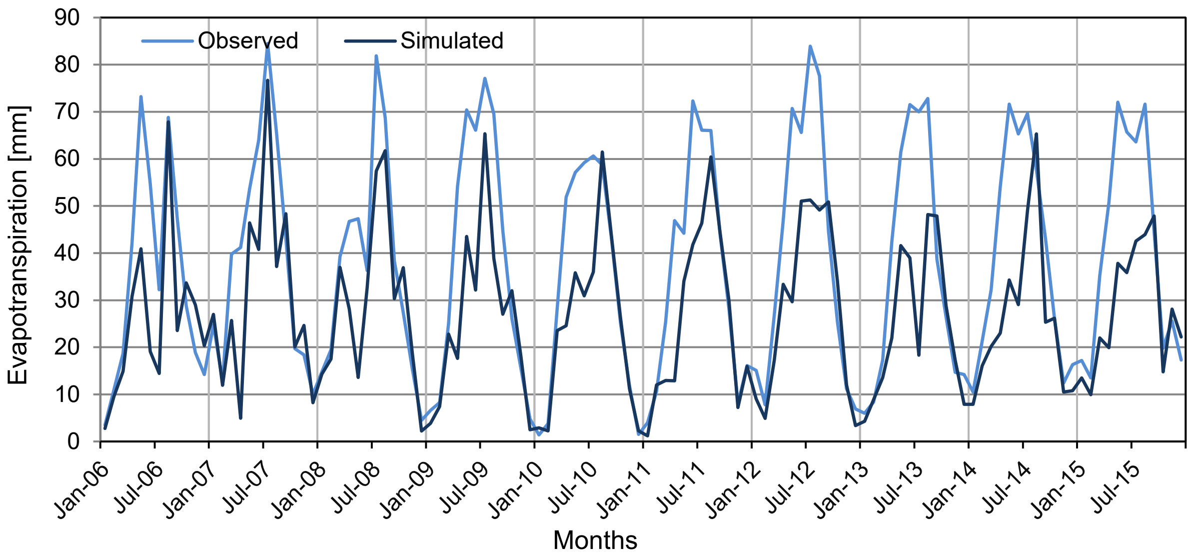


Figure 3-8. Time-series of observed and simulated evapotranspiration (2006-2016) prior to calibration in subbasin 128

In addition, the statistical performance coefficients R^2 and NS for this subbasin were calculated to decide if hydrological calibration is necessary. Comparing the threshold of R^2 and NS coefficient (see Table 3-4) and their values in Table 3-5 for three different periods indicates the essential need for calibration to improve the performance of the model.

Table 3-5. Statistical performance assessment prior to calibration

Period	R^2	*NS*
2006-2010	0.7	0.42
2011-2016	0.66	0.27
2006-2016	0.65	0.44

4.1.2 Hydrological parameter sensitivity analysis

Due to the significant differences between observed and simulated evapotranspiration, the developed model should be calibrated (Weyer, 2016). The first step is recognizing the most sensitive parameters. For this aim, a global sensitivity analysis was performed based on 400 simulation runs for the period from 2006 to 2010. This analysis focused on the sensitivity of 20 preselected parameters, which influence more the predicted model outputs. The statistical coefficients t-stat and p-value were used to assess sensitivity. In this regard small p-values and high t-stat values indicate high sensitivity.

Thereafter, saturated hydraulic conductivity (SOL_K), curve number for moisture condition II (CN2), soil evaporation compensation factor (ESCO), plant uptake compensation factor (EPCO), Manning's value for overland flow (OV_N), baseflow alpha factor (ALPHA_BF) and, the threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN) were identified as the seven most important parameters, which are presented in Table 3-6.

4.1.3 Model calibration and validation

Once the most sensitive parameters are detected, the model is optimized by calibration and validation. The uncalibrated baseline scenario was first calibrated for the observed evapotranspiration data on a monthly time-step for the period between 2006 and 2010. The model was then validated for the period 2011-2016 to test its prediction ability for periods outside the calibration period. The initial and final optimized values of sensitive parameters achieved by hydrological calibration are presented in Table 3-6.

Table 3-6. Sensitive hydrological parameters in ArcSWAT, their initial and final values

Rank	SWAT parameter	Description	Initial value	Final value
1	SOL_K	Saturated hydraulic conductivity [mm/hr]	22.71	0.04
2	CN2	SCS runoff CN for moisture condition II [-]	72-92	62.04-79.27
3	ESCO	Soil evaporation compensation factor [-]	0.95	0.80
4	EPCO	Plant uptake compensation factor [-]	1	0.69
5	OV_N	Manning's "n" value for overland flow [-]	0.1-0.15	0.08-0.13
6	ALPHA_BF	Baseflow alpha factor [1/d]	0.01	0.46
7	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur [mm]	1000	1183.95
8	GW_REVAP	Groundwater "revap" coefficient [-]	0.02	0.09
9	CH_N2	Manning's "n" value for the main channel [-]	0.014	0.30
10	RCHRG_DP	Groundwater recharge to deep aquifer fraction [-]	0.05	0.83
11	HRU_SLP	Average slope steepness [m/m]	0.01-0.12	0.01-0.12
12	REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur [mm]	750	3.70
13	EVRCH	Reach evaporation adjustment factor [-]	1	0.55
14	GW_DELAY	Groundwater delay [d]	31	466.05
15	SURLAG	Surface runoff lag time coefficient [-]	4	14.95
16	SHALLST	Initial depth of water in the shallow aquifer [mm]	1000	5000
17	CANMX	Maximum canopy storage [mm]	0	0
18	SOL_BD	Moist bulk density [g/cm3]	1.1	0.90
19	SOL_AWC	Available water capacity of the soil layer [mm/mm soil]	0	0
20	SLSUBBSN	Average slope length [m]	60.98-121.95	50.07-100.13

The optimized parameters are the best simulation values, which increase the performance of the model in simulating the ArcSWAT outputs. Figure 3-9 presents simulated and observed evapotranspiration after the calibration process in calibration period. The comparison of Figure 3-8 and Figure 3-9 demonstrates the effect of calibration and the improvement in the performance of the model with new parameters set.

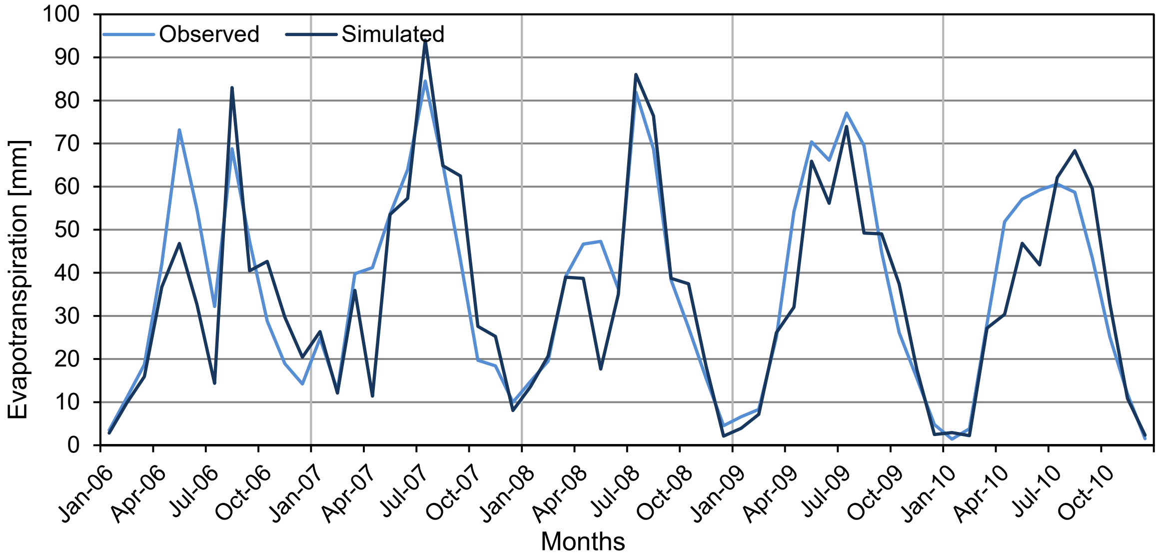


Figure 3-9. Time-series of observed and simulated evapotranspiration (2006-2010) after calibration

The validation was performed after calibration using the same adjusted parameter set reported in Table 3-6. The observed and simulated evapotranspiration after validation are presented in Figure 3-10. As seen, simulated values are close to the observed data, which shows the reasonable prediction of the calibrated model for the whole simulation period.

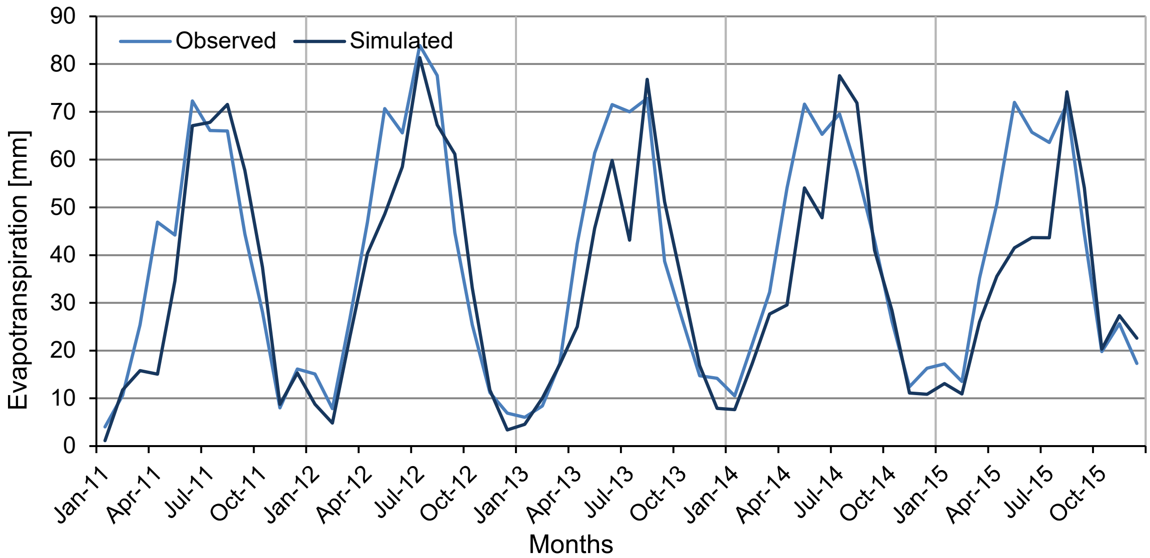


Figure 3-10. Time-series of observed and simulated evapotranspiration (2011-2016) after validation

Table 3-7 reports the statistical performance coefficients R^2 and NS of the model for both calibration and validation period on a monthly scale. Comparing their values with their threshold in Table 3-4 shows the good performance of the calibrated model in predicting the hydrologic budget.

Table 3-7. Performance assessment of calibration and validation

Process	**Period**	R^2	***NS***
Calibration	2006-2010	0.80	0.78
Validation	2011-2016	0.80	0.76

4.1.4 Uncertainty analysis

Statistical and computational procedures described previously were performed by SUFI-2 to quantify the uncertainties associated with simulations. The uncertainty analysis was implemented in the optimization process and terminated when satisfactory uncertainty criteria were achieved. During model optimization, parameter uncertainties were reduced in a stepwise approach. Figure 3-11 portrays the 95 % prediction uncertainty range of simulated evapotranspiration data for the last calibration iteration as well as corresponding observed data.

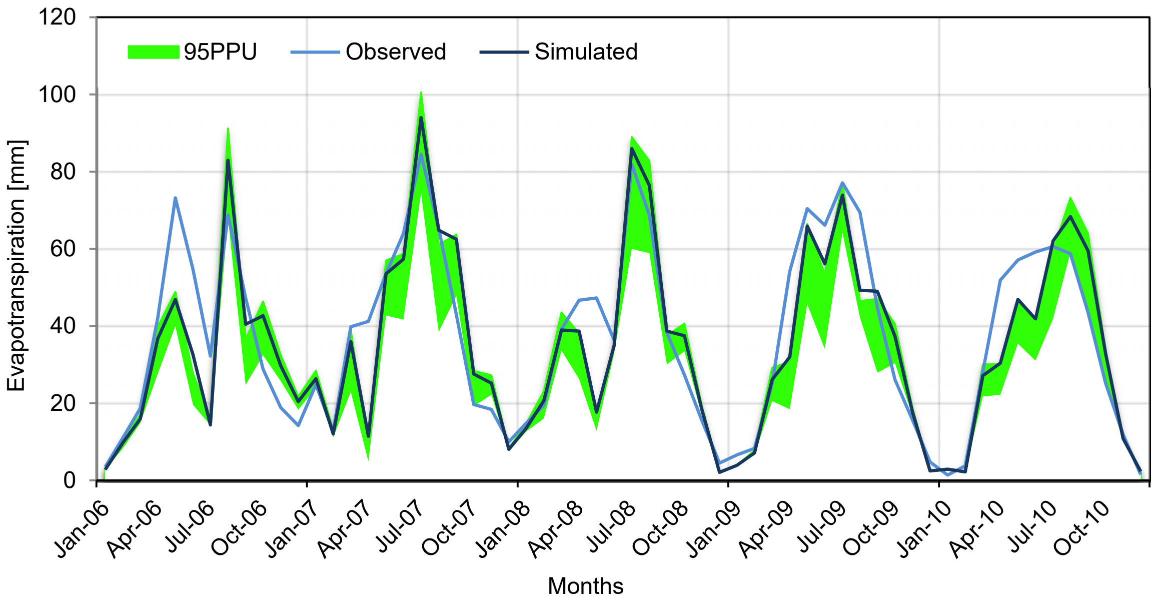


Figure 3-11. 95% prediction uncertainty interval in the calibration period

Following, in the validation process, 43 % (P-factor) of the observed evapotranspiration data were captured by the 95PPP interval and an R-factor of 0.39 was attained. Figure 3-12 illustrates the 95PPU interval of the validation period between 2011 and 2016.

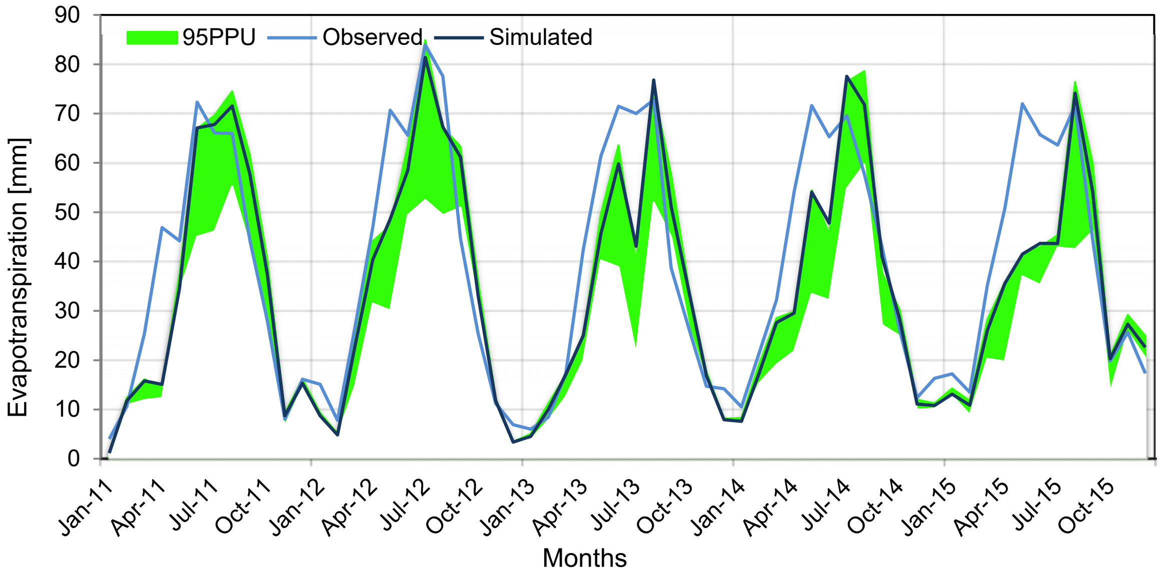


Figure 3-12. 95% prediction uncertainty interval in the validation period

4.2 Crop yield calibration (second stage of calibration)

The hydrological calibrated model achieved in the previous step, was used to investigate and to improve the performance of the developed model in predicting crop yields.

4.2.1 Crop parameter sensitivity analysis

As other calibration process, the first step is to identify the most sensitive crop parameters. According to literature (Faramarzi *et al.*, 2010; Nair *et al.*, 2011), harvest index (HVSTI), maximum leaf area index (BLAI), and radiation-use efficiency (BIO_E) are the most sensitive crop parameters which were used in this study. Then, these parameters were adjusted for the agricultural crops to achieve a good prediction of yield. Table 3-8 summarizes the selected sensitive crop parameters as well as their default and adjusted values. As can be seen, except from the spring barley for which the default values of SWAT database have been used, the parameters of maise, spring canola, and winter wheat have been adjusted for this aim.

4.2.2 Model calibration

Figure 3-13 evaluates the accuracy of the hydrological calibrated model in crop yield prediction before and after the second stage of calibration. According to the figure, there are differences between the simulated and reported crop yield before the calibration of crop growth. However, the model performance has been improved significantly by adjusting the sensitive parameters in section 4.2.1 and there is a good agreement between the reported and simulated crop yields after second stage of calibration.

Table 3-8. Sensitive crop parameters in ArcSWAT, their initial and final values

SWAT parameter	Description	Initial value	Final value
BIO_E Maise	Plant radiation use efficiency for maise [(kg/ha)/(MJ/m^2)]	39	90
BIO_E Spring Barley	Plant radiation use efficiency for spring barley [(kg/ha)/(MJ/m^2)]	35	35
BIO_E Winter Wheat	Plant radiation use efficiency for winter wheat [(kg/ha)/(MJ/m^2)]	30	90
BIO_E Spring Canola	Plant radiation use efficiency for spring canola [(kg/ha)/(MJ/m^2)]	34	43
HVSTI Maise	Harvest index for maise [(kg/ha)/(kg/ha)]	0.9	1.25
HVSTI Spring Barley	Harvest index for spring barley [(kg/ha)/(kg/ha)]	0.54	0.54
HVSTI Winter Wheat	Harvest index for winter wheat [(kg/ha)/(kg/ha)]	0.4	1.25
HVSTI Spring Canola	Harvest index for spring canola [(kg/ha)/(kg/ha)]	0.3	0.9
BLAI Maise	Maximum leaf area index for maise [m^2/m^2]	4	10
BLAI Spring Barley	Maximum leaf area index for spring barley [m^2/m^2]	4	4
BLAI Winter Wheat	Maximum leaf area index for winter wheat [m^2/m^2]	4	10
BLAI Spring Canola	Maximum leaf area index for spring canola [m^2/m^2]	4.5	4.6

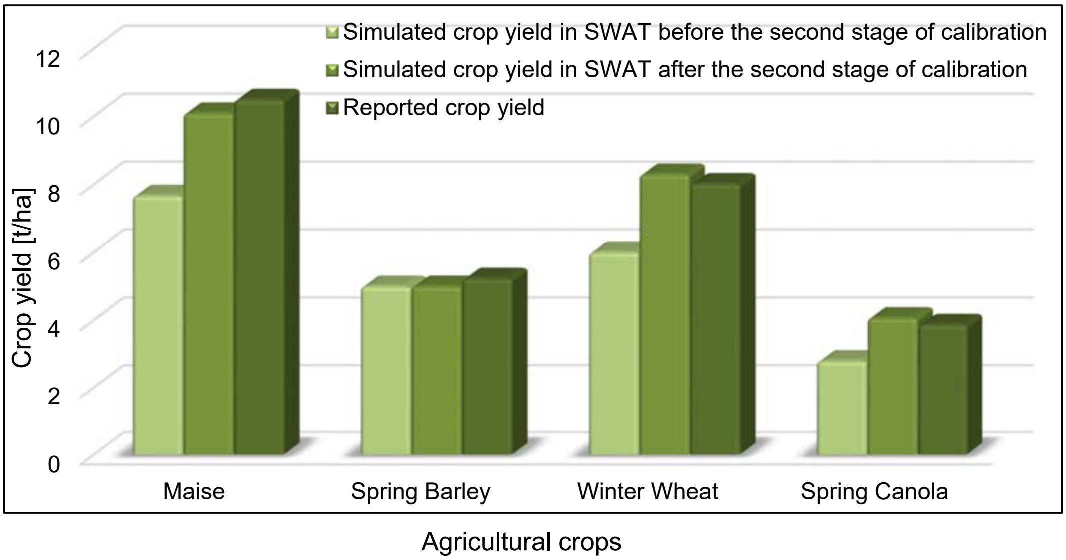


Figure 3-13. Reported and simulated crop yields in SWAT before and after calibration

4.3 Crop yield simulation on the field-scale

Once the developed model is calibrated for both water balance and crop growth components, it is ready to be used for further analyses. To the best of the author' knowledge, crop yield on the farmers' fields has been not explored in the previous studies using SWAT. Almost all researches have reported crop yields on HRUs since there is not a good connection between HRUs in SWAT and farmer's field in reality. We addressed this issue by adjusting threshold for land/slope/soil overlaying process which allows us to generate HRUs spatial distribution map in ArcSWAT and to identify the group of HRUs comprising each farmers' field. As a result, crop yields can be extracted on HRUs to compute the crop productivity of fields. Overall, it enables researchers and decision makers to explore any desired outputs on the field-scale and more particularly in this research, the model can predict how much yield each farmer can produce within one year.

According to the telephone talk with one of the farmers living on the Pellworm Island, about 37 families earn their living from farming on the Island. Due to lack of data, a semi-hypothetical population of 37 farmers is investigated. Agricultural lands and crops have been randomly distributed among farmers in such a way that the total covered areas of crops are fulfilled, as reported in Table 3-1. Figure 3-14 illustrates the spatial distribution of cultivated crops in year 2006, as an example. The crop productivity of farmers' fields is shown in Figure 3-15 for the same year, which has been estimated by the 2-stage calibrated hydrological module.

Figure 3-14. Spatial distribution of cultivated crops on the Pellworm Island in year 2006

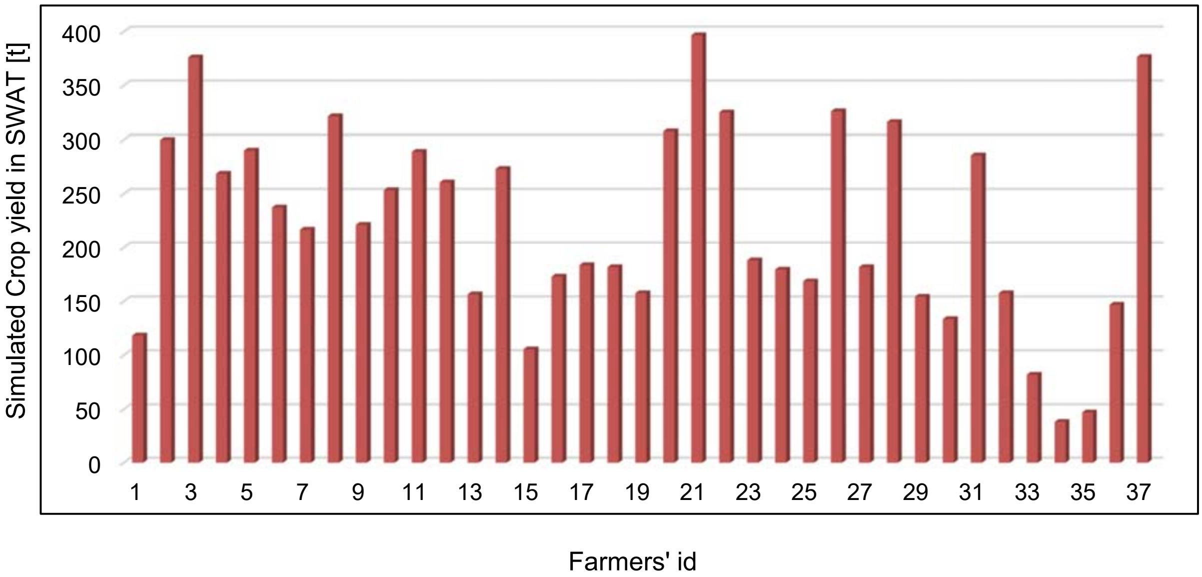


Figure 3-15. Estimated crop yields on field-scale for each individual farmer in year 2006

5. Conclusions and outlook

The purpose of this chapter was to develop a hydrological module to predict crop yields on the field-scale. Due to complex interconnection between crop productivity and hydrological phenomena, hydrologic simulation tools that include the crop growth model are the most appropriate ones. Among them, SWAT was used in this study to develop the desired Hydrological Module in connection with other modules. To achieve its goal, firstly the baseline scenario was set up by preparing required input data, delineating the watershed, overlaying soil/land use/slop map, and creating HRUs. Since the created HRUs map does not match the spatial distribution of land use, it is not possible to make a connection between SWAT outputs on the HRUs level and field level in reality. To overcome this issue, we adjusted the threshold in overlaying process to generate the spatial map of HRUs. Therefore, by identifying HRUs on each individual field, it was possible to generate any desired outputs on the field-scale that assist decision makers to take agricultural adaptive policies on the field-scale.

In order to increase the model efficiencies in simulating water budget and crop growth components, a 2-stage calibration procedure including hydrological and crop yield calibration was established. Results from monthly evapotranspiration calibration and validation procedure showed that the hydrological performance of the developed model was within acceptable ranges. The hydrological calibrated model could predict the spring barley yields wells. However, the model under predicted the yields of other cultivated crops which were then improved through manual calibration and parameter adjustment. The final crop yield simulation matches closely with those reported in previous studies.

Thereafter, the developed hydrological module is used in connection with other modules developed in the next chapters of the research to simulate the yearly crop productivity of individual farmers under unchanged geological and topographical conditions of the study area over the simulation years (see Figure 3-16).

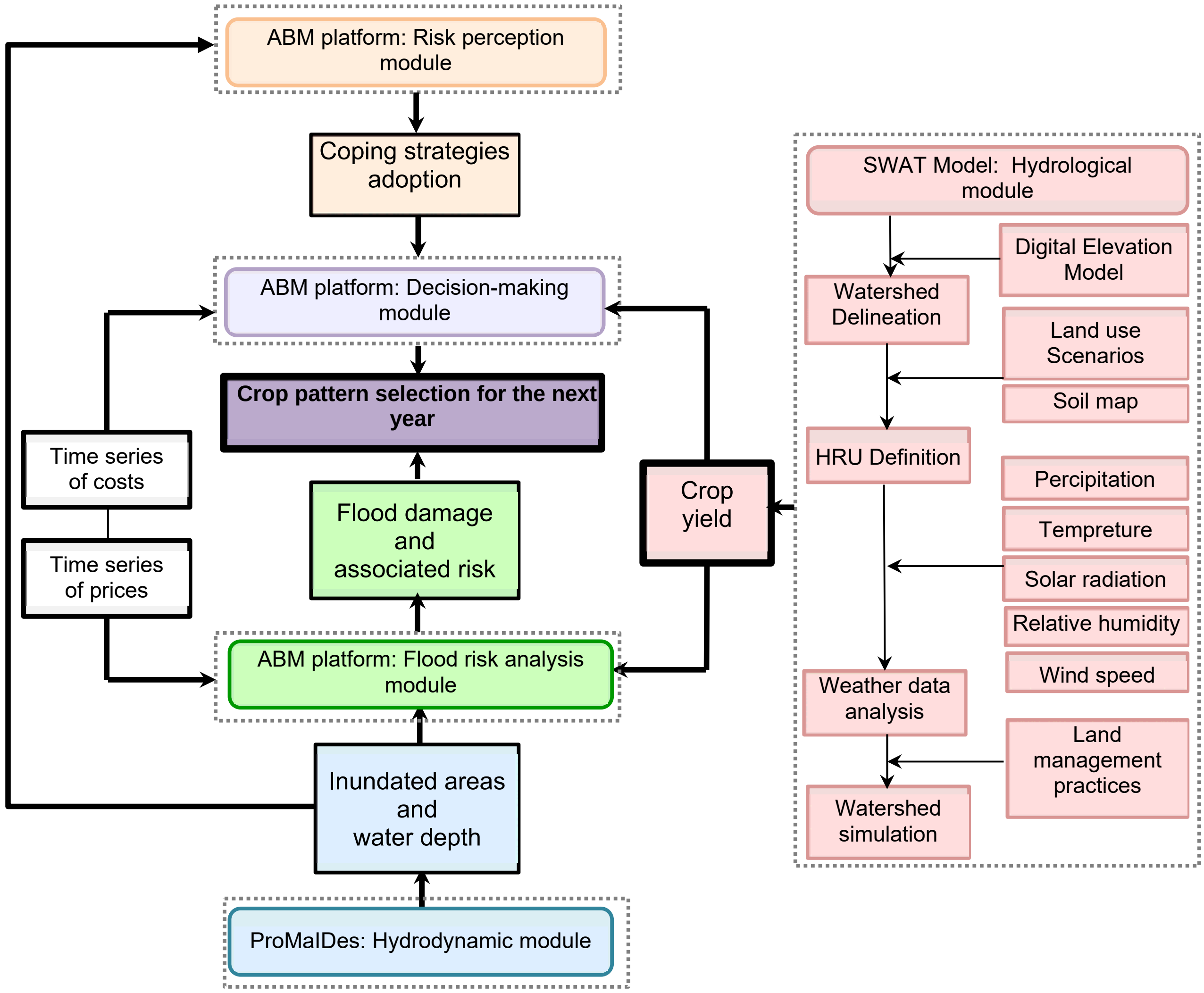


Figure 3-16. Connection of hydrological module with other modules in each year

Chapter 4 Predicting inundated agricultural areas and associated water depth

1. Introduction

Coasts are fertile agricultural lands, but are also threatened by coastal flooding. Farmers who are living in these areas are exposed to storm surges which increase due to climate change. In the time of flooding, agricultural lands are inundated with saltwater which causes flood-related crop losses. This agricultural economic damage may continue for a number of years even after flooding and affects farmers' decision-making for the following years. One key activity to identify areas at-risk of flooding, and subsequently to improve flood risk management (FRM) is to assess and map flood hazards. While flood hazard assessment predicts flood intensities and characteristics by analyzing probable flood scenarios, flood hazard mapping visualizes endangered areas and inundated lands under given flood events. Flood hazard assessment and mapping assists land planners and local authorities in mitigating potential flood damage. Furthermore, experts and governments can communicate with the public using flood hazard maps and inform them about their local flood risk which increases the risk perception of people, prepares the public for future floods, and motivates individuals to undertake actions.

2. Research question and objective

Flood hazard assessment in general focuses on the estimation of the probability of flood occurrence, identification of corresponding inundated areas, and computation of hydraulic variables such as water depth, inundation duration, arrival time, and flow velocity. Although there are different types of evaluations, approaches, and purposes in flood hazard assessment, the framework behind is quite standard (Sy *et al.*, 2019). Analysis of flood hazard can be best done using a hydrodynamic model, which allows including different flood sources as well as structural measures. Such a model forms the basis for hydrodynamic modeling of flood-prone areas and enables modelers to specify a variety of boundary conditions to investigate associated flood damage and risk.

The primary objective of this chapter is to develop a hydrodynamic module to carry out coastal hazard assessment and investigate expected extent and depth of flooding in the agricultural lands of Pellworm Island under probable flood scenarios. To achieve the main goals, following sub-objectives were defined: i) to identify sources of flooding and probable flood scenarios, ii) to analyze agricultural inundated areas and calculate specific flood parameters, and iii) to create flood inundation and exposure maps for probable flood scenarios. The developed hydrodynamic module will be the basis for flood risk analysis module. The generated flood hazard maps are also applied in risk perception module to establish flood risk awareness among farmers.

This chapter is organized as follows: section 3 begins with a short presentation of flood risk analysis and its components to better understand the chain of causes and effects in a flood event. It is then continued with hydrodynamic modeling as well as the software used in section 4. Modeling steps and overview of the hydrodynamic modeling are also discussed in this section. Results and discussion are presented in section 5, which is followed by conclusions and outlook section.

3. Concepts of flood risk assessment

3.1 Definition of flood risk

General definitions

Risk is applied in different disciplines to present dimensions relating to environmental or social issues, economy, and safety (Sayers *et al.*, 2003), and there is no unique definition. For instance, in medicine, risk is quantified as the occurrence probability of the side effects of drugs. In insurance, risk refers to the financial damage associated with an adverse event. Risk has also different definitions from the technical-scientific points of view. For example, in environmental risk assessment, the impact intensity versus sensitivity represents the environmental risk, while in hydrology, risk is the likelihood of the discharge Q to be more than the designed discharge within the lifetime of a hydraulic structure.

International definitions

There are international-technical definitions for risk such as "The probability of harmful consequences, or expected loss of lives, people injured, property, livelihoods, economic activity disrupted (or environment damaged) resulting from interactions between natural or human induced hazards and vulnerable conditions." (UNDP - Bureau for Crisis Prevention and Recovery, 2004). According to UNISDR, risk is "The combination of the probability of an event and its negative consequences." (UNISDR, 2009). EU Flood Directive defines flood risk as the combination of the occurrence probability of flood events and potential adverse effects on human health, the environment, cultural heritage, and economic activities (EU, 2007).

Mathematical definitions

In order to quantify flood risk, there is a key need to a mathematical definition. In literature (Blong, 1996; De la Cruz-Reyna, 1996; Helm, 1996; Granger *et al.*, 1999) various equations have been used to quantify the risk:

$Risk = Hazard * Vulnerability$ (Blong, 1996) (4-1)

$Risk = Hazard * Exposure * Vulnerability$ (Granger *et al.*, 1999) (4-2)

$Risk = Hazard * Vulnerability * Value/Preparedness$ (De La Cruz-Reyna, 1996) (4-3)

$Risk = Probablity\ * Consequences$ (Helm, 1996) (4-4)

Flood hazard analysis is performed based on hydraulic and hydrologic studies which is then combined with socio-economic analysis. The consequences of flooding depend on at-risk elements (exposure) as well as their potential to be harmed by flood events (vulnerability).

3.2 Components of flood risk

Flood risk consists of hazard, vulnerability, exposure, and susceptibility, as illustrated in Figure 4-1. According to the UNISDR (UNISDR, 2009), *hazard* is a physical event, phenomenon, or human activity with the potential to result in harm, *vulnerability* is the characteristics and circumstances of a system that makes it susceptible to the damaging effects of a hazard, *exposure* refers to the spatial or temporal overlay of hazard characteristics and vulnerable entities such as people and properties, and *resilience* is the ability of a system to recover from adverse effects of the hazard and to cope with that in a timely and efficient manner. *Susceptibility* is understood as the negative consequences of lack of resilience (Adger, 2006; Birkmann *et al.*, 2013).

3.3 Flood risk analysis

Flood risk analysis serves to determine the extent of resulting damage from existing or potential flooding threats. Risk analysis is an important component of risk management, as it uses the results of risk avoidance, mitigation, and limitation (Birkmann *et al.*, 2013). The actual risk can be evaluated in the normative terms by quantifying the probability of occurrence and the consequences, which are better understood through risk components. In this regard, an integrated risk analysis, which combines hazard analysis, reliability analysis, hydrodynamic analysis, and consequence analysis, represents one of the most appropriate approach. For this aim, identifying the chain of causes and effects is beneficial. Source-Pathway-Receptor-Consequences (SPRC) model is a specific form of such a chain (Klijn, 2009) which allows distancing between flood hazard (sources), pathways (defence structures and flood plains), and receptors (people and properties). Figure 4-2 depicts integrated flood risk analysis based on the SPRC model for coastal areas.

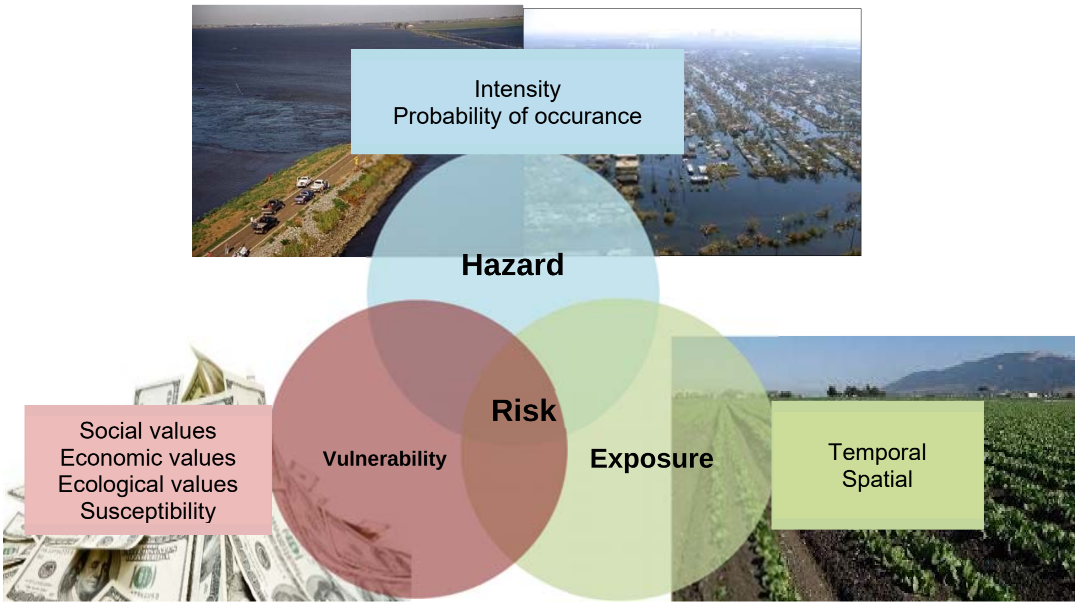


Figure 4-1. Flood risk and its components

4. Hydrodynamic modeling

4.1 Software selection

In order to assess flood events and to predict their behavior in the hinterlands, flood inundation models have been developed over the decades (Teng *et al.*, 2017). These models are extensively used for purposes such as flood risk assessment (Thieken *et al.*, 2007), flood risk mapping (Sanders, 2007), flood damage analysis (Merz *et al.*, 2010;

Nabinejad and Schüttrumpf, 2018), morphological prediction (Ghani *et al.*, 2016) as well as flood forecasting and early warning system (Bevington *et al.*, 2018; Bhola *et al.*, 2019). In addition, there is a growing interest toward adaptive FRM under climate change (Woodward *et al.*, 2014). Modeling flood insurance policies have also gained attention in the recent years (Dubbelboer *et al.*, 2017).

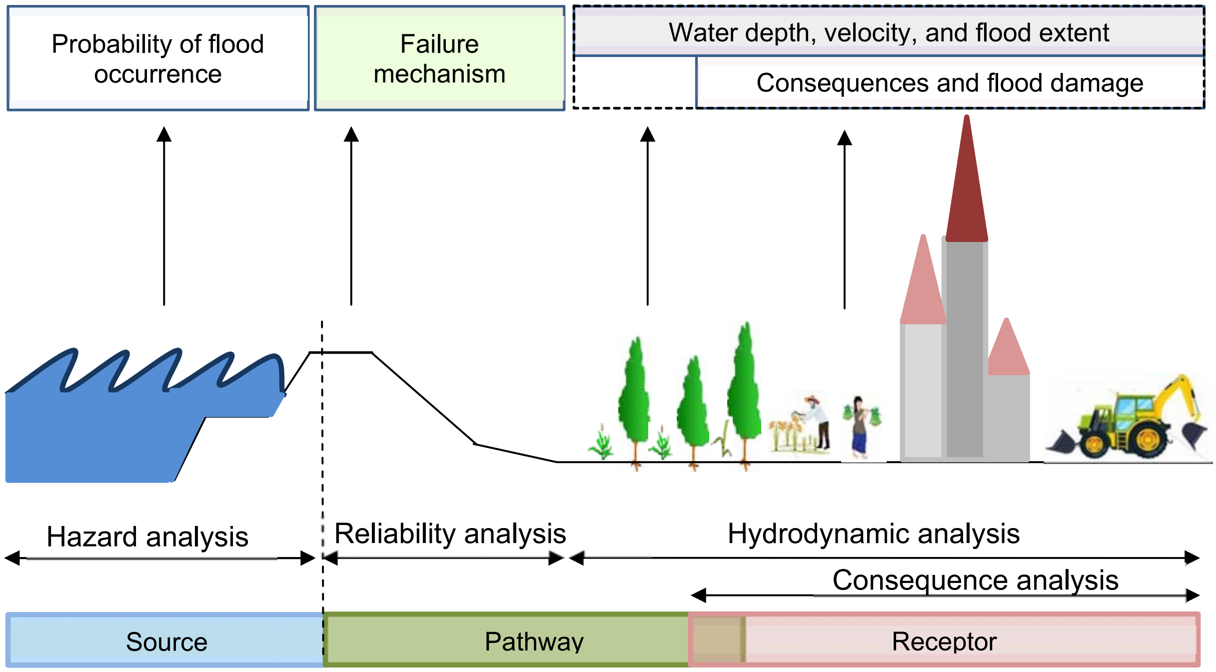


Figure 4-2. Integrated flood risk analysis and SPRC model in coasts

Over the past years, empirical models and hydrodynamic models have attracted the most attention for flood inundation modeling (Teng *et al.*, 2017). Hydrodynamic modeling serves as a practical tool in predicting the behavior of flood events in the hinterland and assists to estimate the water depth and flood extent, which are essential for flood risk analysis. More specifically, hydrodynamic modeling is a popular method that combines the preliminary steps in conducting the FRM. Selecting a suitable model depends on the application purpose, the level of accuracy required, the outputs of interest, and the spatial and temporal scales (Teng *et al.*, 2017).

In this study, the software Protection Measures against Inundation Decision Support (ProMaIDes) is applied (Bachmann, 2012) for flood inundation modeling since it is freely available and comprises all relevant analyses in one package. The software helps user to select the most preferred flood protection measure according to risk criteria and associated costs for measures' implementation. Another advantage is that its hydraulic model is quite strong and has been calibrated for several case studies. Furthermore, it is possible to connect ProMaIDes with QGIS/PostGreDatabase to visualize the data and results for better assessment (Bachmann, 2012).

4.2 Software components and explanation

ProMaIDes is a modular DSS primarily developed for flood risk assessment in river basin areas at the Institute of Hydraulic Engineering and Water Resources Management (IWW), RWTH Aachen University (Bachmann, 2012). The software was, then, adapted for the coast specific loads and structure types to be applied for FRM in coastal regions (Bachmann *et al.*, 2012). The calculation of flood risk in ProMaIDes is based on three basic analyses shown in Figure 4-3.

Reliability analysis

The goal of the reliability analysis is to evaluate the performance of flood defence structures under varying load conditions. It can be performed based on breach development or fragility curves and reflects the reliability of a structure conditioned on the water level (Bachmann *et al.*, 2012). More information regarding the reliability analysis in ProMaIDes can be found in (Bachmann, 2012).

Hydrodynamic analysis

In this sub-process, a numerical flooding simulation is carried out in the study area. The hydrodynamic analysis computes the water level as well as flow velocity of the inundated areas for each flood event after failure of defence structures or overflowing. The hydrodynamic analysis in ProMaIDes is based on the finite difference approach discretizing the diffusive wave (Tsai, 2003), in which the hinterland is represented by a 2D grid in the model.

Analysis of consequences

On the basis of the calculated hydraulic variables, the expected damage is determined in the last basic analysis of the flood risk calculation. Finally, the whole region is considered as one system and the total flood risk is computed by combining the results of three sub-modules.

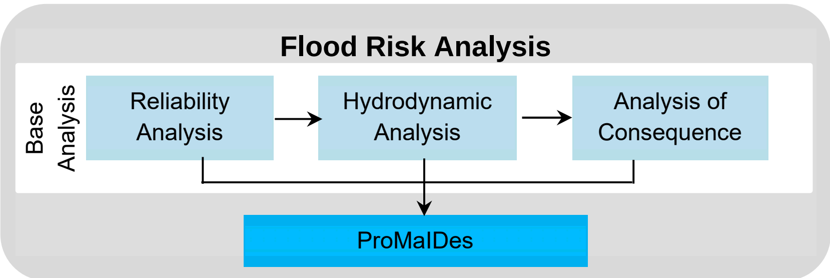


Figure 4-3. Modular program package ProMaIDes

4.3 Overview and modeling steps

The methodological approach and required input data for establishing the hydrodynamic module is depicted in Figure 4-4. Although ProMaIDes has been developed to perform a complete flood risk analysis, it is used in this study only for the purpose of flood inundation modeling to calculate flood submerged areas and water depth for probable storm surge scenarios. Flood risk analysis is, therefore, carried out through the internally developed module "flood risk analysis module" which is explained later in chapter 6 as an integrated part of the ABM platform (see chapter 6 for details). There are two reasons for that. Firstly, it allows gaining advantages of coupling human behavior and flood risk assessment in one platform. Secondly, it enables us to calculate the flood risk at any desired level (e.g. the micro-level) comparing to other models such as ProMaIDes that computes the risk of the whole area.

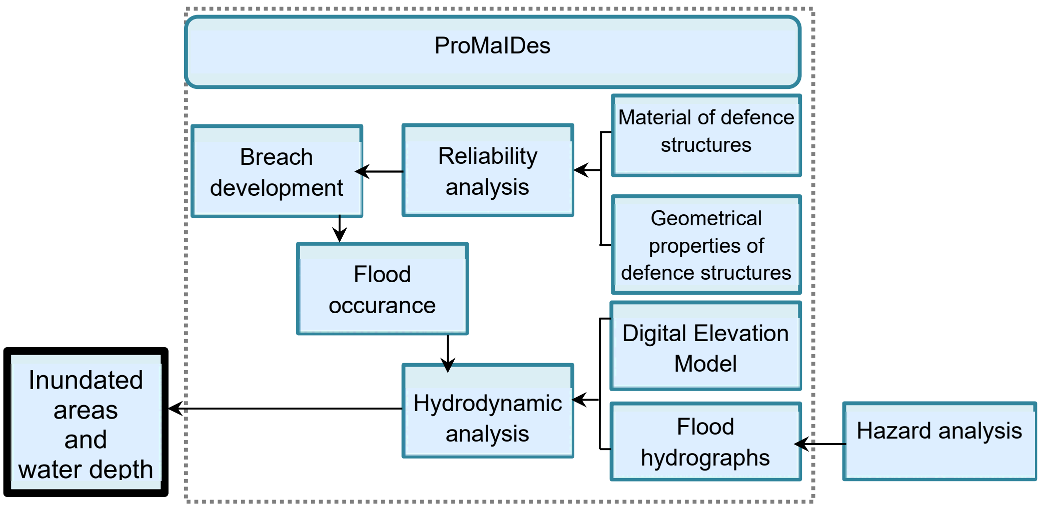


Figure 4-4. The methodological approach and components of the hydrodynamic module

4.4 Input data

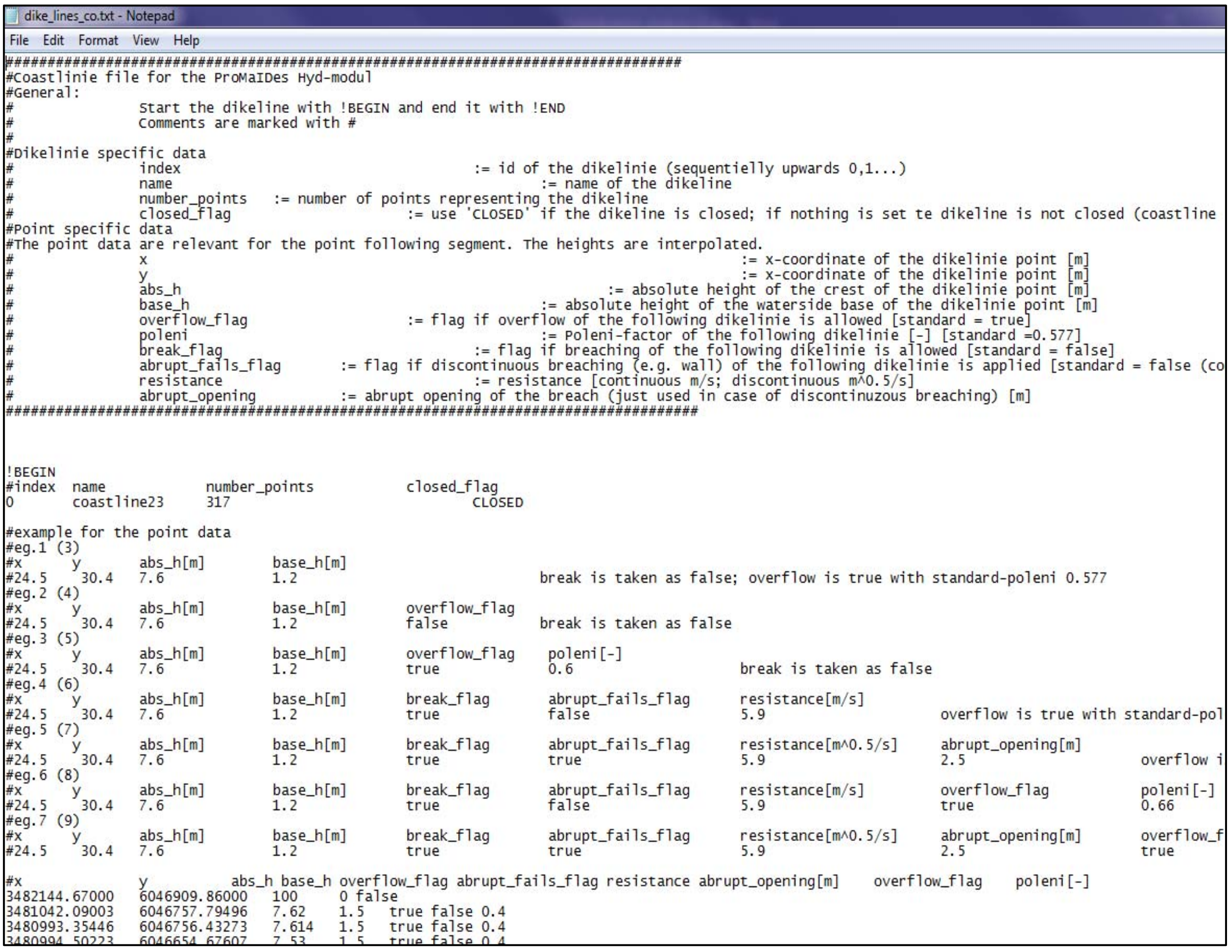
As shown in Figure 4-4, each analysis requires various input data that should be prepared and converted to the appropriate format for ProMaIDes. Geometry and material of flood protection measures are the most important inputs for reliability analysis. Hydrodynamic analysis is done based on flood scenarios data and topography as well as performance of flood protection measures evaluated in reliability analysis.

4.4.1 Topographical data

The Digital Elevation Model (DEM) provided for the hydrological module (see Figure 3-3), is used as the topographical data for the hydrodynamic module. The cell size of the provided DEM was 1m, which was interpolated to a 50m resolution DEM in ArcGIS. The new DEM was then converted to the text file to be readable by ProMaIDes.

4.4.2 Geometry and material of flood protection measures

In order to perform reliability analysis, properties of flood defence structures such as height of the sea dike and its resistance play important role. For this aim, detailed data including absolute height of the crest and waterside base of the dike, Poleni-factor as well as the resistance in various segments of the flood protection structure are fed into ProMaIDes, as can be seen in Figure 4-5.



```
dike_lines_co.txt - Notepad
File  Edit  Format  View  Help
#################################################################################
#Coastlinie file for the ProMaIDes Hyd-modul
#General:
#               Start the dikeline with !BEGIN and end it with !END
#               Comments are marked with #
#
#Dikelinie specific data
#               index                                 := id of the dikelinie (sequentielly upwards 0,1...)
#               name                                          := name of the dikeline
#               number_points   := number of points representing the dikeline
#               closed_flag                   := use 'CLOSED' if the dikeline is closed; if nothing is set te dikeline is not closed (coastline
#Point specific data
#The point data are relevant for the point following segment. The heights are interpolated.
#               x                                                               := x-coordinate of the dikelinie point [m]
#               y                                                               := x-coordinate of the dikelinie point [m]
#               abs_h                                           := absolute height of the crest of the dikelinie point [m]
#               base_h                                  := absolute height of the waterside base of the dikelinie point [m]
#               overflow_flag                 := flag if overflow of the following dikelinie is allowed [standard = true]
#               poleni                                  := Poleni-factor of the following dikelinie [-] [standard =0.577]
#               break_flag                            := flag if breaching of the following dikelinie is allowed [standard = false]
#               abrupt_fails_flag       := flag if discontinuous breaching (e.g. wall) of the following dikelinie is applied [standard = false (co
#               resistance                            := resistance [continuous m/s; discontinuous m^0.5/s]
#               abrupt_opening          := abrupt opening of the breach (just used in case of discontinuzous breaching) [m]
#################################################################################


!BEGIN
#index  name            number_points           closed_flag
0       coastline23     317                             CLOSED

#example for the point data
#eg.1 (3)
#x      y       abs_h[m]        base_h[m]
#24.5    30.4   7.6             1.2                             break is taken as false; overflow is true with standard-poleni 0.577
#eg.2 (4)
#x      y       abs_h[m]        base_h[m]       overflow_flag
#24.5    30.4   7.6             1.2             false           break is taken as false
#eg.3 (5)
#x      y       abs_h[m]        base_h[m]       overflow_flag    poleni[-]
#24.5    30.4   7.6             1.2             true             0.6                    break is taken as false
#eg.4 (6)
#x      y       abs_h[m]        base_h[m]       break_flag       abrupt_fails_flag      resistance[m/s]
#24.5    30.4   7.6             1.2             true             false                  5.9                     overflow is true with standard-pol
#eg.5 (7)
#x      y       abs_h[m]        base_h[m]       break_flag       abrupt_fails_flag      resistance[m^0.5/s]     abrupt_opening[m]
#24.5    30.4   7.6             1.2             true             true                   5.9                     2.5                     overflow i
#eg.6 (8)
#x      y       abs_h[m]        base_h[m]       break_flag       abrupt_fails_flag      resistance[m/s]         overflow_flag           poleni[-]
#24.5    30.4   7.6             1.2             true             false                  5.9                     true                    0.66
#eg.7 (9)
#x      y       abs_h[m]        base_h[m]       break_flag       abrupt_fails_flag      resistance[m^0.5/s]     abrupt_opening[m]       overflow_f
#24.5    30.4   7.6             1.2             true             true                   5.9                     2.5                     true

#x              y           abs_h base_h overflow_flag abrupt_fails_flag resistance abrupt_opening[m]    overflow_flag    poleni[-]
3482144.67000   6046909.86000   100     0 false
3481042.09003   6046757.79496   7.62    1.5   true false 0.4
3480993.35446   6046756.43273   7.614   1.5   true false 0.4
3480994.50223   6046654.67607   7.53    1.5   true false 0.4
```

Figure 4-5. Geometry and material of the sea dike fed into ProMaIDes

Due to the lack of data for Monte Carlo analysis, the failure mechanism of the dike is modeled based on the breach development. Dike breaches are selected according to the vulnerable sections of the coastal defense line on Pellworm (LKN, 2012). Accordingly, three breaches were defined in distance of 160m (Westerkoog at the south-west coast), 205m (Alter Koog at the west coast), and 239m (Johann-Heimreichs-Koog at the north coast) from the initial point, as illustrated in Figure 4-6. Breach development is implemented in ProMaIDes initiated at the water level 3m (NN) with the maximum possible breach width 150m.

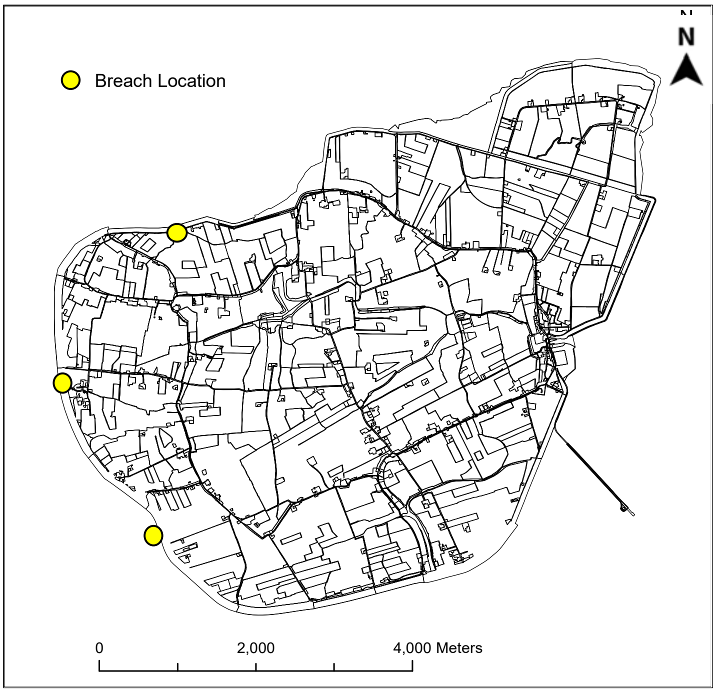


Figure 4-6. Breach locations defined in the failure mechanism of the dike in Pellworm Island

4.4.3 Storm surge hydrograph

Three storm surge hydrographs with the 100-year, 200-year, 1000-year return period are considered as the hypothetical flooding events along the coast for the hydrodynamic simulation (see Figure 4-7). These three hydrographs were created based on historical data and are used further for the flood risk analysis in chapter 6 and 7.

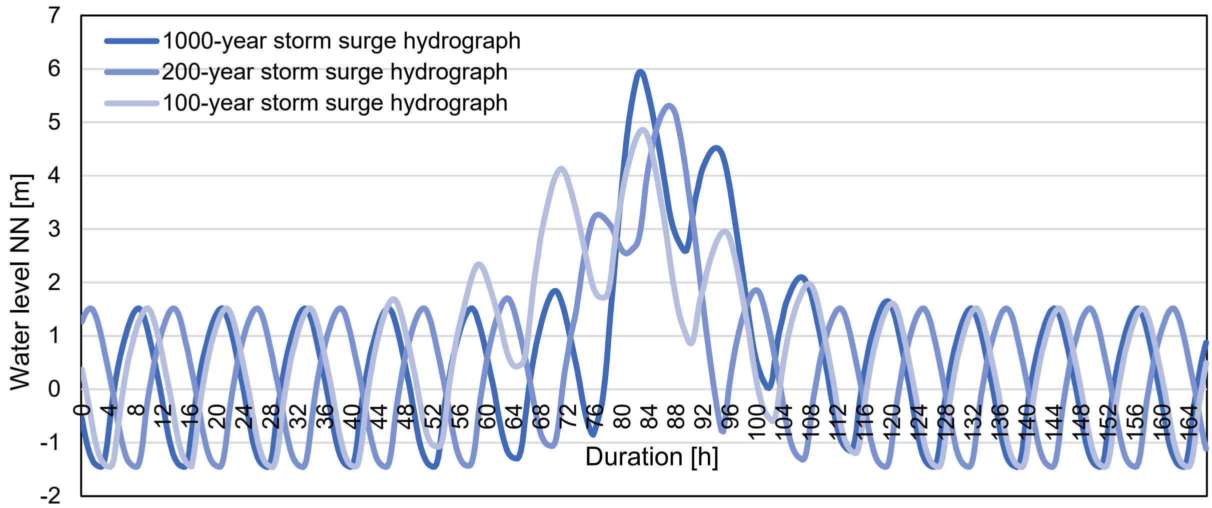


Figure 4-7. Hypothetical flood events

4.4.4 Land use data

To perform agricultural exposure analysis, agricultural land use map is prepared based on the land use map provided by the State Department of Agriculture, Environment and Rural Areas of Schleswig-Holstein (see chapter 3). Figure 4-8 illustrates the distribution of agricultural lands on Pellworm Island.

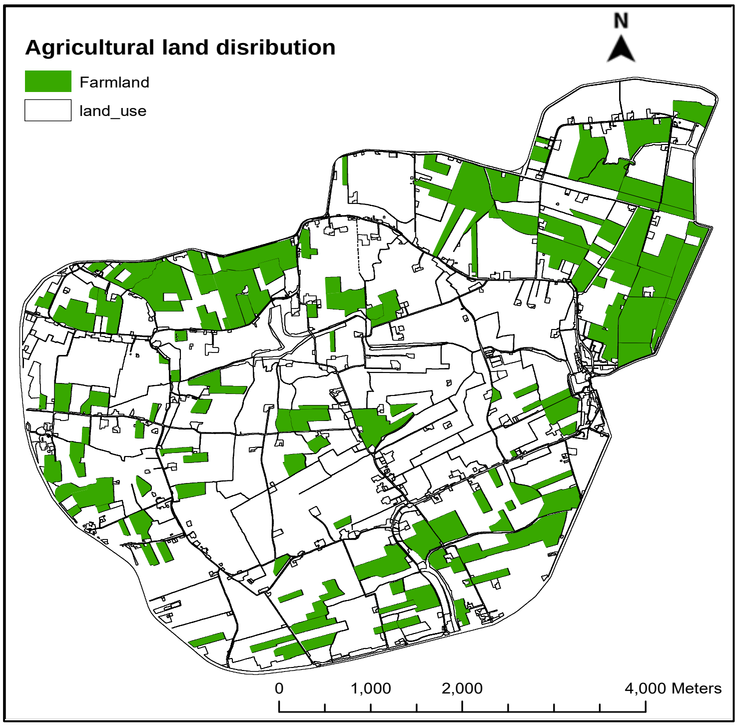


Figure 4-8. Agricultural land map on Pellworm Island

4.4.5 Hazard scenarios

Based on three flood hydrographs, three hazard scenarios are developed in this study for the hydrodynamic modeling, in all of which three breaches are assumed to occur in the dike due to weak spots along the defence lines.

5. Results and discussion

Preparing the required input data, the hydrodynamic analysis was performed using ProMaIDes for the study area to predict inundated areas and water depths on the Island. Overlying maps of agricultural land and flood inundation, exposure maps are generated which enable us to identify the agricultural farms at the risk of flooding. Figure 4-9, Figure 4-10, and Figure 4-11 illustrate exposure maps and flood-affected farmlands under 100-year, 200-year, and 1000-year flood scenario, respectively.

Table 4-1 compares inundated areas and depth of water for three hazard scenarios. As can be seen, under the 100-year flood event, 24.3 km^2 of the total area of the Pellworm Island is flooded with the mean water depth 0.7 m while the maximum water depth on the flood plain is about 4.86 m. Under the 200-year flood event, inundated area, mean and maximum water depth are computed as 27.82km^2, 0.84 m, and 5.31 m, respectively. As expected, the inundated area in scenario 3 (1000-year flood event) is increased to 33.28 km^2 with the maximum water depth 5.9 m and average water depth 1.6 m on the flood plain.

Table 4-1. Inundated areas as well as maximum and mean water depth under various hazard scenarios

	100-year flood	200-year flood	1000-year flood
Mean water depth [m]	0.7	0.84	1.6
Max water depth [m]	4.86	5.31	5.9
Inundated areas [km^2]	24.3	27.82	33.28

It is worth noting that more than 59 percent of the farmlands are exposed to 100-year flood event representing 4.27 km^2 of the agricultural areas. This percentage increases to 75 and 95 percent under the 200-year and 1000-year flood event, respectively, which is equivalent to 5.42 km^2 and 6.81 km^2 of the agricultural lands.

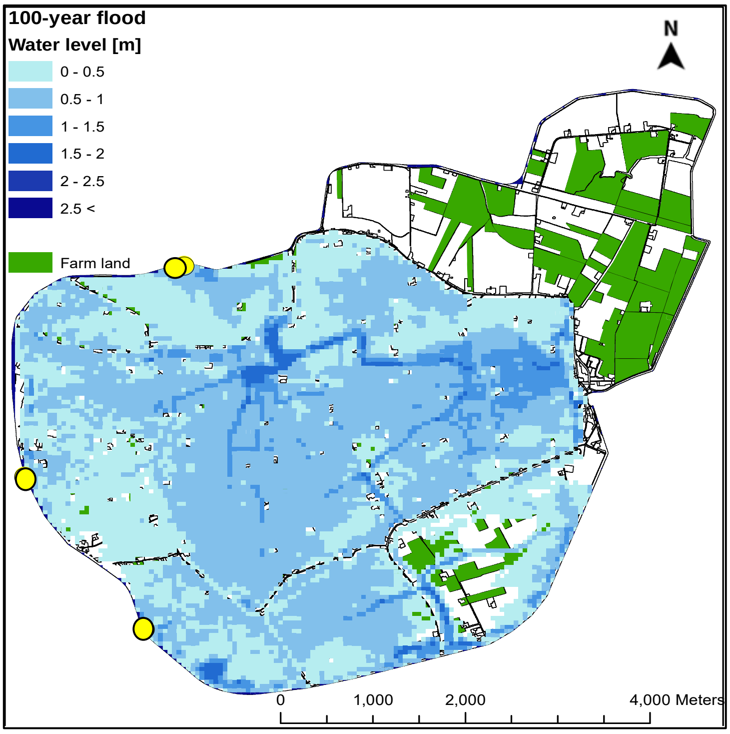


Figure 4-9. Inundated agricultural areas and water depth under 100-year flood in Pellworm Island

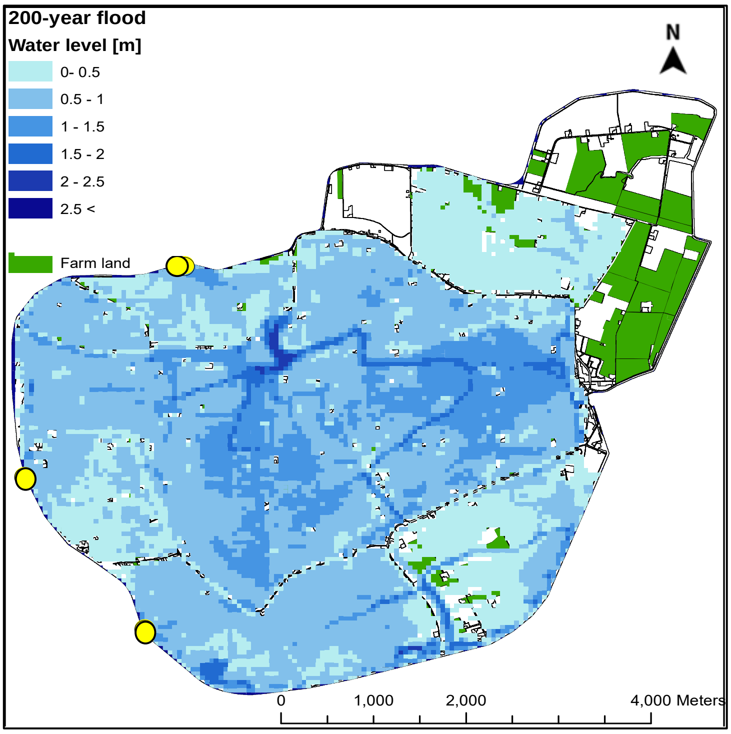


Figure 4-10. Inundated agricultural areas and water depth under 200-year flood in Pellworm Island

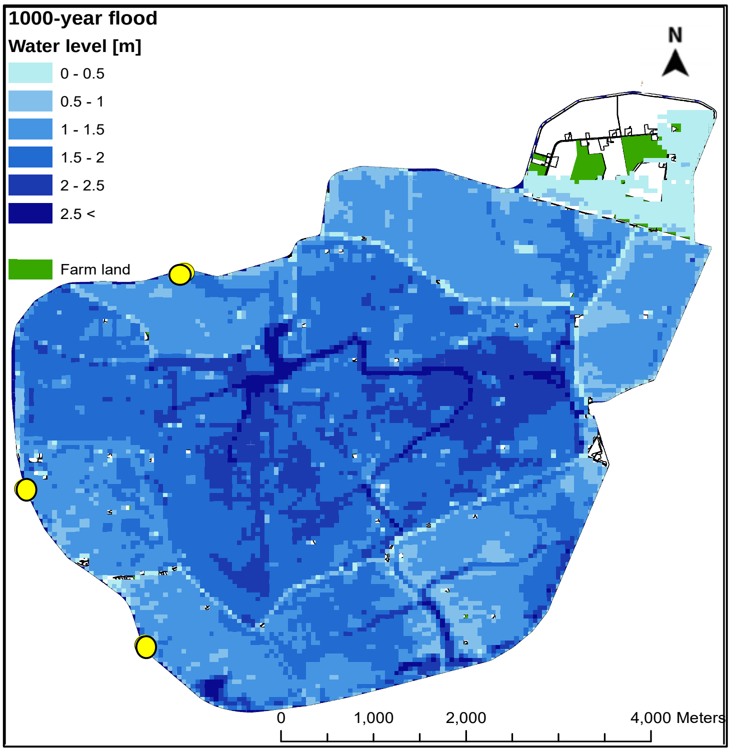


Figure 4-11. Inundated agricultural areas and water depth under 1000-year flood in Pellworm Island

6. Conclusions and outlook

The purpose of this chapter was to develop a hydrodynamic module to estimate the flood extent and water level for the whole area and more particularly for the agricultural lands. ProMaIDes was selected to be used for the flood inundation modeling. After identifying the sources of flood hazard in the area, the reliability analysis was performed based on the breach development in the sea dike to model defence stability against the existing loads. In the next step, flooded areas were identified and hydraulic variables such as water depth, velocity, and duration were calculated. Then, the inundation and agricultural exposure maps were generated to visualize the information and make them understandable for various users.

The achieved results and created maps are used in the next chapters in connection with the farmers' decision-making module, flood analysis module, and risk perception module integrated in the ABM platform to calculate yearly flood damage and risk, and to establish the risk perception of farmers over the simulation period (see Figure 4-12)

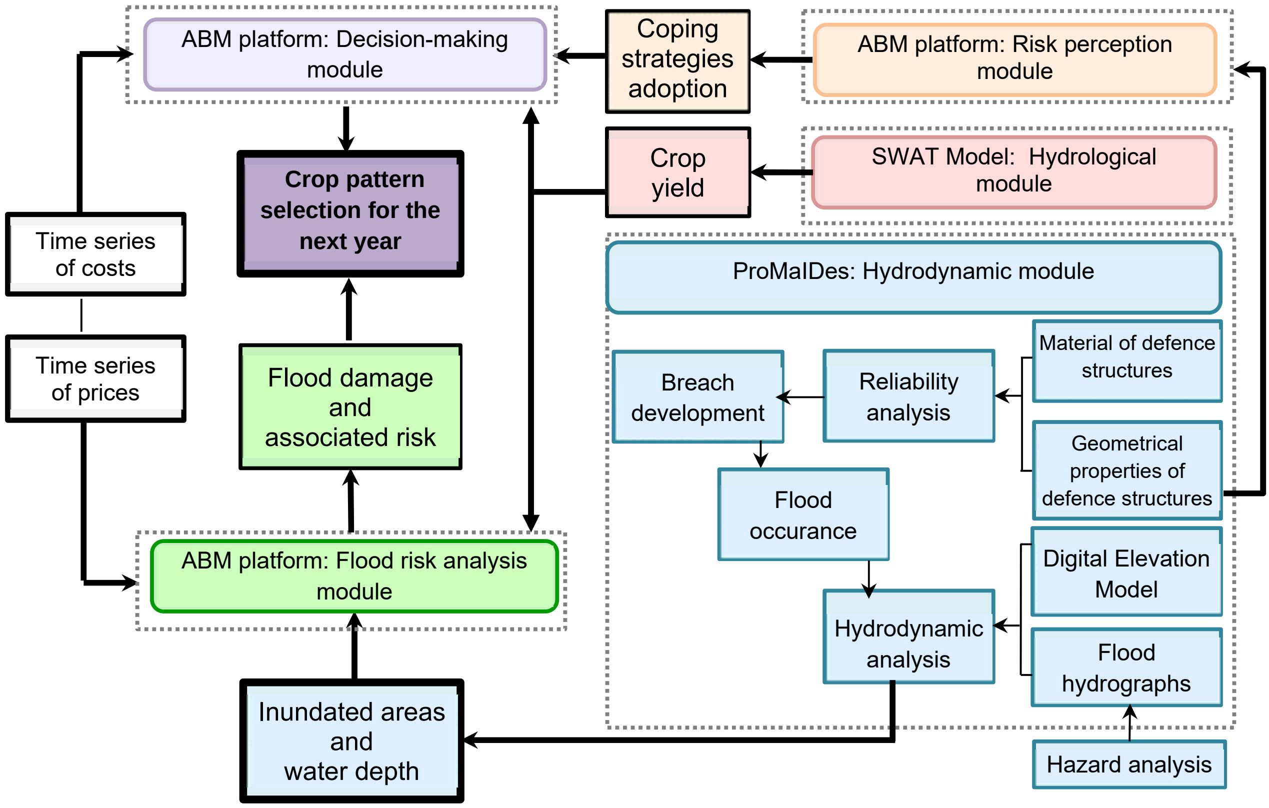


Figure 4-12. Connection of hydrodynamic module with other modules in each year

Chapter 5 Developing damage function for agricultural crops under coastal flooding

1. Introduction

Due to flood events with devastating damage to agriculture, many models have been prepared to deal with the economic impacts of flooding to the agricultural sector. In this regard, there are models differentiating only between damage to arable land and to grassland, whereas other models assess damage to crops under flood hazard parameter (Merz *et al.*, 2010). For example, Förster et al. applied the empirical data gathered by surveys and expert knowledge to evaluate the damage to crops depending on month of flooding and inundation duration for the detention area of Elbe River (Förster *et al.*, 2008). Dutta et al. investigated flood negative impacts to agricultural crops in Ichinomiya river basin based on data from the Japanese Ministry of construction. In their study, inundation duration and depth of flooding were the dominant factors (Dutta *et al.*, 2003). Some other studies prepared a set of duration-damage functions for various crops to represent the relation between crop damage and inundation duration for the riverine flooding (Maroof, 2016). Shrestha et al. used both flood depth and inundation as key hazard parameters in assessing flood damage to plants in Indus River basin in Pakistan (Shrestha *et al.*, 2018).

In coastal areas, however, seawater salinity is the main damage influential factor to agricultural crops and the loss depends on salt-tolerance of crops. Despite its importance, studies have not paid much attention to crop failure due to the inundation of farmlands with saltwater flooding (Haque, 2006) and there are no wide-ranging approaches in this regard.

2. Research question and objective

An appropriate approach to estimate flood economic damage to crops is establishing flood damage functions. Such functions allow us to investigate crop failure due to saltwater intrusion from the sea in the hinterland. In order to be used as a practical framework, the function must be able to model flood damage to crops under coastal flood and crop characteristics. To achieve its goal, this chapter answers the following research question: "*How much is the relative damage to agricultural crops due to storm surge flooding?* "

The main aim of this chapter is to develop flood damage curves for agricultural crops and to represent the mathematical relationships between salinity (S) and temperature (T) of seawater, resistance of crops (R_{crop}), and the amount of resulting damage (YD), in the form of $f\ (S, T, R_{crop}, YD)$. To achieve the main goal, the chapter specifies following objectives: i) to provide an overview of the flood damage influencing factors on agriculture, ii) to determine the dominant hazard parameter for coastal flooding, iii) to identify the flood resistance parameters of agricultural crops, and iv) to build the crop damage function in order to estimate the crop yield reduction under various levels of salinity and water temperature. The damage function of crops developed in this chapter is applied later in flood risk analysis module in the ABM platform to compute flood risk and inform farmers about their decisions.

The structure of this chapter is as follows: section 3 provides information about flood damage categories and importance of temporal and spatial scale in damage assessment. Economic flood damage to agriculture is presented in section 4 continued by factors affecting vulnerability of agricultural crops as well as their relevant indicators. Section 5 discusses the effects of seawater salinity, as the main influential factor on crops in coasts, and crop yield response to such a threat. Results and discussion are presented in section 6 followed by conclusions and outlook section.

3. Concepts of flood damage assessment

Damage assessment is an important instrument in decision support and policy development of flood risk management as it provides essential information for optimal decisions on flood mitigation. Furthermore, possible flood damage is dependent on the vulnerability of elements at-risk, which can be reduced through appropriate measures. The evaluation of flood damage is also of high importance for the insurance since the expected extent of economic damage as well as probable maximum loss have to be calculated (Merz *et al.*, 2010) to assess if currently applied steps are cost-effective.

3.1 Flood damage classification

According to literature, flood damage can be classified into *tangible* and *intangible damage* depending on whether or not they can be evaluated in monetary values (Parker, 1995). Another distinction is commonly made between *direct and indirect damage* representing the spatial distinction. According to Jonkman et al., direct damage results from physical contact of floodwater with the elements at-risk, whereas indirect damage corresponds to the damage occurring outside of inundated areas (Jonkman *et al.*, 2008). Third category is about temporal distinction of flood losses where *primary damage* occurs during or immediately after flooding and *secondary damage* occurs later in time (Merz *et al.*, 2010). Figure 5-1 illustrates the flood damage categories.

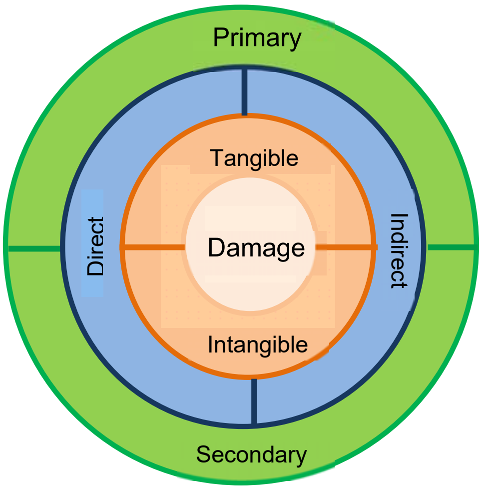


Figure 5-1. Flood damage categories

3.2 Spatial and temporal scale

Apart from the spatial and temporal extent of damage classification (see section 3.1), there is a methodological distinction in this regard. Concerning the temporal extent, flood may cause long-term consequences such as crop yield reduction for a couple of years, which are not considered if the damage analysis is performed for a shorter time horizon (Merz *et al.*, 2010). Concerning the spatial scale, flood damage assessment can be differentiated into micro, meso-, and macro-scale analysis (Kutschera, 2010). Modeling scale depends on the spatial extent of the study area and flood impacts, aim and demands for precision as well as availability of data. It should be noted that there are different interpretations of the terms micro, meso and macro. However, the main differences lie in the spatial extent of the study area, accuracy or level of details and associated effort.

In the *micro-scale* modeling, the exposure and vulnerability assessment are performed at the object level where each individual receptor is modelled (Merz *et al.*, 2010). *Meso-scale* analysis corresponds to a scale between micro and macro where a group of flood receptors are lumped together (Klijn, 2009). In the *macro-scale* modeling, the differences among objects are supposed to be small. Accordingly, elements are lumped together, which results in the less-detailed representation of the study area.

4. Flood damage assessment of agricultural sector

4.1 Tangible agricultural damage

Based on the damage categories discussed in section 3.1, economic damage to the agriculture is classified into four main groups. An example is crop yield loss occurring in the first year (primary direct flood damage), which may last for a number of years (secondary damage). The crop loss causes reduction in farmers' profit (primary indirect damage), selling the farmlands as well as farmers' migration from the area (secondary indirect damage). Therefore, agricultural damage classes are interdependent and influence each other. Further examples of tangible agricultural damage are reported in Table 5-1.

Table 5-1. Classification of tangible agricultural damage

	Primary	Secondary
Direct	- Crop loss and yield reduction - Livestock fatalities - Loss of livestock products (e.g. milk) - Damage to perennial plant material - Damage to soil - Damage to buildings - Damage to machinery - Damage to stored inputs - Damage to infrastructure (e.g. roads)	- Loss of added value due to the loss of yield in the first years after replanting perennial plant material (orchards, vineyard) or reseeding grass - Loss of added value due to unavailability of production factors (machinery, inputs, etc.) - Cost of relocation of premature sales of livestock - Cost of additional food for livestock
Indirect	- Increase in travel time due to the damage to infrastructure - Delay or cancellation of supply from the flooded area (inputs, machinery, etc.) - Reduction in farmers' income	- Loss of added value outside the flooded area due to business interruption of assets in the flooded area - Loss of added value outside the flooded area due to damage to infrastructure - Selling farmlands - Farmers' migration

4.2 Damage influencing factors

Within the scope of flood damage assessment, agriculture is mostly modelled as a whole. However, various spatial boundaries such as plot, farmland, groups of farmlands, and agricultural sector can be studied, with its own components exposed to flooding. For example, at the plot level, crops, soils, buildings, machineries, cattle, and infrastructures can be negatively affected. Apart from that, farmers living in the flood-prone areas suffer from the agricultural flood damage due to the reduction in their profits or the economic shocks at national- or regional-level. Therefore, spatial extent of the flooded area and chosen boundaries play crucial role in identifying at-risk elements within the boundaries.

In general, agricultural flood vulnerability is a function of flood hazard parameters, degree of exposure, and resistance (Jose *et al.*, 2017). Whereas hazard parameters depend on the magnitude and intensity of flooding, two other parameters depend on the characteristics of at-risk objects. Although human response and flood adaptation play key role in reducing the damage and associated risk (see section 2.3 in chapter 2), current flood risk analysis methods do not pay attention to the adaptive capacity of the people subjected to flooding. To address this aspect, we propose a forth parameter called “adaptive behaviour” as an external parameter, which may affect the damage influential factors positively. This parameter will be discussed with more details in the next chapters and will be embedded in the relevant modules in the ABM platform (see chapter 6)

4.2.1 Hazard parameters

Hazard parameters reflect the specific characteristics of flood events that cause negative impacts on exposed objects. Compared to residential or industrial sectors for which water depth is the main hazard parameter in establishing the damage functions, flood damage to agricultural sector depends on several hazard parameters as follows.

Time of flood occurrence

One of the major differences in damage evaluation of agricultural sector is the importance of the time of flood occurrence respecting crop growth stages and land management activities (Thorne *et al.*, 2007). For example, flooding in July can cause higher damage to the crops that should be harvested in August than those whose harvesting time is in October. Given that vegetative cycle of crops depends on climatic conditions, the relation between time of flooding and crop damage is case specific (Brémond *et al.*, 2013). To consider the seasonality as an essential parameter, studies define various crop damage coefficients linked to seasons of the year (Brémond *et al.*, 2009; Brémond *et al.*, 2013). The temperature of floodwater is another important feature that is related to the time of flooding. It is particularly important in the coastal zones where seawater salinity varies under different temperatures.

Flood duration

Along with the period of occurrence, duration of flooding is a substantial aspect (Lotsch *et al.*, 2010) in estimating the required time for the soil to be dried (Brémond *et al.*, 2013).

Water depth

Depth of the floodwater contributes to the physical damage to agricultural components (Lotsch *et al.*, 2010). Similar to other sectors, water depth is probably the main hazard parameter to evaluate the flood damage to farm buildings, machineries, plant materials, and soils (Hoes and Schuurmans, 2006; Jonkman *et al.*, 2008).

Velocity

Water velocity is of high importance in flash flood where the flow velocity destroys the plant materials and leads to soil erosion (Kato and Torii, 2002; Tsakiris *et al.*, 2009).

Silt and salinity

Transportation of silt and salinity from the sea into the hinterland causes negative impacts on crops. Depending on the crop type, salinity causes different levels of crop damage. For instance, vegetables such as tomatoes are very sensitive to salinity whereas grain crops such as barley are more tolerant towards salt (FAO, 2005). Therefore, salt-tolerance of crops is of high importance in evaluation of potential flood damage. Along with the crop type, fertility and texture of saline soil play role in agricultural damage assessment (Haque, 2006).

Type of flooding

Depending on the flood type, different type and amount of damage may occur (Kron, 2013) due to different flood origins and characteristics. For instance, flash flood has a higher flow velocity leading to soil degradation. Coastal flooding carries salinity into the hinterland, which has long-term impacts on crops. Comparing to others, fluvial flooding gives more time to farmers to take appropriate actions such as early harvest (Mao *et al.*, 2016).

4.2.2 Exposure

Flood exposure is the degree to which the components are subject to flooding. In literature, exposure refers to the location of the elements within flood-prone areas.

4.2.3 Resistance

Resistance expresses the capability of at-risk elements to resist to the hazard. Resistance is the opposite of sensitivity, which can be distinguished into biophysical sensitivity (e.g. sensitivity to salt) and socio-economic sensitivity (e.g. sensitivity to price change) (Förster *et al.*, 2008). In the agricultural sector, typical biophysical resistance parameters are the type, height, susceptibility to flooding, and growth stage of crops (Lotsch *et al.*, 2010), while field parameters such as soil structure are also crucial.

4.2.4 Adaptive behaviours

Farmers are one of the most vulnerable social groups (Jamshidi *et al.*, 2018) whose vulnerability should be considered in the flood damage assessment of agricultural sector. As discussed in section 2.3 in chapter 2, determinants such as socio-economic factors, psychological characteristics, and social interaction influence human adaptive behaviours and shape the adaptive capacity of farmers exposed to flooding. In general, *adaptive capacity* is a social and technical skill of individuals to adjust to the environmental changes such as flood or drought and to cope with the negative impacts (Jose *et al.*, 2017). Although it is not possible to mitigate hazard parameters directly through adaption, it has influences on resistance factors and exposure (Merz *et al.*, 2010). For instance, farmers may sell their farmland and move to the out of flooded area, which leads to reduction in the exposure of crops and machineries. Changing the crops to the flood-tolerant ones is an example of human adaptation which results in increasing the resistance of at-risk objects. The detailed information about adaptive behaviours and their influential factors can be found in section 2.3 in chapter 2.

4.2.5 Agricultural flood vulnerability indictors

Identification of indicators helps to understand the agricultural vulnerability in flood events. In this regard, a wide range of indicators may contribute to the damaging factors. However, each study area has certain characteristics making some indicators more relevant than others in vulnerability assessment. Table 5-2 shows a list of the indicators related to the influencing factors on crops, discussed in the previous sections.

Table 5-2. Indictors of flood damage influential factors on agriculture

Damage influencing factors	Hazard parameters	Exposure	Resistance	Flood adaptive behaviour
Indicators	- Period of occurrence - Duration of flooding - Depth of water - Flow velocity - Silt and salinity - Type of flood	- Location of at-risk elements	- Crop type - Topography - Growth stage - Height of crop - Soil structure - Market price - Size/structure of buildings	- Socio-economic factors - Demographic characteristics - Social interaction - Psychological factors - Risk perception - Trust in expert risk assessment

The level of details in flood damage analysis highly depends on the methodological scales (see section 3.2). Table 5-3 compares micro- and macro-scale approaches in agricultural damage assessment in terms of the at-risk elements, damage functions, and individual adaptive behaviour.

Table 5-3.Comparison of micro-and macro-scale approaches in agricultural damage assessment

Methodological scale	**Spatial scale**	**At-risk elements (receptors)**	**Individual adaptive behaviour?**	**Damage function**	**Level of aggregation**
Micro-scale approach	- Farm level	- Crops - Machenieries - Soil - Plant materials - Individual farmers	- Yes - Social intercation - Socio-phsycological factors - Risk perception	Using individual damage function for each at-risk element	Aggregating one or a few number of farmlands/farmers
Macro-scale approach	- Agricultural sector	- A group of crops and properties - Whole agricultural sector	- No	Using one damage function for the whole agricultural sector	Aggreagting several farmlands/farmers to one repensetitive farmland/farmer

Due to the interdependency of flood adaptive behavior and other influential factors, a multi-criteria evaluation is essential. However, there is a lack of research to include individual adaptive behavior in flood damage and risk analysis. One reason is the limited knowledge about its importance and effects. More importantly, the complexity and difficulty in predicting and modeling the interactions between human behavior and other influential factors result in neglecting such dynamic factors.

To address the issue, in this study, first three damage influential factors are included in flood damage curve of crops developed in this chapter. The forth-introduced parameter-human adaptive behavior- will be modeled later in the chapter 6, in risk perception module within ABM platform which will be in connection with flood risk analysis and decision-making module. Such an alternative approach reinforces standard flood risk models by including different dimensions of vulnerability and their interactions.

5. Salinity and damage to agricultural crops in coasts

Flow velocity and water depth play role in crop yield losses in flood events. In coastal areas, however, salinity of the seawater is the major limiting factor since salt will accumulate in the rooting depth to damaging concentration and if it becomes excessive, losses in crop yield will be resulted (Brémond *et al.*, 2013). Salinity affects crop growth by reducing its ability to absorb water. Due to the exposure of the study area (Pellworm Island) to the coastal flooding, the focus of the rest of the chapter is mainly on the salinity and resulting economic damage to crops. To achieve its objectives, our research is based on the micro-scale analysis for which farmlands are chosen as the research unit and agricultural crops are the main components in the damage analysis. Besides, losses are limited to the tangible damage due to lack of required data as well as the complexity involved in modelling of intangible damage.

5.1 Salinity

Salinity (S) is the number of grams of dissolved solids in one kilogram of typical seawater (g/kg) and indicates the salt concentration. This quantity is usually expressed as the measure of parts salt per thousand parts seawater (ppt or ‰) (Baker *et al.*, 2007). In addition to hydrogen and oxygen atoms, seawater in the ocean has many elements dissolved in it but only eleven make more than 99% of all the dissolved salts (Sverdrup *et al.*, 1942). The relative proportions of the eleven ions are nearly constant across all seas, which are reported in Table 5-4.

Table 5-4. Major constituents of seawater (Sverdrup et al., 1942)

Substance	**Weight in the seawater [‰]**	**Weight in the seawater [%]**
Chloride (Cl^-)	18.980	55.04
Sodium (Na^+)	10.556	30.61
Sulfate (SO_4^{2-})	2.649	7.68
Magnesium (Mg^{2+})	1.272	3.69
Calcium (Ca^{2+})	0.400	1.16
Potassium (K^+)	0.380	1.10
Bicarbonate (HCO_3^-)	0.140	0.41
Bromide (Br^-)	0.065	0.19
Borid acid (H_3BO_3)	0.026	0.07
Strontium (Sr^{2+})	0.013	0.04
Fluoride (F^-)	0.001	0.00
Total	34.482	99.99

5.2 Effects of salinity

The salt content in the water has various negative and positive effects. For instance, slight changes in salinity in high latitude have large influences on the thermohaline circulation (Wunsch, 2002). The salinity and temperature work as a global conveyer, connect the five oceans, and transport mass and thermal energy, which increases the water density (Talley *et al.*, 2011). In addition, salinity affects some main physical properties of water as presented in Table 5-5.

Rising the salinity leads to an increase in the electrical conductivity of water, which is in connection with the percentage of the damage to the cultivated plants caused by contact with salty water (Maas and Hoffman, 1977). Thus, it is of high importance to investigate the relation between salinity, water electrical conductivity, and the extent of damage to crops.

Table 5-5. Effects of salinity on the physical properties of water (Talley et al., 2011)

Increase of salinity	
Increasing effect	**Decreasing effect**
Electrical conductivity	Freezing point
Density	Temperature of maximum density
Refractive index	Compressibility
Speed of sound	Specific heat
Surface tension	Solubility of non-reacting gases

5.3 Crop yield response to salinity

Response of plants to salinity is influenced by three factors: soil factor, plant factor, and environmental factor (Maas and Hoffman, 1977). The soil quality and proper use of fertilizer can have positive impacts. Temperature, humidity, and air pollution are the environmental factors that change the crop response to salinity. The resistance of crops against salty water, however, is an important parameter resulting in different responses at the same level of salinity. For example, onion is more vulnerable to salty water than sugar beet. In this regard, growth stage of plants plays a crucial role, as some plants are more sensitive to salinity in their early growth phase (Förster *et al.*, 2008).

One of the most common approaches to represent response of crops to salty water is the Maas-Hoffman model (Maas and Hoffman, 1977). In the model, the salt-tolerance of crops is described by two parameters: slope and threshold salinity. The salinity below the threshold will not affect the crop yield. Exceeding the threshold salinity, the reduction in relative crop yield is started, which is shown by slope. The relative crop yield can be estimated by the following equation (Maas and Hoffman, 1977):

$$Y_r = 100 - b * (EC_e - a) \quad (5\text{-}1)$$

where Y_r is the relative yield in percent, a is the salinity threshold in deci siemens per meter (dS/m), b is the slope experessed in percent yield decrease per unit increase (% per dS/m), and EC_e presents the mean electrical conductivity of a saturated paste of the soil in the root zone.

EC_e is the traditional soil salinity measurement expressed in dS/m. The higher the electrical conductivity of the soil, the higher the level of salts in the water, the more difficult the plant growth, and the more the reduction in the crop yield. Salinity threshold presents the highest level of salinity tolerable by the plant without any yield loss. Slope is the decrease in the crop yield at the soil salinity above the threshold.

5.3.1 Salinity tolerance of crops

Salt-tolerance of crops is the maximum salinity level crops tolerate without any reduction in their productivity. Concerning the salt-tolerance, agricultural crops are classified into sensitive, moderately sensitive, moderately tolerant, and tolerant for the soil electrical conductivity in the range of 0-32 dS/m (Maas and Hoffman, 1977). In 2006, Schleiff introduced the fifth category as very tolerant crops which are resistant toward very salty soil with the electrical conductivity up to 42.5 dS/m (Schleiff, 2006). Table 5-6 presents a list of crops and their salinity tolerance (Tanji and Kielne, 2002). It should be noted that the salt-tolerance characteristics in Table 5-6 are valid in the soils that chloride is the predominant anion (Tanji and Kielne, 2002).

Apart from the salt-tolerant crops listed in Table 5-6, quinoa is slowly establishing itself in Germany as it tolerates dry periods as well as frost (Illner, 2017). In Germany, about 100 hectares of the farmlands are planted with quinoa (Illner, 2017). The crop is frequently examined, whereby no clear salinity thresholds and limit values are fixed yet. Literature reports a possible threshold value of 6 dS/m and a yield reduction of 50 % at a concentration of 40 dS/m (Hamdy, 2016). Regarding the salt problem of farmers in coastal areas, the plant represents a great potential for improvement if further progress is made.

5.3.2 Electrical conductivity of the soil (EC_e)

After each irrigation or coastal flooding, the soil becomes saltier and if the salts are accumulated in the rooting depth, crop yield will be reduced. By applying sufficient water, a portion of the salt may be leached from the root zone to the lower layers and thus the amount of salts in the root zone will be reduced. The fraction of applied water leached below the root zone is called *leaching fraction* (LF). The higher the LF, the less the salt accumulation in the root zone. The salinity of the drainage water is estimated as (Tanji and Kielne, 2002):

$$EC_{dw} = \frac{EC_w}{LF} \tag{5-2}$$

where EC_{dw} and EC_w are the drainage water salinity moving to lower layers below the root zone and the applied water salinity, respectively. Soil salinity is often measured on the saturation extract of the soil and at LF equal to 15-20 percent.

Table 5-6. Salt-tolerance of crops (FAO, 2002)

Crop	Salinity threshold (a) [dS/m]	Slope (b) [% per dS/m]
Sensitive crops		
Bean	1.0	19
Carrot	1.0	14
Strawberry	1.0	33
Onion	1.2	16
Blackberry/ Boysenberry	1.5	22
Plum: prune	1.5	18
Apricot	1.6	24
Orange	1.7	16
Peach	1.7	21
Grapefruit	1.8	16
Moderately sensitive crops		
Turnip	0.9	9.0
Radish	1.2	13
Lettuce	1.3	13
Pepper	1.5	14
Sweet potato	1.5	11
Corn/ Flax/ Potato	1.7	12
Sugarcane	1.7	5.9
Cabbage	1.8	9.7
Celery	1.8	6.2
Spinach	2.0	7.6
Cucumber	2.5	13
Tomato	2.5	9.9
Broccoli	2.8	9.2
Paddy rice	3.0	12
Moderately tolerant crops		
Wildrye, beardless	2.7	6.0
Wheatgrass	3.5	4.0
Beet, red	4.0	9.0
Squash, zucchini	4.7	9.4
Cowpea	4.9	12
Soybean	5.0	20
Ryegrass, perennial	5.6	7.6
Wheat, durum	5.7	5.4
Barley (forage)	6.0	7.1
Wheat	6.0	7.1
Sorghum	6.8	16
Tolerant crops		
Date palm	4.0	3.6
Bermudagrass	6.9	6.4
Sugar beet	7.0	5.9
Wheatgrass, fairway crested	7.5	6.9
Wheatgrass, tall	7.5	4.2
Cotton	7.7	5.2
Barley	8.0	5.0

As a result, the following equations are achieved governing the general relationship between electrical conductivity of water (EC_w), of drainage water (EC_{dw}), and of soil (EC_e) (Tanji and Kielne, 2002):

$$EC_{dw} = 3 * EC_w \tag{5-3}$$

$$EC_e = 1.5 * EC_w \tag{5-4}$$

$$EC_{dw} = 2 * EC_e \tag{5-5}$$

Above equations are based on the LF in arid areas where the crops are irrigated continuously with saline water. However, flooding by storm surges is less frequent than irrigating with salty water in the arid areas. Moreover, in the coasts especially in the northern Germany, higher precipitation is expected (Wetterdienst, 2017), which results in greater leaching than assumed. By an increase of 30 percent in the LF in arid areas (Schüttrumpf *et al.*, 2013), the soil salinity along coastal regions can be estimated as:

$$EC_e = 0.8 * EC_w \tag{5-6}$$

5.3.3 Electrical conductivity of the water (EC_w)

Water electrical conductivity (EC_w) is the water capability to pass the electrical flow. As a result, electrical conductivity is a measure of saltiness of the water and is closely related to the salt concentration, temperature, mobility of ions, and valence of ions (Weyl, 1964). To estimate the EC_w under various ranges of seawater salinity and temperature, two approaches are commonly used in literature:

First approach: water electrical conductivity as a function of the chloride

In 1964, Weyl developed an empirical equation to calculate the electrical conductivity of water as a function of two variables: chlorinity and temperature (Weyl, 1964):

$$\begin{aligned} Log\, EC_{w,T} = {} & 0.57627 + 0.892 * log\, Cl - 10 - 4 * \tau \\ & * [88.3 + 0.55 * \tau + 0.0107 * \tau^2 - Cl \\ & * (0.145 - 0.002 * \tau + 0.0002 * \tau^2)] \end{aligned} \tag{5-7}$$

$$\tau = 25 - T \tag{5-8}$$

where Cl is the chlorinity in ‰, T is the temperature in °C, and $EC_{w,T}$ is the water electrical conductivity in mho/cm. This equation can be applied over chlorinity range 17-20 ‰ and temperature range 0-25 °C.

Assuming that Chloride is the main component of salty seawater, UNESCO defined the following relationship between chlorinity and salinity (UNESCO, 1981):

$$Cl = S/1.80655 \tag{5-9}$$

where S is the seawater salinity expressed in ‰. The above equation is valid over a salinity range 30-35 ppt.

Second approach: water electrical conductivity as a function of water salinity

Kramer et al. defined three water categories including freshwater, brackish-water, and saltwater depending on the salinity level (Kramer *et al.*, 1994). Later, Hockensmith proposed Figure 5-2 to relate water salinity with water electrical conductivity of three categories at 25 °C (Hockensmith, 2004). As can be seen, the diagram can be used for a wide range of salinity from 0 to 40 ppt to determine the EC_w at 25 °C. Since the EC_w varies with temperature, Hayashi developed the following equation to calculate water electrical conductivity at any desired temperature in the range of 0-30 °C (Hayashi, 2004):

$$EC_{W,T} = EC_{W,25} * [1 + \alpha * (T - 25)] \tag{5-10}$$

$EC_{W,25}$ and $EC_{W,T}$ indicate water electrical conductivity in dS/m at 25 °C and temperature T in °C, respectively. α is a constant parameter in 1/°C varying from 0.0184 to 0.0189 for the water salinity in the range of 0 to 40 ppt. To make a simplification, this parameter can be determined as its mean value, 0.0187, with error less than 2.4 % (Hayashi, 2004).

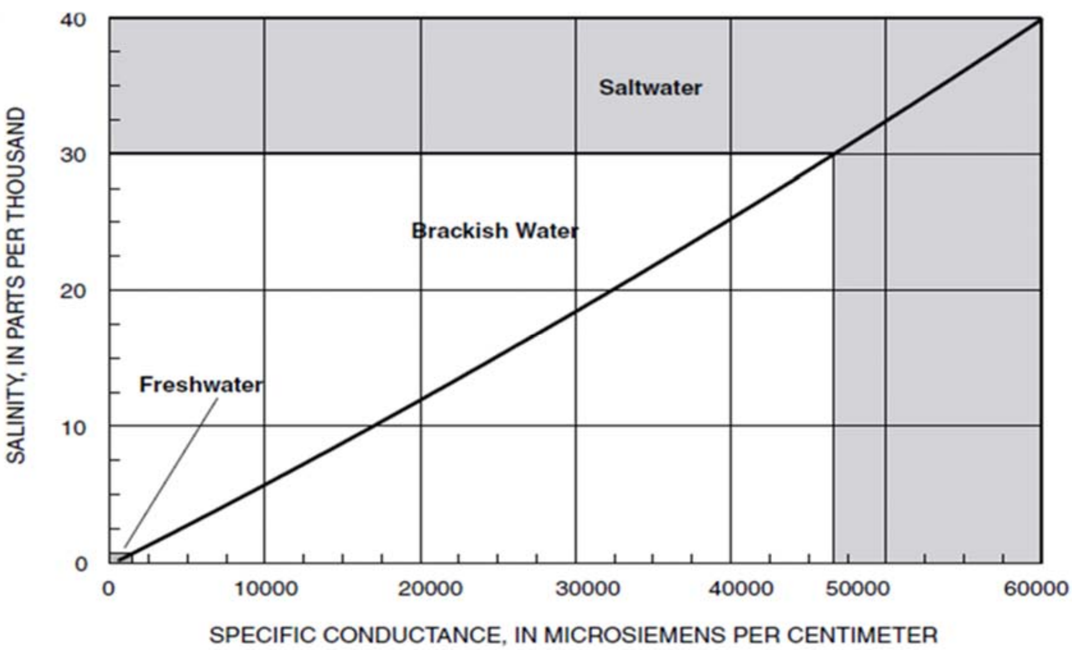


Figure 5-2. Correlation between salinity and water electrical conductivity (at 25 °C) (Hockensmith, 2004)

6. Results and discussion

6.1 Damage function of agricultural crops

To develop flood damage curve for agricultural crops in coasts, we take the following steps: formulating agricultural crop failure, determining flood characteristics, specifying crop characteristics, estimating soli electrical conductivity, and establishing the crop damage function.

As discussed in the previous sections, the dominant hazard parameter for coastal flooding contributing to the physical damage to agricultural crops is seawater salinity (section 5.3) that varies with water temperature. Crop resistance to flooding is another important factor determining the flood damage ratio of crops. Accordingly, the flood damage function of agricultural crops should provide a mathematical relationship between crop characteristics, flood hazard parameters, and flood damage ratio. Therefore, we formulate agricultural crop failure (YD) due to the saltwater intrusion from the sea in the hinterland as:

$$YD = g(crop\ characteristics, flood\ hazard\ parameters) \quad (5\text{-}11)$$

In which crop characteristics are governed by the decrease in yield at the soil salinity above the threshold (b in percent per dS/m) and by maximum soil salinity without yield loss (a in percent per dS/m) (see also section 5.3):

$$Crop\ characteristics = R_{crop} = h(a, b) \quad (5\text{-}12)$$

The primary hazard parameters that control crop damage under the coastal flooding are salinity (S in ppt) and temperature (T in °C) of seawater:

$$Flood\ hazard\ parameters = k(S, T) \quad (5\text{-}13)$$

As a result, the agricultural crop failure due to coastal flooding is a function of all above variables:

$$YD = g(h(a, b), k(S, T)) \quad (5\text{-}14)$$

On the other hand, crop yield response to the salinity can be best modeled with a linear relationship between salt-tolerance of crops and soil electrical conductivity (see section 5.3). Taking the discussed linear relationship between the two parameters (see section 5-3), we propose the following crop damage function as an appropriate equation for estimating the damage ratio of flood affected crops in coasts:

$$YD = b * (EC_e - a) = b * (0.8 * EC_w - a) \quad (5\text{-}15)$$

Since EC_w is a nonlinear function of seawater salinity and temperature (see also section 5.3.3), Eq. (5-15) represents a nonlinear function, as well. Replacing EC_w by function $l(T,S)$ for the simplification, the proposed crop damage function can be formulated as:

$$YD = b * (0.8 * l(T,S) - a) \quad (5\text{-}16)$$

Eq. (5-16) indicates the nonlinear relationship among all mentioned variables. Under the specified level of salinity and temperature, the proposed crop damage function has a linear relationship with crop characteristics.

6.2 Modeling framework for crop damage function in coasts

Modeling framework and required data for establishing crop damage function under coastal floods are illustrated in Figure 5-3. As can be seen, flood and crop characteristics should be first identified for the study area after which the temperature and salinity of seawater are estimated. Next, soil electrical conductivity will be calculated, which can be done in two different ways depending on the range of seawater salinity (see section 5.3.2). In the last step, damage curve of crops will be generated as a function of salinity tolerance of crops and soil salinity. The presented framework is applied in the next sections to construct flood damage function of agricultural crops in the Pellworm Island.

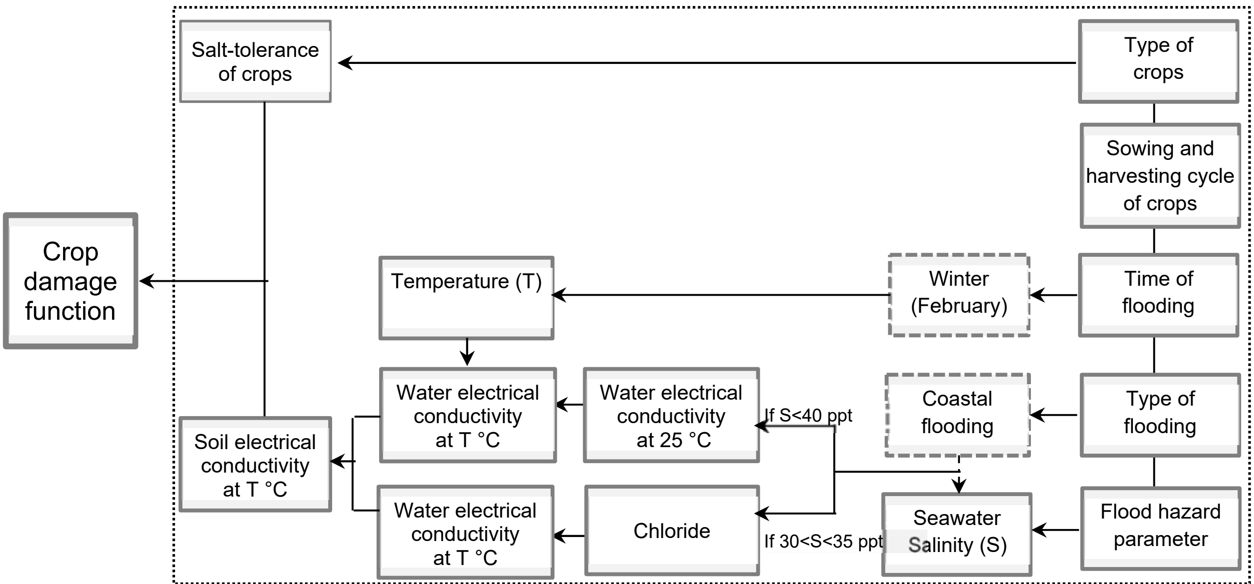


Figure 5-3. Modeling steps for establishing crop damage function under coastal flooding

6.3 Input data and model setup

In order to build the flood damage function of agricultural crops, a number of flood and crop data are required to calculate soil electrical conductivity as well as crop damage factor. Relevant inputs are seasonality and type of flooding, key flood hazard parameter(s) as well as salinity tolerance of crops and their sowing/harvesting cycle.

6.3.1 Flood characteristics

Pellworm Island is threatened by storm surge flooding in the winter when the water temperature is relatively low. Since the hinterland is flooded by the salty seawater, salinity is the most influential factor governing damage characteristics. Schaber et al. carried out a study to compare the salinity between the North Sea and Baltic Sea. They found out that salinities in the Wadden Sea region of the North Sea are lower than in open seas due to the freshwater from rivers such as Weser, Elbe, and Eider (Schaber *et al.*, 2011). According to their research, average summer sea surface salinity around Pellworm Island is 28 ppt (see Figure 5-4). As the salinity in Wadden Sea decreases in the early spring-February to May- (Voynova *et al.*, 2018), assuming the seawater salinity equal to 28 ppt in February for this study could be a good estimation.

Another important input is the seawater temperature in flooding time around the Pellworm Island. The Weather Spark has recorded water temperature around the Island in February in the range of 1 - 6 °C with the average 3 °C (Weather Spark, 2019). In our study, the seawater temperature is assumed to be 3 °C for further analysis.

6.3.2 Crop characteristics

Table 5-7 provides salt-tolerance of crops that are cultivated in Germany and thus can grow on the Pellworm Island. The traditional crops cultivated in the Pellworm are bolded in the table.

In addition to salt-tolerance of crops, the crop yield loss depends on the growing stage of plants at the time of flooding (see Figure 5-3). In comparison to flooding with fresh water occurring throughout the whole year, the German North Sea coasts have been highly exposed to storm surges between November to February. During this period, some agricultural crops such as winter crops are at an early stage of growth or in the winter rest. A number of fruits such as potato and sugar beet have been harvested and the grassland has been cut or used for grazing. In addition, the majority of operational expenses such as fertilization, plant protection, labor, or ordering the crops for summer cultivation have been not expensed by February and will be paid after, if there is no flooding.

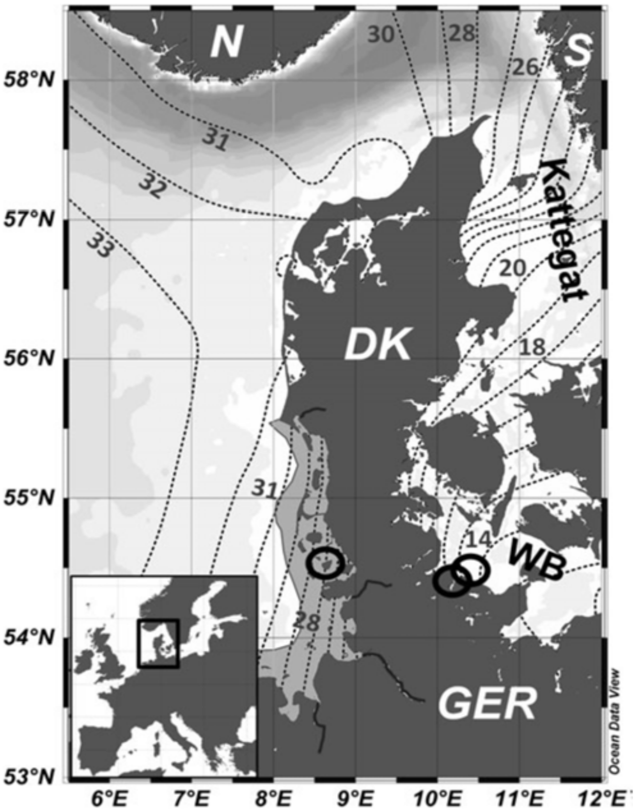


Figure 5-4. Average summer sea surface salinity of Wadden Sea region of North Sea (Schaber et al., 2011)

Table 5-7. Salt-tolerance of crops in Germany (FAO, 2002)

Crops	Salt-Tolerance	Salinity threshold [dS/m]	Slope [% per dS/m]
Rye	Tolerant	11.4	10.8
Rye for forage	Tolerant	7.6	4.9
Spring barley	**Tolerant**	**8**	**5**
Triticale	Tolerant	6.1	2.5
Asparagus	Tolerant	4.1	2
Sugar-beet	Tolerant	7	5.9
Wheatgrass, tall	Tolerant	8,6	3
Ryegrass	Moderate tolerant	5.6	7.6
Spring canola	**Moderate tolerant**	**11**	**13**
Winter wheat	**Moderate tolerant**	**6**	**7.1**
Maize	**Moderate sensitive**	**1.7**	**9.6**
Corn silage	Moderate sensitive	1.7	12
Potato	Moderate sensitive	1.7	12
Clover red	Moderate sensitive	1.5	12

6.4 Soil electrical conductivity in Pellworm Island

To calculate the electrical conductivity of soil, it is first needed to extract the water electrical conductivity. This parameter can be estimated in two ways (see section 5.3.3 and Figure 5-3) depending on the range of seawater salinity. Table 5-8 presents soil and water electrical conductivity in the Pellworm Island calculated with two approaches discussed before. As can be seen, both methods give very similar results and the difference is less than 2 % since the salinity in the seawater is close to 30 ppt. As expected, water and soil electrical conductivity in winter (temperature 3 °C) are much lower than those in summer (temperature 25 °C). Monthly variation of water and soil electrical conductivity are depicted in Figure 5-5. The higher the temperature, the more the water and soil electrical conductivity, and the more the flood damage to agricultural crops.

Table 5-8. Soil and water electrical conductivity of Pellworm Island under coastal flooding

	Approach 1: EC_W as a function of Cl	**Approach 2: EC_W as a function of S**
Seawater temperature (T) in winter	3 °C	3 °C
Seawater salinity (S)	28 ppt	28 ppt
Chloride (Cl)	15.49 ppt	-
Water electrical conductivity at 25 °C (EC_W)	-	43.45 dS/m
Water electrical conductivity at 3 °C (EC_W)	25.06 dS/m	25.57 dS/m
Soil electrical conductivity at 25 °C (EC_e)	34.76 dS/m	34.76 dS/m
Soil electrical conductivity at 3 °C (EC_e)	20.05 dS/m	20.46 dS/m

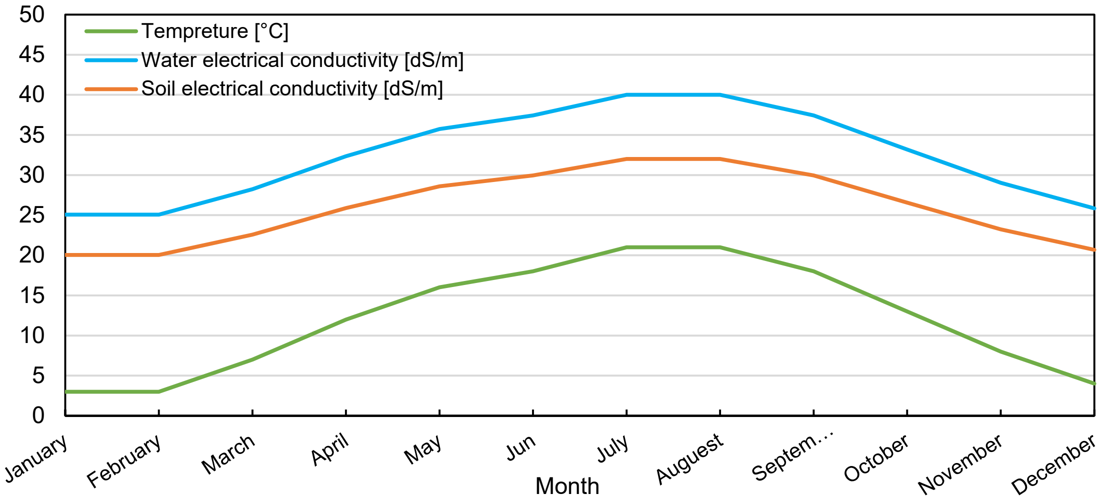


Figure 5-5. Monthly variations of temperature as well soil and water electrical conductivity in Pellworm Island

6.5 Crop damage function

Figure 5-6 illustrates the developed salinity-damage curves for agricultural crops based on the crop salt-tolerance data provided by FAO and those of spring barley, wheat, and maize, as examples (Tanji and Kielne, 2002). Given the salt-tolerance of crop, flood damage curve is a linear function of soil electrical conductivity lying in one of the five shaded regions in the figure. Table 5-9 reports the range of soil electrical conductivity in which crops experience no damage. In comparison to very tolerant crops, sensitive crops lose their yield under very low salinity level.

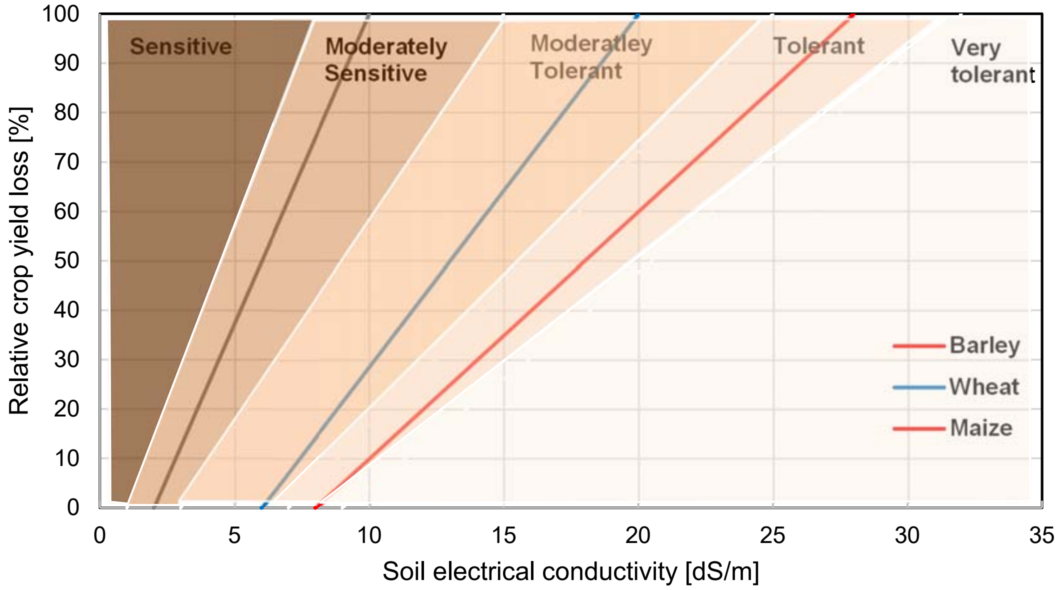


Figure 5-6. Salinity-damage function for agricultural crops under different salt-tolerance characteristics

Table 5-9. Tolerated soil electrical conductivity at zero damage level

Salt-tolerance of crop	Tolerated EC_e (dS/m)
Sensitive	0 - 1
Moderately sensitive	1- 3
Moderately tolerant	3 - 7
Tolerant	7 - 9
Very Tolerant	9-35

Damage factor of crops varies by seawater temperature due to the change in soil electrical conductivity. Table 5-10 compares crop yield loss in the Island in winter (temperature 3 °C) and summer (temperature 25 °C). In comparison to summer in which all crops are damaged completely, in winter only sensitive and moderately sensitive crops will be completely destroyed, and moderately tolerant crops lose 70 to 100 percentage of their yield. As seen, cultivating very tolerant crops reduces yield loss to less than 50%.

Table 5-10. Calculated crop yield loss in Pellworm Island in winter and summer

Salt-tolerance of crops	Damage factor [%]	
	Summer (25 °C)	Winter (3 °C)
Sensitive	100	100
Moderately sensitive	100	100
Moderately tolerant	100	70-100
Tolerant	100	50-70
Very tolerant	100	0-50

Figure 5-7 shows depth-damage curve of crops under the salinity of Wadden Sea around Pellworm. Solid lines represent damage functions of crops cultivated traditionally on the Island while dashed lines are related to the crops that can grow in the area because of the proper climatic condition. As can be seen, except for spring barley, other three traditional crops are damaged completely once their farmlands are inundated by salty seawater. Among other crops, asparagus and triticale are resistant to the salinity, as expected from their slope and salinity threshold in Table 5-7. Since salinity is the main influential damage factor in the coasts, flood depth plays no important role in this case.

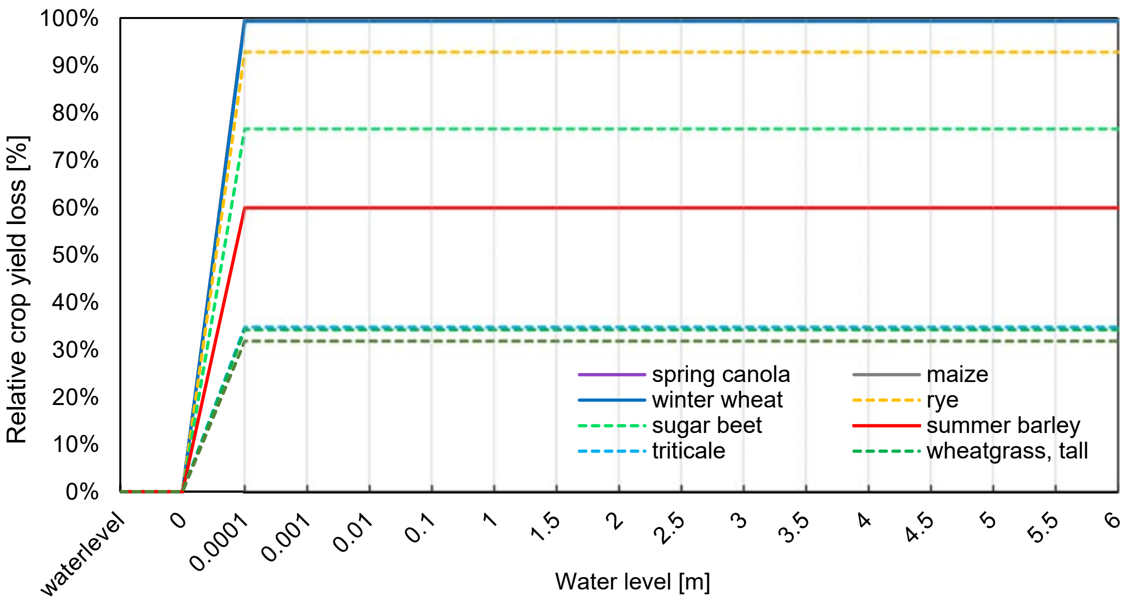


Figure 5-7. Depth-damage function of crops under salinity of Wadden Sea around Pellworm Island in winter

7. Conclusions and outlook

In coastal regions, storm surges transport salinity into the hinterland, which negatively affects the crop production. The more the salt content of the water, the more probable the crop failure. Although salinity is the key underlying parameter that limits plant productivity, other factors such as time of flooding, seawater temperature, growth stage of plant, crop type, and crop characteristics also determine the amount of damage to the crops. So, there is an essential need to a comprehensive function-based framework to integrate all above-mentioned parameters. This allows assessing flood damage to crops under any range of seawater salinity and temperature as well as different levels of crop salt-resistance.

This chapter aimed to establish such a flood damage function of agricultural crops when the farmlands are inundated by seawater. Identifying type of flooding and its seasonality in the study area, seawater temperature and salinity were extracted from literature. Given the crop salt-resistance, a linear function governs the relationship between soil electrical conductivity and the crop yield reduction. Under the specified seawater salinity and temperature, water and soil electrical conductivity were calculated for the study area, which were further used to estimate the damage factor for crops. Subsequently, we could present the salinity-damage curve of crops as well as their depth-damage curve per salinity level. Both developed curves are used in the next chapters to perform flood damage assessment as the core of the flood risk analysis module (see Figure 5-8).

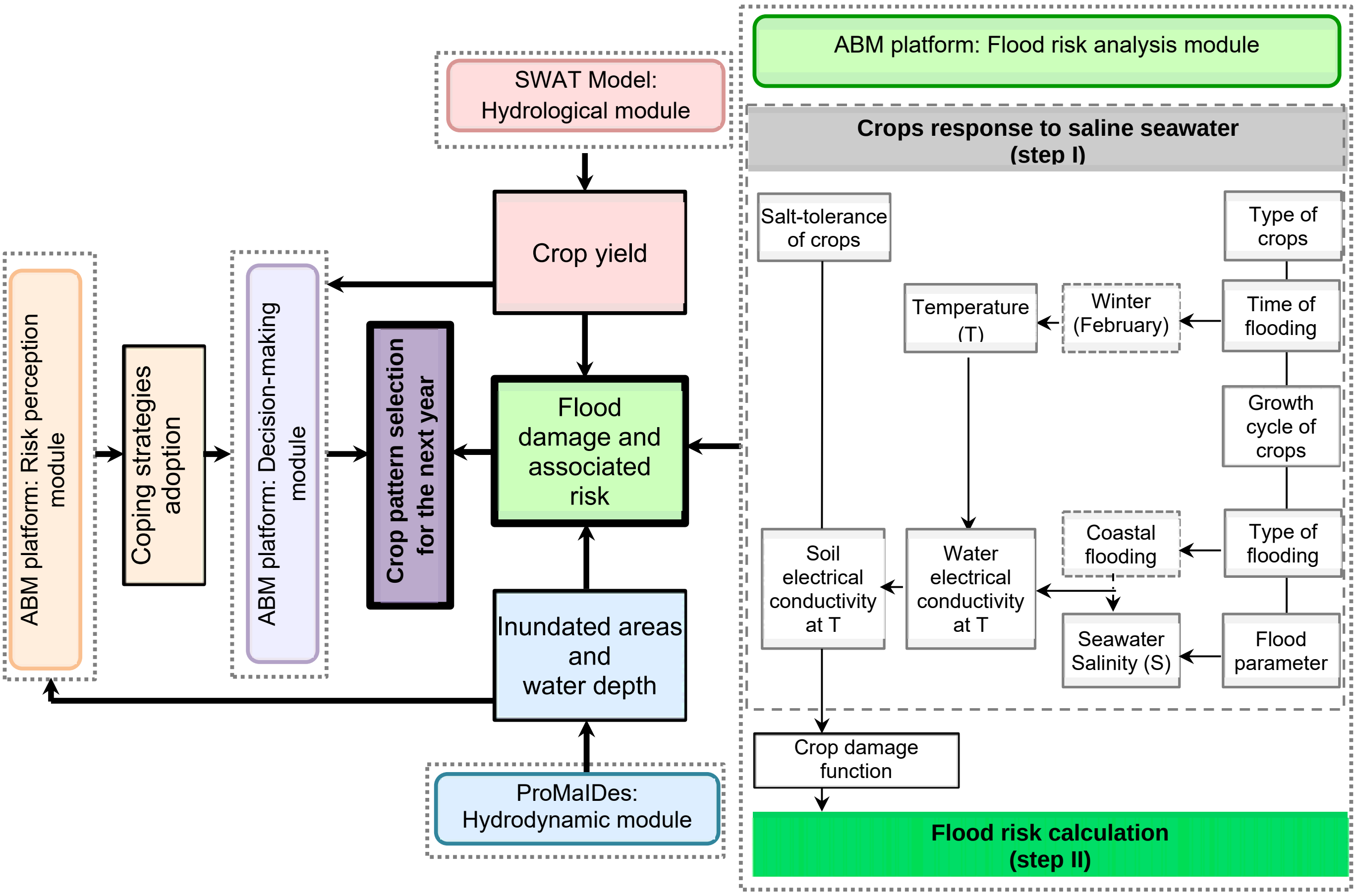


Figure 5-8. Connection of crop response to saline water sub-module with other modules in each year

Chapter 6 Modeling farmers' decision-making in response to flood under the influence of social interaction, individual risk perception, flood memory, and limited information

1. Introduction

Farmers living in flood prone-areas are exposed to flooding and suffer from that. Even in some less severe floods, they lose their expected incomes due to the soil erosion as well as crop yield reduction which may continue for a number of years. These negative consequences result in selling farms, migrating from the area, and increasing the unemployment (FAO, 2015).

To reduce the adverse impacts, farmers may employ strategies to cope with flooding and reduce their vulnerability (Becker *et al.*, 2015). Research shows a close relation between individual risk awareness and motivation to respond to flooding (Becker *et al.*, 2015), which are influenced by individuals' observations, expectations, and experiences. These all lead to heterogeneity in farmers' decision-making under risk and change in their vulnerability over time. Moreover, limitations to the availability of information as well as to the processing capacities of farmers result in non-optimizing behaviors and bounded-rationality (Simon, 1990). In this regard, social networks play crucial role in information exchange about individual decisions and adaptive behaviors.

These aspects of humans (farmers)-flood interaction are, however, poorly understood in both flood risk management (FRM) and farmers’ decision-making studies. Thus, there is a need to change the perspective from macro- to micro-level and apply an interdisciplinary approach that can address the mentioned aspects on one hand and integrate both disciplines on the other hand as none of them are capable of dealing with such issues alone.

2. Research question and objective

Agent Based Modeling is an interdisciplinary approach and a new style of modeling to present social processes and complexities of human behaviors from the bottom-up and in combination with engineering practices. In this study, we establish an ABM platform to link individual adaptive decision-making under risk and FRM in which decision-making module, flood risk analysis module, and individual risk perception module are being developed and connected together. It allows gaining advantages of coupling human behavior and flood risk assessment in one platform. More importantly, it enables us to simulate the interaction and behavior of humans and their changing risk environment that results in a more holistic flood risk assessment approach. To fulfill the purposes, this chapter seeks to address “how do farmers in the coastal areas make yearly decisions in the context of flood risk management and how do individual risk perception, social interaction, bounded-rationality, flood memory, and diversity amongst people play role in this regard?”

The primary objective of this chapter is to develop an experimental platform to link farmers’ decision-making and FRM for a population of semi-hypothetical farmers in order to (i) include farmers-flood interaction in FRM, (ii) understand the influence of farmers’ interactions through social networks, (iii) investigate the relationship between flood risk perception and private adaptive behaviors, (iv) explore the role of flood memory, and (v) model farmers’ adaptive decision-making under bounded-rationality. The ABM platform developed in this chapter is connected with the modules established in the previous chapters to present an **A**gent **B**ased **M**odel for **fa**rmer-**flo**od interaction, called ABMFaFo.

The structure of this chapter is as follows: an overview of the model is provided in section 3 followed by a brief explanation of overall flow as well as model parameters and data. Section 4 presents the development of the flood risk analysis module within the ABM platform. Section 5 provides a step-by-step approach to develop individual decision-making under the influence of social interactions and flood memory within the ABM platform. This section also includes the non-rational behavior as well as cognitive strategies and presents their implementation in the decision-making module. The role of individual risk perception is discussed in section 6 and a rule-based procedure is presented to formulate risk perception in individual decision-making. The main conclusions are summarized in section 7.

3. Overview of the model

The main aim of the study is accomplished by linking the individual adaptive decision-making in flood-prone areas within an ABM platform (presented in this chapter), hydrological module (see chapter 3), and hydrodynamic module (see chapter 4). The platform consists of three parts including farmers' decision-making, flood risk analysis as well as risk perception and adaptive behavior. The ABM platform is implemented in Netlogo version 5.2.1 and is spatially explicit for farmlands location, cultivated crops, crop distribution, and inundated areas.

The agent classes of the model are farmers, farmlands, crops, and social networks. A population of 37 semi-hypothetical farmers are the central decision-makers in the model. The population size is in accordance with the farmers' number in the Pellworm Island and is based on the telephone talk with one of the farmers of the area. Crop cultivation is the main economic activity farm agents do in the model to earn money and their decision for the next year affects their farm profit. Farm agents make yearly decisions as they update their knowledge about crop yields, market prices, climate, and flood characteristics. They gain information from personal experience, interaction with others, the physical environment, and publicly available data. Social networks of each farm agent are characterized by the degree of proximity and farm-size similarity based on the homophiliy principle (McPherson *et al.*, 2001).

Farm agents are heterogeneous in their behavioral rules and interaction groups. They are also unique in terms of farm-size, income, and exposure to flooding. Other factors differentiating one farmer from another are risk perception and personal characteristics such as risk tolerance, satisfaction threshold, and uncertainty threshold. Crop yields can also vary from farmer to farmer if there are any differences in the soil type or land management practices, and from year to year due to differences in the weather. Some farm agents' attributes such as farm-size, farm-position, satisfaction threshold, and uncertainty threshold as well as risk tolerance are not changed during the simulation whereas economic attributes (income) and decision-making attributes (satisfaction, uncertainty, and behavioral types) change over time.

Agent classes are connected within the physical and social environment. The physical environment consists of crops, soil, farmlands, climate, flood protection structures, and the surrounding sea. It provides farm agents with new information about the crop productivity as well as flood situation and characteristics in the following year. For this aim, our ABM platform is linked to the hydrological and hydrodynamic modules developed externally (see chapter 3 and chapter 4). The social environment includes farm agents and their interacting groups and is represented explicitly in our study through establishing the social networks. It is worth nothing that the whole physical environment is parameterized based on the real data of Pellworm Island (see chapter 1, 3, 4, and 5). Due to lack of empirical data, however, we made assumptions about the social environment which are explained in more details in the following sections.

The simulations are carried out for the period 2005-2016. For the purpose of this study, we hypothesize that three "200-year flood" occur in the simulation period on the Island. Based on the survey questionnaire conducted in the HoRisK project (Schüttrumpf *et al.*, 2013), farmers believe that their crop productivity decreases by 25% in the following year after flooding. Therefore, such a crop yield reduction has been considered in the study. Figure 6-1 shows the hypothetical timeline of the flood events.

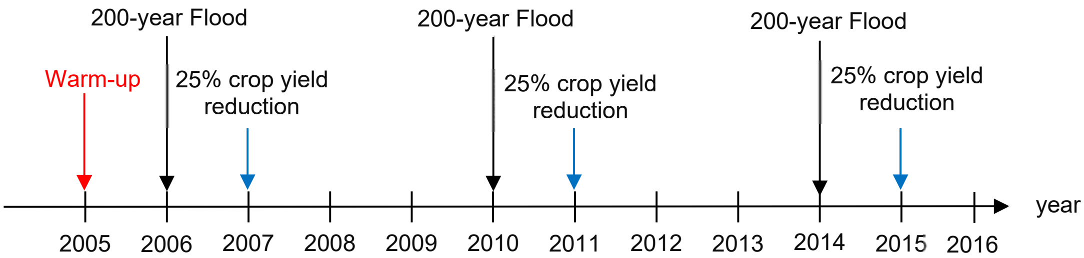


Figure 6-1. Assumed flood events in the simulation period

A yearly time step is assumed for farmers' decision-making, which is consistent with the yearly modification of crop composition by farmers in reality. The smallest unit considered in the ABM platform is one cell in a grid, which represents 31m * 31m. The model is run at the spatial scale of a farmland comprising a number of cells.

Figure 6-2 provides a schematic of the ABMFaFo activity diagram. More information regarding the interlinkage of modules and their input data can be found in chapter 1. At the beginning of the simulation, before the start of the first year in the simulation period, farmers' satisfaction threshold, uncertainty threshold, flood memory, and risk tolerance are set. In the next step, two interacting groups are defined for each farmer: neighbors within the specified radius and neighbors with similar farm-size. Simulations are then carried out iteratively, year by year through which farmers choose yearly crop pattern under the influence of crop prices, individual experiences and expectations, and observing others' decision as well as their perceived risk of floods.

Within each year, a sequence of activities takes place in the order. At the start of each year, flood hazard assessment is carried out using the hydrodynamic module to determine the extent of agricultural land inundation under probable flood scenarios. As a result, inundation and flood hazard maps are created for the study area, which are then assessed to define different flood zones for varying levels of flood danger. Subsequently, a degree of danger is assigned to each defined zone in the way that is understandable to the public. In the next step, the decrease in crop yields of flooded agricultural lands is calculated using the flood risk analysis module to estimate the damage to agricultural crops under seawater salinity. At the end of the growing season, climatic and soil conditions as well as the topology of the area are fed into the hydrological module to compute the productivity of cultivated crops.

Then, farm agents will update their knowledge about the weather, flooding situation, and crops in the market as well as prices and associated costs. Observing their crop production, farmers will be aware of their crop yield in the current year. They will also become conscious of their crop yield reduction due to saline seawater. Meanwhile, farmers’ perception of flood danger is shaped. Hence, the rational farmer assesses the level of danger and decides to deal with flood risk through or without adaptation strategies in her/his decision-making.

At the end of each year, farm agents make their decision and choose crops for the next year. For this aim, farmers estimate their farm income, evaluate their satisfaction by comparing the actual profit and potential profit, and assess their uncertainty in terms of the ratio of actual to expected profit for this year. Depending on her/his satisfaction and uncertainty level, each farmer follows a certain behavioral strategy to take her/his decision for the next year. For instance, uncertain farmers consult their peers in the social network to update their information about others’ decisions and adaptive responses. Farmers, who have high level of satisfaction, will engage in the imitation or repeat their previous behavior. In contrast, those who are dissatisfied with the outcomes of their decision in the current year, try to obtain more satisfied outcomes by deliberating or engaging in social comparison. Flood memories of dissatisfied farmers play role in their objective function. While farmers with long-lasting flood memory aim to minimize their expected flood damage, farmers with short-term flood memory select the crop with highest expected profit.

After farmers’ decision-making is completed, it is considered to be the end of the year. At this point, decisions taken by farmers will be fed back into the developed modules and the explained process will be continued year by year over the time horizon as the result of feedback between ABM platform and other modules.

It should be noted that updating of crop data perceptions such as crops in the market and yields as well as prices and associated costs is only carried out by specified farm agents. The kind and amount of information each farmer has access to, depends on her/his behavioral strategy in the current year and her/his interacting groups, which also determines farmer' perception of the crop data. Indeed, it is assumed that not all crop data are readily available to all farmers, but only to those who follow certain cognitive strategies. For example, a farmer who deliberates, assesses the consequences of all possible decisions in order to optimize her/his output. Such a farmer accesses to complete information and is capable of processing it. She/he is aware of all crops in the market, their yields, and costs as well as their resistance to saline seawater in the current year. In comparison, the farmer who engages in the social comparison, only has access to the data of those crops that have been cultivated in the current year by her/himself or one of the peers in her/his social networks.

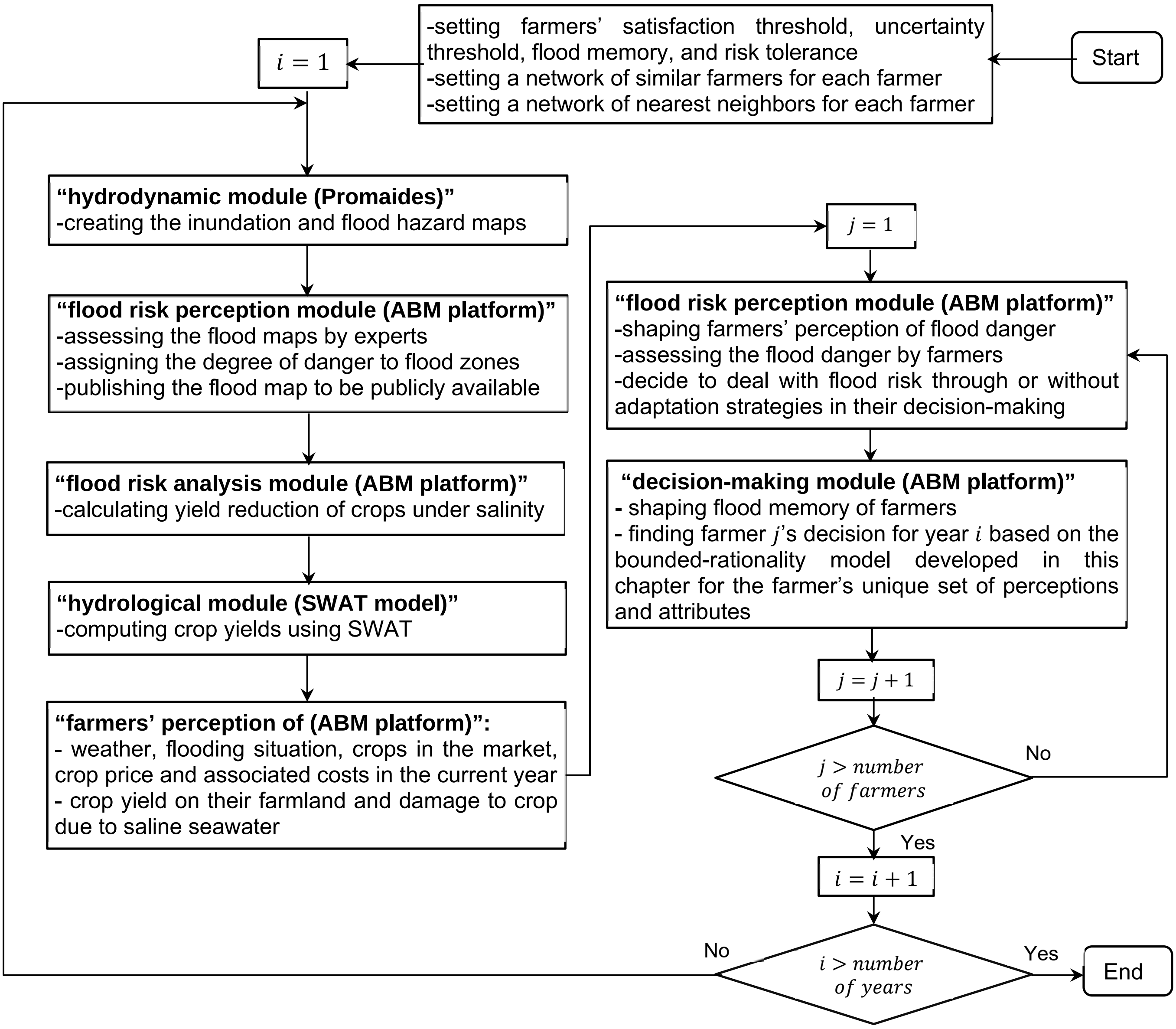


Figure 6-2. Activity diagram of the ABMFaFo

As can be seen in Figure 6-2, the model simulates both spatial and temporal dynamics in farmers' decision-making and consists of two loops: an outer loop for time (year) incrementation and an inner loop for agent (farmer) incrementation. The outer loop includes updating farmers' perception of weather, flooding situation, crop data, and crop damage due to salinity. It also contains calling all modules including hydrodynamic module to create flood map, flood risk perception module to assign the degree of danger to flood zones, flood risk analysis module to compute crop yield reduction, and hydrological module to estimate crop yield. For each iteration of the outer loop, the inner loop is repeated 37 times to shape the risk perception of farm agents and simulate their decision-making process for the following year.

3.1 Model parameters and data

The model makes use of rich empirical data. Firstly, we use GIS files such as land use map and farmland spatial distribution, based on which the physical environment is initialized. Secondly, climate scenarios and characteristics of hypothetical flood events are obtained from the empirical observations and historical data. Thirdly, crop data such as sale prices and costs as well as land management practices come from the real data. Finally, attributes of farm agents including population size and their initial cropping pattern are assigned based on the real data. Due to lack of data, however, we make assumptions about farmers' location, behavioral factors, and parameters of social networks.

4. ABM platform: Flood risk analysis module

To model human-flood interactions and their changes, we develop the flood risk analysis module within the ABM platform, which is then integrated into the decision-making module. Such a model is capable of including complex human behaviors in the FRM resulting in a more holistic flood risk assessment approach. It also enables us to calculate the flood risk at the micro-level comparing to other softwares such as ProMaIDes in which the risk is computed for the whole area.

Modeling steps and required data for developing the flood risk analysis module in the ABM platform are presented in Figure 6-3. In order to calculate the expected damage for any flood event, the most common approach is to combine flood hazard characteristics, the degree of exposure of at-risk elements, and their resistance or susceptibility to the particular hazard (see chapter 5). In the first step, flood damage functions are established to estimate how susceptible at-risk elements are to the given flood hazards. Identifying the most influential hazard parameter in the area, exposure maps are generated by overlaying the flood inundation maps (see chapter 4) and land use maps. Finally, calculated flood damage is combined with the occurrence probability of such events to estimate the associated flood risk (Ward *et al.*, 2011). Following sections present more details regarding two modeling steps of flood risk analysis module.

4.1 Crop yield response to saline seawater (step I)

The first step is to establish crop damage functions under coastal flooding, for which the required data should be prepared (see chapter 5) and fed into the platform via the graphical user interface (GUI) of Netlogo. As a result, the salinity- and depth-damage functions of crops are generated. These damage functions describe yield response of plants to the seawater salinity under the given temperature. Subsequently, it is possible to compute the yield reduction of crops under any desired water salinity and temperature. Detailed information regarding the required data, modeling steps, and established damage function for crops can be found in chapter 5.

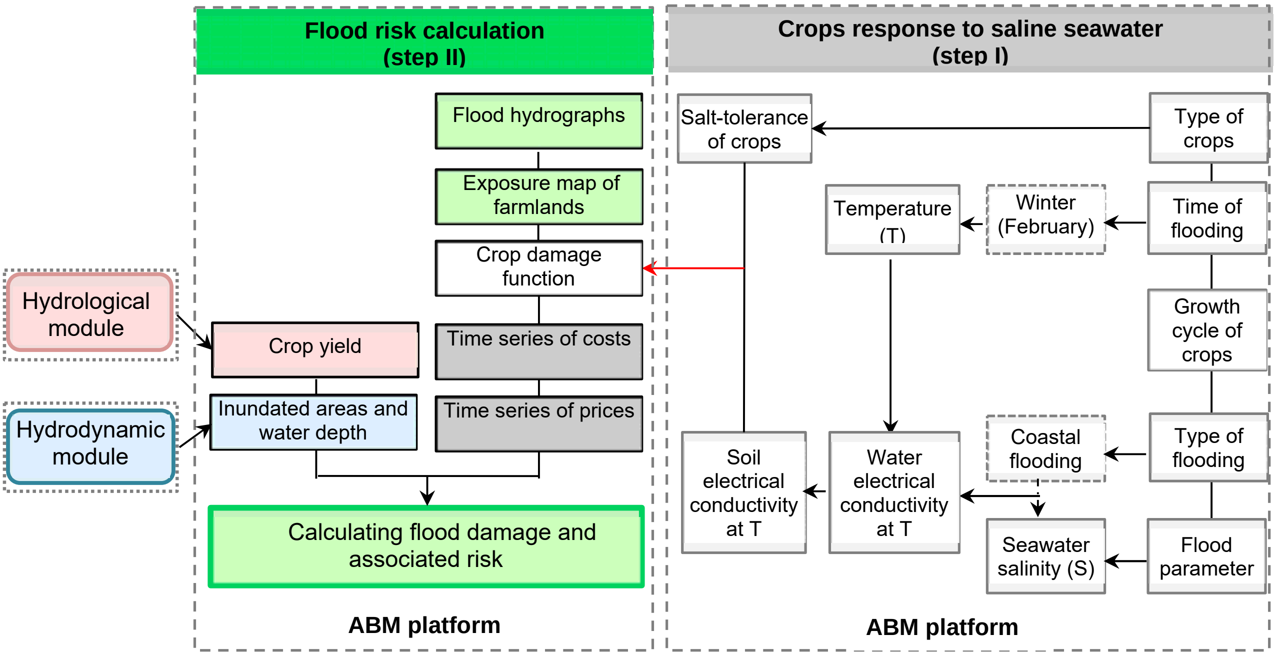


Figure 6-3. Modeling steps and components of the flood risk analysis module in the ABM platform

4.2 Flood risk calculation (step II)

The next step is to compute the agricultural crop damage and associated risk. So, simulated annual crop yield (see chapter 3) as well as computed submerged areas and water depths of three flood scenarios (see chapter 4) are fed into the model. Other required inputs such as flood hydrographs, exposure maps of farmlands, and time series of crop prices and costs are exogenous to the model. The risk is, then, approximated as the area under the plotted probability-damage curve or as the sum over the product of probability and negative consequences of floods of several return period:

$$R = EAD\ (x) = \int f(x) * D(x) * dx \cong \sum p_i * D_i \tag{6-1}$$

where R is the flood risk, $f(x)$ defines the probability density function of the flood event x, and $D(x)$ is the consequences function due to the flood event x. In the case that the random variable x is a countable set of probable flood events with negative consequences D_i and occurrence probability of p_i, the discrete sum represents the associated flood risk.

One way to derive the occurrence probability of the given flood events is to define a number of event classes, each includes flood hazards of several return periods (Bachmann, 2012). The assumptions made are: 1) the occurrence probability of each class is the difference between the upper bound and lower bound likelihood, 2) the damage is constant for the floods belonging to that event class and is equal to the damage of the given flooding lying in that class, 3) the damage is zero for the events with the exceedance probability higher than the last class, and 4) the associated damage of less frequent flood is equal to that of the first class.

In our study, 100-, 200-, and 1000-year flood constitute the hypothetical set of probable flood events (see chapter 4), based on which the probability-damage curve is generated, as illustrated in Figure 6-4. The occurrence probability and flood damage of event classes are reported in Table 6-1. As can be seen, several state variables are required to be identified in order to compute the flood damage and associated risk in the flood risk analysis module, which are summarized in Table 6-2.

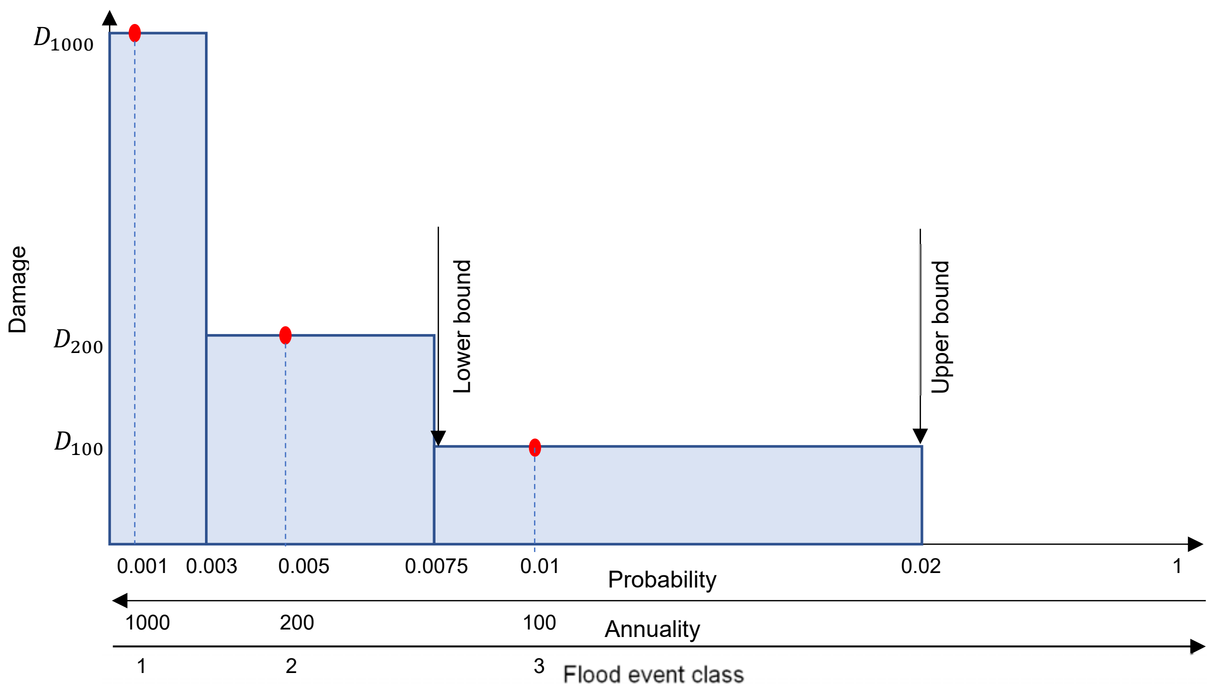


Figure 6-4. Probability-damage curve based on three flood events

Table 6-1. Occurrence probability and associated damage of flood event classes

Flood event class	Occurrence probability	Flood damage
Class 1	0.003	D_{1000}
Class 2	0.0045	D_{200}
Class 3	0.0125	D_{100}

Table 6-2. State variables of flood risk analysis module

State variable	Implementation	Source	Value
Seawater salinity	global	External source	28 ppt
Temperature	global	External source	3 °C
Salt-tolerance of crops	global	External source	Table 5-7
Soil electrical conductivity	Eq. (5-2) to Eq. (5-6)	Endogenous	Table 5-8
Water electrical conductivity	Eq. (5-7) to Eq. (5-10)	Endogenous	Table 5-8
Crop damage function	Eq. (5-11) to Eq. (5-16)	Endogenous	Figure 5-7
Time series of crop yield	global	Hydrological module	Final results
Flood hydrographs	global	External source	Figure 4-7
Exposure map of farmlands	global	External source	Figure 4-8
Inundated areas	global	Hydrodynamic module	Figure 4-9, Figure 4-10, and Figure 4-11
Probability-damage curve of floods	global	Endogenous	Figure 6-4

5. ABM platform: Decision-making module

In the next step, farmers choose their cropping pattern for the following year. Factors such as risk perception, social interaction, flood memory, and economic status influence farmers' decision-making under risk (see chapter 2). Furthermore, the uneven distribution of such influential factors across the population causes dissimilarities in choosing the behavioral strategy. To meet the objectives, we develop the decision-making module in combination with the flood risk analysis module within the ABM platform. A multi-stage process is designed and at each stage, the mentioned influential factors are added to the model as new features. This multi-stage process includes building the base farmers' decision-making model, creating geographically explicit decision-making, integrating human interactions, including flood memories, and incorporating principles of bounded-rationality into the model. Figure 6-5 illustrates the modeling steps and required data for developing the decision-making module in the ABM platform.

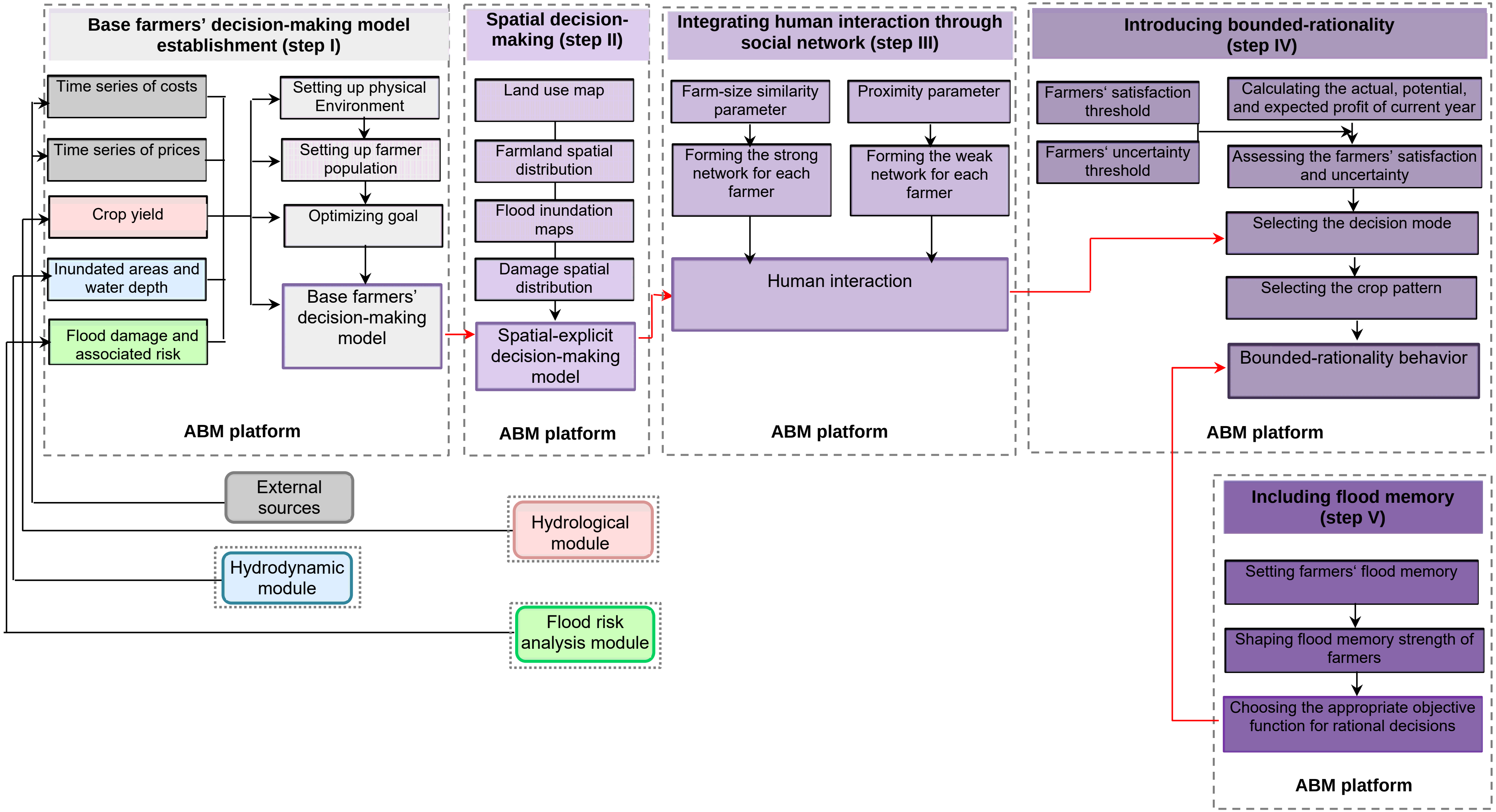


Figure 6-5. Modeling steps and required data for developing the decision-making module in the ABM platform

5.1 Establishing the base farmers’ decision-making model (step I)

We start to formulate farmers’ decision-making under uncertainty based on the standard agricultural economic models, in which farmers optimize their goal (Toft and O’Hanlon, 1979; Benli and Kodal, 2003). The rationale behind is that 1) people have access to complete and accurate information, 2) they are capable of using and processing the information, and 3) they look for the most optimal solution among all alternatives. In the light of such an optimization-based approach, farmers behave as economic optimizers and choose the crops that result in highest profit or lowest loss under the weather condition of the area and the market prices. Therefore, the model at this stage is applied to study the yearly economic decisions of rational farmers under the flood risk.

In this step, the physical environment is set up and matched to the predefined world in the Netlogo as a set of grids. The population of farm agents are then created and the farmlands are randomly assigned to them. The cultivated crops in the first year are distributed among farm agents in such a way that the total covered areas of crops are fulfilled (see Figure 3-14). The crop set in the first year includes spring canola, winter wheat, maise, and spring barley (see chapter 3).

Farmers’ profit

Flood damage to agricultural crops causes income loss of farmers even for a number of years. After the flood occurrence, expenses like costs of fertilizer, plant protection, and harvesting will be saved. However, some additional costs should be spent to improve the soil structure since remedial application of gypsum to neutralize saline soils may be required. Regardless of flooding, fixed costs such as regular labor, machinery, buildings, and land remain unchanged and should be spent.

Literature presents various economic indicators to evaluate flood damage to farmers. A majority of studies rely on the percentage of crop yield loss due to the flood hazard (Pierson *et al.*, 1994; Satrapa *et al.*, 2012). Other researches have used the reduction in gross product as the monetary value of crop yield loss (Dutta et al., 2003; Förster *et al.*, 2008). Gross margin has been also chosen as the damage proxy calculated by reducing variable production costs from the income of a farm (van Duinen *et al.*, 2015). According to Lacewell and Eidman, a suitable proxy is the net margin providing an estimate of average annual profit after subtracting the fixed costs from gross margin (Lacewell and Eidman, 1972). In their updated study, they included additional costs such as treatment and tillage in the net margin calculation (Lacewell *et al.*, 2006).

In our study, we use net margin as the economic indicator, assuming that farm agents observe flood-induced crop loss, perceive the flood damage as the net margin, and decide based on this information. The income of farmer i for the crop x in year t, $I_i(x,t)$, is then equal to:

$$I_i(x,t) = \sum_{k=1}^{N_i} Y_k(x,t) * P_k(x,t) * A(k) \tag{6-2}$$

where N_i is the number of cells constituting the farmland of farmer i and $A(k)$ presents the area of cell k. $Y_k(x,t)$ and $P_k(x,t)$ refer to yield and sell price of cultivated crop x on cell k in year t, respectively. The economic damage caused by flood event j to the farmland i with the cultivated crop x, $D_{j,i}(x,t)$, is estimated as:

$$D_{j,i}(x,t) = \sum_{k=1}^{N_i} Y_k(x,t) * P_k(x,t) * A(k) * YD(x,j) \tag{6-3}$$

where $YD(x,j)$ is damage function of crop x under flood event j (see chapter 5). The total costs, $TC_j(x,t)$, vary depending on the flood situation in the current year:

$$TC_j(x,t) = \sum_{k=1}^{N_i} (VC_{k,1}(x,t) + VC_{k,2}(x,t) + FC_k(x,t) + AC_k(x,t)) \tag{6-4}$$

where $FC_k(x,t)$ denotes the sum of the fixed costs for crop x in year t. $VC_{k,1}(x,t)$ are the expenditures spent before flood occurrence while $VC_{k,2}(x,t)$ refers to the cost for the rest of growing cycle of crop x only if there is no flooding in the year t. $AC_k(x,t)$ represents the additional costs required after the flood occurrence to improve the soil condition. The fixed costs are calculated on the per year basis while the variable costs are calculated on the per event basis as a part of the costs are avoided if no flood event occurs. The sale prices and management costs are obtained from (KTBL(a), 2019; KTBL(b), 2019), respectively. Figure 6-6 shows the sale prices of crops in the period 2005-2016.

Due to the uncertainty associated with flood events, the expected utility function plays role in decision-making under risk. If there is any flood insurance[2] that farmers can buy to compensate the flood damage to their crops, the expected profit of farmer i, $exp\_PR_i(x,t)$, is calculated as[3]:

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[2] As there is no insurance policy in Germany for farmers against storm surge, the relevant variables are assumed to be zero in the model. As a result, no flood insurance scenario can be investigated in our study.

[3] In general, the function of expected profit can be written as:

$$f(x,t) = exp\_PR(x,t) = I(x,t) - \sum_{k=1}^{N_i} ((VC_{k,1}(x,t) + FC_k(x,t)) - \sum_{j=1}^{N_j} P_j * D_j(x,t) - \sum_{j=1}^{N_j} P_j * AC_j(x,t) - I_p(t) + I_{average}(j)$$

$$exp\_PR_i(x,t) = I_i(x,t) - \sum_{k=1}^{N_i}((VC_{k,1}(x,t) + FC_k(x,t)) - \sum_{j=1}^{N_j} P_j * D_{j,} \sum_{j=1}^{N_j} P_j * AC_j(x,t) - I_{i,p}(t) + I_{i,average}(j) \quad (6\text{-}5)$$

where P_j presents the occurrence probability of flood event j (see section 4.2), I_p denotes the annual insurance premium paid by farmers, and $I_{i,average}$ is the cost paid to farmers after flood event j. Accordingly, the expected flood damage to farmer i, $exp\_D_i(x,t)$, is:

$$exp\_D_i(x,t) = \sum_{j=1}^{N_j} P_j * D_{j,i}(x,t) \quad (6\text{-}6)$$

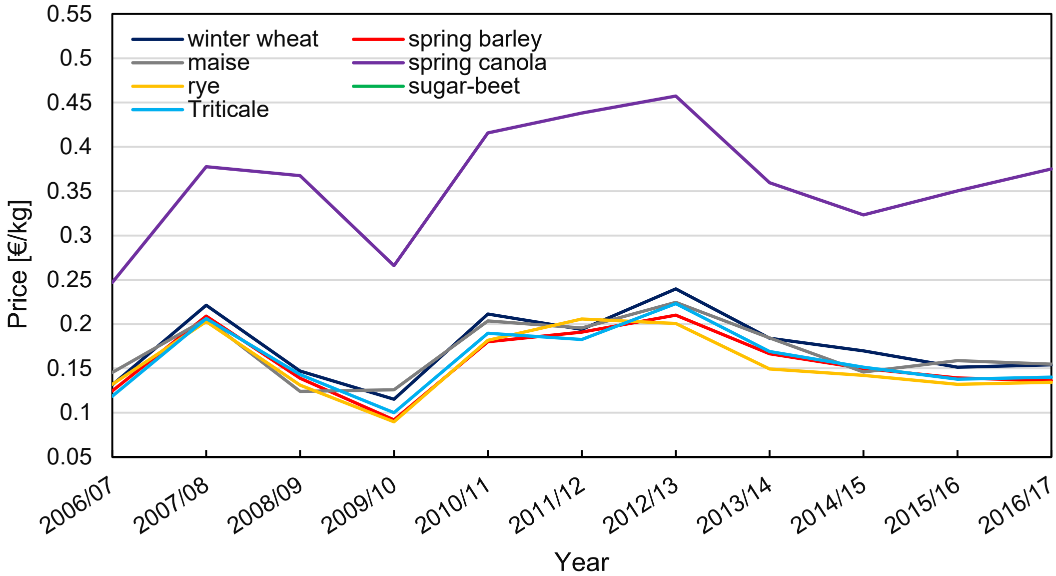


Figure 6-6. Sale price of crops (KTBL(b), 2019)

5.2 Creating spatially-explicit decision-making model (step II)

As discussed, farmers are heterogeneous in their attributes. Furthermore, they tend to interact with people who are living in neighborhoods or are similar in dimensions such as farm-size or age. This space-dependency of model properties demands a spatially-explicit decision-making module. Therefore, the spatial data achieved from the detailed GIS mapping are further integrated into the initial model. As a result, the real data can be assigned to the farmlands. In addition, it allows adding more layers to the model regarding the spatial distribution of farmers and the cultivated crops as well as the inundation areas under various flood scenarios. Such an explicit space representation assists in defining and visualizing spatial heterogeneity among farm agents. Figure 6-7 depicts the established spatially-explicit decision-making model which is further applied to develop human interactions within social networks.

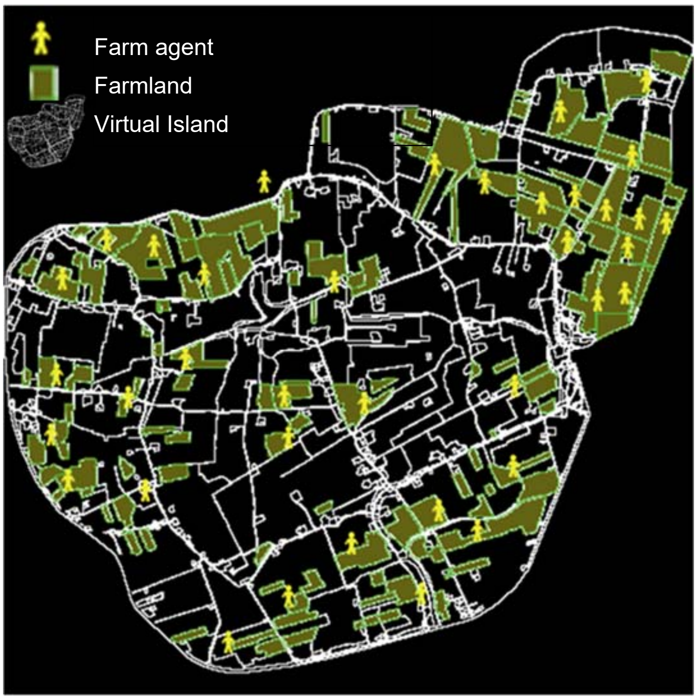


Figure 6-7. Spatially-explicit decision-making model in Netlogo

5.3 Integrating human interaction (social networks) (step III)

People do not make decisions in isolation, rather others influence them (Bougheas, Nieboer and Sefton, 2013; Le Dang *et al.*, 2014). Social networks have a significant effect on the individual decision-making since they enable people to be informed of new technologies and products in their communities. Based on the information exchange, individuals become aware of risks and adaptive strategies which may change their risk perception and cause them to rely on others in taking the decisions. Research has also shown how flood risk communication can propagate through social networks (Haer *et al.*, 2016).

To address human interactions, we construct the social networks and integrate them into the model. Farmers are connected by network links. It gives the possibility to explore the influence of social networks in the diffusion of individual decision-making over time. Whether or not the opinion and decision of neighboring farmer is influential at a given time, depends on the similarity between farmers. It should be noted that the constructed networks are unidirectional, only allow data to pass from one member to another, and not the other way around. As a result, farmers are unique in their social networks.

The topology of the social networks relies on the homophily principle, where the degree of similarity structures the desired networks (McPherson *et al.*, 2001). Similarity in farm-size and farm proximity are chosen as proxies in this study to explore the interaction of each farmer in his/her social networks. These are the parameters of the model and can be set directly by the user through the GUI of Netlogo. While the former shows how the similarity in the characteristics of two individuals may connect them, the latter represents the interaction of the people in close proximity. As a result, two social networks have influences on the decision-making process of farmer i: network of similar farmers ($NW_{i,s}$) and network of nearest neighbors ($NW_{i,n}$). For each farmer i, the social network size is dependent on the networks' parameters.

Due to lack of empirical data, we make assumptions about the two network parameters. It is also supposed that all farmers have the same degree of farm-size similarity and proximity. Table 6-3 reports assumed parameters to build the networks of farmers. Figure 6-8 shows similar farmers (green links) as well as neighboring farmers (red links) in social networks, represented in the GUI of Netlogo.

Table 6-3. Parameters of farmers' social network

Social network	Farm-size similarity	Proximity
	0.2	30

Figure 6-8. Networks of similar farmers ($\boldsymbol{NW_s}$) and of nearest neighbors ($\boldsymbol{NW_n}$) in Netlogo

5.4 Introducing bounded-rationality (step IV)

Limitations to the availability of information as well as to the processing capacities of humans in reality (see chapter 2) indicate the primary drawbacks of the rational decision-making. To get closer to the real, some unrealistic assumptions of the standard economic approaches are relaxed in this stage to equip the model with bounded-rationality principle. For this aim, Consumat approach (see chapter 2) is applied which is capable of addressing various decision strategies rather than pure optimization. Such an alternative approach allows for simulating a number of key processes especially in the situations, where people select a behavior from a set of options. Another advantage is the possibility to study the effects of different cognitive processes on individual decision-making over time. In Consumat approach, agents are equipped explicitly with the behavioral rules that are dependent on the information gained from the environment as well as their individual expectation. As a result, individual decision-making deviates from the objective risk perception and is influenced by social interactions.

Farmer need, satisfaction, and uncertainty

According to Consumat approach, each agent has three main needs including existence, social, and personality need, which can be satisfied by performing a behavior (Jager and Janssen, 2012). As crop cultivation is the main economic and profitable activity of farmers, behaviors such as crop pattern selection refer to economical dimensions of existence and satisfy the income need of farmers.

Farmer i' income satisfaction at time t, $S_i(t)$, is formulated as the ratio of her/his actual profit to her/his potential profit:

$$S_i(t) = \begin{cases} \dfrac{act\_PR_i(x,t)}{pot\_PR_i(x,t)}, & 0 < act\_PR_i(x,t) < pot\_PR_i(x,t) \\ 1, & 0 < pot\_PR_i(x,t) \leq act\_PR_i(x,t) \\ 0, & act\_PR_i(x,t) \leq 0 \end{cases} \tag{6-7}$$

while the actual profit of farmer i, $act\_PR_i(x,t)$, is calculated as follows:

$$act\_PR_i(x,t) = I_i(x,t) - TC_j(x,t) - D_{j,i}(x,t) - I_{i,p}(t) + I_{i,average}(j) \tag{6-8}$$

The potential profit, $pot\_PR_i(x,t)$, refers to the highest profit, a farmer can earn, which is equal to the farmers' profit in no flood occurrence situation:

$$pot\_PR_i(x,t) = I_i(x,t) - \sum_{k=1}^{N_i}(VC_{k,1}(x,t) + VC_{k,2}(x,t) + FC_k(x,t)) - I_{i,p}(t) \tag{6-9}$$

To distinguish between negative and positive experience, the uncertainty of farmer i at time t ($UC_i(t)$) is formulated as the conditional function in which only the negative experience results in the uncertainty level equaling to the ratio of the absolute difference between her/his expected profit and the actual profit, to the expected profit:

$$UC_i(t) = \begin{cases} \frac{|exp\_PR_i(x,t) - act\_PR_i(x,t)|}{|exp\_PR_i(x,t)|}, & 0 < act\_PR_i(x,t) < exp\_PR_i(x,t) \\ 0, & 0 < exp\_PR_i(x,t) \le act\_PR_i(x,t) \\ 1, & act\_PR_i(x,t) \le 0 \end{cases} \tag{6-10}$$

As $S_i(t)$ and $UC_i(t)$ vary between zero and one, dissatisfaction ($DS_i(t)$) and certainty level ($C_i(t)$) of farmer i can be calculated as the complimentary item of her/his satisfaction and uncertainty, respectively:

$$DS_i(t) = 1 - S_i(t) \tag{6-11}$$

$$C_i(t) = 1 - UC_i(t) \tag{6-12}$$

$DS_i(t)$ shows to what extent farmer i is dissatisfied with her/his actual profit in comparison to her/his potential profit. $C_i(t)$ depicts certainly level of farmer i as the ratio of her/his actual profit to the expected profit. Farmers' minimum satisfaction level ($S_{i,min}$) and maximum uncertainty level ($UC_{i,max}$) are model parameters assumed to be normally distributed across farmers with N (0.5, 0.16). Accordingly, farmers are heterogeneous in

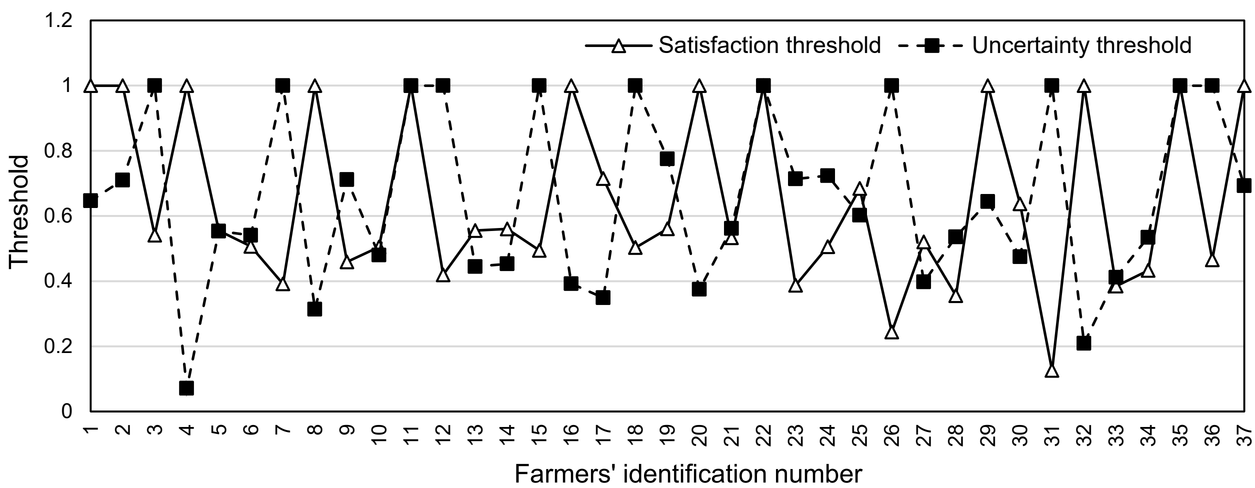


Figure 6-9. Satisfaction and uncertainty threshold of farm agents

their satisfaction as well as uncertainty tolerance. Figure 6-9 shows the assumed satisfaction and uncertainty threshold of farmers.

Behavioral options

Figure 6-10 illustrates the four cognitive decision-making strategies in Consumat approach (see also chapter 2). Depending on their level of need satisfaction and uncertainty, farmers engage in different cognitive processes to choose a behavior that make them feel more satisfied and certain. While satisfied farmers rely on strategies with less cognitive efforts such as repetition and imitation, dissatisfied farmers engage in reasoned behaviors (deliberation and inquiring) to increase their level of satisfaction. Uncertain farmers tend to become more certain by gaining more information about flood risk and others' decisions under risk. As a result, they are involved in social processing such as inquiring and imitation. Only the certain and satisfied farmer follows the habitual behavior and repeats the previous strategy.

Repetition

Repetition refers to the classical condition theory assuming that satisfying outcome reinforces the behavior (Skinner, 1938). Farmer i engages in the repetition strategy at the time t when she/he is certain ($UC_{i,t} < UC_{i,max}$) and satisfy ($S_{i,t} > S_{i,min}$). As a result, she/he will repeat her/his behavior X in the previous time step to remain satisfied:

$$X(i,t) = X(i,t-1) \tag{6-13}$$

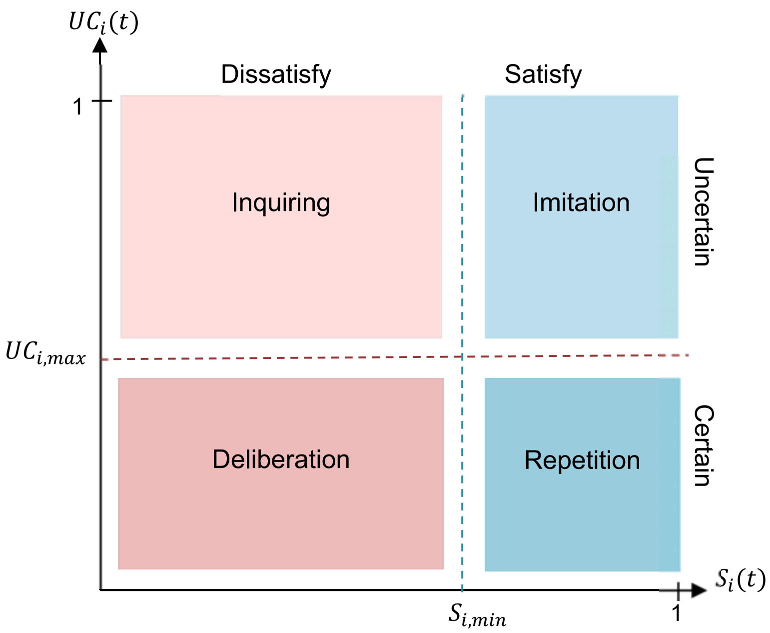


Figure 6-10. Consumat strategies depending on satisfaction and uncertainty level

Imitation

Imitation is related to the social leaning theory and theory of normative conduct (Cialdini *et al.*, 1991), based on which an agent imitates others if she/he is satisfied ($S_{i,t} > S_{i,min}$) but uncertain ($UC_{i,t} > UC_{i,max}$). Subsequently, farmer i considers the previous behavioral options of all farmers who are similar to her/him in terms of the farm-size. Then, she/he imitates the successful strategy implemented by the majority:

$$X(i,t) = X(\dots,t-1) \text{ of the majority} \in NW_{i,s} \tag{6-14}$$

Therefore, social network is considered enormously important to provide individuals with information about the behaviors of other.

Deliberation

Deliberation is governed by the standard economic theory for decision-making. Accordingly, when farmers are dissatisfied ($S_{i,t} < S_{i,min}$) and certain ($UC_{i,t} < UC_{i,max}$), they assess all options and choose the one that optimizes (maximize or minimize) their expected outcome (expected profit, expected damage, and etc.). Indeed, social networks do not play any special roles in optimizing decision-making as it is assumed that individuals access to the detailed and complete information about all behavioral options.

$$X(i,t) = f^{-1}(\text{optimize } [expected\ outcome_i(x,t-1)]) \tag{6-15}$$

Inquiring

According to the social comparison theory and theory of reasoned action (Fishbein and Ajzen, 1975), an agent engages in the inquiring if she/he is dissatisfied ($S_{i,t} < S_{i,min}$) and uncertain ($UC_{i,t} > UC_{i,max}$). Farmer i observes the previous behavioral options of all farmers who are similar to her/him or located nearby. Then, she/he seeks the successful strategy adopted by the majority and updates her/his mental map. Finally, she/he compares the expected outcome of that behavioral option with her/his own previous behavior and chooses the one that optimizes her/his expected outcome in the current time step:

$$X_1(i,t) = X(\dots,t-1) \text{ of the majority} \in NW_{i,s} \cup NW_{i,n} \tag{6-16}$$

$$X_2(i,t) = X(i,t-1) \tag{6-17}$$

$$X(i,t) = f^{-1}\left(\text{optimize } [expected\ outcome_i\left(X_1(i,t)\right), expected\ outcome_i\left(X_2(i,t)\right)]\right) \tag{6-18}$$

It should be noted that data and information regarding the behavioral options of others are only accessible by farmers over their social network.

5.5 Including flood memory (step V)

Past flood experiences can affect the individual decision-making and responsive behaviors if the person has not forgotten the event. As a result, such a flood memory provides a platform for increasing the individual adaptive capacity and flood resilience. According to the decay theory, memory weakens as more time passes resulting in less availability of information for later recovery (Thorndike, 1913). Memory strength can vary from second to a life time (McGaugh, 2000), as represented in Figure 6-11. While some events can be remembered even after long periods, some are forgotten immediately.

To explore the role of flood remembrance, we include the individuals' flood memory in the decision-making process and connect that with their objective function. For the purpose of the study, three flood memory scenarios are developed differing in the duration of individuals' flood memory as well as their yearly objective functions.

Table 6-4 summarizes the assumed flood memory scenarios. In the scenario that individuals have long-lasting memory, they will never forget flooding. Accordingly, they are assumed to minimize their expected damage in the rational behaviors. On the contrary, when people forget the flood event immediately, such a flood experience will not influence their actual and future decisions. Therefore, an economic optimizer chooses the crop with the highest expected profit. However, scenario with the long-term flood memory leads to remembering the flooding only for a limited number of years after the event. Here, we assume that farmers will forget flooding after two years. As a result, in the first two years after flood occurrence, their goal is to minimize their expected damage in their rational behaviors, while in the following years rational farmers try to earn the highest expected profit.

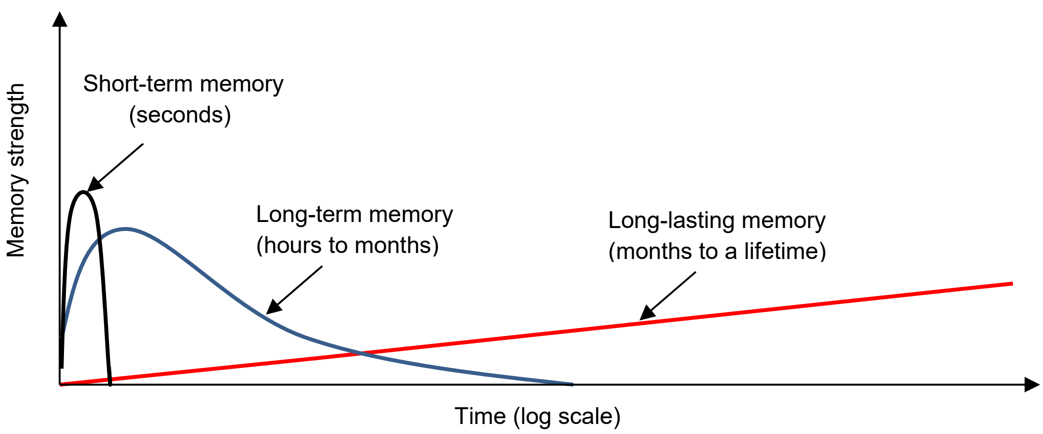


Figure 6-11. Memory consolidation phases (adapted from McGaugh, 2000)

Table 6-4. Flood memory scenarios and their assumptions

Flood memory scenario	Flood memory	Yearly objective function of rational farmers
Scenario 1	Short-term flood memory (Forgetting flood in a very short time)	$\max\ [exp\_PR_i(x,t)]$
Scenario 2	Long-lasting flood memory (remembering flood for the whole life)	$\min\ [exp\_D_i(x,t)]$
Scenario 3	Long-term flood memory (remembering flood only for the first two years after flooding)	$\min\ [exp\ \_D_i(x,t)]$ or $\max\ [exp\_PR_i(x,t)]$

As can be seen, decision-making module makes use of several state variables from other modules as well as the external sources. Table 6-5 reports the state variables of decision-making module.

Table 6-5. State variables of decision-making module

State variable	Implementation	Source	Value
Time series of crop yield	global	Hydrological module	Final results
Time series of crop prices	global	External source	Figure 6-6
Farmland spatial distribution	global	External source	Figure 4-8
Flood inundation maps	global	Hydrodynamic module	Figure 4-9, Figure 4-10, and Figure 4-11
Damage spatial distribution	global	Flood risk analysis module	Final results
Actual flood damage to farmers	Eq. (6-3)	Endogenous	Final results
Flood events in the simulation period	-	Assumption	Figure 6-1
Farm-size similarity	global	Assumption	Table 6-3
Proximity	global	Assumption	Table 6-3
Farmers' satisfaction threshold	random	Assumption	Figure 6-9
Farmers' uncertainty threshold	random	Assumption	Figure 6-9
Actual profit of farmers	Eq. (6-8)	Endogenous	Final results
Potential profit of farmers	Eq. (6-9)	Endogenous	Final results
Expected profit of farmers	Eq. (6-5)	Endogenous	Final results
Expected damage of farmers	Eq. (6-6)	Endogenous	Final results
Satisfaction level of farmers	Eq. (6-7)	Endogenous	Final results
Uncertainty level of farmers	Eq. (6-10)	Endogenous	Final results
Decision mode of farmers	Eq. (6-13) to Eq. (6-18)	Endogenous	Final results
Farmers' flood memory	Table 6-4	Assumption	Table 6-4 and Figure 6-11
List of crops	global	External source	Winter wheat, Maize, Spring barley, and Spring canola

6. ABM platform: Risk perception module

To mitigate the flood damage and associated risk, engagement of individuals in FRM plays a crucial role. Farmers as the most vulnerable group in farming community need to be informed about the flood risk, which may motivate them to pursue private adaptive responses. Risk perception "denotes the process of collecting, selecting, and interpreting signals about uncertain impacts of events" (Wachinger *et al.*, 2013). Therefore, it is the individual interpretation of flood hazards and needs to be incorporated into the decision-making process (Plattner *et al.*, 2006). However, risk perception has a complex framework influenced by factors such as individual feelings and previous flood experience (see chapter 2). Understanding the flood risk is also associated with the effective risk communication (Soane *et al.*, 2010; Meyer *et al.*, 2012; Bubeck *et al.*, 2013). On the other hand, socio-economic status of individuals and social networks play crucial role (Kreibich *et al.*, 2011).

Despite its importance, risk perception is rarely considered in the decision-making models due to its complexity and there is no standard approach in this domain. Particularly, when the focus shifts to the FRM, the role of risk perception is often ignored or under-developed and attempts to incorporate risk perception into flood management are limited to approaches such as expected utility theory (EUT) or Prospect theory. These two theories account for early variable-based approaches that quantify the flood risk based on the characteristics of risk itself and express that in the form of "Expected annual damage (EAD)" variable. Although both theories rely on a coherent set of economic assumptions, they are different in determining the individual risk judgment. While in EUT, risk is formulated as an objective property of an object or a situation and relies exclusively on the expert assessment, in the Prospect theory, risk is regarded as a subjective mental construction based on personal feelings and beliefs about the hazard occurrence or outcomes. Another example to represent the risk perception as a variable is the Bayesian Prospect theory (Haer *et al.*, 2017). Some studies determine the individual attitude toward uncertainty as the risk aversion variable and include that in the objective function (Ng *et al.*, 2011; Kind *et al.*, 2017).

Empirical research in the area of FRM and behavioral economics shows, however, the shortcomings of variable-based approaches. One challenge relates to the issue of modeling the risk perception as a variable that complies with the behavioral characteristics of individuals. Furthermore, determining a proper value that reflects aspects of individual risk judgment is not an easy task. Key findings in recent scientific advances in flood risk assessment also reveal that individual perceptions of the flood risk are largely shaped by thinking processes (Botzen and van den Bergh, 2012) and not only by a particular variable such as the likelihood occurrence of probable flood events.

According to Kunreuther, simple rules can sometimes better explain why people interpret a risky event as “a zero chance of occurrence” event to them (Kunreuther, 1996). Therefore, rule-based procedure is a more suitable approach within which a set of rules or heuristics are defined to formulate the individual risk perception (Abdulkareem *et al.*, 2018). Some studies develop a topology for flood hazards based on individual judgments about risk characteristics (Raaijmakers *et al.*, 2008; Altarawneh *et al.*, 2016). Another approach applied in the FRM, is the "as low as reasonably practicable" (ALARP) principle (FLOODsite, 2009). Such rule-based methods replace the risk perception variable with a procedure that is capable of incorporating the influential factors of risk perception in its formulation, particularly when empirical studies are conducted by social scientists to verify the process.

To investigate the role of individual risk judgment in adaptive behaviors, we equip our decision-making module with risk perception. Namely, we extend the spatially-explicit decision-making model established in section 5 to make a link between individual risk awareness, decision-making, and adaptive responses. To achieve the goals, a rule-based model of risk perception is developed to explore how individual adaptive behaviors are connected with the risk perception of flood hazards. Our risk perception model consists of three sequential steps including expert danger assessment, individual understanding of flood danger, and adoption of coping strategies, as depicted in Figure 6-12. Detailed information regarding risk perception and the influential factors can be found in chapter 2.

6.1 Assessing the danger of flood by experts (step I)

Flood risk communication plays a crucial role in risk management as it provides information that influences individual risk perception (Kellens *et al.*, 2009; Minano and Peddle, 2018). Furthermore, an effective flood risk communication can stimulate people to take informed decisions to protect themselves and their assets (Haer *et al.*, 2016). Commonly, governments are responsible for such a risk communication and information dissemination through guidelines, media, or internet websites.

EU Flood Directive encourages the member states to use flood maps to communicate flood risks to the public (Kellens *et al.*, 2009; Haer *et al.*, 2016). Flood maps are often recognized as a clear communication tool to inform people about the flood danger and to raise their awareness (Minano and Peddle, 2018). Obviously, maps need to be easily understandable by the public and accompanied with simple explanations (Kellens *et al.*, 2009). Furthermore, danger perception of people is correlated with the expert danger assessment (Siegrist and Gutscher, 2006) and, maps are more likely to be effective when the public trusts experts and governments (Meyer *et al.*, 2012).

Flood maps are presented in different forms, but in general, it is distinguished between flood hazard and flood risk maps. While the former provides information about the occurrence probability of various flood events and the associated inundated areas, the latter contains additional information about the consequences such as economic damage and number of fatalities.

For the purpose of this study, we use the flood hazard map as a tool to communicate with farmers and to define flood zones since such maps account for effective risk mitigation measures (Kellens *et al.*, 2009) and are widely applied in Germany (Meon *et al.*, 2006). Using hydrodynamic module, flood hazard maps are generated and analyzed. Next, different flood zones are defined for varying levels of flood danger. Areas that will be inundated by the flood event having a 1-percent annual chance occurrence in any given year are labeled as high hazard zones. Moderate and low hazard zones are the areas flooded between the limits of the 100- and 200-year flood, and 200- and 1000-year flood, respectively. The areas outside the inundated lands of 1000-year flood are labels as very low hazard zones. Subsequently, four zones are identified in our study ranging from high to very low hazard zones. Then, a degree of danger is assigned to each flood zone, as presented in Table 6-6. Finally, the flood hazard map is generated that contains information about flood zones and their danger level (D) and is understandable to public (see Figure 6-13).

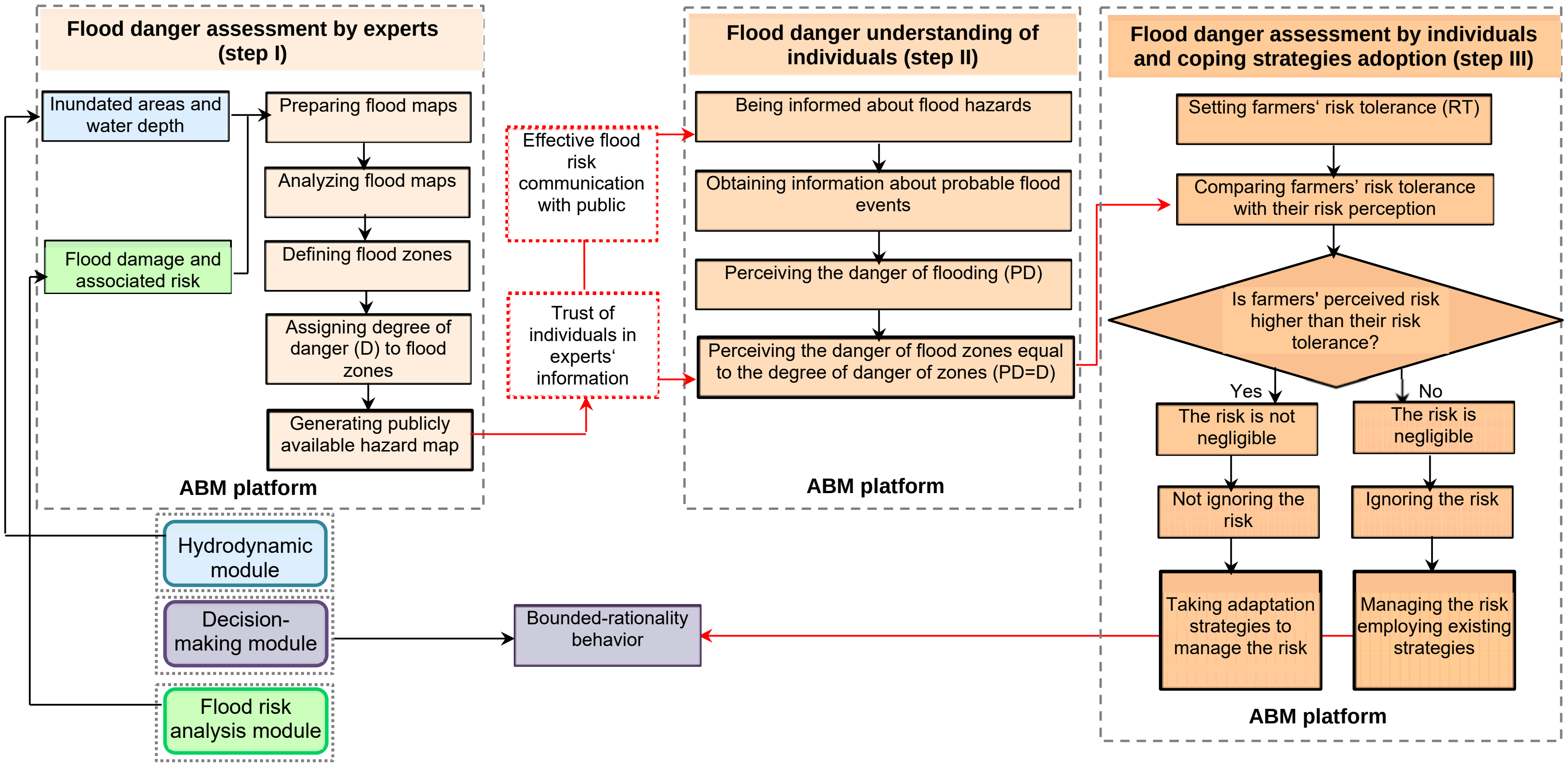


Figure 6-12. Modeling steps and components of individual cognition of the flood risk in the ABM platform

Table 6-6. Classified flood zones and defined danger levels

Zone	Hazard zone	Description	Degree of danger
Zone 1	High hazard	Flood at least once in 100 years	6
Zone 2	Moderate hazard	Flood at least once in 100-200 years	5
Zone 3	Low hazard	Flood at least once in 200-1000 years	4
Zone 4	Very low hazard	Flood rare than once in 1000 years or never	3

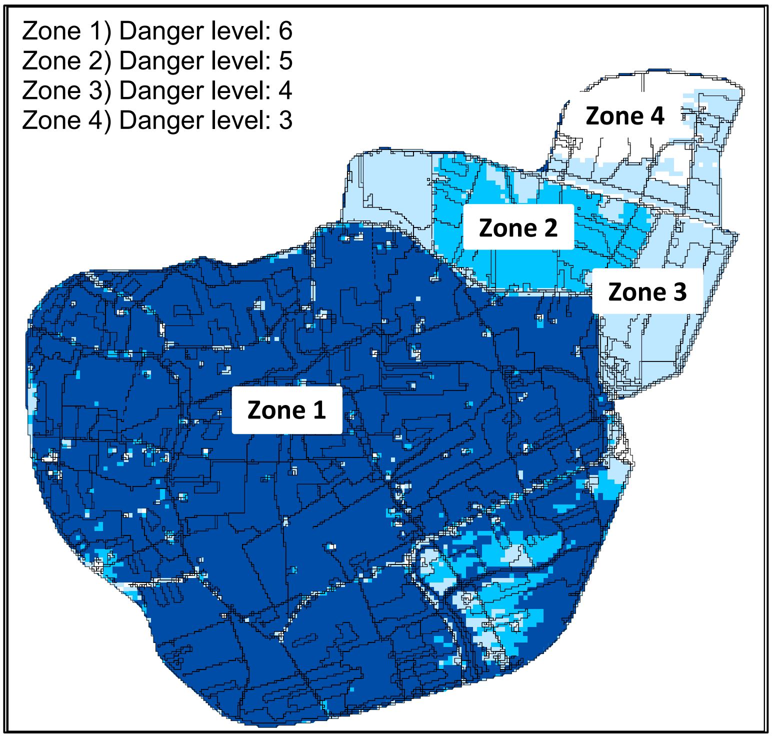


Figure 6-13. Flood hazard map showing hazard zones with four danger levels

6.2 Perceiving the flood danger by individuals (step II)

Using the flood hazard map as an aid for the effective communication of flood risk, farmers get informed about flood hazards and obtain information about the probable flood events. Assuming that farmers trust the flood hazard map provided by experts and published by the government, each individual perceives the flood danger (PD_i) of the area she/he is living in, equivalent to the level of danger (D_i) provided by experts in the maps:

$$PD_i = D_i \tag{6-19}$$

Figure 6-14 indicates the level of flood danger that farmers perceive depending on the zone they are living in. The danger level varies from very low to high among farmers illustrated by four color codes. It can be observed that farmers who are living in the northeast of the Island, perceive the flood danger at a low level due to the lower exposure of their farmland to probable flood events.

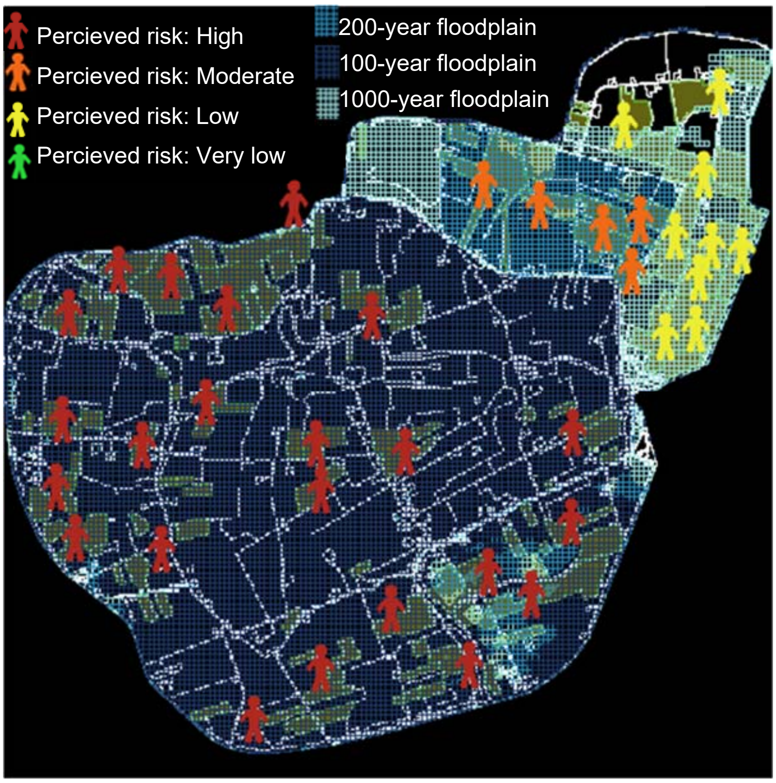


Figure 6-14. Flood risk perception of farm agents (illustrated in Netlogo)

6.3 Assessing the flood danger by individuals and taking adaptation responses (step III)

In the last step, individuals relate their danger perception (PD) to their risk tolerance (RT). The risk tolerance is the individual willingness to avoid or accept risk. So, the perceived risk below the risk tolerance is regarded as insignificant and further effort is not likely to be required to reduce the damage and associated risk. This is in accordance with the ALARP principle, which is widely accepted across most disciplines for the evaluation of tolerable risk (Sayers *et al.*, 2003).

For the purpose of this study, three farm populations are defined differing in the level of risk tolerance: risk-averse, risk-taker, and mix population. The risk tolerance is assigned to farm agents at random ranging from 0-2 to risk-averse farm population, 7-9 to risk-taker farm population, and 0-9 to the mix farm population. Figure 6-15 indicates the risk tolerance of three groups as well as their risk perception (see also Figure 6-14). Risk-averse farm population consists of the most cautious farm agents who are more likely to choose risk mitigation strategies. Each farmer compares her/his danger perception shaped after observing the flood hazard maps (see section 6.2) with her/his risk tolerance and therefore, pays less attention to the flood if her/his perception is below her/his risk tolerance. Accordingly, such a farmer does not consider adaptation responses but rather he manages the risk by employing existing strategies in her/his individual decision-making.

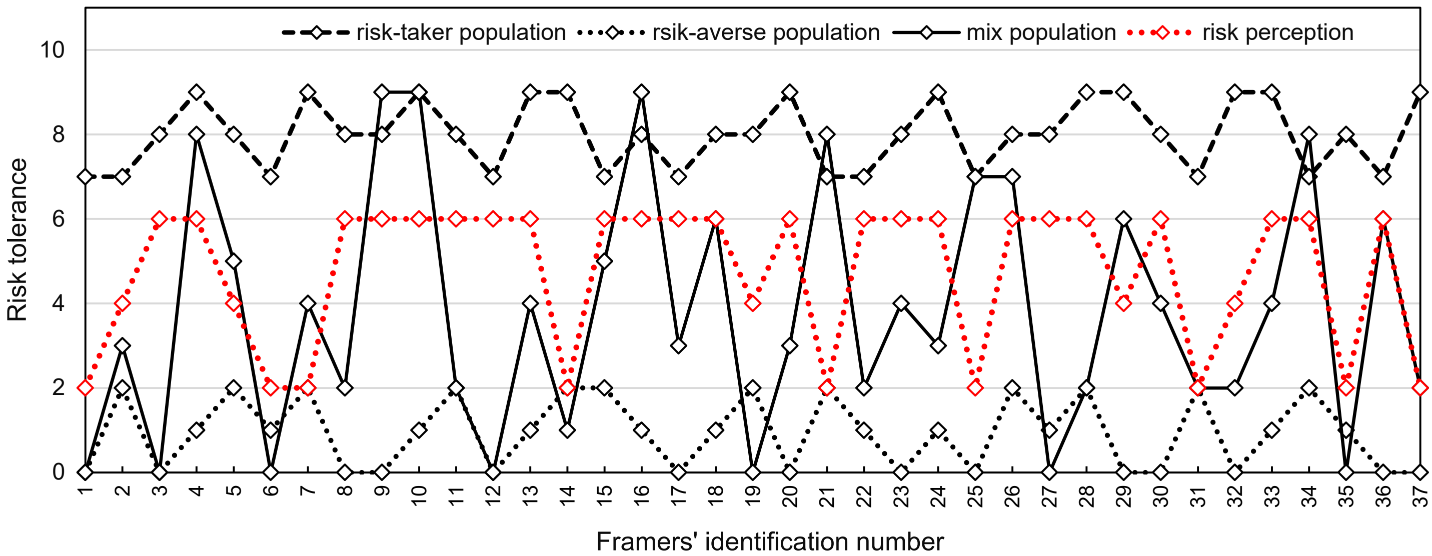


Figure 6-15. Risk tolerance of farm populations

According to a survey questionnaire conducted in the HoRisK project (Schüttrumpf *et al.*, 2013), farmers living in the coastal zones of the North Sea, are aware of salinity issues and damage to crops due to saline seawater. Hence, agricultural adaptation policies such as insurance and changing crop pattern as well as cultivating salt-tolerant crops can help farmers to mitigate their crop damage or compensate a part of their economic loss.

In Germany, however, no flood insurance is available to help farmers recover after storm surge floods and there is lack of data in this regard. Consequently, we have implemented two adaptation options in the model: changing crop pattern and cultivating salt-tolerant crops in the region. To meet the objectives, a number of salt-tolerant crops are introduced at the beginning of the simulation for sustainable management of flood in agriculture. A list of salt-tolerant crops in Germany is presented in Table 5-7. The state variables of three steps of the risk perception module are reported in Table 6-7.

Table 6-7. State variables of risk perception module

State variable	Implementation	Source	Value
Farmland spatial distribution	global	External source	Figure 4-8
Flood inundation maps	global	Hydrodynamic module	Figure 4-9, Figure 4-10, and Figure 4-11
Damage spatial distribution	global	Flood risk analysis module	Final results
Flood plain zoning	-	Endogenous	Figure 6-13
Danger degree of flood zones	global	Endogenous	Table 6-6
Farmers’ risk perception	Eq. (6-19)	Endogenous	Figure 6-14
Farmers’ risk tolerance	random	Assumption	Figure 6-15
Existing strategies	global	External source	Choosing among traditional crops: Winter wheat, Maize, Spring barley, and Spring canola
Adaptation strategies	global	External source	Changing crop pattern/using salt-tolerant crops
List of salt-tolerant crops	global	External source	Table 5-7: Rye, Sugar beet, and Triticale

7. Conclusions and outlook

The purpose of this chapter was to develop an experimental platform to simulate farmers’ decision-making in response to flood under the influence of social interaction, individual risk perception, flood memory, and limited access to information. Due to the complexities of human behaviors in the social environment, interdisciplinary approaches that can address the above aspects are the most appropriate ones. Among them, Agent Based Modeling is used in this study to integrate FRM and individual adaptive decision-making under risk for a semi-hypothetical farm population living in the coastal region. This new style of modeling allows us to include complexities of human behaviors in the social environment, on one hand, and steps of flood management process, on the other hand. Such an experimental platform also provides us with the possibility to simulate the human interactions and changing environment resulting in a more holistic flood risk assessment approach. More specifically, we established the ABM platform in a way to be used as a basis for all desired modules.

To achieve the goals, firstly, the flood risk analysis module was developed to perform flood risk assessment within the ABM platform. Connecting with the hydrological module and hydrodynamic module, crop yield response to saline water was modeled which was then used to calculate the flood risk at the micro-level. In combination with the flood risk analysis module, the base farmers' decision-making model was established to study the annual economic decisions of rational farm agents under risk of flooding. Due to space-dependency of model properties, spatial features were added and the spatial-explicit decision-making model was developed. Since people do not make their decisions in isolation, we then equipped our farm agents with social interactions through two social networks: network of similar farmers and network of nearest neighbors. As there are limitations to the availability of information as well as to the processing capabilities of humans in reality, some unrealistic assumptions of economic approaches were relaxed in the next step to allow farm agents to make decisions under bounded-rationality principles. In order to explore the role of flood remembrance in farmers' response, individuals' flood memory was included in the decision-making process. Finally, the developed decision-making module was extended to make a link between risk awareness, decision-making, and adaptive responses. For this aim, a 3-step rule-based model of risk perception was developed which enables farm agents to engage in private adaptive responses in FRM.

It should be noted that the model takes advantage of real data (of Pellworm Island) in establishing the hydrological module, hydrodynamic module, and flood risk analysis module. However, due to lack of empirical data, we made assumptions about the required parameters of decision-making module as well as risk perception module. Figure 6-16 provides an interface of the established ABM platform in GUI of Netlogo. A part of the implemented codes is presented in Figure 6-17. The established ABM platform, called ABMFaFo, is used in the next chapter (in connection with other modules developed in the previous chapters of the research) to simulate yearly farmers' decision-making in response to flood under the influence of social behaviors (see Figure 6-18).

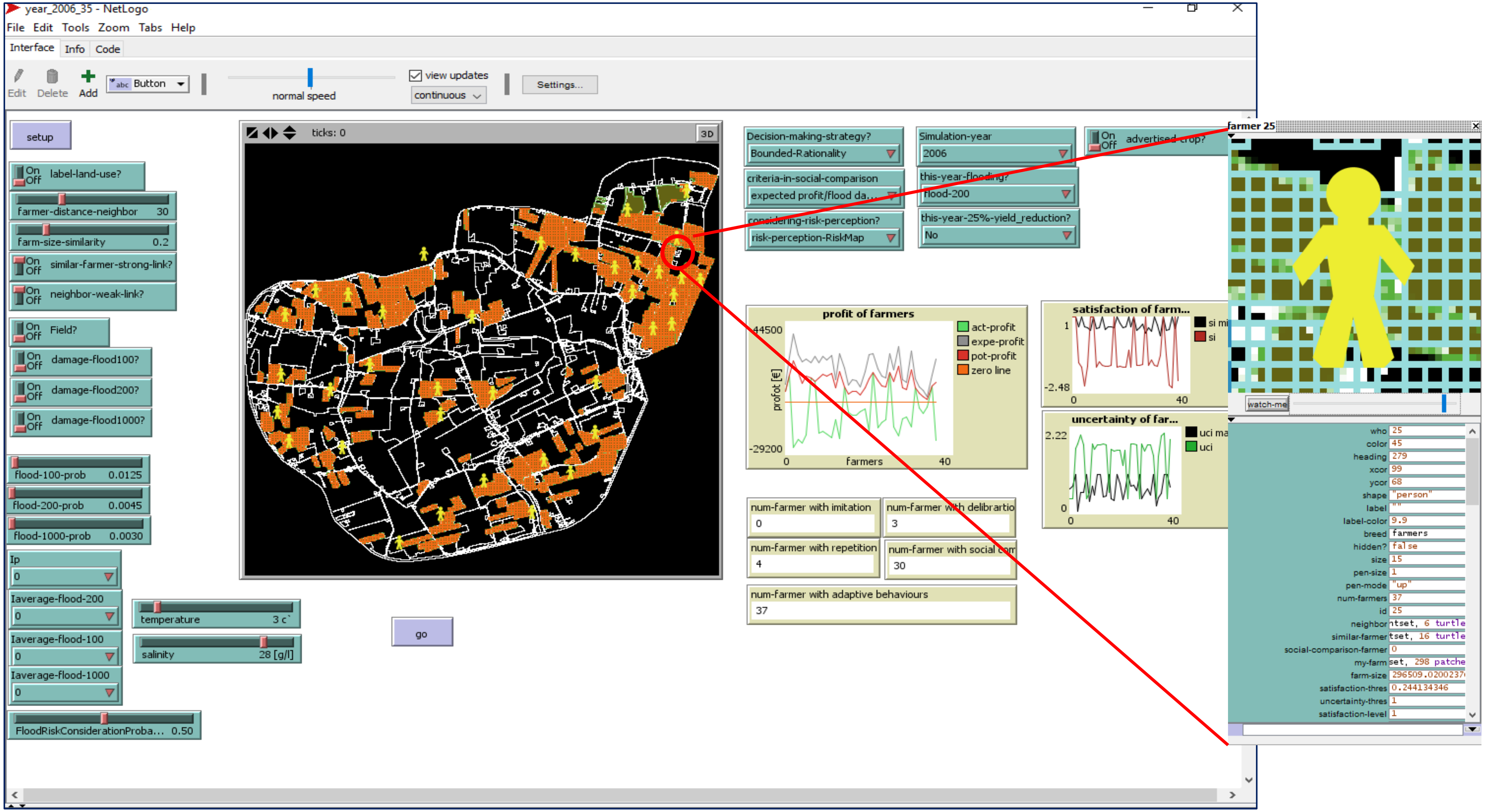
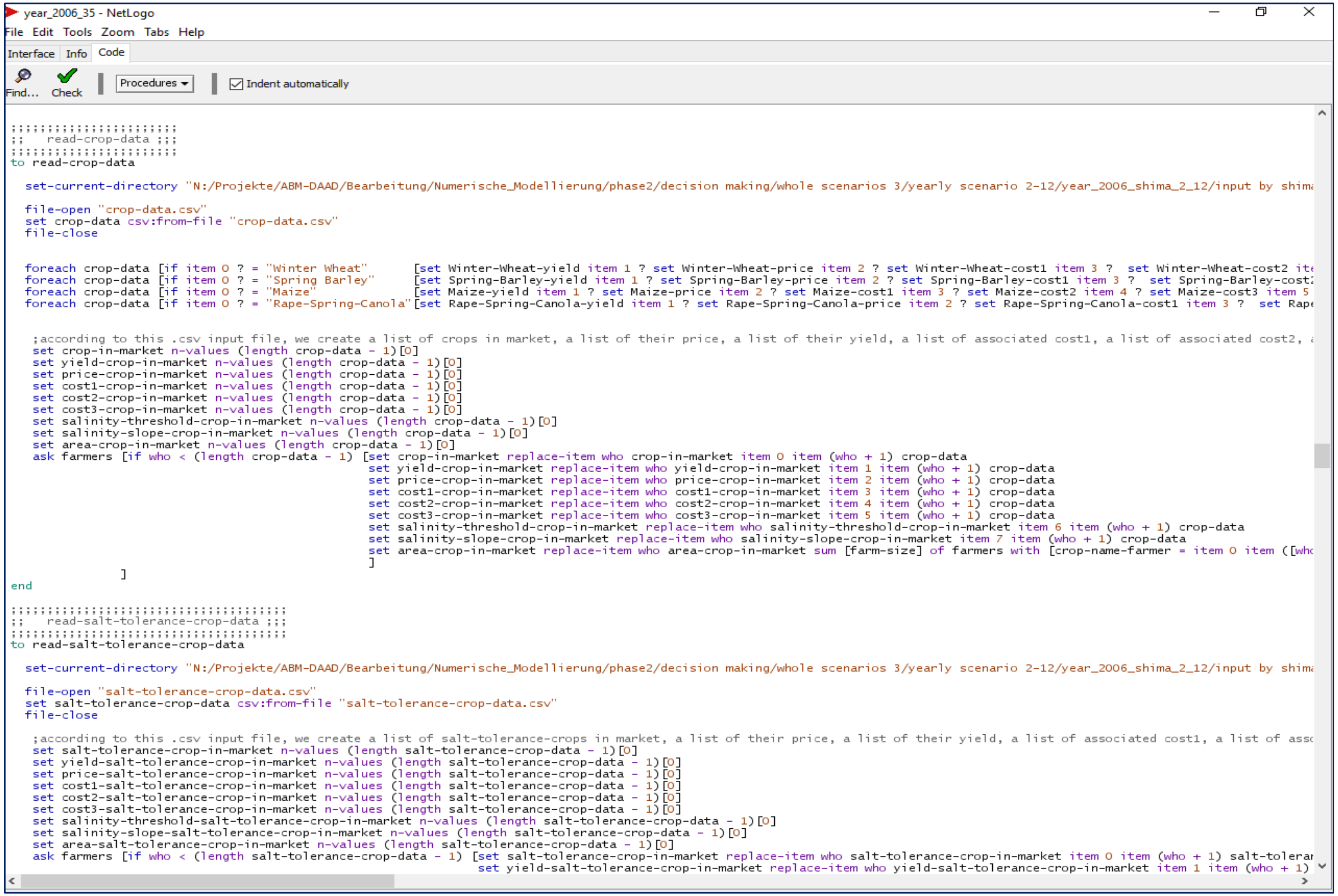


Figure 6-16. The interface of the established ABM platform in GUI of Netlogo




```
;;;;;;;;;;;;;;;;;;;;;;;
;;   read-crop-data ;;;
;;;;;;;;;;;;;;;;;;;;;;;
to read-crop-data

  set-current-directory "N:/Projekte/ABM-DAAD/Bearbeitung/Numerische_Modellierung/phase2/decision making/whole scenarios 3/yearly scenario 2-12/year_2006_shima_2_12/input by shima

  file-open "crop-data.csv"
  set crop-data csv:from-file "crop-data.csv"
  file-close


  foreach crop-data [if item 0 ? = "Winter Wheat"      [set Winter-Wheat-yield item 1 ? set Winter-Wheat-price item 2 ? set Winter-Wheat-cost1 item 3 ?  set Winter-Wheat-cost2 ite
  foreach crop-data [if item 0 ? = "Spring Barley"     [set Spring-Barley-yield item 1 ? set Spring-Barley-price item 2 ? set Spring-Barley-cost1 item 3 ?  set Spring-Barley-cost
  foreach crop-data [if item 0 ? = "Maize"             [set Maize-yield item 1 ? set Maize-price item 2 ? set Maize-cost1 item 3 ? set Maize-cost2 item 4 ? set Maize-cost3 item 5
  foreach crop-data [if item 0 ? = "Rape-Spring-Canola"[set Rape-Spring-Canola-yield item 1 ? set Rape-Spring-Canola-price item 2 ? set Rape-Spring-Canola-cost1 item 3 ?  set Rape

   ;according to this .csv input file, we create a list of crops in market, a list of their price, a list of their yield, a list of associated cost1, a list of associated cost2,
   set crop-in-market n-values (length crop-data - 1)[0]
   set yield-crop-in-market n-values (length crop-data - 1)[0]
   set price-crop-in-market n-values (length crop-data - 1)[0]
   set cost1-crop-in-market n-values (length crop-data - 1)[0]
   set cost2-crop-in-market n-values (length crop-data - 1)[0]
   set cost3-crop-in-market n-values (length crop-data - 1)[0]
   set salinity-threshold-crop-in-market n-values (length crop-data - 1)[0]
   set salinity-slope-crop-in-market n-values (length crop-data - 1)[0]
   set area-crop-in-market n-values (length crop-data - 1)[0]
   ask farmers [if who < (length crop-data - 1) [set crop-in-market replace-item who crop-in-market item 0 item (who + 1) crop-data
                                                 set yield-crop-in-market replace-item who yield-crop-in-market item 1 item (who + 1) crop-data
                                                 set price-crop-in-market replace-item who price-crop-in-market item 2 item (who + 1) crop-data
                                                 set cost1-crop-in-market replace-item who cost1-crop-in-market item 3 item (who + 1) crop-data
                                                 set cost2-crop-in-market replace-item who cost2-crop-in-market item 4 item (who + 1) crop-data
                                                 set cost3-crop-in-market replace-item who cost3-crop-in-market item 5 item (who + 1) crop-data
                                                 set salinity-threshold-crop-in-market replace-item who salinity-threshold-crop-in-market item 6 item (who + 1) crop-data
                                                 set salinity-slope-crop-in-market replace-item who salinity-slope-crop-in-market item 7 item (who + 1) crop-data
                                                 set area-crop-in-market replace-item who area-crop-in-market sum [farm-size] of farmers with [crop-name-farmer = item 0 item ([wh
                                                 ]
               ]
end

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;   read-salt-tolerance-crop-data ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
to read-salt-tolerance-crop-data

  set-current-directory "N:/Projekte/ABM-DAAD/Bearbeitung/Numerische_Modellierung/phase2/decision making/whole scenarios 3/yearly scenario 2-12/year_2006_shima_2_12/input by shima

  file-open "salt-tolerance-crop-data.csv"
  set salt-tolerance-crop-data csv:from-file "salt-tolerance-crop-data.csv"
  file-close

   ;according to this .csv input file, we create a list of salt-tolerance-crops in market, a list of their price, a list of their yield, a list of associated cost1, a list of ass
   set salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   set yield-salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   set price-salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   set cost1-salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   set cost2-salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   set cost3-salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   set salinity-threshold-salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   set salinity-slope-salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   set area-salt-tolerance-crop-in-market n-values (length salt-tolerance-crop-data - 1)[0]
   ask farmers [if who < (length salt-tolerance-crop-data - 1) [set salt-tolerance-crop-in-market replace-item who salt-tolerance-crop-in-market item 0 item (who + 1) salt-tolera
                                                                set yield-salt-tolerance-crop-in-market replace-item who yield-salt-tolerance-crop-in-market item 1 item (who + 1)
```

Figure 6-17. A part of the implemented codes of the ABM platform in Netlogo

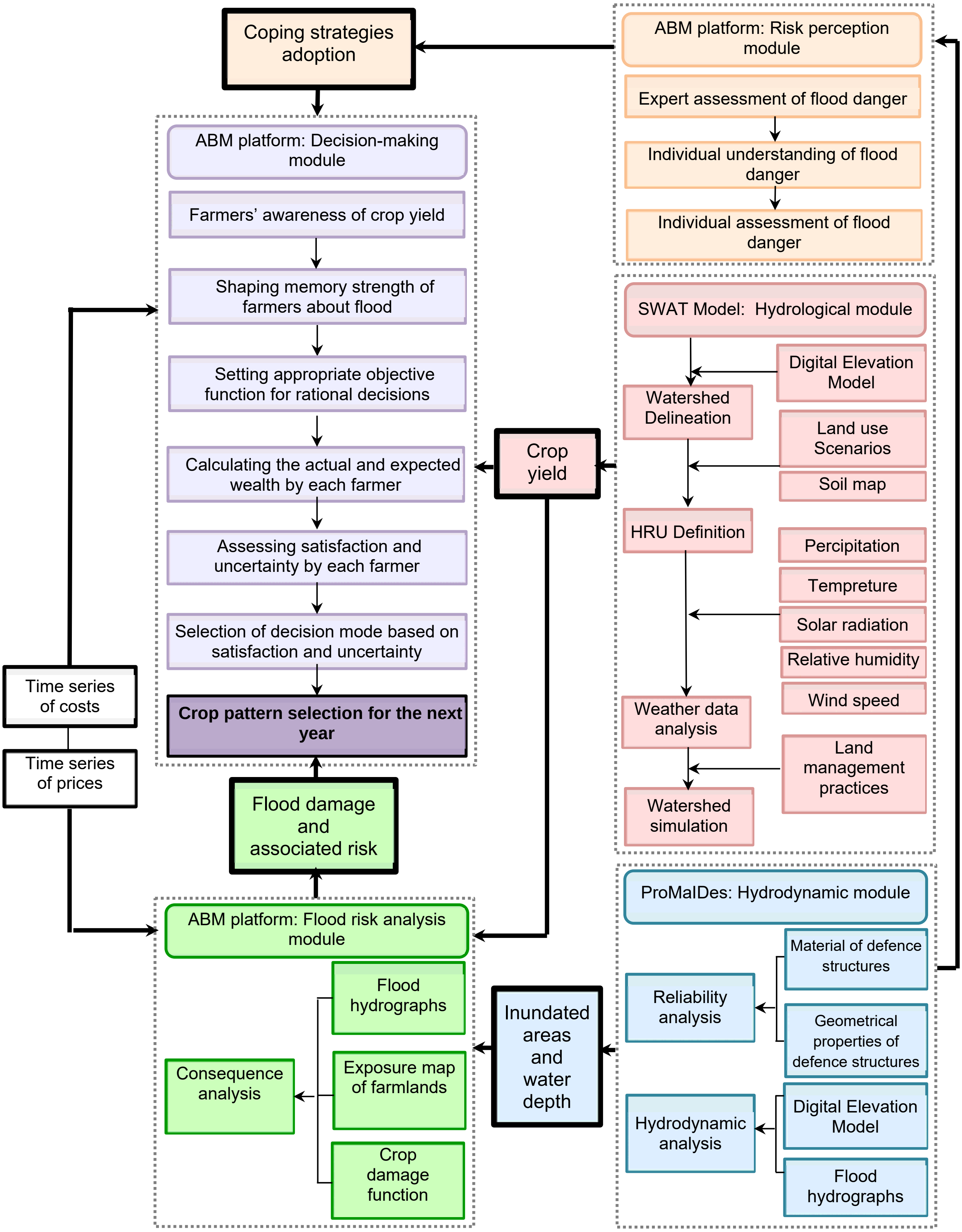


Figure 6-18. Flow diagram of the ABMFaFo in each year, the modules, and their connections

Chapter 7 Results and discussion

1. Simulation experiments

The "**A**gent **B**ased **M**odel for **fa**rmer-**flo**od interaction (ABMFaFo)" described in the previous chapters is run to study farmers' decision-making in response to flood under the influence of individual flood risk perception, social interaction, flood memory, and limited information. To achieve the goals, the following questions are addressed: (i) how flood occurrence changes the farmers' decision-making, (ii) how individual risk perception influences adaptive behaviors, (iii) how farmers adjust their behaviors over time under the influence of social interactions, and (iv) how past flood experiences and flood memory play role.

Table 7-1 presents the simulation scenarios that are conducted in the study. As seen, the experiments differ in flood risk perception and flood memory of the farm agents constituting the population. They also vary in the frequency of "200-year flood" in the simulation period. To answer the research questions, we compare a set of simulation scenarios which are different only in one aspect. Such a comparison allows us to investigate the impacts of the desired feature at a time.

Note that farm agents in all scenarios are bounded-rational and make their decision based on the heuristic rules in Consumat approach. Every experiment is run for the time horizon 2005-2016, including one year of warm up period for the model. Initial cropping pattern at the start of all simulations consists of winter wheat, spring barley, maize, and spring canola. Figure 7-1 illustrates areas of cultivated crops on the Pellworm Island in year 2006.

Table 7-1. Simulation scenarios

Experiment	Flood risk perception	Flood memory	Flood frequency
Exp1	A Population of 37 risk-averse farmers	Long-lasting	200-year flood in year 2006,2010, 2014
Exp2	A Population of 37 risk-averse farmers	Long-term	200-year flood in year 2006,2010, 2014
Exp3	A Population of 37 risk-taker farmers	Long-lasting	200-year flood in year 2006,2010, 2014
Exp4	A Population of 37 risk-taker farmers	Long-term	200-year flood in year 2006,2010, 2014
Exp5	A Population of 37 risk-taker farmers	Short-term	200-year flood in year 2006,2010, 2014
Exp6	A population of risk-taker and risk-averse farmers	Long-term	200-year flood in year 2006,2010, 2014
Exp7	A Population of 37 risk-averse farmers	Long-lasting	No flood in the simulation period
Exp8	A Population of 37 risk-taker farmers	Long-lasting	No flood in the simulation period
Exp9	A Population of 37 risk-taker farmers	Short-term	No flood in the simulation period
Exp10	A population of risk-taker and risk-averse farmers	Short-term	No flood in the simulation period

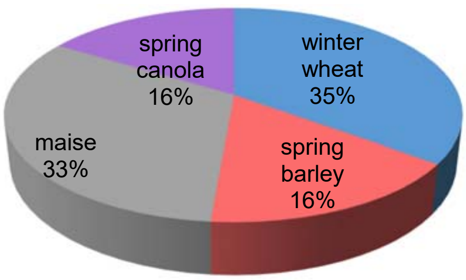


Figure 7-1. Agricultural land use area [%] in year 2006

Except for farmers' risk perception, flood memory, and flood frequency, same land management practices as well as time series of crop prices, costs, and weather variables are applied across all simulations. In addition, farmers' uncertainty threshold, farmers' satisfaction threshold, farmers' risk tolerance, farm-size similarity and proximity, farmland distribution and size, and danger degree of flood zones remain unchanged over time and experiments.

2. Results

2.1 Role of flood frequency

We explore the influence of flood frequency on system dynamics, in particular on farmers' behaviors over time. For this aim, two experiments Exp1 and Exp7 are run to compare the decision-making of risk-averse farmers with long-lasting flood memory under two flood scenarios: 1) occurrence of three "200-year flood" and 2) no flood occurrence in the simulation period. Note that although in the latter scenario no flood occurs in the simulation period, there is still the risk of flooding and farm agents are aware of that.

Figure 7-2 depicts actual agricultural flood damage of the region when three "200-year flood" strike the area in the simulation period. As can be seen, shortly after the disaster, flooding causes extensive (agricultural) economic damage because of sudden onset of the event. It is in contrast with slow-onset events such as drought which lasts from weeks to years and whose effects are accumulated slowly over time.

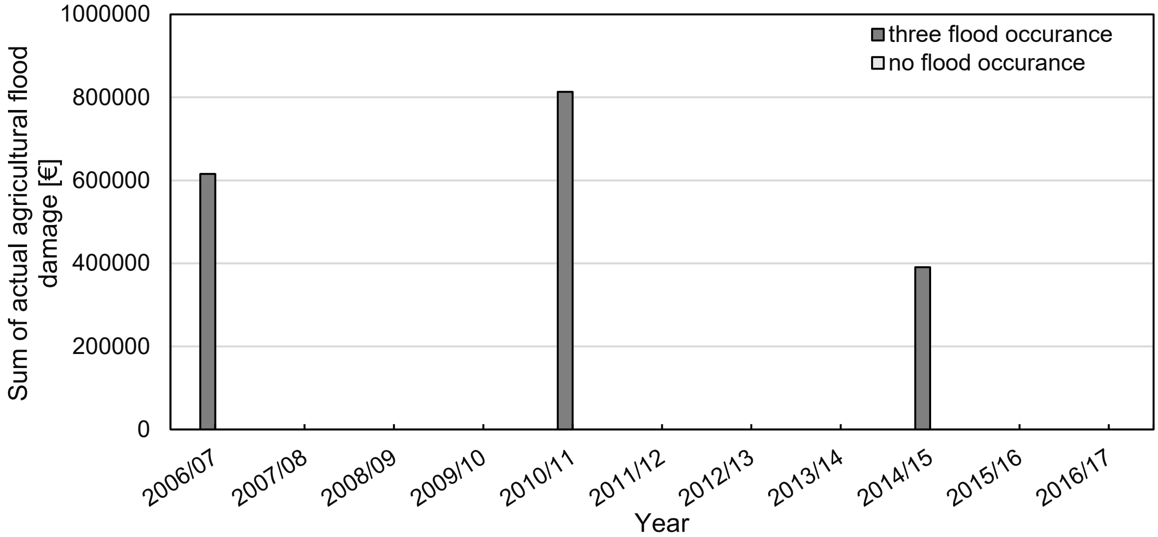


Figure 7-2. Actual agricultural flood damage at the regional-level over years for the risk-averse farm population with long-lasting flood memory when 200-year flood occurs in year 2006, 2010, and 2014 (Exp1) and when no flood occurs in the simulation period (Exp7)

In this manner, flooding impacts actual profits of the farm agents whose farmland is exposed to the 200-year flood. The more inundated the farmland, the more sensitive the farmer to the flood. Figure 7-3 compares regional agricultural profit under the two flood frequency scenarios. From the figure it is apparent that farmers' profit is always positive when no flood occurs in the simulation period. According to the figure, flood occurrence causes income loss of the regional system over the whole simulation period. It can be observed that in year 2006, flooding acts as a shock and reduces actual profits of endangered farmers in such a strong way that the regional actual profit turns negative. However, the regional profit gets positive again in the following year because of maintenance practices such as improvement in the soil structure. The figure shows that impacts of flooding diminish progressively over time. The reason is that farmers have long-lasting flood memory with adaptive learning. Note that annual variability of the weather condition as well as prices and crop yields lead to fluctuations in the actual profits in both scenarios.

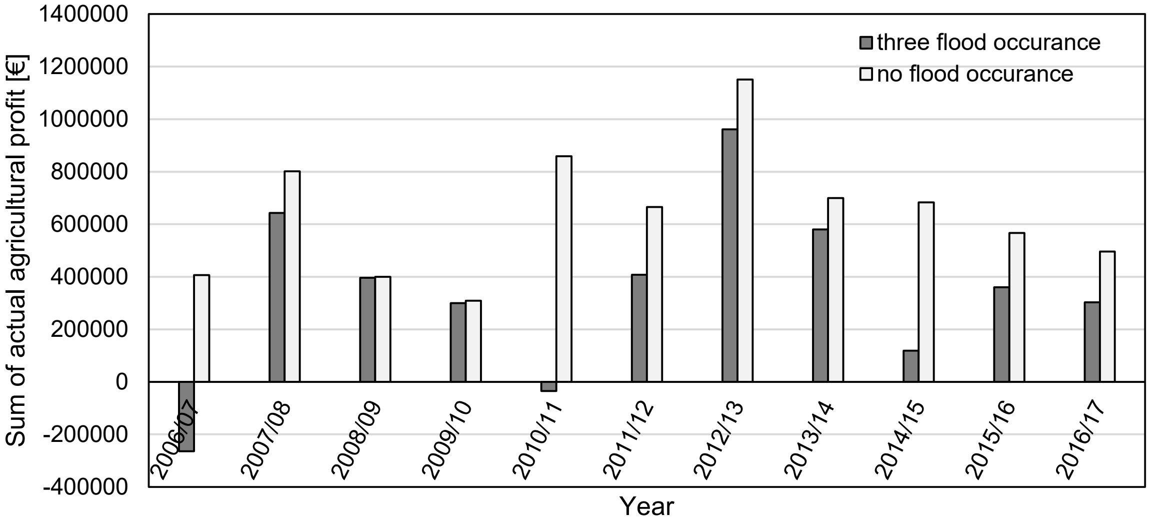


Figure 7-3. Actual agricultural profit at the regional-level for the risk-averse farm population with long-lasting flood memory when 200-year flood occurs in year 2006, 2010, and 2014 (Exp1) and when no flood occurs in the simulation period(Exp7)

To investigate responses of farmers under various flood scenarios, Figure 7-4 and Figure 7-5 compare the percentage of farm agents cultivating each crop over the simulation period in no flood occurrence and three “200-year flood” occurrences scenario, respectively. As risk-averse farmers with long-lasting flood memory constitute the farm populations in both scenarios, it is a trend to take adaptive strategies and to select the more resistant crop to saline seawater (see Figure 5-7). Therefore, year 2007 sees a significant growth in cultivation of triticale in both scenarios.

The results, however, show the larger share of farm agents in adoption of triticale in year 2007 under no flood occurrence scenario. It is due to the fact that triticale is new to local farmers and only those who deliberate, access to complete information of the crop. Subsequently, cultivation of triticale should be started up by economic optimizing agents. In this manner, the more the number of farmers deliberating, the more the popularity of this new crop. To compare the number of deliberators under both scenarios, Figure 7-6 and Figure 7-7 show how risk-averse farmers with long-lasting flood memory switch between the four behavioral strategies in Consumat approach in the two flood frequency scenarios. In the beginning of Exp1, a 200-year flood happens and most farmers face sudden loss of income even to negative values (see Figure 7-3). Such a shock event causes the majority (81%) of farmers engage in inquiring (see Figure 7-7), which in turn decreases the number of economic optimizing farmers to 8 %. In contrast, when no flood occurs in the beginning, 18% of the farm population engage in the deliberation. As a result, more farmers grow triticale in the region in year 2007 under no flood occurrence scenario.

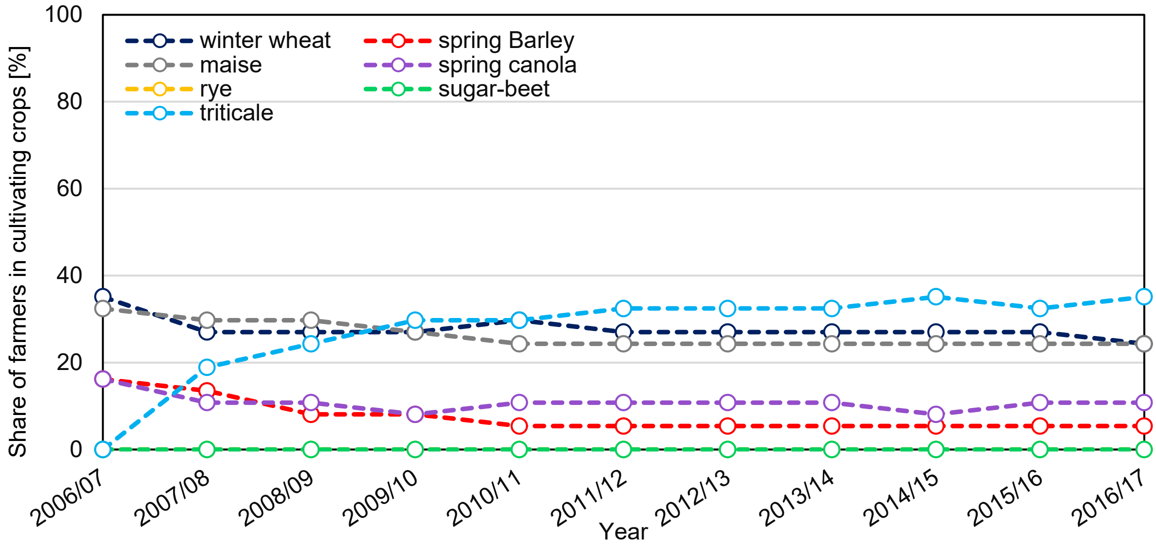


Figure 7-4. Dynamics of share of risk-averse farm agents with long-lasting memory in cultivating crops when no flood occurs in the simulation period (Exp7)

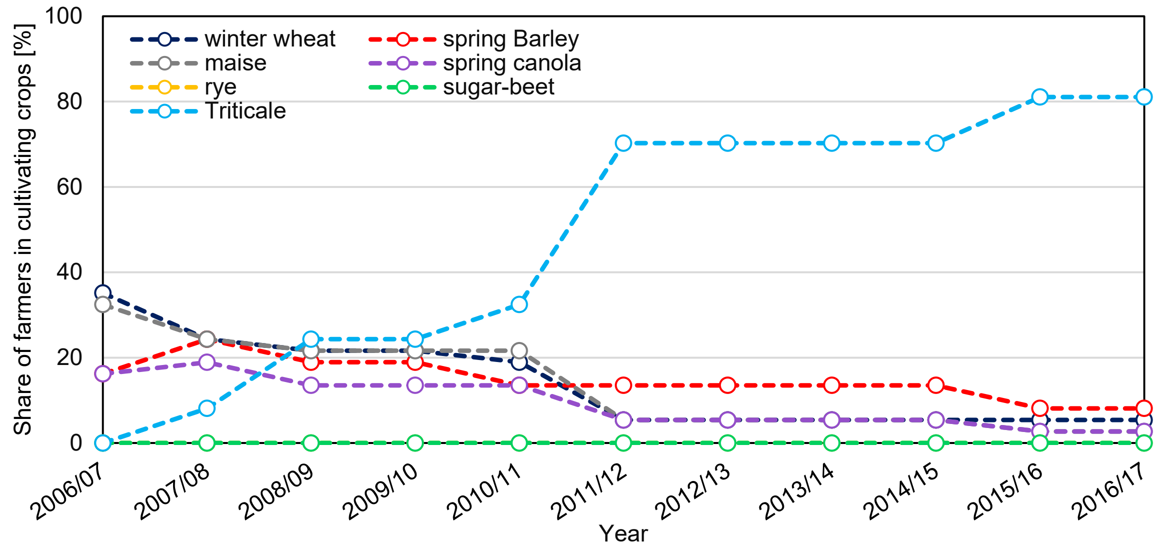


Figure 7-5. Dynamics of share of risk-averse farm agents with long-lasting memory in cultivating crops when 200-year flood occurs in year 2006, 2010, and 2014 (Exp1)

It can be seen in Figure 7-4 and Figure 7-5 that over the next three years (2008, 2009, and 2010), there is a steady increase in adopting triticale by farmers in both scenarios which makes the crop relatively popular. However, flood occurrence in year 2010 in Exp1 causes a large number of farm agents engage again in the inquiring (see Figure 7-7).

Since triticale is now popular enough among farmers, it is adopted by the majority (up to 70% of farmers). Its adoption then rises for the consecutive years reaching to 80% in year 2016 (see Figure 7-5). In contrast, in no flood occurrence scenario, there is no shock of flooding and thus, percentage of farmers cultivating triticale increases slightly reaching only to 35 % in year 2016. Meanwhile, the cultivation of other crops drops in both scenarios (see Figure 7-4 and Figure 7-5).

Comparing the dynamics of cognitive strategies in two flood scenarios also reveals that flood occurrence in year 2006, 2010, and 2014 affects the actual and expected profit of farmers in a way that most of them feel dissatisfied and uncertain and tend to inquire in those years. However, if no flood happens, the majority of farmers repeat their behavior in the previous year to remain satisfied. Overall, a smooth transition is observable in the dynamics of cognitive strategy and share of farmers cultivating crops in Exp7 comparing to those of Exp1. This raises the question of how no flood occurrence for relatively long time can result in such different individual behaviors. The answer is that flood has been a part of everyday life for the farmers, as the inhabitants of the region, which appears to remove much of worry. This observation highlights that living in flood-prone areas is not enough to be well-prepared to cope with flooding and lack of flood experience may pose serious threads for future. These findings are also consistent with discussions in other studies (Raaijmakers *et al.*, 2008; Scolobig *et al.*, 2012).

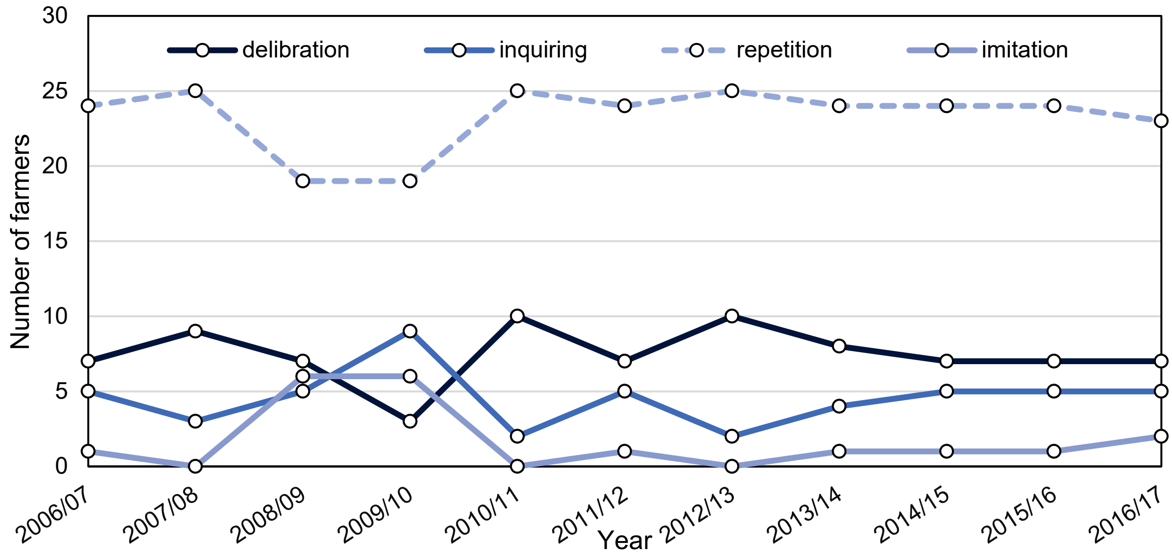


Figure 7-6. Dynamics of cognitive strategy of the risk-averse farm agents with long-lasting memory when no flood occurs in the simulation period (Exp7)

To investigate the influence of flood frequency on the spatial distribution of crops, Figure 7-8 illustrates cropping pattern under the two flood frequency scenarios in year 2008 and 2015, as examples. As can be seen, there is a growing interest among farmers to change their crop pattern over years to more salt-tolerant crops. Taking a closer look demonstrates when no flood happens in the simulation period, most of the farmlands are cultivated with winter wheat and maise in year 2008, a part of which are then replaced by triticale in year 2015. Under flood occurrence scenario, however, a different cropping pattern is observable. While in year 2008 four major crops including winter wheat, maise, spring barley, and triticale are identifiable, in year 2015, triticale is the most common crop grown in the region.

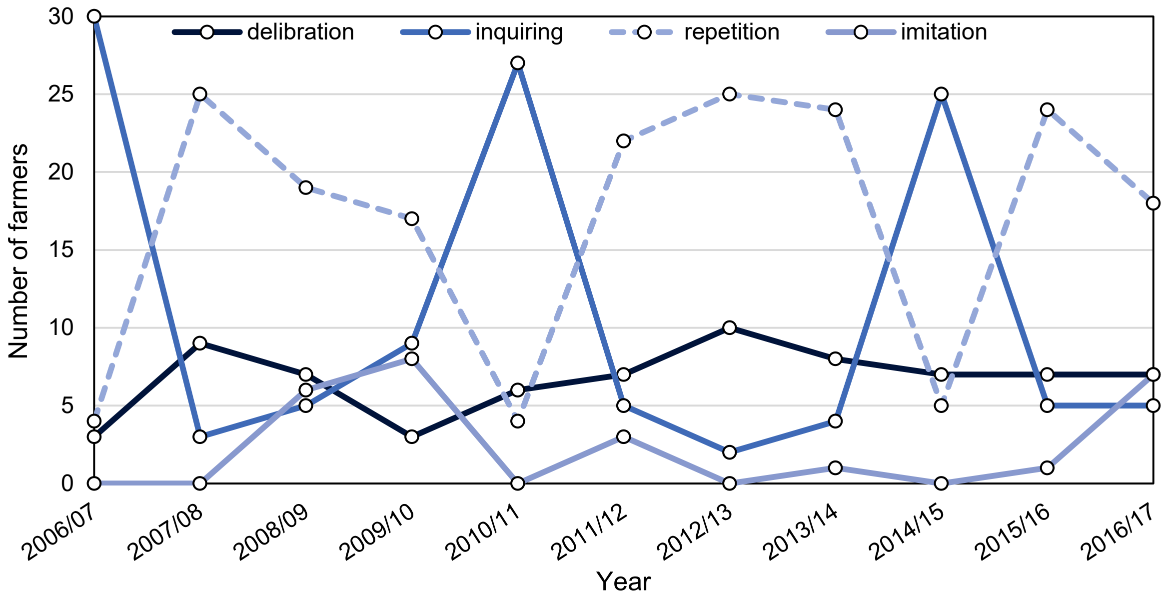


Figure 7-7. Dynamics of cognitive strategy of the risk-averse farm agents with long-lasting memory when 200-year flood occurs in year 2006, 2010, and 2014 (Exp1)

Figure 7-9 shows the sum of agricultural flood risk over time at the micro (farm)-level under the two flood scenarios. It can be seen that farmers experience less total flood risk when flood happens in the simulation period. An explanation for this is that farm agents learn about the risks and adaptation options over time which changes their behavioral strategy and improves the adaptive capacity. Furthermore, flooding is a rapid-onset event with tremendous damage in very short time and acts as a shock to the society. As a result, when farmers are exposed to frequent flood events (here three 200-year flood events), they learn from their experiences, form their expectation based on the observed damage in past years, and prepare themselves to cope with flooding. This interesting phenomenon shows how frequent floods have positive effects on farm agents' preparedness and involvement in precautionary measures to reduce their vulnerability which agree with observations and discussions in literature (Barendrecht *et al.*, 2017; Fuchs *et al.*, 2017). The higher rate of adopter in Exp1 also confirms the findings.

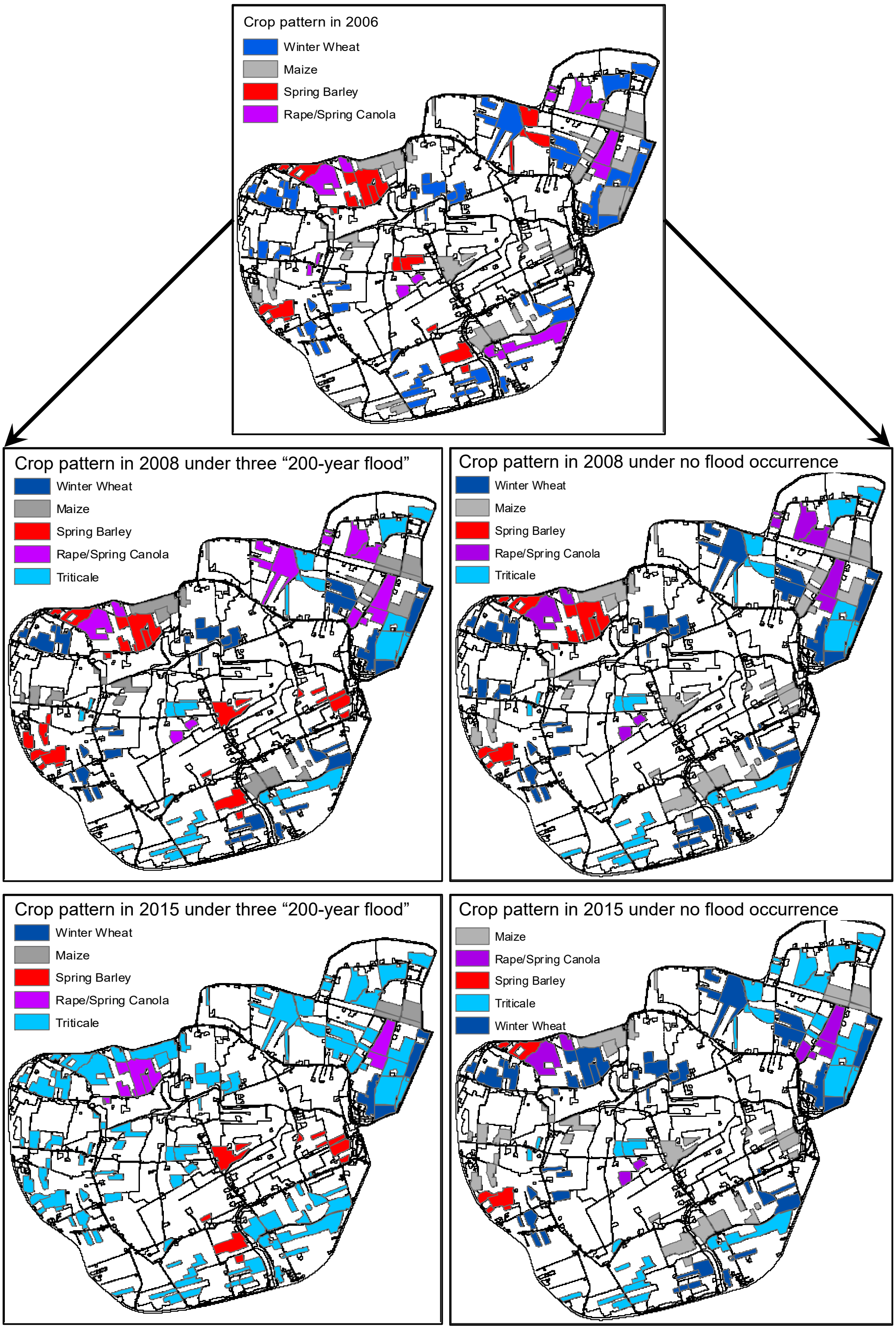


Figure 7-8. Crop patterns in year 2006, 2008, and 2015 in no flood occurrence (right) and three flood occurrence (left) scenarios

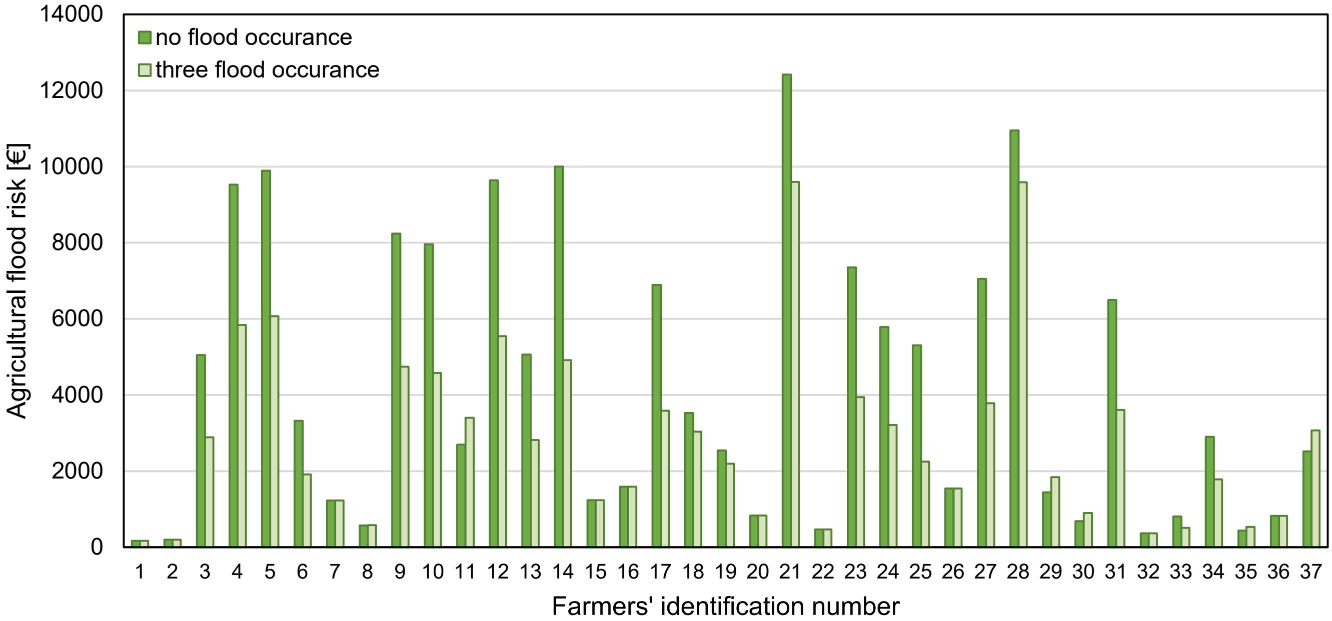


Figure 7-9. Spatial distribution of agricultural flood risk at the farm-level when 200-year flood occurs in year 2006, 2010, and 2014 (Exp1) and when no flood occurs in the simulation period (Exp7)

To explore the interdependencies between flood vulnerability of agricultural sector at farm-level and regional-level, Figure 7-10 and Figure 7-11 compare the two flood scenarios in terms of yearly regional agricultural flood risk and expected profit, respectively. According to Figure 7-10, the region faces more agricultural flood risk over years when no flood occurs in the simulation period, reaching a peak of 20261 € in year 2012. This observation is consistent with the flood risk at the individual level (see Figure 7-9) and indicates how the vulnerability of agricultural agents at the farm-level affects the vulnerability of the whole region. It is an evidence on how the economic problems that the regional agricultural sector tackles can originate from the individual level (see also Figure 2-1).

Comparing total agricultural expected profit of both scenarios in Figure 7-11 depicts that more regional agricultural expected profit is achieved over years when no flood occurs in the simulation periods. Higher expected profit in this flood scenario is the result of not being suffered by flooding on one hand, and cultivating more profitable crops over years, on the other hand.

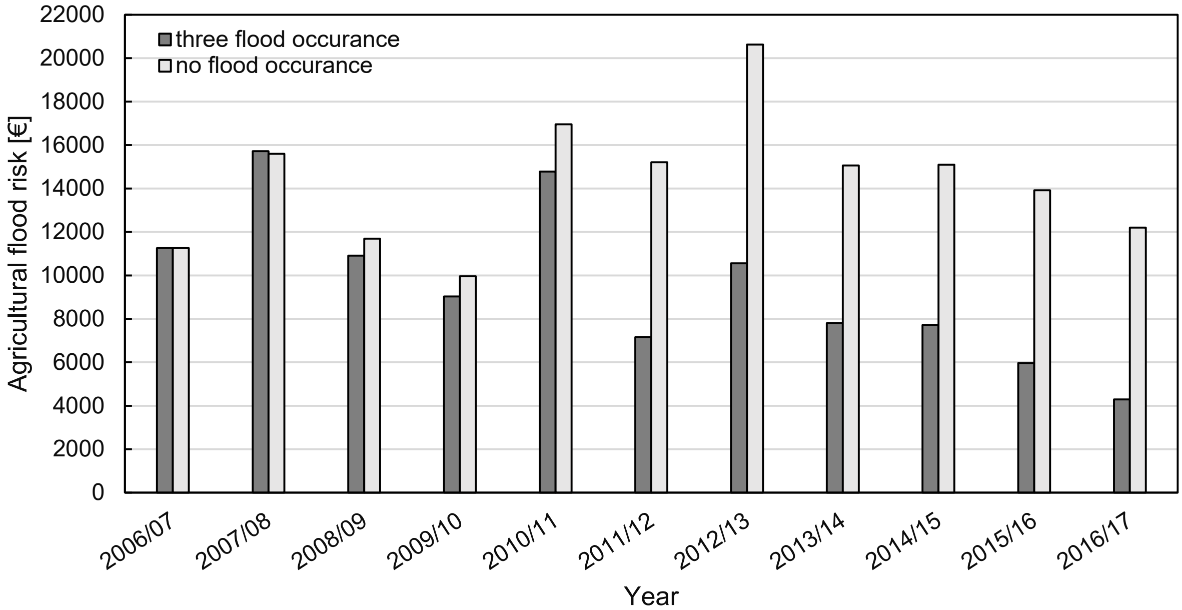


Figure 7-10. Agricultural flood risk at the regional-level over years for risk-averse farmers with long-lasting flood memory when 200-year flood occurs in year 2006, 2010, and 2014 (Exp1) and when no flood occurs in the simulation period (Exp7)

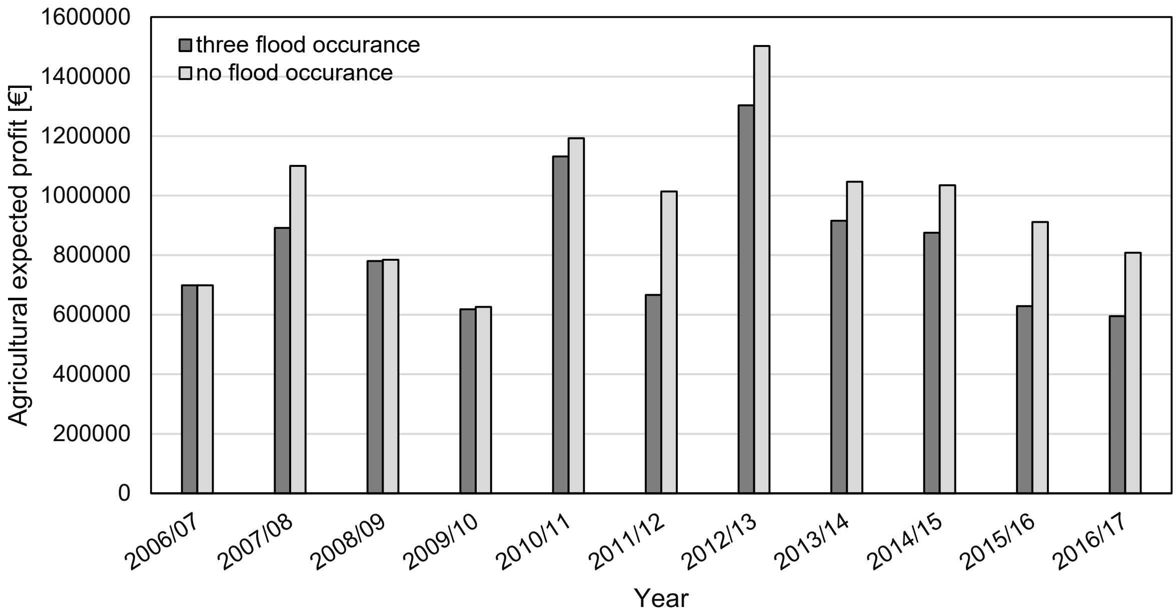


Figure 7-11. Agricultural expected profit at the regional-level over years for risk-averse farmers with long-lasting flood memory when 200-year flood occurs in year 2006, 2010, and 2014 (Exp1) and when no flood occurs in the simulation period (Exp7)

2.2 Role of flood risk perception

We explore the role of individual flood risk perception in FRM when the 200-year flood hits the region in year 2006, 2010, and 2014. For this purpose, behaviors of two farm populations that differ in the level of risk tolerance are compared: a population of 37 risk-averse farmers (Exp1) and a population of 37 risk-taker farmers (Exp3). More information regarding risk tolerance and its connection to adaptive behavior and decision-making can be found in section 6 of chapter 6.

Figure 7-12 and Figure 7-13 provide information on the fraction of the area in various agricultural crops over time for above flood risk perception scenarios. A closer look at Figure 7-12 shows that risk-taker farmers would consider only existing traditional crops even though other choices such as salt-tolerant crops are introduced to them at the beginning of the simulation. According to the figure, there is one dominant crop (here spring barley) over years whose cultivation has a steady growth till year 2010 followed by a sharp rise of 33% in year 2011. Then, its acreage remains unchanged over years until it reaches its highest value in year 2016 (89%). At the same time, fraction of the area in winter wheat, spring canola, and maise decreases slowly to a low of only 3% in the last simulation year.

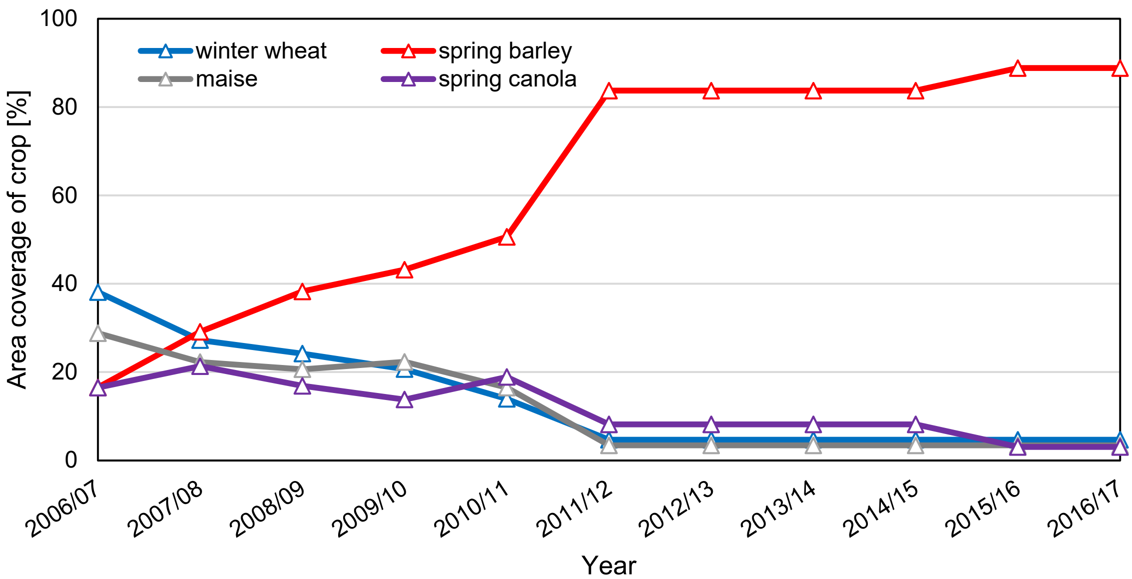


Figure 7-12. Proportion of crops over years for risk-taker farmers with long-lasting flood memory (Exp3) when 200-year flood occurs in year 2006, 2010, and 2014

A similar pattern is observable for the population of risk-averse farmers in Figure 7-13 in which farmlands are dominated by one major crop (here triticale). The dynamics of strategies helps in explanation of such a pattern (see Figure 7-7). In year 2006, a 200-year flood occurs causing dissatisfied farmers in the population (Exp3) adopt triticale as the most salt-resistant crop among all crop choices in the market. In the next three years, there is no flooding; however, due to interactions within the networks, information on the cultivation of triticale spreads around leading to rises in the share of farmers growing the crop. In year 2010, the 200-year flood hits the region again which results in a sudden reduction in farmer' profit. Therefore, the number of dissatisfied and uncertain farm agents increases abruptly (up to 81%) which causes them rely on the strategies involving social interactions. As during the years, more farmers tend to adopt triticale, the crop is more likely to be the most successful practice in farmers' networks and thus year 2010 sees a significant growth in the acreage of the dominant crop.

Comparing Figure 7-12 and Figure 7-13 shows, however, a steady fall in cultivation of spring barley over years in Exp1 reaching its lowest point in year 2016. Instead, triticale becomes the dominant crop over years. We observe this dynamic because risk tolerance of risk-averse farmers is always equal or lower than their perceived flood risk (see Figure 6-15). Even, those who live in the zone 4 with the minimum level of flood danger (see Figure 6-13 and Table 6-6), will not ignore the risk and tend to engage in FRM by pursuing private adaptive responses such as changing crop pattern and cultivating salt-tolerant crops. Therefore, they choose triticale, as the most salt-tolerant crop among both traditional and new crops, and start to grow that from a very early period (year 2007). Such a different tendency of the two farm populations in growing the crops reveals that risk-averse farmers are adaptive and more likely to be involved in private adaptation strategies. It can be an evidence on how the success of a salt-tolerant crop program depends on the risk perception and individual adaptive behaviors of the local farmers.

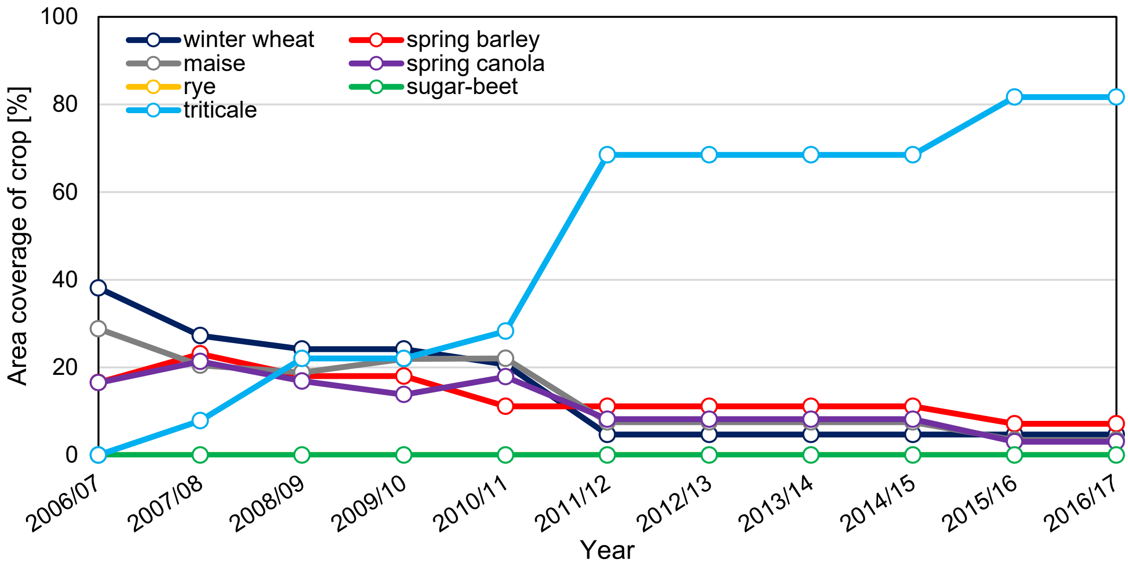


Figure 7-13. Proportion of crops over years for risk-averse farmers with long-lasting flood memory (Exp1) when 200-year flood occurs in year 2006, 2010, and 2014

Another interesting aspect that emerges from the comparison of two figures is that in contrast with the dominant crop of Exp3 (spring barley) whose cultivation area sees a steady growth to 30%, 50%, and 90% in year 2007, 2010, and 2016, respectively, the coverage area of the dominant crop in Exp1 (triticale) rises only to 10%, 30%, and 80% in those years. Such a difference depicts that the rate of adoption of the dominant crop in Exp3 is quicker than in Exp1 and farm population in Exp1 is relatively slow to adjust their decisions. This observation shows that taking flood adaption strategies do not occur suddenly and take several simulation periods. There are two reasons for this. Firstly, cultivating salt-tolerant crops such as triticale is a new practice with which local farmers have no prior experience at the start of the simulation (year 2006). So, they have high hesitation in triticale cultivation at the beginning. Secondly, limitations to the availability of information as well as to the processing capacity of farmers result in not all crop data be readily available to all farmers but only to the economic optimizers at that time step.

Therefore, taking such new practices should be initiated by the few farmers who engage in deliberation in the current year. Once deliberators select that new practice (because it optimizes her/his outcomes), it is observed by farm agents who rely on their social network, and as a result, non-deliberators are willing to adopt that. Such a decision is propagated from one farm agent to another through social interactions and finally includes almost the whole population (up to 80% in year 2016). Thus, it takes time for non-deliberators to interact and learn from agents belonging to their social networks. Accordingly, interactions involve exchange of information and knowledge on (new) adaptive strategies such as salt-tolerant crops, their yield, and costs. As is shown in Figure 7-13, farmers' adoption of the new practice forms an S-shape curve over time which agrees with the prediction of Bass model in new production diffusion as well as empirical stylized facts of diffusion (Bass, 1969; Rogers, 2004).

To shed light on the effect of farmers' interaction, Figure 7-14 provides the evidence on the role of social interaction in adoption of adaptation strategies in the risk context. The figure illustrates share of risk-averse farmers engaging in each cognitive strategy as well as their share in cultivating crops, in year 2007, 2010, and 2016, when they have long-lasting flood memory. In year 2007 (the following year after the first 200-year flood), only 8% of farmers are certain and dissatisfied with their decision in the previous year. This leads this small share of farmers to assess all options and choose triticale with the lowest expected damage. This notion is supported by the percentage of farmers growing triticale in year 2007 (8%). In year 2010, more farmers tend to adopt triticale (up to 32%), although the share of deliberators remains unchanged (8%). Even in year 2016, triticale becomes the most cultivated crops among farm agents (up to 81%) while only 19 % of the population engages in the deliberation. This nonuniform increase in the rate of adopters over time, on one hand, and its incompatibility with the percentage of deliberators, on the other hand, demonstrates how social interaction plays crucial role in information dissemination about decisions and adaptive behaviors. This highlights the importance of exchange of information and knowledge which leads to learning at the micro-level and emergent phenomena at macro-level (regional-level).

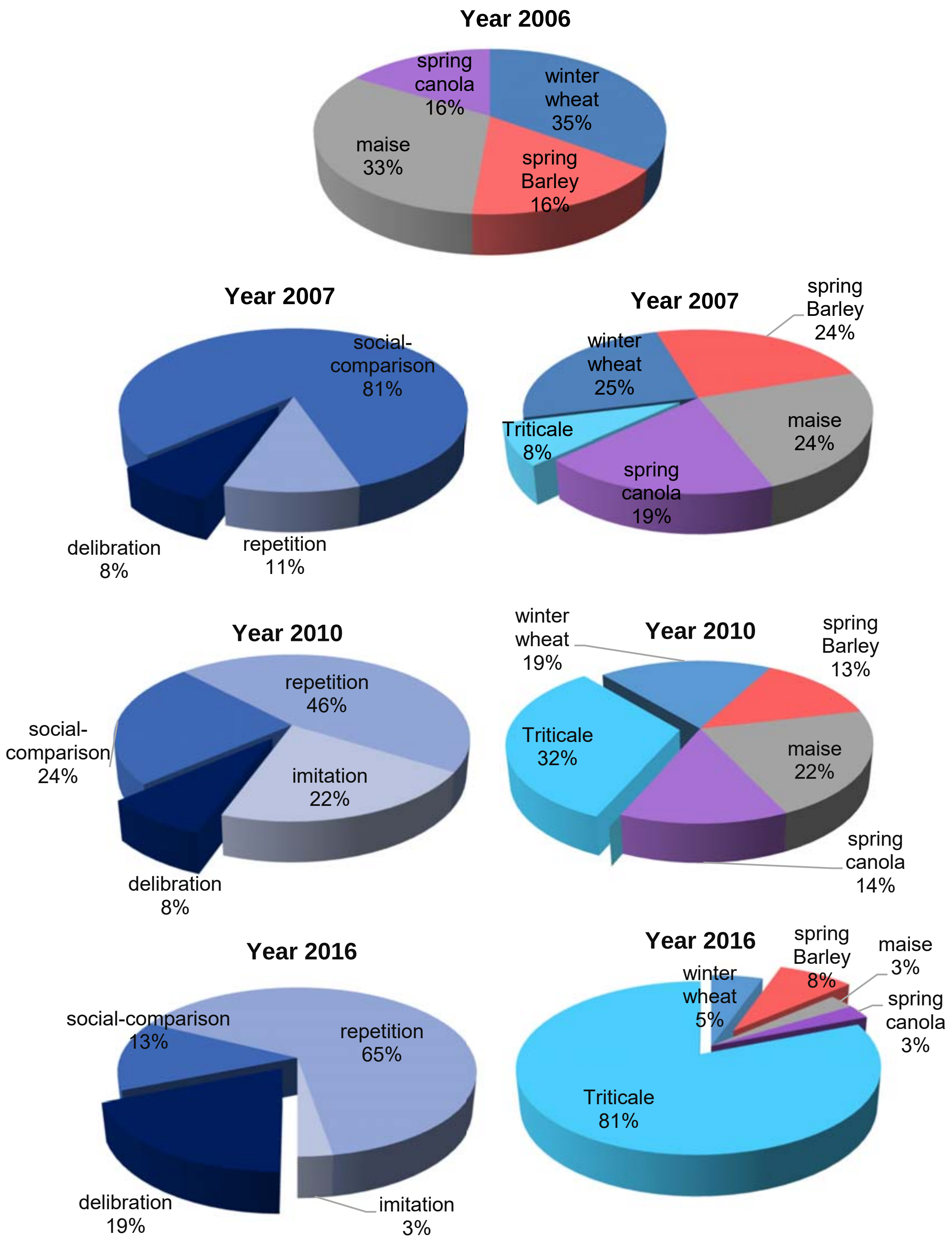


Figure 7-14. Share of risk-averse farmers with long-lasting memory (Exp1) in cognitive strategies (left) and cultivated crops (right) in year 2007, 2010, and 2016

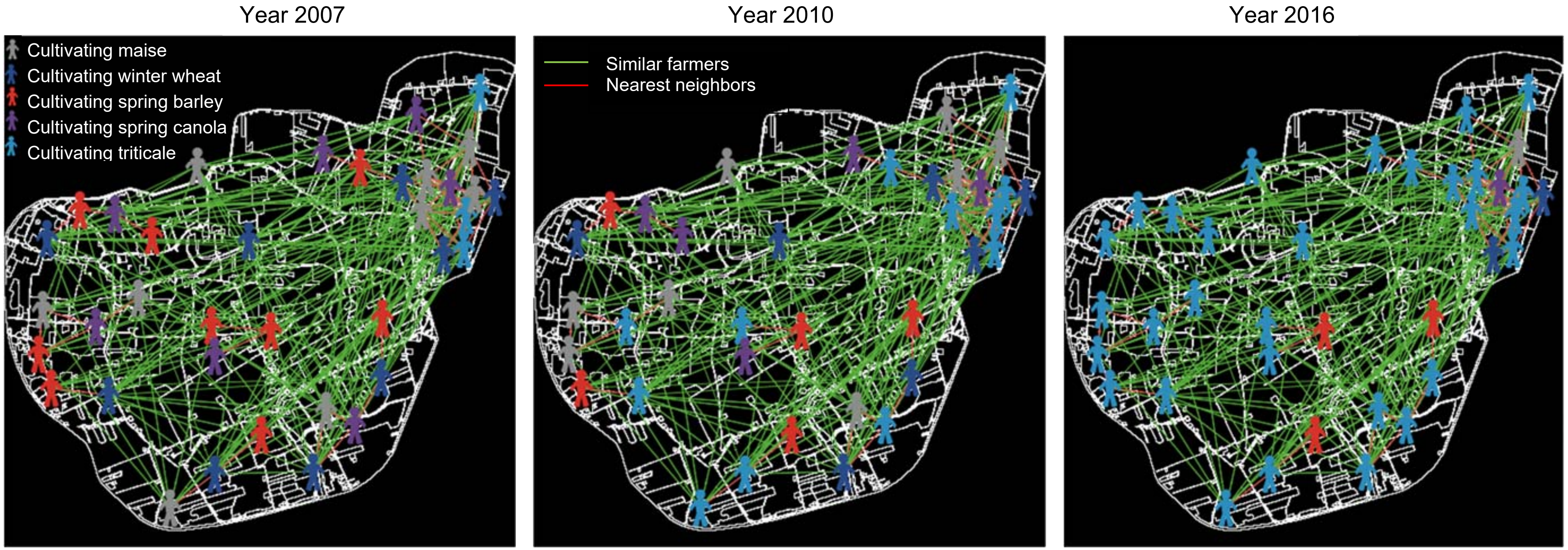


Figure 7-15. Diffusion of adaptive policies through social interactions in the population of risk-averse farmers (Exp1)

Figure 7-15 indicates how social interaction results in farmers' behavioral change in the population of 37 risk-averse farmers in year 2007, 2010, and 2016. The figure visualizes the interconnections between farm agents and maps the information dissemination over time through green links (network of similar farmers) and red links (network of nearest neighbors). It can be observed that triticale cultivation spreads around making this new crop the most common private adaptation strategy among farm agents in year 2016. In fact, farmers search for reliable information about the probable flood risks and ways to reduce the adverse impacts of flooding. Thus, they communicate with others to be informed about new strategies and private adaptive policies. In this manner, social networks play key role in information exchange and dissemination of adaptive policies over time.

Figure 7-16 sheds light on the agricultural flood risk at the micro-level for both flood risk perception scenarios. The results clearly show remarkable differences in vulnerability of farm agents in both farm populations. More importantly, it can be seen that individual risk perception changes the dynamic of farm agent' behavior in such a way that the individual flood risk is mitigated. Such a significant reduction in sums of expected damage of farm agents shows the effectiveness of individual risk awareness and responses.

To explore the effect of private adaptive responses on the micro-level outcomes, Figure 7-17 compares agricultural flood risk of two individual farmers over time. In this figure, the adaptive farmer is an agent who employs adaptive strategies (here salt-tolerant crops) very quickly (from the second simulation year) to cope with flood while the non-adaptive farmer does not adapt to flood over the simulation years. It should be noted that both farmers belong to the risk-averse farm population and are similar in their farm-size and initial crop pattern. In addition, the degree of exposure of their farmlands to probable flood scenarios is the same. The figure illustrates a significant difference between agricultural flood risk of two farm agents over time. As it is observed, in comparison with the non-adaptive farmer, the adaptive farmer mitigates her/his individual flood risk from 100 € in year 2006 to 30 € in the last simulation year.

Such a different trend in agricultural flood risk arises from the heterogeneity of behavioral properties between the two farmers. Their attributes such as uncertainty and satisfaction threshold as well as their interaction groups play key role in this regard causing dissimilarity in their behavioral characteristics and making different choices. These results demonstrate the significance of private adaptive response in reducing the individual vulnerability to flood over years.

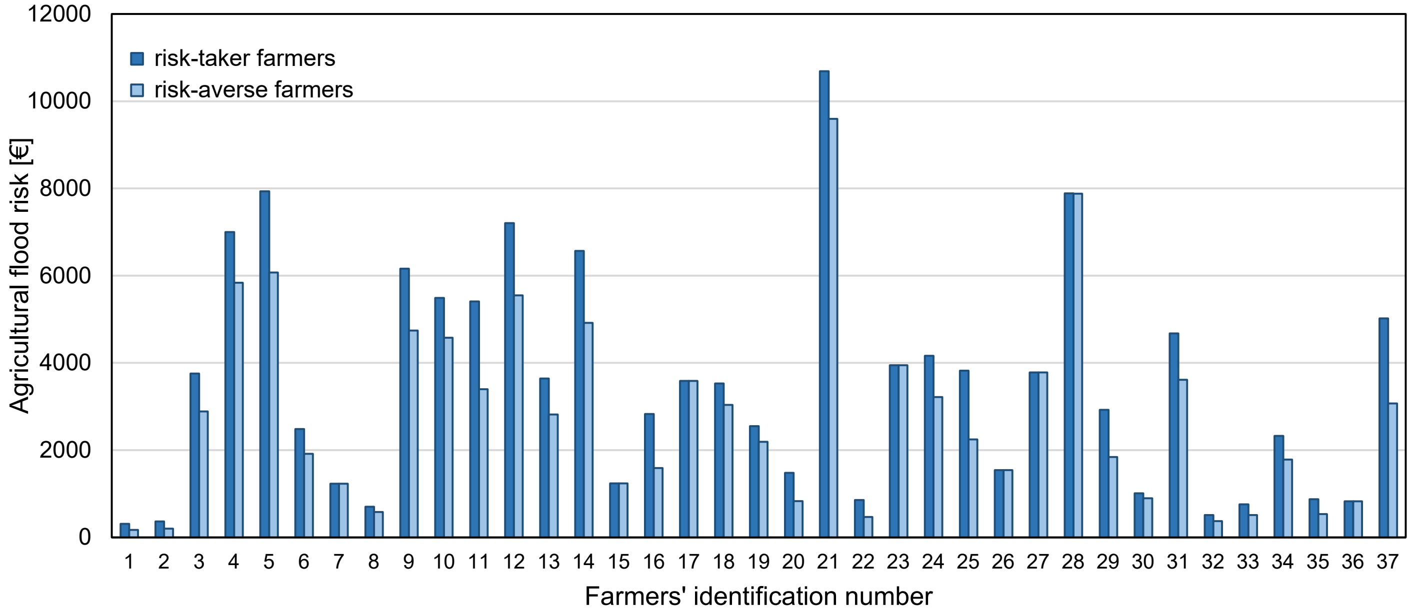


Figure 7-16. Spatial distribution of agricultural flood risk at the farm-level for the risk-taker farm population (Exp3) and risk-averse farm population (Exp1)

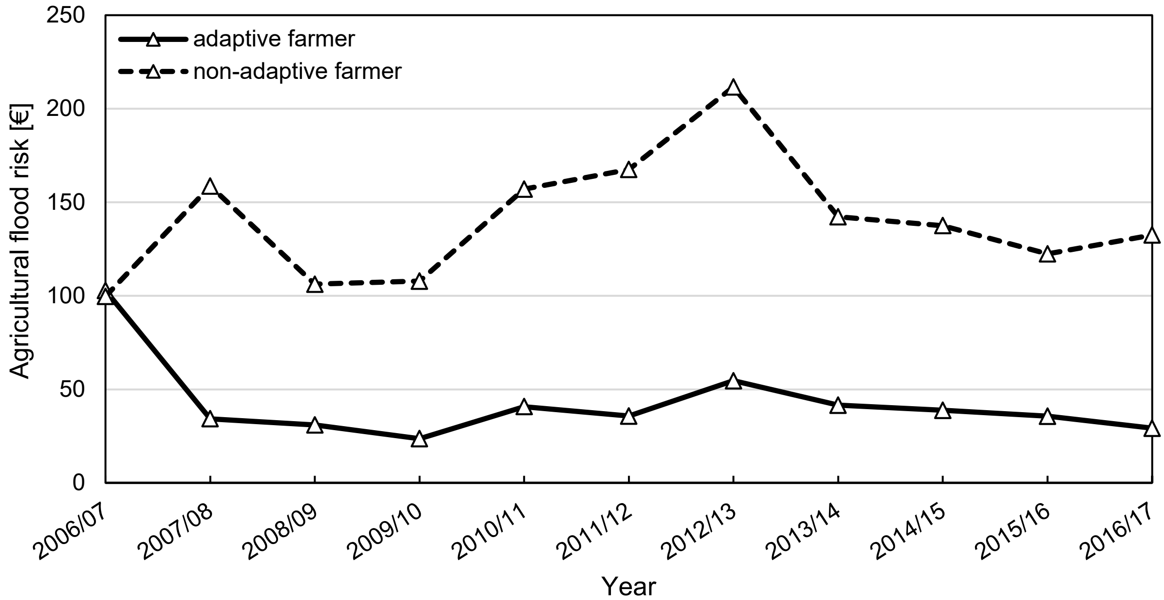


Figure 7-17. Time variation of agricultural flood risk for adaptive and non-adaptive agent in the population of risk-averse farmers (Exp1)

To examine how individual risk perception and adaptive behavior contribute to FRM, Figure 7-18 compares agricultural flood risk of the whole region for the two farm populations. As can be observed, even though adaptation takes place from the beginning of Exp1, it is not enough to offset the impact of flood occurrence, and regional flood risk of two scenarios is almost close to each other in the first simulation years. This observation arises from the slow adaptation process which causes a large share of farm agents not still employ private adaptive strategies to cope with flooding in year 2009. However, results show that reduction in the regional vulnerability increases over time for risk-averse farm population, which highlights the importance of continues adaptation of farm agents over time to achieve lower regional flood risk. It also demonstrates how private adaptation strategies such as salt-tolerant crops at the micro-level can change the vulnerability of agricultural sector at the macro-level. Such a link between adaptation on the individual-scale and vulnerability on the macro-scale confirms the effects of individual behaviors on emergent phenomena and their significance in large-scale decision-makings.

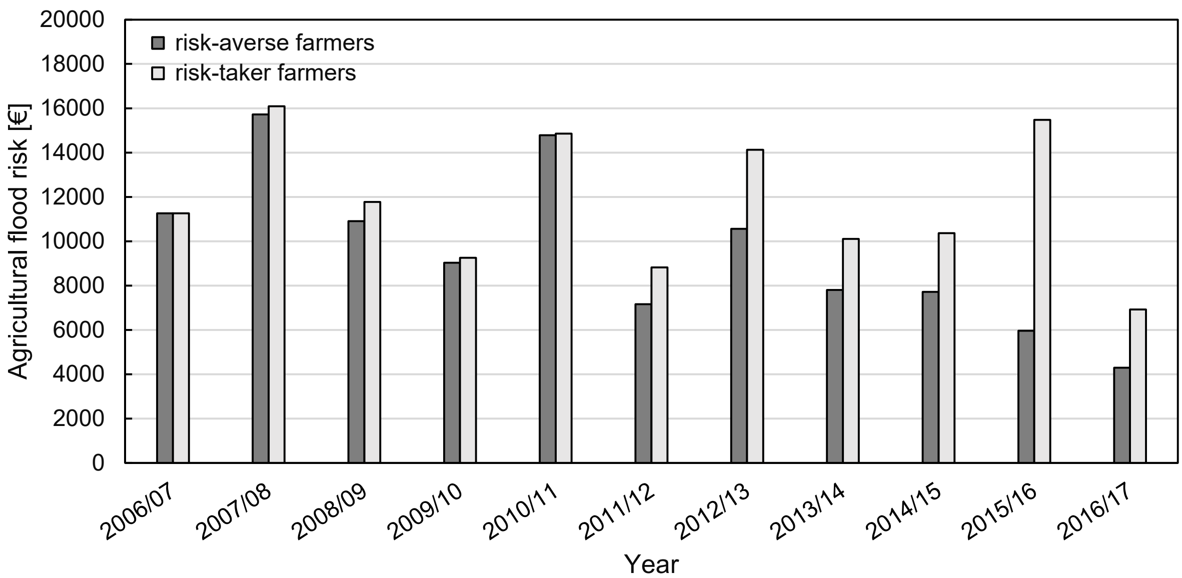


Figure 7-18. Agricultural flood risk at the regional-level over years for two flood risk perception scenarios

Annual agricultural expected profit of the whole region is depicted for both experiments in Figure 7-19. It can be seen that in total, regional agricultural sector achieves more expected profit over years if the farm population consists of risk-taker farmers. This arises from higher sale-price as well as productivity of crops that are adopted by risk-taker farmers during the simulation.

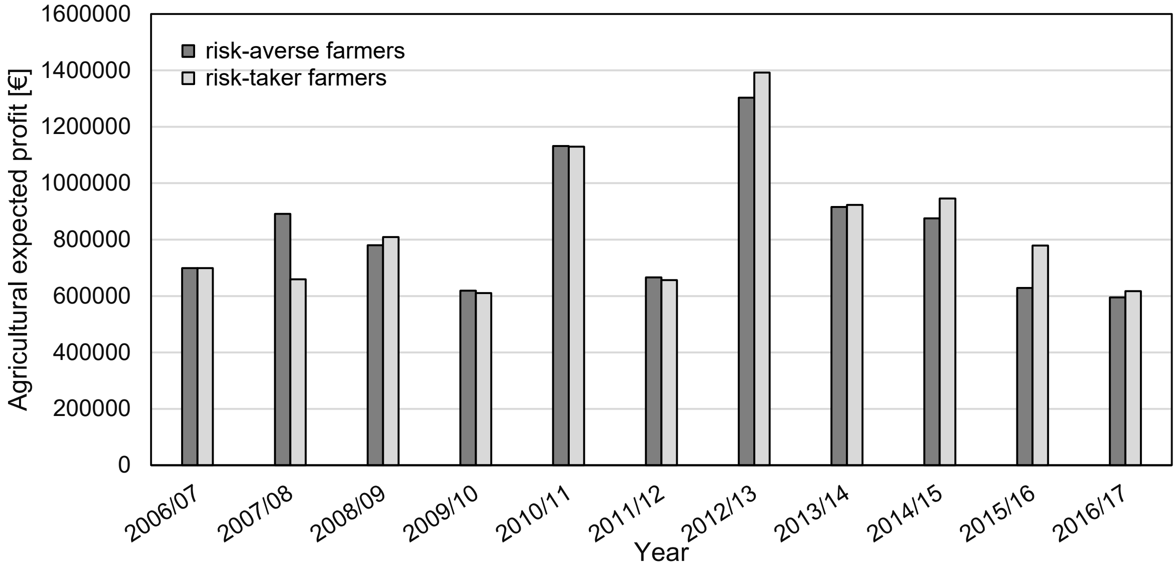


Figure 7-19. Agricultural expected profit at the regional-level over years for two flood risk perception scenarios

2.3 Role of flood memory

We examine the impact of flood memory on two groups of farmers: a population of 37 risk-averse farmers and a population of 37 risk-taker farmers. In both sets of experiments, it is assumed that the 200-year flood event strikes the study area in year 2006, 2010, and 2014 (see Figure 6-1).

2.3.1 Impact on risk-averse farmers

To study the role of flood remembrance in risky-choices of risk-averse farmers, we make a comparison between risk-averse farmers with long-lasting flood memory (Exp1) and long-term flood memory (Exp2). Such a comparison sheds light on differences in farmers' decisions when they never forget flooding and when they forget the event after some years. Under these circumstances, dissatisfied farmers with long-lasting memory remember flooding for their whole life and always choose the adaptive strategy with the lowest expected damage, whereas, those with long-term flood memory minimize their expected damage in the first couple of years after flooding (here two years). Then, they will forget that in the following years which results in seeking the best option with the highest expected profit (see also Table 6-4).

Figure 7-20 and Figure 7-21 depict the time variation of total crop production of risk-averse farmers with long-lasting flood memory and long-term memory, respectively. As expected, it is seen that risk-averse farmers choose among salt-tolerant crops in addition to the traditional crops as their risk tolerance is below their perceived risk leading to risk management through adaptation strategies. Variability in meteorological patterns presents significant challenges to crop production and causes fluctuation in crop yields in both scenarios. Comparison of two figures shows that the type of flood memory has a considerable influence on farmers' decision-making over time, as dissatisfied farmers that forget the occurred flood after two years, start to choose sugar beet with the yield up to a yearly average of 68.5 t/ha which is much higher than others, even though its flood damage factor is relatively high. In contrast, farmers with long-lasting flood memory never choose such a crop with high flood damage factor (see Figure 5-7) due to its potentiality for extensive flood damage.

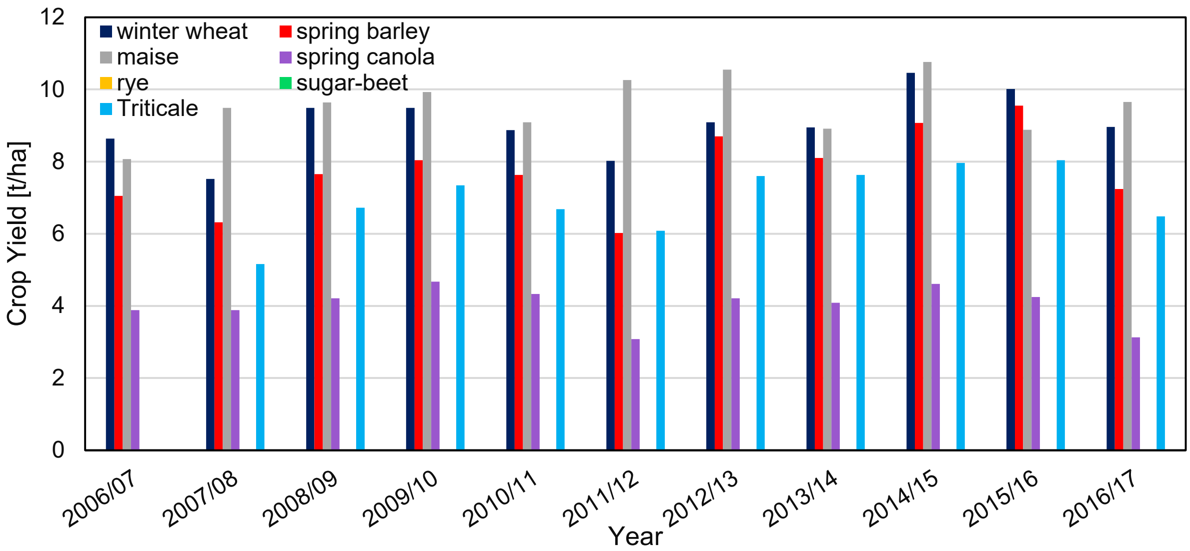


Figure 7-20. Annual yields of cultivated crops of the study area when risk-averse farmers have long-lasting flood memory and the 200-year flood occurs in year 2006, 2010, and 2014

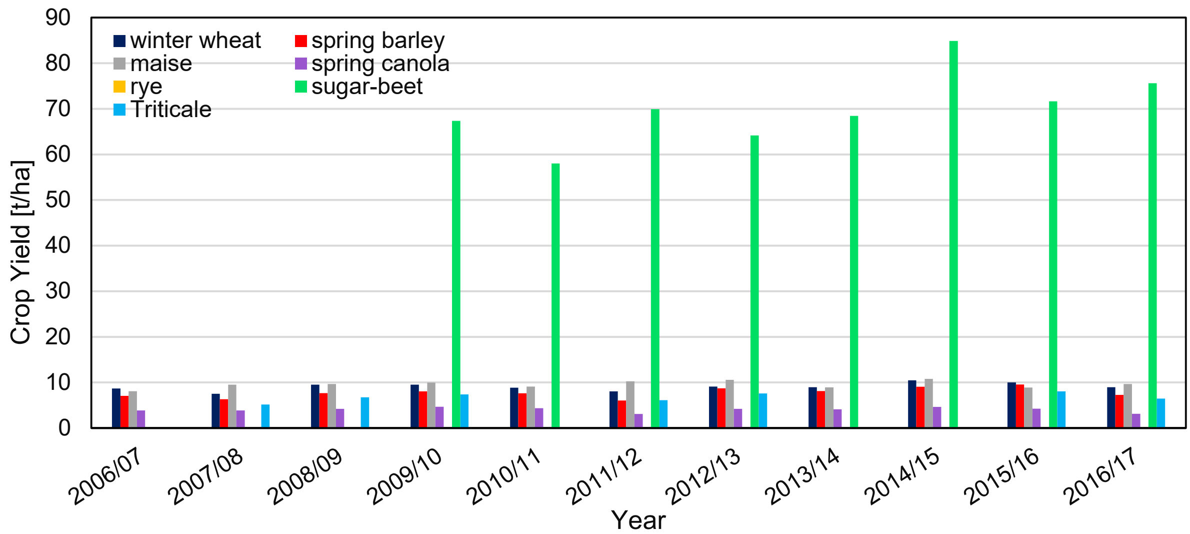
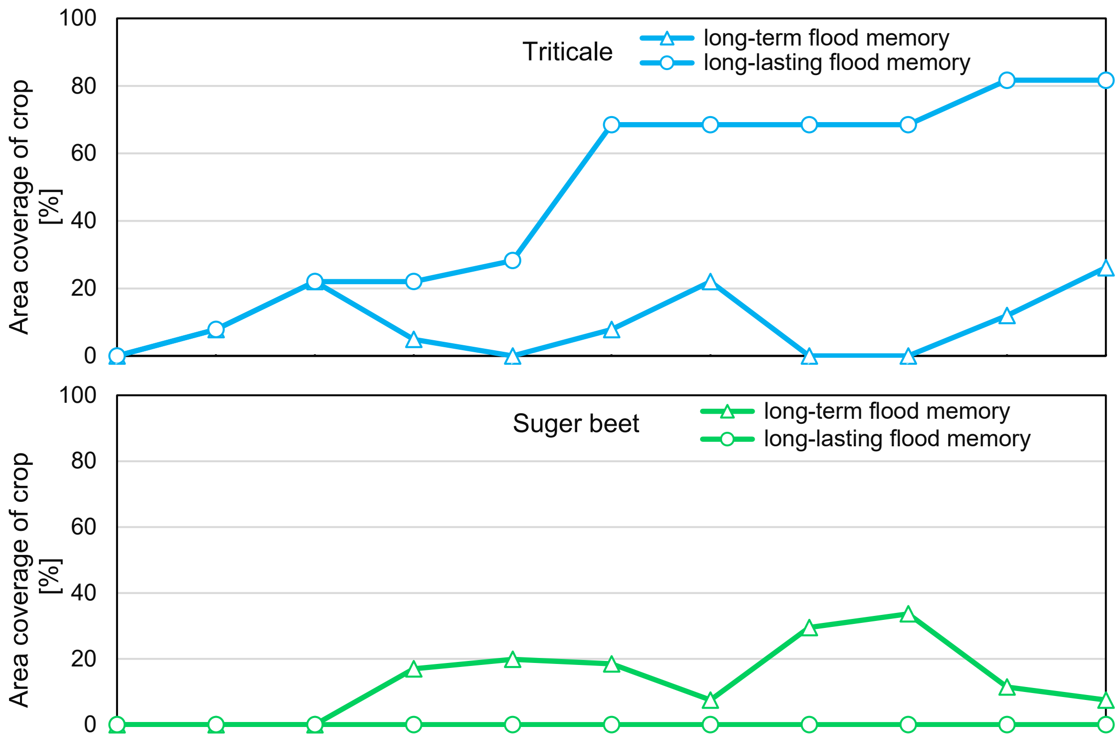


Figure 7-21. Annual yields of cultivated crops of the study area when risk-averse farmers have long-term flood memory and the 200-year flood occurs in year 2006, 2010, and 2014

Figure 7-22 compares cropping pattern in the study area over time as the result of decisions of risk-averse farmers with long-lasting memory versus those with long-term memory. In the first three years of simulation, the cultivated areas of all crops are equal between two scenarios. The reason is that farmers with long-term flood memory have not forgotten the flood event yet and behave similar to farmers with long-lasting memory. As can be observed in the figure, triticale becomes slowly popular among farmers and the proportion of area under triticale increases to 22% in year 2008 for both scenarios.

However, in year 2009, the cropping pattern starts to change. Farmers with long-lasting flood memory continue to adopt triticale over years as it results in the lowest amount of agricultural expected damage. Subsequently, triticale becomes the dominant crop over time in Exp1 and takes up almost 68% and 81% of the farmlands in year 2012 and 2016, respectively. Meanwhile, planted area of other crops such as winter wheat, maise, spring canola, and spring barley, which are cultivated traditionally by the local farmers, decreases year by year. In contrast, farm population with long-term memory switch from triticale to sugar beet in the third and fourth year after every flood occurrence (for example in year 2009 and 2010). Such a transition process in Exp2, leads to the diversity in the crops adopted by farmers and almost all crops are cultivated with the relative equal acreage in year 2016.



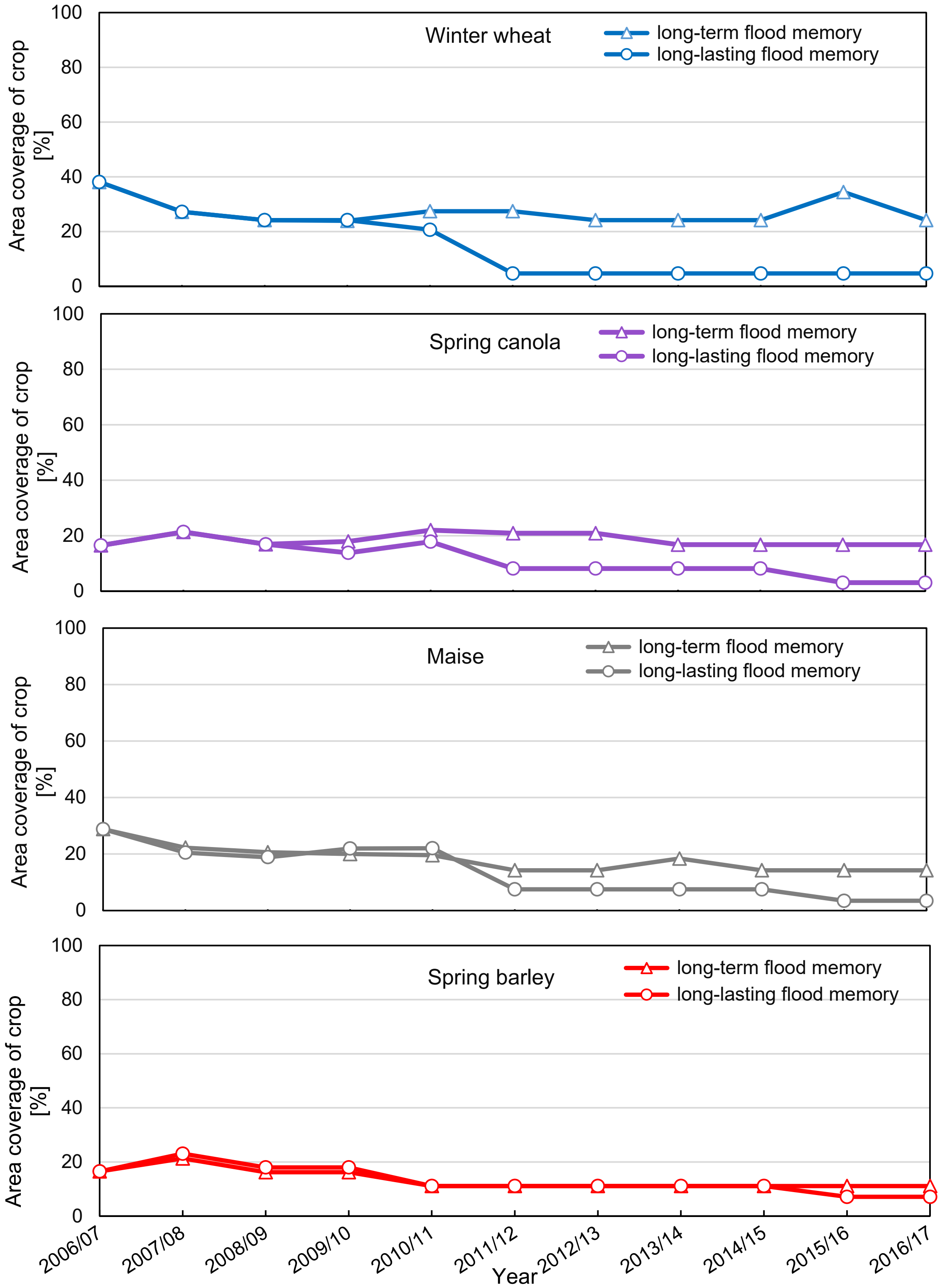


Figure 7-22. Proportion of crops over years for risk-averse farmers with long-lasting flood memory (Exp1) and long-term flood memory (Exp2) when 200-year flood occurs in year 2006, 2010, and 2014

Figure 7-23 compares the regional agricultural flood risk over time for the population of risk-averse farmers with two types of flood memory. As can be seen in the figure, total agricultural flood risk is the same in year 2006, 2007, and 2008 under both scenarios and is independent of types of farmers' flood memory. It is due to the fact that dissatisfied farmers with long-term memory are also strongly influenced by occurred flood in the first two years and try to minimize their expected flood damage. As the initial crop patterns are similar for both farm populations, their total agricultural flood risk is equal in the two following years (2007 and 2008).

The first differences in the flood risk appear in fourth year of simulation (year 2009), where dissatisfied farmers with long-term flood memory forget flooding and set their goal to maximize the profit. Subsequently, the total agricultural flood risk for the farm population with long-term memory is much higher than that with long-lasting memory, indicating an increase in risk of 16%-65% over simulation years. This observation demonstrates the significance of individual flood memory in the flood risk that the whole region faces.

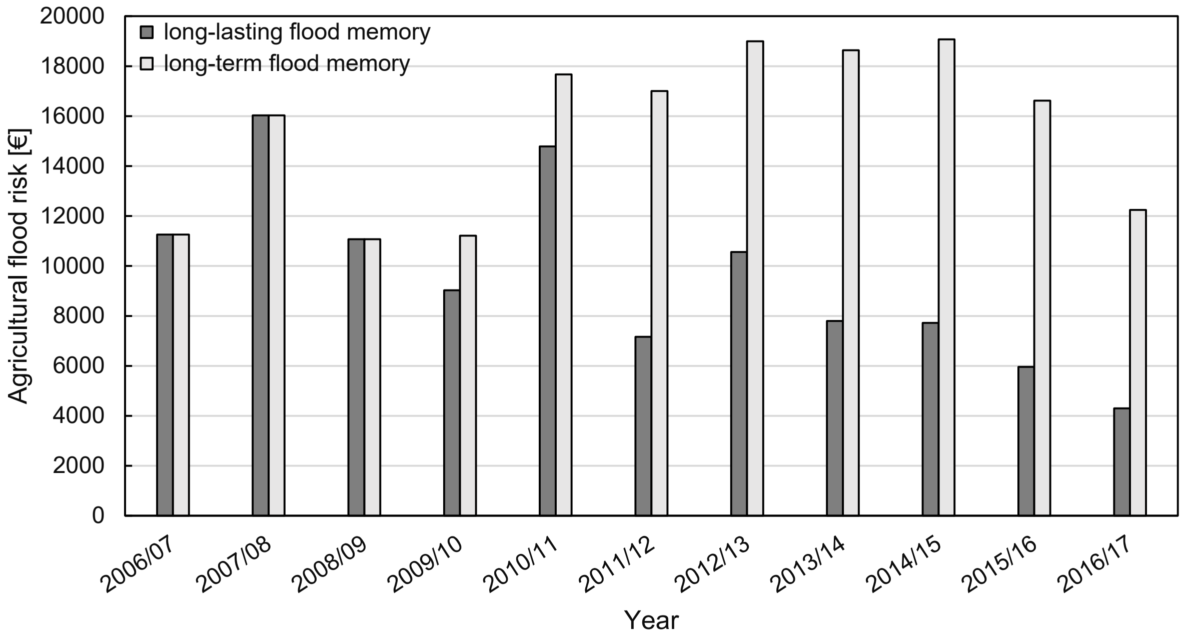


Figure 7-23. Agricultural flood risk at the regional-level over years for risk-averse farmers with long-lasting flood memory (Exp1) and long-term flood memory (Exp2) when 200-year flood occurs in year 2006, 2010, and 2014

To evaluate the temporal changes in expected profit at the regional-level, Figure 7-24 shows sum of agricultural expected profits over years under both scenarios. It can be seen that risk-averse farmers with long-term memory achieve more expected profits. The reason is that they forget flooding after two years which results in choosing the crop with the highest profit if farm agents feel dissatisfied with their previous decision. Once such a crop is cultivated in the area, it has a chance to be adopted by other farm agents and spread around. Subsequently, the regional expected profit grows over years.

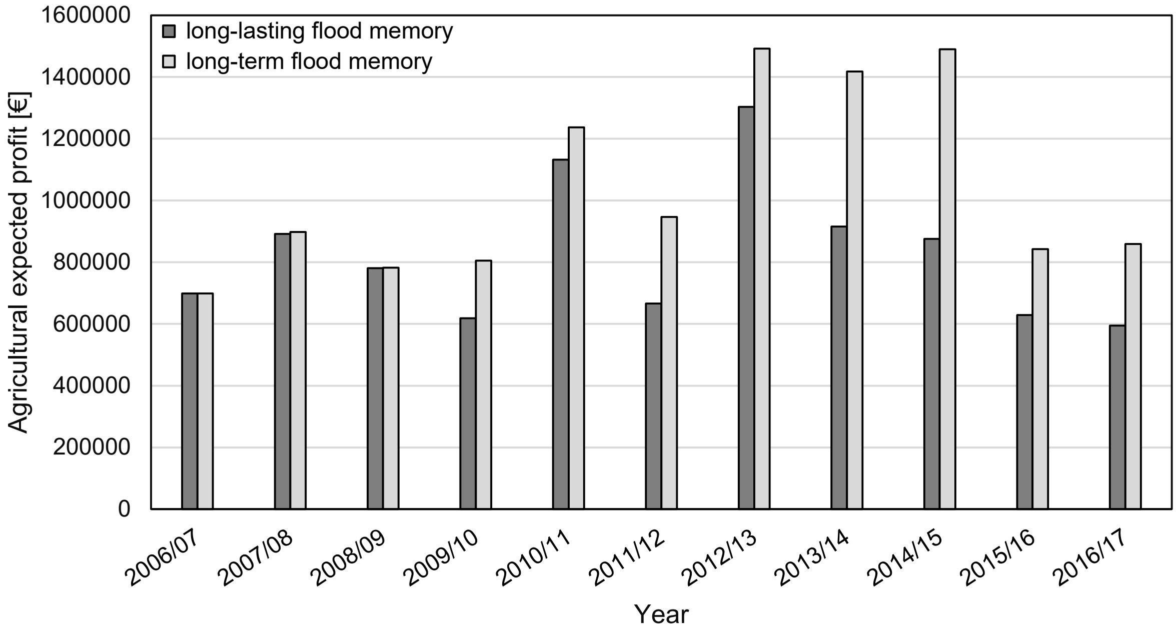


Figure 7-24. Agricultural expected profit at the regional-level over years for risk-averse farmers with long-lasting flood memory (Exp1) and long-term flood memory (Exp2) when 200-year flood occurs in year 2006, 2010, and 2014

To explore the potential changes in risk at the micro-scale under the influence of flood memory, Figure 7-25 illustrates the spatial distribution of agricultural flood risk mitigation in year 2009, 2010, 2013, and 2014, when moving from scenario with long-term flood memory to scenario with long-lasting flood memory (farmers are risk-averse in both cases). The model results show that farm agents whose flood memory lasts for their whole life instead of just two years after the event, experience less flood risk in all four simulation years. The contribution of long-lasting flood memory in risk mitigation is especially visible for the southern and central parts of the Island where the flood risk decreases by 743.5-996.5 € in year 2014. However, the reduction in flood risks of farmers that live in the northeastern part of the Island is not as much as others. The reason is that they have less flood exposures and their fields are inundated only by 1000-year flood (see Figure 4-9, Figure 4-10, and Figure 4-11). These results emphasize the importance of long-lasting flood memory especially in risk mitigation of flood-prone regions. Figure 7-25 also depicts that over time more flood risk reduction is achieved by farmers with long-lasting memory which is an evidence on how farmers' deep-rooted memory can help them to reduce their vulnerability to flooding with time.

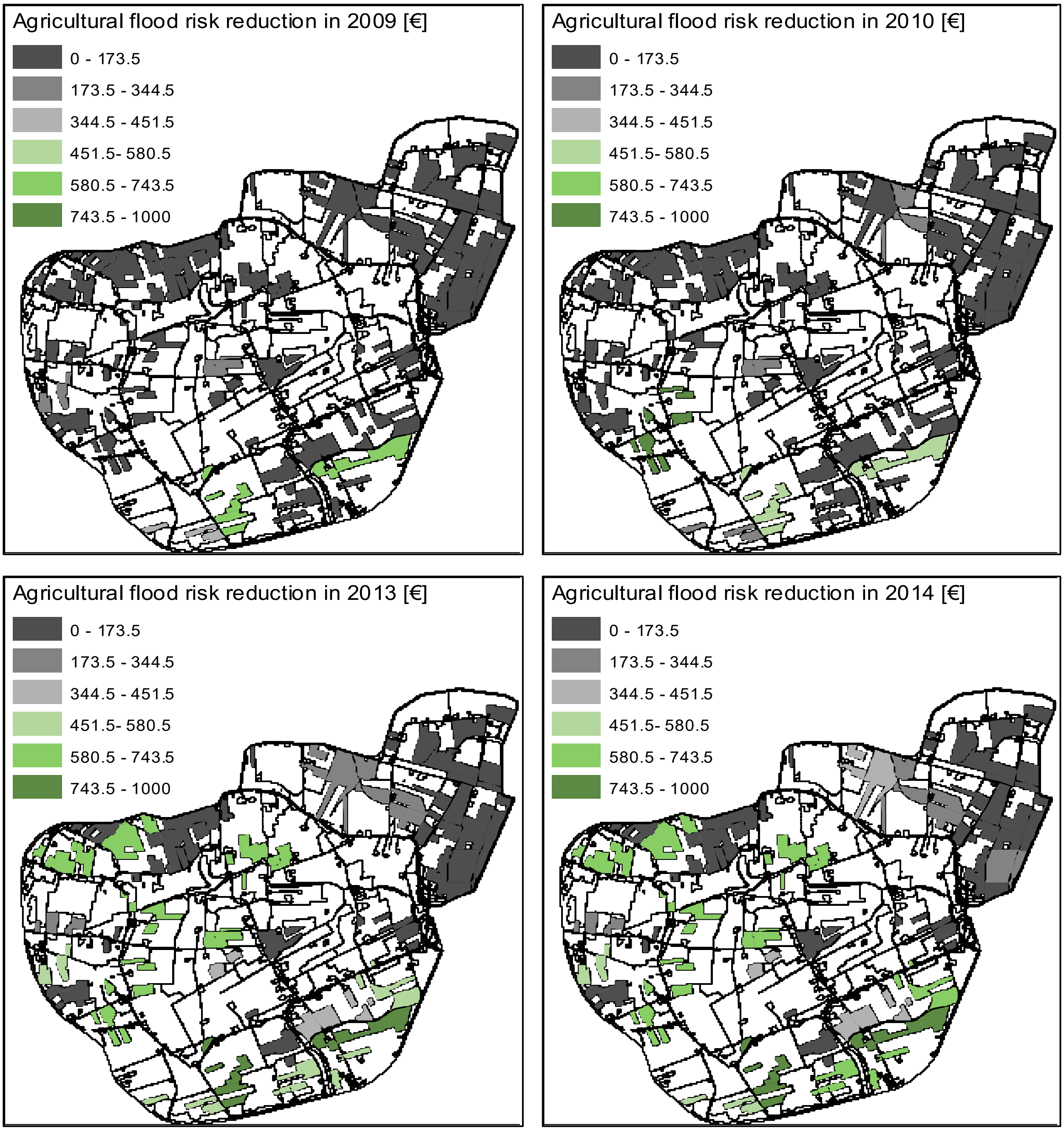


Figure 7-25. Reduction in agricultural flood risk in year 2009, 2010, 2013, and 2014 by moving from scenario with long-term flood memory to scenario with long-lasting flood memory

2.3.2 Impact on risk-taker farmers

To investigate the effect of flood memory on the decisions of risk-taker farmers, three farm populations are considered differing in the duration of flood memory: long-lasting flood memory (Exp3), long-term flood memory (Exp4), and short-term flood memory (Exp5). In comparison to Exp3 and Exp4 in which farm agents remember the occurred flood at least for two years, in Exp5, the duration of farmers' memory is short and they forget the event immediately. Subsequently, risk-taker farmers with short-term flood memory always choose the crops with the highest expected profits to cultivate in the following year, if they are dissatisfied with their outputs in the current year.

Figure 7-26 and Figure 7-27 show the aggregates of farmers' crop for the risk-taker farm population with long-term flood memory and with short-term flood memory, respectively. The results are presented as time series of fractions of the total farmlands on the Island in winter wheat, spring canola, maise, and spring barley. Cropping pattern of the risk-taker farm population with long-lasting flood memory is illustrated in Figure 7-12.

Comparing three experiments indicates that different assumptions of farmers' flood memory lead to very different cropping patterns. It is also apparent that proportion of crops varies among farm populations in terms of stability of individual decision-making. Time series of fraction of the region in various crops tend to be more stable with time for farmers with long-lasting memory. The reason is that they never forget the flood and always will to avoid more crop losses. In this manner, farmers' decisions are more stable over time and ensure greater consistency.

According to Figure 7-26, risk-taker farmers with short-term memory have no tendency to grow spring barley on their farmland in spite of its low crop loss. Here, farmers' personality in forgetting the flood plays a crucial role as they always tend to maximize their expected profit if they feel dissatisfied and uncertain. Such a tendency is disseminated across farmers' networks causing none of them cultivate the crop over time. Annual variability of the weather condition as well as prices and crop yields lead to fluctuations in crops' profits and in turn their adoption. These observations are in contrast to the behavioral patterns of risk-taker farmers with long-lasting flood memory where more farmers are willing to commit their farmland to the spring barley leading to increases in the cultivation area of spring barley over time (see Figure 7-12).

Cropping pattern of risk-taker farmers with long-term flood memory (see Figure 7-27) shows a combined behavior of two previous farm populations. To explain the observation, consider for example proportion of crops in year 2006-2008 in which spring barley becomes the most common crop in the region covering 45 % of the agricultural lands in year 2008. In contrast, in the two consecutive years from 2008 to 2010, its acreage falls and reaches to a low of 27% in year 2010. Such a regular upward and downward trend, which is also observable in the next following years, shows how decisions of farmers with long-term memory vary in the years that they remember flooding and years that they forget the event.

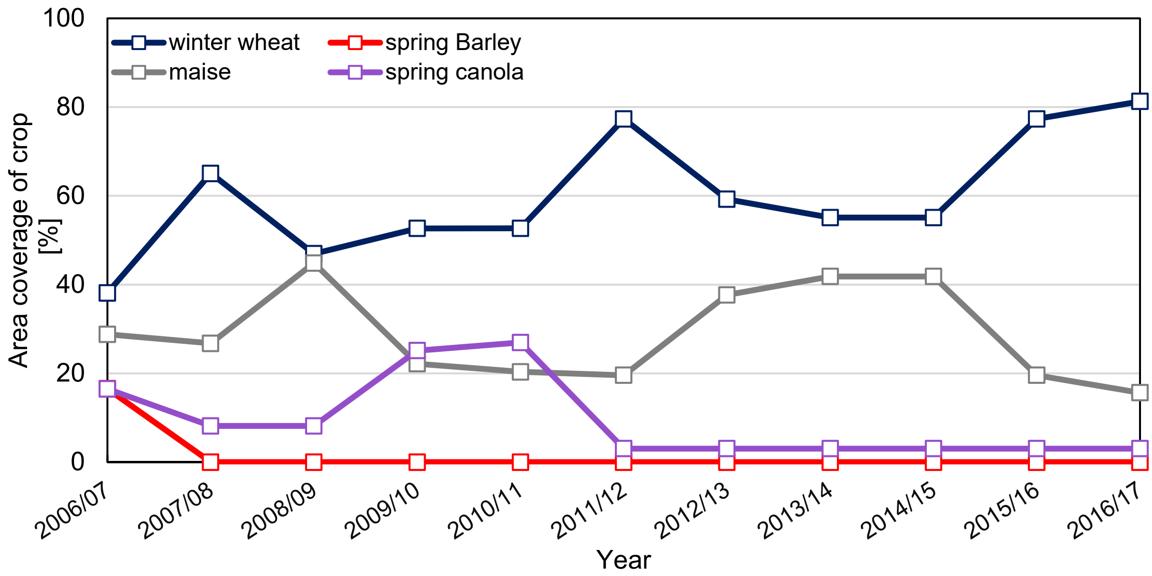


Figure 7-26. Proportion of crops over years for risk-taker farmers with short-term flood memory (Exp5) when 200-year flood occurs in year 2006, 2010, 2014

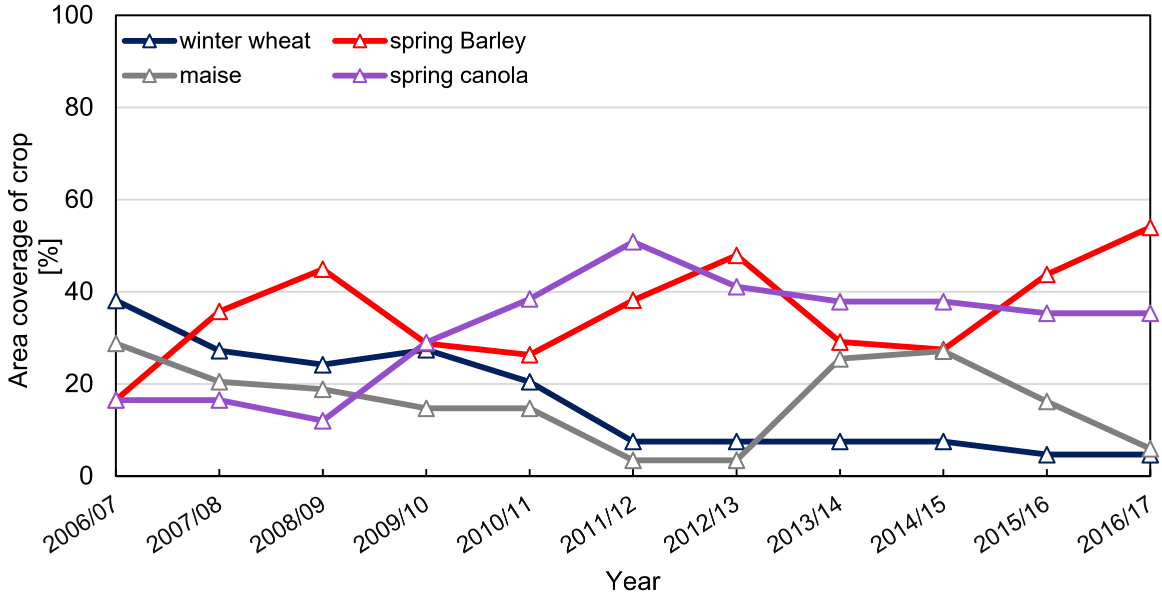


Figure 7-27. Proportion of crops over years for risk-taker farmers with long-term flood memory (Exp4) when 200-year flood occurs in year 2006, 2010, 2014

Figure 7-28 shows the significance of flood memory in spatial representation of agricultural expected damage and expected profit of each individual farmer in two simulation years 2010 and 2014. According to the figure, in total, farmers achieve more expected profit when they have shorter flood memory.

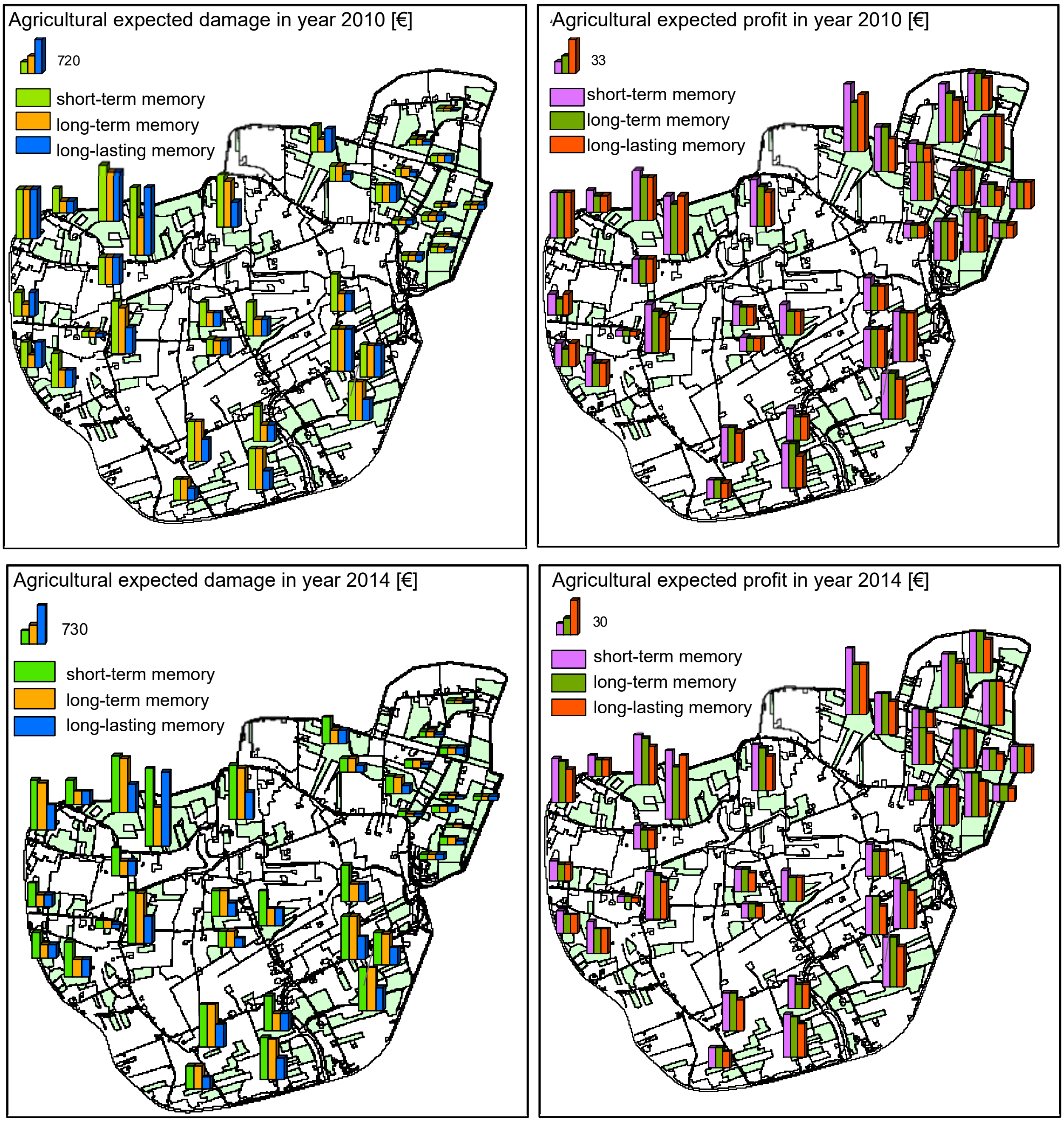


Figure 7-28. Agricultural flood risk (left) and expected profit (right) at the individual level in year 2010 and 2014 for risk-taker farmer with long-lasting flood memory (Exp3), long-term flood memory (Exp4), and short-term flood memory (Exp5) when 200-year flood occurs in year 2006, 2010, and 2014

As can be observed in the figure, on the micro-level, the behaviors of the majority of farmers lead to less individual agricultural flood risk when they have longer duration of flood memory. In year 2010, however, a few farmers are exposed to more flood risk when their memory is long-lasting. Having a closer look at the behavioral strategies of these farmers with long-lasting flood memory reveals that they rely on the strategies involving social interaction (imitation or social comparison) and thus, functioning of social networks is the key to explain this observation. The model results show, however, that the effect of flood memories on risk reduction is larger than social networks in such a way that all most all farmers face less risk in 2014 when they have long-lasting memory.

Figure 7-28 also indicates that farmers living in the northeastern part of the Island face very low expected flood damage in comparison to others. Spatial exposure analysis supports this phenomenon depicting that these farmers are less exposed to the probable flood events (see also Figure 4-9, Figure 4-10, and Figure 4-11).

Figure 7-29 and Figure 7-30 illustrate macro-level effects of individual flood memory and decision-making on regional agricultural flood risk and expected profit, respectively. According to Figure 7-29, the longer the duration of flood memory of individual farmers, the less the regional agricultural flood risk. This finding highlights the linkage between the vulnerability of the agricultural sector at micro-and macro-level. It can be observed in Figure 7-30 that total expected profit of agricultural sector also depends on the flood memory. In particular, agricultural sector makes more expected profits when the farm population consists of farm agents with shorter flood memory.

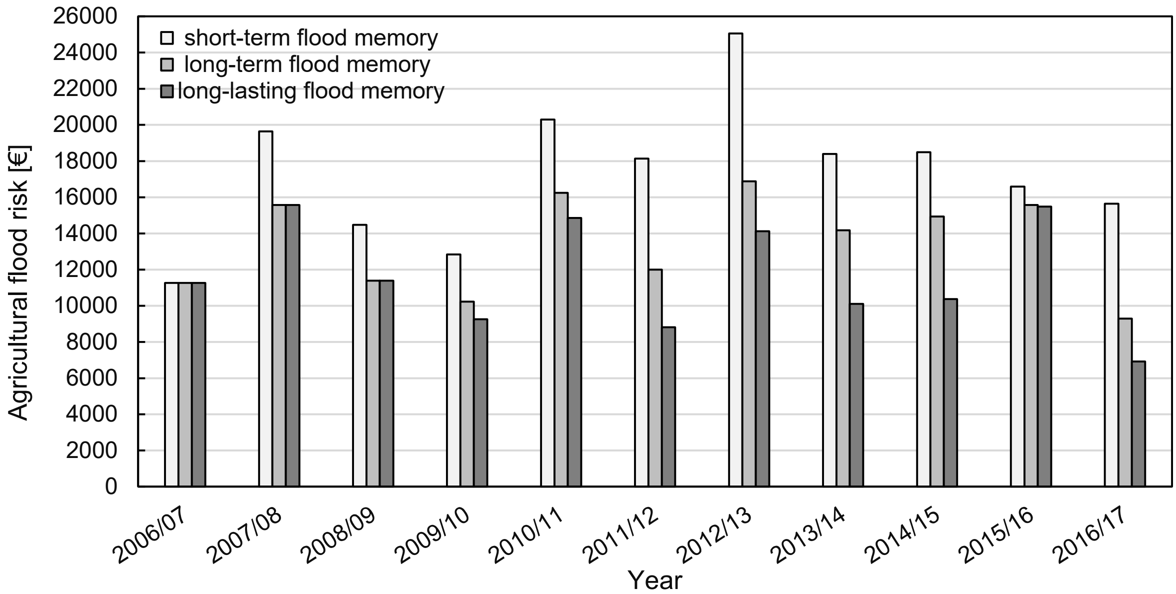


Figure 7-29. Agricultural flood risk at the regional-level over years for risk-taker farmers with long-lasting flood memory (Exp3), long-term flood memory (Exp4), and short-term flood memory (Exp5) when 200-year flood occurs in year 2006, 2010, and 2014

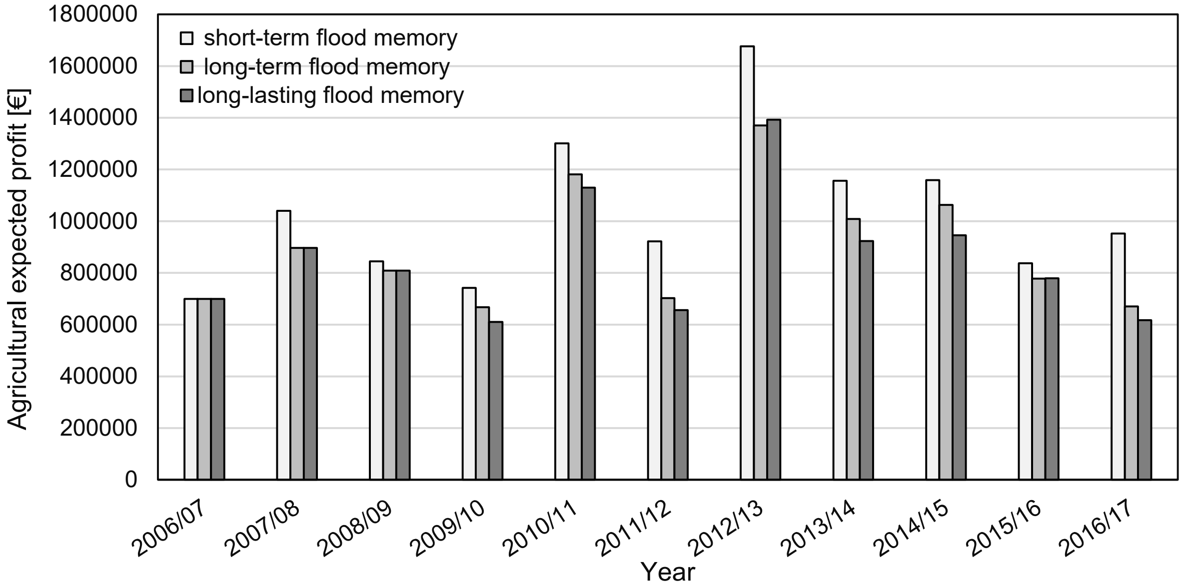


Figure 7-30. Agricultural expected profit at the regional-level over years for risk-taker farmers with long-lasting flood memory (Exp3), long-term flood memory (Exp4), and short-term flood memory (Exp5) when 200-year flood occurs in year 2006, 2010, and 2014

2.4 Conclusions and discussion

The ABMFaFo developed in the previous chapters was applied in this chapter to investigate farmers-flood interaction and its contribution to FRM at the individual level. More specifically, series of in silico experiments were run to examine the influence of flood frequency, individual flood memory, individual risk perception, and social interaction, on the regional dynamics. All simulations were carried out for the period 2005-2016 to explore the trend in micro-and macro-level outcomes. The same land management practices as well as time series of crop prices, costs, and weather variables were applied across all simulations. Farm populations were supposed to be similar in initial cropping pattern as well as in their attributes such as uncertainty threshold, satisfaction threshold, risk tolerance, farm-size similarity and proximity, farmland distribution, and farm-size. The impacts of the influential factors on farmers' decision-making and regional outcomes were quantified through the application of developed ABMFaFo for exploring farmers-flood interaction in coasts. For this aim, Pellworm Island in Germany was chosen as the virtual island which gives the opportunity to develop the physical environment of the ABMFaFo based on the real data.

The role of flood frequency was first evaluated with respect to the behavior of risk-averse farm population with long-lasting flood memory in two different flood scenarios: three "200-year flood" scenario and no flood occurrence scenario. The results indicate that flood vulnerability of the regional agricultural sector is significantly mitigated (6%-65%) when farm agents experience flooding in the simulation period. The remarkable increase (by 37.8 % in year 2013 and by 46.6 % in year 2016) in the percentage of farmers taking the private adaptive strategy when three “200-year flood” occur, shows also the positive influence of “flood experience”. These findings highlight that once individuals are directly affected by the hazard, flood damage is no longer hypothetical, but actual. Thus, they make more effort to prepare themselves to cope with flooding. In contrast, when flood disaster does not occur in the region for a long time, individuals experience no hazardous event and they use to live with flood. Such a lack of experience is likely to result in a lack of individual preparedness. As a result, farm agents face more expected flood damage at the micro-level which in turn causes regional agricultural sector tackle more economic problems. Empirical studies conducted by Harries and Penning-Rowsell (Harries and Penning-Rowsell, 2011), Bubeck et al. (Kreibich *et al.*, 2017), and Kienzler et al. (Kienzler *et al.*, 2015) confirm the findings.

In the next step, the influence of risk perception was examined on two farm populations that only differ in their level of risk tolerance. It was assumed that both populations are subject to the regular flooding (three “200-year flood”). In addition, possible private adaptive strategies were introduced at the beginning of the simulations. The results reveal that taking private adaptive responses and being involved in FRM can outweigh the effect of flooding at both individual and regional-level. Although the farm agents were not familiar with salt-tolerant crops before, existing a small share of rational optimizers were enough to help the whole population to be aware of such new practices over time and choose them as best practices. This newness of adaptation strategy, however, caused the slow adoption of the adaptive responses across the population indicating the need for continues engagement of farmers in FRM. The findings also demonstrate that social interaction plays an important role in the diffusion of information and the degree of individual involvement in FRM.

To study the role of flood remembrance in risky-choices of farm agents, two sets of experiments were conducted, each investigated the farmers’ responses to flood under different flood memory assumptions. It is obvious from the results that when individuals forget the flood event immediately, such a flood experience does not influence their actual and future decisions which causes more income loss comparing to the farm populations with longer flood memory. The results also demonstrate that farmers with long-lasting flood memory show more stability in their decisions and responses to flooding over time. Finally, the findings emphasize the importance of longer (stronger) flood memory in flood risk mitigation of individual farmers as well as that of the regional agricultural sector.

Overall, the results shed light that differences in flood risk dynamics of agricultural sector at regional-level highly depend on the behaviors of farm agents at the micro-level. It could be observed how collective properties arise from the properties of entities. From the results presented in this chapter, it can be also seen that different influential factors are not equal in their effectiveness in vulnerability reduction at both farm- and regional-level. For the particular scenarios examined in this study, it can be concluded that probably the most effective combination of factors in achieving the highest reduction in regional agricultural flood risk is to have farm agents who are risk-averse, have flood experience, and never forget flooding in their life time.

Chapter 8 Summary and outlook

1. Summary

The study investigates farmers' decision-making in response to flood under the influence of individual risk perception, social interaction, flood memory, and limited access to information. For this aim, the study employs "Agent Based Modeling" within the framework of flood risk management (FRM) and presents an experimental platform to simulate farmers' adaptive behavior patterns in coastal regions. To the best of author's knowledge, this research is one of the first attempts to take such a bottom-up approach in flood studies in order to include social aspects of human-flood interaction in FRM.

Agent Based Modeling is relatively a new style of modeling in flood management studies where the overall flood loss in the system is traditionally computed as the metric of the society vulnerability to be further managed through risk reduction strategies. This macro-scale perspective in flood management is valid only under specific assumptions: at-risk individuals (and their surrounding environment) are inactive, they are homogenous in their socio-economic attributes, they access to complete information, they behave as economic optimizers and rational agents, and their vulnerability is constant over time. However, social aspects of human behavior such as individual adaptation responses, knowledge exchange, flood memory, and flood risk perception cause temporal changes in exposure as well as in vulnerability and shape a new mode of human-flood interaction. Subsequently, new conditions are imposed to the system that cannot be addressed by traditional FRM models. Agent Based Modeling provides an innovative approach to formulate the system from the perspectives of individuals, preserves the heterogeneity among agents, and allows modeling social aspects and complexities of human behaviors in FRM and in combination with engineering practices.

To achieve the goals, an Agent Based Model (ABM) platform of farmers' decision-making is developed and linked to the hydrological module as well as hydrodynamic module designed for this purpose, to examine the change in flood risk and dynamic of farmers' behavior. The coupled model, which is called "**A**gent **B**ased **M**odel for **fa**rmer-**flo**od interaction (ABMFaFo)", introduces the interactions among farmers about new coping strategies and market opportunities and includes flood memory as well as individual perception and assessment of flood risk in farmers' decision-making under uncertainty. Additionally, farmers' decisions are formulated in the ABMFaFo through bounded-rationality theory to consider limited information availability as well as limited information processing capacities of people.

The ABMFaFo takes an integrated modeling approach and consists of five main modules including two external and three internal parts. The hydrological module is based on the Soil and Water Assessment Tool (SWAT) to predict crop productivity. In order to increase the model efficiencies in simulating water budget and crop growth components, a 2-stage calibration procedure including hydrological and crop yield calibration is established. The calibrated-validated hydrological module is then used to simulate annual crop yield on the field-scale as the result of farmers' yearly decision-making. Another external part is the hydrodynamic module which is designed based on Protection Measures against Inundation Decision Support (ProMaIDes) in order to compute water levels and velocities as well as inundation areas under different flooding scenarios. Finally, the ABM platform is established to model farmers' decision-making in response to flood. For this purpose, three modules including farmers' decision-making module, risk perception module, and flood risk analysis module are developed and embedded in the ABM platform which is then linked to the two external modules. The module of farmers' decision-making is based on socio-economic approaches and mathematical programming principles equipped with individual risk judgment and adaptive responses in risk perception module. The flood risk analysis module is coupled with the established modules to compute agricultural flood damage and associated risks in coasts based on the developed modeling framework for flood damage function of crops.

Pellworm Island in north of Germany is chosen as the virtual study area and the established ABMFaFo is applied to 37 semi-hypothetical farmers living on the Island. The agent classes of the ABMFaFo are farmers, farmlands, crops, and social networks. Crop cultivation is the main economic activity farm agents do in the model to earn money and their decision for the next year affects their farm profit. Farm agents are heterogeneous in their behavioral rules and interaction groups. They are also heterogeneous in terms of farm-size, income, and exposure to flooding. Other factors differentiating one farmer from another are risk perception and personal characteristics such as risk tolerance, satisfaction threshold, and uncertainty threshold. Crop productivities can also vary from farmer to farmer if there are any differences in the soil type or land management practices, and from year to year due to differences in the weather.

In the ABMFaFo, agent classes are connected within the physical and social environment. The physical environment comprises crops, soil, farmlands, climate, flood protection structures, and the surrounding sea and is parameterized based on the real data of Pellworm Island. The social environment consists of farm agents and their social networks. Due to lack of empirical data, assumptions are made about the required parameters of the social environment.

At the end of the year, each farmer has to choose the suitable crop for cultivation in the next year. For this aim, farmers estimate their farm income and evaluate their satisfaction and uncertainty in the current year. Depending on her/his satisfaction and uncertainty level, each farmer follows a certain behavioral strategy to take her/his decision for the next year. Uncertain farmers consult their peers in the social network to update their information about others' decisions and adaptive responses. Farmers, who have high level of satisfaction, will engage in the imitation or repeat their previous behavior. In contrast, dissatisfied farmers try to obtain more satisfied outcomes by deliberating or engaging in social comparison. Flood memory of these farmers plays a crucial role in their objective function. While long-lasting flood memory causes farmers minimize their expected flood damage, short-term flood memory results in selecting the crop with highest expected profit.

Farmers' knowledge of the weather, flooding situation, and crops in the market as well as prices and associated costs are updated during each simulation year. Computing the crop production on the field-scale by hydrological module, each individual farmer will be aware of her/his crop yield in the current year. She/he will also become conscious of the potential damage to agricultural crops due to the coastal flooding. Meanwhile, farmers' perception of flood danger is shaped. Hence, the rational farmer assesses the level of danger and decides to deal with flood risk through or without adaptation strategies in her/his decision-making. Due to lack of empirical data, it is not possible to know the value for risk tolerance. Therefore, three farm populations are defined differing in their risk tolerance: risk-averse, risk-taker, and mix farm population. The risk tolerance ranges from 0-2, 7-9, and 0-9 for risk-averse farm population, risk-taker farm population, and mix farm population, respectively.

After farmers' decision-making is completed, it is considered to be the end of the year. At this point, decisions taken by farmers will be fed back into the developed modules and the explained process will be continued year by year over the time horizon as the result of feedback between ABM platform and other modules.

The established ABMFaFo is run using a series of in silico experiments to investigate farmers' decision-making in flood-prone areas in response to coastal flooding. More specifically, the effect of flood frequency, risk perception, social interaction, past experience, and flood memory are examined and discussed. In addition, the interdependencies between agricultural sector at farm-level and regional-level are explored using several macro-metrics. Farm agents in all scenarios are bounded-rational and make their decision based on the heuristic rules in Consumat approach. Every experiment is run for the time horizon 2005-2016, including one year of warm up period for the model.

2. Major findings

The results of hydrological module indicate its potential in predicting annual crop productivity of individual farmers in order to model their yearly decision-making. The established hydrological module provides a basis for simulating any desired outputs on the field-scale. The implication of the findings is in the micro economic analysis where behaviors of individual farmers are the key components of decision-making process.

The results of flood damage assessment of agricultural sector highlight the contribution of a wide range of factors to crop damage under coastal flooding. Although seawater salinity is the major underlying parameter, other influential factors such as time of flooding, seawater temperature, growth stage of plant, crop type, and crop characteristics also play vital role in this regard. The study presents the nonlinear mathematical equation which governs the relationship between above-mentioned factors and agricultural crop failure due to coastal flooding. To estimate the flood damage to crop, a function-based framework is proposed and integrated in the flood risk analysis module.

The results of agricultural flood damage assessment reveal that salinity-damage curve of crops is a linear function of soil salinity. In comparison to very tolerant crops, sensitive crops lose their yield even under very low soil electrical conductivity (1 dS/m). The outcomes also confirm the significance of time of flooding on the amount of damage to crops as it plays role in seawater temperature as well as salinity. According to the results, coastal flooding in summer damages all crops completely, whereas winter flooding destroys only sensitive and moderately sensitive crops severely. As Pellworm Island is threatened by storm surge flooding in winter, except for barely, all traditional crops are damaged completely once their farmlands are inundated by salty seawater in winter. The implication of the results is that a salt-tolerant crop program can help farmers in the coasts, to mitigate their crop yield loss and in turn their individual vulnerability to flooding. Such loss reduction strategies at farm-level promote not only the well-being of individual farmers but also improve the performance of agricultural sector at regional-level.

The results of the ABMFaFo show the positive side of frequent flooding which is relatively unfamiliar. Although three “200-year flood” occurrence causes extensive actual flood damage to the agricultural sector (400000€ to 800000€), the resulting regional agricultural flood risk under this scenario is 6%-65% less than the total agricultural flood risk when no flood occurs in the simulation period. Such a “flood experience” effect is also observable in the expected flood damage of individual farmers under the two flood frequency scenarios. According to the findings, share of risk-averse farmers who have experienced flood events in the simulation period, in cultivating salt-tolerant crops in year 2016 is 2.3 times than that of without direct experience. These results emphasize the positive influence of flood experience on the preparedness of farmers in terms of adaptive responses. Another important implication is that living in flood-prone areas may not be enough to be well-prepared to cope with flooding as lack of flood experience results in lack of individual preparedness which may pose serious threads for future at both farm- and regional level.

The findings indicate that flood experience is more effective when farm agents have longer flood memory. It is also striking that farmers with long-lasting flood memory show more stability in their decisions and responses to flooding. The broad implication of the present results is how memory of flood events plays a crucial role in the individual’s sense of preparedness. To ensure the longer flood memory, it is, therefore, essential for governments and policy makers to strengthen the public memory by embedding symbols in the landscape (such as flood marks and flood gauges) and materialization (such as photographs and stories). Posting photos and events on social media can also improve the memory of certain events.

Comparing the behaviour of risk-averse farm population and risk-taker farm population indicates that different risk tolerances lead to different individual responses to flooding. While risk-takers manage the flood risk through existing crops, risk-averse farm agents engage in FRM by adaptive strategies such as changing their cropping pattern and employing salt-tolerant crops. It is observed that risk-averse farmers are reluctant at the beginning of the simulation to adopt the new practice as they are unfamiliar with that. They also show slow adjustment in their decisions. Here, social interaction plays a crucial role in diffusion of information and dissemination of this new strategy as well as adaptive policies. It can be also seen that adaptation is more effective in reducing the flood vulnerability of agricultural sector when at least a few numbers of risk-averse farmers start to engage in private adaptation strategies from the very beginning and continue their adaptation over time. Such a contribution in FRM at the individual level leads to the remarkable reduction in the vulnerability of agricultural sector especially in the last years of simulation (up to 60% in year 2015) which sheds light on the interconnection of various levels in agricultural sector. These highlight the importance of “Adaptation” effect in outweighing the effect of flooding at both individual and regional-level. The implication of the results is that a salt-tolerant crop program (or more generally adaptation policies) may not be completely effective in achieving it goals; in order to increase the chance of succeed, governments should raise the risk awareness of people to ensure their continues involvement. It is also essential to communicate flood risk to individuals in the way that it is understandable and provide them with sufficient information about coping strategies.

It should be noted that different determinants are not equal in their effectiveness in the flood vulnerability reduction. For the particular scenarios examined in this study, it can be concluded that probably the most effective combination of factors in achieving the highest reduction in regional agricultural flood risk is to have farm agents who are risk-averse, have flood experience, and never forget flooding in their life time. In addition, due to nonlinear behaviors in such a coupled human-natural system, there is a tradeoff among different influential factors of which policy makers should be aware.

Overall, the results shed light on how Agent Based Modelling improves our understanding about human-flood interactions and how the approach incorporates such social phenomena into engineering practices. They also highlight the potential of Agent Based Modelling in capturing the complexities of social behaviour patterns and its contribution in representing the interactive entities of the system. The results also demonstrate the ability of the approach in addressing the challenges regarding micro-level decision-making. Another promising finding is the usefulness of the integrated approach taken to establish the ABMFaFo in incorporating the characteristics of such an interdisciplinary problem. More specifically, the proposed framework couples a set of processes representing the complete flood risk chain for the desired problem: hydrologic-agronomic process, hydrodynamic process, flood damage assessment and analysis, and social behavior model. Subsequently, this integrated model provides a feedback mechanism between farm agents as well as the physical and social environment in flood-prone areas through linking the five modules designed for this purpose.

3. Limitations and future work

The results indicate the capability of established model in capturing complexities of human behaviors and including them in FRM. However, there are several limitations that could be addressed in future research. The first is the parameterization which is a challenge in any simulation model, and especially in ABMs due to their bottom-up approach and multi-level structures (Zenobia *et al.*, 2009; Kasaie and Kelton, 2015). In the present work, assumptions were made regarding some attributes of farmers such as satisfaction, uncertainty, risk tolerance threshold, and social networks which can be improved by real data to enrich the model for developing more realistic rules. This is primarily because of lack of empirical data on the behavioral characteristics of local farmers living on the Island. Therefore, for the purpose of this study, these attributes were quantified based on random values which can be the reason why in reality, less farmers (than expected) may have tendency to engage in private adaptive policies.

The second limitation concerns the constant flood risk perception of farm agents, which may be not entirely realistic. Risk perception is not only an individual but also a social phenomenon that may change over time in response to fluctuations in problem severity. While studies provide evidence on the dynamic process in risk perception (Loewenstein and Mather, 1990; Moussaïd, Brighton and Gaissmaier, 2015), there is little empirical research to show how risk perception changes over time and which factors influence such a dynamic. In the present work, static condition was assumed for individual judgment of flood danger as no empirical study is available that can be used to define an updating procedure for flood danger perception over the simulation period.

In addition, there may be relationships between past experience, risk perception, and personal characteristic resulting in tradeoffs between influential factors. Such interlinkages lead to complexities in human behavior and individual decision-making in the risk context. It is not also an easy task to include their interdependencies in the model without conduction of socio-physiological studies, collaboration of relevant experts, and access to rich empirical data. Due to the above-mentioned reasons, current study includes these variables independently in the model to take some first steps toward addressing the crucial roles of these determinants.

Hence, it is worthwhile in future attempts to gather empirical data about attributes and behaviors of farmers living on the Island through experimentation and observation. It is very much the key component to conduct surveys, questionnaires, and interviews with local farmers to enrich the model with more real data. To achieve the goals, collaboration of researchers from different disciplines as well as expert judgments are in demand. Such an interdisciplinary work provides engineers, economists, and sociologists with the opportunity for open discussion across various disciplines to overcome the interdisciplinary challenges. Field survey and observation data are also beneficial to compare the outputs of the model with those in reality and improve the model performance.

Future research could include other possible private adaptation strategies of farmers living in flood-prone areas. In this regard, collaboration of local farmers and experts in the field of agriculture are useful. It would be also interesting to examine the role of external incentives, such as financial support provided by governments or flood insurance policy, in individuals' engagement in FRM. It should be noted that such policy instruments demand long-term impact assessment in addition to the short one to identify their effects on the decision-making at the micro-scale.

It may be also the question of future research to explore the changes at the regional agriculture driven by behavioral micro-foundations under various climate change scenarios. The current study does not consider future climatic condition as it was not within the scope of research. Nevertheless, it can be of future interest to address such an issue, as flood events are expected to occur more frequently and become more severe due to climate change. Therefore, future studies could explore individual responses to flood under climate change scenarios and identify agents that are not able to adapt. This provides a good starting point for discussion about mechanisms and policies that can stimulate these farmers to take loss-reduction strategies under future climatic condition.

For future work, it would be meaningful to conduct the research for other study areas, as the results are case-specific and subject to change if the area under study is dissimilar in the physical and social environment.

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Curriculum Vitae

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Scientific Career

09.2019-12.2019	Guest Researcher in German Federal Institute of Hydrology (BfG), Koblenz, Germany
Since 2015	PhD., Civil Engineering (Water Engineering), IWW, RWTH Aachen University, Aachen, Germany
2011-2013	Research associate, Civil Engineering (Water Engineering), Sharif University of Technology, Tehran, Iran
2008-2011	M.Sc., Civil Engineering (Water Engineering), Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran
2004-2008	B.Sc., Civil Engineering (Structural Engineering), Isfahan University of Technology, Isfahan, Iran

Honors and awards

2016	Being awarded for participating in one-week 7th ESSA summer school in Social simulation, Rome, Italy
2015-2019	Winning and being awarded DAAD scholarships “Sustainable Water Management- NaWaM” for doctoral study in Germany
2015	Winning DAAD scholarship “Research Grants and study scholarship”
2014	Being awarded for participating in 12 days school “applied hydrology in rural area” in Ruhr university of Bochum, financed by German IHP/HWRP, Germany
2008-2011	1st rank among 18 students of civil engineering (Water Engineering and Environment), Amirkabir University of Technology in M.Sc. Program,Tehran,Iran
2007	Being awarded for participating in two-week summer school "Earthquake-Safe Housing Creates Jobs" Bergische Universität Wuppertal (BUW), Germany
2004-2008	Graduated with honors, Bachelor degree, Isfahan University of Technology